# HYBRID-TAYBERRY, SELF-HELP REGIME, ADAM'S ALE SEQUENCE, METOZA APPETITE AND BARBARY FALCON SEARCH ALGORITHM FOR REAL POWER LOSS REDUCTION IN ELECTRICAL TRANSMISSION NETWORK

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## Abstract

**Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite, and Barbary Falcon Search Algorithm (HTSAMB) designed to solve the real power loss reduction problem. Key objectives are Real power loss reduction, Voltage stability enhancement, and deviation minimization. The Tayberry Algorithm is based on the propagation of the plant Tayberry and it grows rationally well in almost all types of soils and even in deep shade conditions. The Self-help Regime Optimization algorithm is designed by imitating the humanoid societal functioning. Adam's ale Sequence procedure starts with the supposition of water flow and oceanic is selected as the premium entity. Metoza's Appetite based search algorithm is based on actions of Metoza during starving conditions and mutual deportments. Barbary Falcon search optimization algorithm is based on the Search and stalking progression. The projected HTSAMB algorithm has been validated in IEEE 57, 354, and 220 KV systems.**

**Keywords:** **Population; runner; stalking; water flow**

## Introduction

In this paper Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite and Barbary Falcon Search Algorithm (HTSAMB) is designed to solve the Real power loss reduction problem. Tayberry Algorithm is based on the propagation of the plant Tayberry and it grow rationally well in almost all the type of soils and even in deep shade conditions. In this planned process, rendering to the private familiarities, constellation understandings, and sequential involvements of each entity chooses the succeeding place. Drive strategy and fresh locus of the affiliate will be demarcated with orientation to the premeditated appropriateness rate and in assessment. Grounded on the contemporary location first crusade dogma for the ith affiliate is engaged up. Adam's ale Sequence procedure starts with presupposition of shower and oceanic is selected as the premium

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entity. In beginning of the watercourse the Adam's ale rivulets move into waterways rendering to the power of the flow of Adam's ale. Metoza Appetite based search algorithm is based on action of Metoza during appetite conditions and mutual deportment's. Energetic, power and acclimatizing exploration method expenditures the elementary value of Appetite as one of the vital steady enticements and elucidations for performance, movements, and pronouncements to permit the optimization method to be more spontaneous and candid for the investigator's survival of all classes. Metoza Appetite based search algorithm is based on the natural activities of Metoza. In divergence, binary forms are hypothetical to accomplish sound if castoff correspondingly in the meantime the exploration zone is limited to twofold standards for each facet. Transfer utility requisite be castoff to allocate the Appetite standards to the possibilities of famishments so that the location can be rationalized. Fresh locations of the appetite originated by confined or universal exploration is requiring incessant output, nonetheless these incessant locations ought to be transformed into binary. This alteration is attained by altering incessant locations of every facet by employing a Sigmoidal Transfer utility, which guides the appetite to mobile in a binary position. Barbary falcon search optimization algorithm is stimulated by Barbary Falcon Search and stalking progression. Barbary Falcon starts the exploration for prey in this exploration zone by moving in a helix silhouette to accelerate the exploration. Projected HTSAMB algorithm has been validated in IEEE 57, 354, and 220 KV systems.

## Problem Formulation

Objective function of the problem is defined as,

$$Min\ \bar{F}(\bar{g},\bar{h}) \tag{1}$$

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

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

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

$$g = [VLG_1,..,VLG_{Ng}; QC_1,..,QC_{Nc}; T_1,..,T_{N_T}] \tag{4}$$

$$h = [PG_{slack}; VL_1,..,VL_{N_{Load}}; QG_1,..,QG_{Ng}; SL_1,..,SL_{N_T}] \tag{5}$$

$Q_c$ →reactive power compensator
$T$ →Transformer tap
$V_g$ →Generator voltage
$PG_{slack}$ →Slack generator
$V_L$ →Voltage in transmission lines
$Q_G$ →Reactive power generator

Fitness functions are defined as follows,

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

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

$$F_3 = Minimize\ L_{MaxImum} \tag{8}$$

$S_L \rightarrow Apparent\ power$

$$L_{Max} = Max[L_j]; j = 1; N_{LB} \tag{9}$$

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

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

Parity constraints

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

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

Disparity constraints

$$\mathrm{P_{gsl}^{min}} \le \mathrm{P_{gsl}} \le \mathrm{P_{gsl}^{max}} \tag{14}$$

$$\mathrm{Q_{gi}^{min}} \le \mathrm{Q_{gi}} \le \mathrm{Q_{gi}^{max}}, \mathrm{i} \in \mathrm{N_g} \tag{15}$$

$$\mathrm{VL_i^{min}} \le \mathrm{VL_i} \le \mathrm{VL_i^{max}}, \mathrm{i} \in \mathrm{NL} \tag{16}$$

$$\mathrm{T_i^{min}} \le \mathrm{T_i} \le \mathrm{T_i^{max}}, \mathrm{i} \in \mathrm{N_T} \tag{17}$$

$$\mathrm{Q_c^{min}} \le \mathrm{Q_c} \le \mathrm{Q_C^{max}}, \mathrm{i} \in \mathrm{N_C} \tag{18}$$

$$|SL_i| \le S_{L_i}^{max}, \mathrm{i} \in \mathrm{N_{TL}} \tag{19}$$

$$\mathrm{VG_i^{min}} \le \mathrm{VG_i} \le \mathrm{VG_i^{max}}, \mathrm{i} \in \mathrm{N_g} \tag{20}$$

$$MF = F_1 + r_iF_2 + uF_3 = F_1 + \left[\sum_{i=1}^{NL} x_v\left[VL_i - VL_i^{min}\right]^2 + \sum_{i=1}^{NG} r_g\left[QG_i - QG_i^{min}\right]^2\right] + r_fF_3 \tag{21}$$

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

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

## Hybrid Tayberry, Self-help Regime, Adam's ale Sequence, Metoza Appetite and Barbary falcon search Algorithm

In this paper Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite and Barbary Falcon Search Algorithm (HTSAMB) is designed to solve the power loss reduction problem. HTSAMB algorithm balances the Exploration and Exploitation sequentially. Tayberry Algorithm is based on the propagation of the plant Tayberry and it grow rationally well in almost all the type of soils and even in deep shade conditions. Once there are adequate nutrients, and sunlit, then it spontaneously adverts in that zone deprived of any additional crusade. Customarily abundant tiny runners are abiding in the specific vicinity in extreme level. Once mother Tayberry is scanty then they resolve to discover an improved predicament for its offspring's. Continuously it will coerce limited runners and additionally arena to explore fresh aloof zones. Tayberry $T_i$ is in quandary $U_i$ with breadth.

$$U_i = \{u_i\}; \text{ for } j = 1,2,3..,n$$

Exploitation is smeared by dissemination of voluminous elfin runners by Tayberrys in good acnes, and exploration is pragmatic by dispersal of diminutive runners by Tayberrys in flimsy acnes. Supreme amount of cohort's is represented by $c_m$, ultimate quantity of conceivable runner is symbolized by $cr_{max}$ for each Tayberry. Sum of Tayberry runners $Tr_\alpha^i$ is computed and it has dimension $Q^i$ is computed by means of the standardized form of the key value at $U_i$,

$$Q^i \in (-1,1)^n$$

Quantity of runners for a specified Tayberry is proportional to its appropriateness value,

$$Tr_\alpha^i = [Tr_{max} V_i \alpha], \alpha \in (0,1) \quad (25)$$

Each solution $U_i$ produces lowest one runner and stretched long runner is proportional to its development;

$$Q_j^i = 2.0(1 - V_i)(\alpha - 0.5), : \ j = 1,2,3,..,n \quad (26)$$

Succeeding zone is determined by,

$$W_{i,j} = u_{i,j} + (h_j - g_j)Q_j^i, for\ j = 1,2,3,..,n \quad (27)$$

In capricious mode populace are engendered

$$u_{i,j} = g_j + (h_j - g_j)\alpha, j = 1,2,3,..,n \quad (28)$$

Proceeding to the streamlining the populace a provisional population Δ to hold fresh elucidations designed from each single in the populace. A secure modification factor $M_m$ nominated and reforming the populace is completed by,

$$u_{i,j}^* = u_{i,j}(1 + \beta), j = 1,2,3,..,n \quad (29)$$

$$u_{i,j}^* = u_{i,j} + (u_{l,j} - u_{k,j})\beta, j = 1,2,3,..,n \quad (30)$$

Self-help Regime Optimization algorithm is designed by imitating the humanoid societal functioning. In this planned process, rendering to the private familiarities, constellation understandings, and sequential involvements of each entity chooses the succeeding place. Drive strategy and fresh locus of the affiliate will be demarcated with orientation to the premeditated appropriateness rate and in assessment. Grounded on the contemporary location first crusade dogma for the ith affiliate is engaged up. Drive strategy is designated by Vacillation Index $VI_i(k)$ for affiliate "I" in iteration "k". Once the key function is sanguine then the $VI_i(k)$ is enunciated as,

$$VI_i(k) = 1 - \alpha_i \frac{v(u^*(k))}{v(u_i(k))} - (1 - \alpha_i)\frac{v(w_i(k))}{v(u_i(k))} \quad (31)$$

$$VI_i(k) = 1 - \alpha_i \frac{v(a(k))}{v(u_i(k))} - (1 - \alpha_i)\frac{vw_i((k))}{v(u_i(k))} \quad (32)$$

Rendering to the rate of $VI_i(k)$ drive rule for the ith affiliate can be enunciated as,

$$A_i^p(k) = \begin{cases} D.U^*(k) & 0 \le VI_i(k) \le \alpha_i \\ D.R\,U_i(k) & \alpha_i \le VI_i(k) \le 1 \end{cases} \quad (33)$$

where $D$ is the drive and $R$ is random

For the ith affiliate in the kth iteration Peripheral indiscretion index $PII_i(k)$ is calculated by,

$$PII_i(k) = 1 - e^{-\theta_i[v(u_i(k)) - v(a(k))]} \quad (34)$$

$$PII_i(k) = 1 - e^{-\delta_{i\,E(k)}} \quad (35)$$

Drive dogma grounded on the locations of other affiliates and is demarcated by considering the onset for $PII_i(k)$,

$$A_i^s(k) = \begin{cases} D.a^{Best} & 0 \leq PII_i(k) \leq Th \\ D.R\,U_i(k) & Th \leq PII_i(k) \leq 1 \end{cases} \tag{36}$$

Interior indiscretion index $\Psi_i(k)$for the ith affiliate in the kth recapitulation is cast-off to describe the drive dogma grounded on preceding locations,

$$\Psi_i(k) = 1 - e^{-\beta_i[f(Y_i(k)) - fP_i((k))]} \tag{37}$$

Drive policy grounded on the locations of other affiliates is demarcated by considering the onset for $\Psi_i(k)$,

$$A_i^{pa}(k) = \begin{cases} D.W_i^{Best} & 0 \leq \Psi_i(k) \leq Th \\ D.R\,U_i(k) & Th \leq \Psi_i(k) \leq 1 \end{cases} \tag{38}$$

where *th* specify the threshold

Adam's ale Sequence procedure starts with presupposition of water flow and oceanic is selected as the premium entity. In beginning of the watercourses (Deng *et al*., 2022), the Adam's ale rivulets move into waterways rendering to the power of the flow of Adam's ale. In proposed Adam's ale Sequence algorithm, an amount of the premium exploration mediators are characterized as waterways and the optimum assimilated solution is taken as oceanic. Collection for particular elucidation is appropriately designated as an Adam's ale Sequence (AS). Adam's ale Sequence is an array of $1\times N_v$ in a $N_v$ space and demarcated as,

$$AS = [U_1, U_2, U_3, .., U_n] \tag{39}$$

Rate of the Adam's ale Sequence is premeditated as,

$$cs_i = \int\left(U_1^i, U_2^i, .., U_{N_v}^i\right) i = 1,2,..,NP \tag{40}$$

Adam's ale Sequence that generate the rivulets which drift down straightforward into the oceanic is premeditated as,

$$N_r = waterways\ sum + 1 \tag{41}$$

$$N_{As} = NP - N_r \tag{42}$$

Power of flow of Adam's ale Sequence into the oceanic or to the tributaries is calculated as,

$$NS_s = r\left\{\left|\frac{cs_n}{\sum_{i=1}^{N_{sr}} cs_i}\right| \times N_{AS}\right\}, n = 1,2,..,N_r \tag{43}$$

Waterways flow into the oceanic and the fresh place of the waterways (w) and rivulets (r) can be demarcated as,

$$U_r^{i+} = U_r^i + rand \times c \times \left(U_w^i - U_r^i\right) \tag{44}$$

$$U_w^{i+} = U_w^i + rand \times c \times \left(U_o^i - U_w^i\right) \tag{45}$$

$E_{max}$ represent the vaporization procedure and the value of $E_{max}$ acclimatizes subsequently,

$$E_{max}^{i+1} = E_{max}^i - \frac{E_{max}^i}{max\ no\ of\ iter} \tag{46}$$

Fresh places of the recently made rivulets is demarcated as,

$$U_r^f = min + rand \times (max - min) \tag{47}$$

$$U_r^f = U_o + \sqrt{\mu} \times rand\ n(1, N_v) \tag{48}$$

Each element is drawn towards its own preeminent and global preeminent solution,

$$\underset{n\to\infty}{\mathrm{L}} U_i(t) = \frac{d_1 B_{b_i}(t) + d_2 \times C_b(t)}{(d_1 + d_2)} \tag{49}$$

Locations are rationalized by,

$$U_i^d(t+1) = \begin{cases} N\begin{pmatrix} 0.5 \times \\ \left[C_b(t) + B_{b_i}(t)\right] \\ \cdot \left|C_b(t) + B_{B_i}(t)\right| \end{pmatrix} \\ \quad if\ q > 0.5 \\ B_{b_i}(t) \\ \quad otherwise \end{cases} \tag{50}$$

Grounded on the Gaussian mutation (Zhang *et al*., 2022), new rivulets and waterways are formed as,

$$U_r^i(t+1) = \begin{cases} N\begin{pmatrix} 0.5 \times \left[U_o^i(t) + U_r^i(t)\right] \cdot \\ \left|U_o^i(t) + U_r^i(t)\right| \end{pmatrix} \\ \quad if\ q > 0.5 \\ if\ \left(e\left(-\frac{k}{M}\right) < rand\right) and \\ (NS_i < Er);\ U_r^f = min + \\ rand \times (max - min)\ or\ else \end{cases} \tag{51}$$

$$U_w^i(t+1) = \begin{cases} N\left(0.5 \times \left[U_o^i(t) + U_w^i(t)\right] \cdot \left|U_o^i(t) + U_w^i(t)\right|\right) \\ \quad if\ q > 0.5 \\ U_r^f = U_O + \mu^{0.5} \times rand\ n(1, N_v) \\ \quad or\ else \end{cases} \tag{52}$$

Rivulets are rationalized by,

$$U_r^i(t+1) = \begin{cases} N\begin{pmatrix} 0.5 \times [U_w^i(t) + U_r^i(t)] \\ \cdot |U_w^i(t) + U_r^i(t)| \end{pmatrix} \\ if\ q > 0.3 \\ N\begin{pmatrix} 0.5 \times [U_o^i(t) + U_r^i(t)] \\ \cdot |U_o^i(t) + U_r^i(t)| \end{pmatrix} \\ if\ \ 0.3 \leq q \leq 0.5 \\ N\begin{pmatrix} 0.5 \times [U_o^i(t) + U_w^i(t)] \\ \cdot |U_o^i(t) + U_w^i(t)| \end{pmatrix} \\ if\ 0.5\ < q \leq 0.7 \\ if\ \left(exp\left(-\frac{k}{M}\right) < rand\right) \\ and\ (NS_i < Er); \\ U_r^f\ = min + ran \times (max - min) \\ or\ else \end{cases} \quad (53)$$

$$U_w^i(t+1) = \begin{cases} N(0.5 \times [U_w^i(t) + U_r^i(t)] \cdot |U_w^i(t) + U_r^i(t)|) \\ if\ q > 0.3 \\ N(0.5 \times [U_o^i(t) + U_r^i(t)] \cdot |U_o^i(t) + U_r^i(t)|) \\ if\ \ 0.3 \leq q \leq 0.5 \\ N(0.5 \times [U_o^i(t) + U_w^i(t)] \cdot |U_o^i(t) + U_w^i(t)|) \\ if\ 0.5\ < q \leq 0.7 \\ \\ U_r^f\ = U_o +\ \mu^{0.5} \times rand\ n(1, N_v) \\ or\ else \end{cases} \quad (54)$$

Metoza Appetite based search algorithm is based on action of Metoza during starving conditions and mutual deportment's. Energetic, power and acclimatizing exploration method expenditures the elementary value of Appetite as one of the vital steady enticements and elucidations for performance, movements, and pronouncements to permit the optimization method to be more spontaneous and candid for the investigator's survival of all classes. Originally, the twofold sections validate that the metaheuristic technique, which has been applied to solve the loss lessening problem. Metoza Appetite based search (MAS) algorithm is based on the activities of Metoza such as edginess of being exterminated by slayers and appetite. Scavenging appetite and specific compassionate activities are defined as,

$$\overrightarrow{M(t+1)} = \overrightarrow{M(t)}\,.(1 + r.n(1)),\ r_1 < k \quad (55)$$

$$\overrightarrow{M(t+1)} =\ \overrightarrow{A_{w1}} \cdot \overrightarrow{M_c} + \vec{Q} \cdot \overrightarrow{A_{w2}} \cdot \left|\overrightarrow{M_c} - \overrightarrow{M(t)}\right|,\ r_1 > k, r_2 > U \quad (56)$$

$$\overrightarrow{M(t+1)} =\ \overrightarrow{A_{w1}} \cdot \overrightarrow{M_c} - \vec{Q} \cdot \overrightarrow{A_{w2}} \cdot \left|\overrightarrow{M_c} - \overrightarrow{M(t)}\right|,\ r_1 > k, r_2 < U \quad (57)$$

where
$\overrightarrow{M(t)}$ specify the location of the entities
$\overrightarrow{M_c}$ indicate the location of the most excellent entity
$\overrightarrow{A_{w1}}$ and $\overrightarrow{A_{w2}}$ specifies the Appetite weights
$\vec{Q} \in [-c, c]$
$r_1$ and $r_2 \in [0,1]$
$r.n(1)$ random integer
$k$ is control parameter
$t$ specify the current iteration
$U$ is the paramter to regulate the location

$$U = H(|CF(i) - EF(i)|)$$

where
$CF(i)$ specify the population cost funtion
$EF(i)$ is Excellent cost funtion
$i$ = 1,2,3..,$n$
$H$ is hyperbolic function

$$H(M) = 2.0/e^M + e^{-M}$$

$\vec{Q}$ = 2.0×$c$×$r$ - $c$
$c$ = 2.0×(1 - $t$ / (maximum iteration))
$r \in [0,1]$ Famishing

The appetite performance of all entities during the exploration is scientifically defined as,

$$\overrightarrow{A_{w1}(\iota)} = \begin{cases} \text{Appetite(i)} \cdot N/T\ \text{Appetite}\ \times r_4,\ r_3 < k \\ 1 \quad r_3 > k \end{cases} \quad (58)$$

$$\overrightarrow{A_{w2}(\iota)} = \left(1 - exp\left(-\left|\begin{matrix}\text{Appetite(i)} \\ -T\ \text{Appetite}\end{matrix}\right|\right)\right) \times r_5 \times 2.0 \quad (59)$$

where
Appetite is Famishing of popultaion
$T$ Appetite is total of Famishing senses in population
$r_3,\ r_4 and\ r_5\ \in [0,1]$
$N$ is the population size Supplemental

The Famishing senses of population is defined as,

$$\text{Appetite(i)} = \begin{cases} 0,\ \ TF(i) == EF \\ \text{Appetite(i)} + V,\ \ TF(i)! == EF \end{cases} \quad (60)$$

where $TF$ is the total fitness
while $V$ is Supplemental of real

Famishing of the popultaion

$$V = \begin{cases} LV \times (1 + r),\ \ SV < LV \\ SV,\ SV \geq LV \end{cases} \quad (60)$$

$SV = \frac{Fitness(i) - Excellent\ Fitness}{Poor\ fitness - Excellent\ Fitness} \times r_6 \times 2.0 \times (max - min)$

$r_6 \in [0,1]$ max and min are limits of the area

Commonly, incessant optimization methods forecast piece amalgamations that optimize organization efficiency, and populaces are castoff in the exploration zone. In divergence, binary forms are hypothetical to accomplish sound if castoff correspondingly in the meantime the exploration zone is limited to twofold standards for each facet. Additionally, binary operatives are tranquil to comprehend than incessant operatives. Every entity can alter its position in confined or universal exploration phases. Transfer utility requisite be castoff to allocate the Appetite standards to the possibilities of famishments so that the location can be rationalized. Transfer utility altering the appetite position vector amongst 0 to 1 and vice versa. Fundamentally, the binary exploration zone is a hypercube, with the populaces of the procedure competent to swing to the hyper cube's remote boundaries by exchange of dissimilar bit quantities. The fresh locations of the appetite originated by confined or universal exploration is requiring incessant output, nonetheless these incessant locations ought to be transformed into binary. This alteration is attained by altering incessant locations of every facet by employing a Sigmoidal Transfer utility, which guides the appetite to mobile in a binary position.

$$STU(D_i^k(t)) = 1/1 + e^{-D_i^k(t)} \tag{62}$$

$D_i^k(t)$ is the continuous value of the appetite

$STU$ is Sigmoidal Transfer utility

In a sigmoidal calculation, the extensively castoff stochastic inception is employed to attain the binary rate,

$$\overrightarrow{M(t+1)} = \begin{cases} 0, if\ r < STU(D_i^k(t)) \\ 1, if\ r > STU(D_i^k(t)) \end{cases} \tag{63}$$

where $\overrightarrow{M(t+1)}$ and $STU\left(D_i^k(t)\right)$ specify the decision factor

Then Value Transfer [60-62] utility is employed,

$$VTU(D_i^k(t)) = \left|erf\left(\sqrt{\pi}/2 \times D_i^k(t)\right)\right| \tag{64}$$

$VTU$ is Value Transfer utility

$$VTU(D_i^k(t)) = \left|\sqrt{\pi}/2 \times \int_0^{\sqrt{\pi}/2 \times D_i^k(t)} e^{-t^2}\right| \tag{65}$$

Then the threshold ways is defined as,

$$\overrightarrow{M(t+1)} = \begin{cases} \overrightarrow{M(t)}^{-1}\ if\ r < VTU(D_i^k(t)) \\ \overrightarrow{M(t)}^{1} if\ r \geq VTU(D_i^k(t)) \end{cases} \tag{66}$$

Transfer utility in this binary technique to change the location of appetite to the possibilities of amending the mechanisms of the position vectors. The Value Transfer utility has the benefit of not compelling appetite to yield value 0 or 1. Barbary falcon search optimization algorithm is stimulated by Barbary Falcon Search activities in the course of the stalking progression. The stalking progression can be alienated as; pick and penetrating the zone.

In the pick out the zone Barbary Falcon elect the zone erratically grounded on the preceding examination info as follows,

$$BF_{fresh,i} = BF_E + \delta \times random(BF_{avg} - BF_i) \tag{67}$$

where

$BF_E$ is prsent excellent search space of the Barbary Falcon

$BF_{avg}$ indicate that Barbary Falcon earned all the locations form Preceding places

$\delta$ is the parameter to regulate the change of location by Barbary Falcon

$$\delta = 1.4898 \cdot (max.iter - t + 1)/max.iter$$

$\delta$ is Factor controls the location of the Barbary Falcon and augments the exploration and exploitation

random $\in [0,1]$

Subsequently choosing the examination zone in the preceding phase, the Barbary Falcon starts the exploration for prey (Enriquez *et al*., 2022) in this zone by stirring in a helix silhouette to accelerate the exploration. In this phase, the Barbary Falcon location is rationalized as,

$$BF_{i,fresh} = BF_i + n(i) \times (BF_i - BF_{i+1})BF_E + m(i) \times random(BF_i - BF_{avg}) \tag{68}$$

$m(i) = m\ \text{random}(i))/\max(|m\ \text{random}|)$

$n(i) = n\ \text{random}(i))/\max(|n\ \text{random}|)$

$m\ \text{random}(i) = \text{random}(i) \times \sin(\theta(i))$

$n\ \text{random}(i) = \text{random}(i) \times \cos(\theta(i))$

$\theta(i) = \delta \times \pi \times \text{random}$

$\text{random}(i) = \theta(i) \times Q \times \text{random}$

$\delta$ value is from 5.1 to 9.99

$Q$ value if from 0.498 to 2.10

In the pouncing phase Barbary Falcon flinch to passage from the superlative examination location in the direction of their prey in a swipe drive.

$$BF_{i,fresh} = random * BF_E + m_1(i) \times (BF_i - u_1 * BF_{avg}) + n_1(i) \times (BF_i - u_2 * BF_{avg}) \quad (69)$$

$mA(i)$ = ($m$ random($i$)) ⁄ max(|$m$ random|)
$nA(i)$ = ($n$ random($i$)) ⁄ max(|$n$ random|)
$m$ random($i$) = random($i$) × sinh($\theta(i)$)
$n$ random($i$) = random($i$) × cosh($\theta(i)$)
$\theta(i) = \delta \times \pi \times$random
random($i$) = $\theta(i)$
$u_1$ and $u_2 \in [1,2]$

Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite and Barbary Falcon Search Algorithm (HTSAMB)

a. Start
b. Set the parameters
c. // Tayberry algorithm//
d. Engender the Tayberry population
e. Tayberry population={$U_i$}; $i$ = 1,2,3,.., $NP$
f. $u_{i,j} = g_j + (h_j - g_j)\alpha, j = 1,2,3,..,n$
g. End if
h. $while\ r > NP\ do$
i. $Compute\ IN_j$
j. End while
k. Estimate roughly the quantity of populace
l. Once population is smeared at that time fix quantity of runners
m. while($ngen < gmax$)do
n. Create Δ
o. For i = 1 to NP do
p. For k = 1 to $u_r$ do
q. $if\ r \leq NP, then$
r. $create\ new\ solution\ u^*_{i,j}$
s. $u^*_{i,j} = u_{i,j}(1+\beta), j = 1,2,3,..,n$
t. Calculate the rate
u. End if
v. $if\ r \leq M_m, then$
w. $create\ new\ solution\ u^*_{i,j}$
x. $u^*_{i,j} = u_{i,j} + (u_{l,j} - u_{k,j})\beta, j = 1,2,3,..,n$
y. Calculate the rate
z. End if
aa. Else
bb. For j = 1: n do
cc. $if\ rand \leq M_m, then$
dd. $U_i = \{u_i\};\ for\ j = 1,2,3..,n$
ee. $u^*_{i,j} = u_{i,j} + (u_{l,j} - u_{k,j})\beta, j = 1,2,3,..,n$
ff. End if
gg. Calculate fresh solution
hh. // Self-help Regime algorithm//
ii. Describe the values
jj. $For\ I = 1: M\ do$
kk. $VI_i(k) = 1 - \alpha_i \frac{v(u^*(k))}{v(u_i(k))} - (1-\alpha_i)\frac{v(w_i(k))}{v(u_i(k))}$
ll. Once $VI_i(k)$ is less than the onset $(U_i(k))$ − at that moment transfer to $U^*(k)$
mm. Otherwise in the direction of an arbitrary integer $(U_i(k))$ will be progressed
nn. End if
oo. End for
pp. $For\ I = 1: M\ do$
qq. $PII_i(k) = 1 - e^{-\theta_i[v(u_i(k)) - v(a(k))]}$
rr. $PII_i(k) = 1 - e^{-\delta_i E(k)}$
ss. Once $VI_i(k)$ is less than the onset $(U_i(k))$ − then transfer to $a^{Best}$
tt. Otherwise in the direction of an arbitrary integer $(U_i(k))$ will be progressed
uu. End if
vv. End for
ww. $For\ I = 1: M\ do$
xx. $\Psi_i(k) = 1 - e^{-\beta_i[f(Y_i(k)) - fP_i((k))]}$
yy. When $\Psi_i(k)$ is less than the onset $(U_i(k))$ − then passage to $W_i^{Best}$
zz. Otherwise in the direction of an arbitrary integer $(U_i(k))$ will be progressed
aaa. End if
bbb. End for
ccc. $For\ I = 1: M\ do$
ddd. By assimilating the drive strategies to streamline the location
eee. For every affiliates of the social order compute the fitness value
fff. End for
ggg. End if
hhh. End for
iii. Establish the population in uphill order
jjj. Amend contemporary optimum solution;
kkk. End while
lll. Return: restructured population.
mmm. // Adam's ale Sequence algorithm//
nnn. Quantity of rivulets are calculated
ooo. Stimulate the rivulets capriciously
ppp. Determine the Power of the rivulet
qqq. $NS_s = r\left\{\left|\frac{cs_n}{\sum_{i=1}^{N_{sr}} cs_i}\right| \times N_{AS}\right\}, n = 1,2,..,N_r$
rrr. While $(t < M)$
sss. For $i = 1;\ NP$
ttt. Streamline the rivulets
uuu. For fresh rivulet appraise the main function
vvv. $if\ cs(r(f)) < cs(w); then$
www. $w = r\ (f)$
xxx. $if\ cs(r(f)) < cs(o); then$
yyy. $o = r\ (f)$
zzz. End if
aaaa. End if
bbbb. Waterways are rationalised
cccc. Determine the objective function for fresh waterway

dddd. $if\ cs(w(f)) < cs(o); then$
eeee. $o = w\ (f)$
ffff. End if
gggg. End for
hhhh. for $i = 1$; $NS_s$
iiii. if (nor($o$ - $r$) < $d\_w$)
jjjj. Stimulate fresh rivulets
kkkk. $U_r^f = U_o + \mu^{0.5} \times rand\ n(1, N_v)$
llll. Shrinkage the rate of $E_{max}$
mmmm. $E_{max}^{i+1} = E_{max}^{i} - E_{max}^{i}/M$
nnnn. End while
oooo. // Metoza Appetite algorithm//
pppp. Obtain the cost function
qqqq. $\overrightarrow{M(t+1)} = \overrightarrow{M(t)} . (1 + r.n(1)),\ r_1 < k$
rrrr. $\overrightarrow{M(t+1)} = \overrightarrow{A_{w1}} \cdot \overrightarrow{M_c} + \vec{Q} \cdot \overrightarrow{A_{w2}} \cdot \left|\overrightarrow{M_c} - \overrightarrow{M(t)}\right|,\ r_1 > k, r_2 > U$
ssss. $\overrightarrow{M(t+1)} = \overrightarrow{A_{w1}} \cdot \overrightarrow{M_c} - \vec{Q} \cdot \overrightarrow{A_{w2}} \cdot \left|\overrightarrow{M_c} - \overrightarrow{M(t)}\right|,\ r_1 > k, r_2 < U$
tttt. Modernize the functional values
uuuu. Obtain the Appetite weights
vvvv. $\text{Appetite(i)} = \begin{cases} 0, & TF(i) == EF \\ \text{Appetite(i)} + V, & TF(i)! == EF \end{cases}$
wwww. $\overrightarrow{A_{w1}(\iota)} = \begin{cases} \text{Appetite(i)} \cdot N/T\ \text{Appetite} \times r_4, & r_3 < k \\ 1 & r_3 > k \end{cases}$
xxxx. $\overrightarrow{A_{w2}(\iota)} = \left(1 - exp(-|\text{Appetite(i)} - T\ \text{Appetite}|)\right) \times r_5 \times 2.0$
yyyy. $U = H(|CF(i) - EF(i)|)$
zzzz. $Update\ the\ population$
aaaaa. $\overrightarrow{M(t+1)} = \begin{cases} 0, if\ r < STU\left(D_i^k(t)\right) \\ 1, if\ r > STU\left(D_i^k(t)\right) \end{cases}$
bbbbb. $\overrightarrow{M(t+1)} = \begin{cases} \overrightarrow{M(t)}^{-1\ if\ r < VTU(D_i^k(t))} \\ \overrightarrow{M(t)}^{1} if\ r \geq VTU\left(D_i^k(t)\right) \end{cases}$
ccccc. Rationalize the location of Q
ddddd. $\vec{Q} = 2.0 \times c \times r - c$
eeeee. $\overrightarrow{M(t+1)} = \overrightarrow{M(t)} . (1 + r.n(1)),\ r_1 < k$
fffff. $\overrightarrow{M(t+1)} = \overrightarrow{A_{w1}} \cdot \overrightarrow{M_c} + \vec{Q} \cdot \overrightarrow{A_{w2}} \cdot \left|\overrightarrow{M_c} - \overrightarrow{M(t)}\right|,\ r_1 > k, r_2 > U$
ggggg. $\overrightarrow{M(t+1)} = \overrightarrow{A_{w1}} \cdot \overrightarrow{M_c} - \vec{Q} \cdot \overrightarrow{A_{w2}} \cdot \left|\overrightarrow{M_c} - \overrightarrow{M(t)}\right|,\ r_1 > k, r_2 < U$
hhhhh. End for
iiiii. $t = t + 1$
jjjjj. End while
kkkkk. $EF(i)$ is Excellent cost funtion
lllll. // Barbary falcon search algorithm//
mmmmm. Start
nnnnn. Set the parameter values
ooooo. Engender the Barbary Falcon population
ppppp. Calculate the fitness rate for the Barbary Falcon population
qqqqq. Stockpile the excellent solution
rrrrr. while ($t \leq$ maximum iteration)
sssss. Streamline the solution
ttttt. $\delta = 1.4898 \cdot (max.iter - t + 1)/max.iter$
uuuuu. Estimate the objective function value
vvvvv. Modernize the obtained most excellent solution
wwwww. $BF_{i,fresh} = BF_i + n(i) \times (BF_i - BF_{i+1})BF_E + m(i) \times random(BF_i - BF_{avg})$
xxxxx. $m(i) = m\ random(i)/max(|m\ random|)$
yyyyy. $n(i) = n\ random(i)/max(|n\ random|)$
zzzzz. $m\ random(i) = random(i) \times sin(\theta(i))$
aaaaaa. $n\ random(i) = random(i) \times cos(\theta(i))$
bbbbbb. $\theta(i) = \delta \times \pi \times random$
cccccc. $random(i) = \theta(i) \times Q \times random$
dddddd. Estimate the objective function value
eeeeee. Modernize the obtained most excellent solution
ffffff. $BF_{i,fresh} = random * BF_E + m_1(i) \times (BF_i - u_1 * BF_{avg}) + n_1(i) \times (BF_i - u_2 * BF_{avg})$
gggggg. $mA(i) = m\ random(i)/max(|m\ random|)$
hhhhhh. $nA(i) = n\ random(i)/max(|n\ random|)$
iiiiii. $m\ random(i) = random(i) \times sinh(\theta(i))$
jjjjjj. $n\ random(i) = random(i) \times cosh(\theta(i))$
kkkkkk. $(i) = \delta \times \pi \times random$
llllll. $random(i) = \theta(i)$
mmmmmm. Modernize the obtained most excellent solution
nnnnnn. End

## Simulation Study

Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite and Barbary Falcon Search (HTSAMB) Algorithm validated in in IEEE 57 bus system (IEEE 57-Bus, 2023). Table 1 and Figures 1-3, show the Real Loss (RSS (MW)), Power incongruity (POY (PU)) and forte (PRT (PU)).

**Table 1. Estimation of consequence (IEEE 57 bus)**

| Scheme | RSS (MW) | POY (PU) | PRT (PU) |
|---|---|---|---|
| PDUCOA (Nagarajan *et al*., 2020) | 24.5358 | 0.6711 | 0.2757 |
| IPDUISAI (Singh *et al*., 2021) | 26.88 | 1.0642 | 0.25297 |
| PDUPSO (Mei *et al*., 2017) | 27.83 | 1.10 | 0.30 |
| PDUFO (Nuaekaew *et al*., 2017) | 24.25 | 1.0179 | 0.2824 |
| PDUCGA (Khazali and Kalantar, 2011) | 25.64 | 1.091 | 0.312 |
| HCACDE (Anil Kumar *et al*., 2022) | 21.9452 | 0.6012 | 0.0948 |
| CTFWO (Abd-El Wahab *et al*., 2022) | 23.3235 | 0.58553 | 0.2561 |
| HTSAMB | 19.92 | 0.51521 | 0.3989 |

**Table 2. Real power loss estimation (IEEE 354 bus)**

| Scheme | RSS (MW) | POY (PU) |
|---|---|---|
| PDUISAI (Chen *et al*., 2016) | 337.37400 | 0.497800 |
| IPDUISAII (Chen *et al*., 2016) | 338.71500 | 0.511700 |
| IPDUISA (Chen *et al*., 2016) | 339.32500 | 0.521600 |
| IPDUCLSO (Tudose *et al*., 2021) | 341.0010 | 0.535400 |
| IPDUPSO (Tudose *et al*., 2021) | 341.1230 | 0.639500 |
| HTSAMB | 318.0989 | 0.441321 |

**Table 3. Real power Loss estimation (WDN GRID 220 KV)**

| System | RSS (MW)) | POY (PU) |
|---|---|---|
| IPDUPSO (Mouwafi *et al*., 2022) | 32.31400 | 0.580000 |
| IPDUBBA (Mouwafi *et al*., 2022) | 33.87500 | 0.632700 |
| IPDUBBA (Mouwafi *et al*., 2022) | 30.78600 | 0.675100 |
| HTSAMB | 27. 09089 | 0.532761 |

**Table 4. Time taken by HTSAMB**

| Method | IEEE 57 busT (S) | IEEE 354 busT (S) | P220 KV T (S) |
|---|---|---|---|
| HTSAMB | 29.14 | 85.32 | 25.29 |

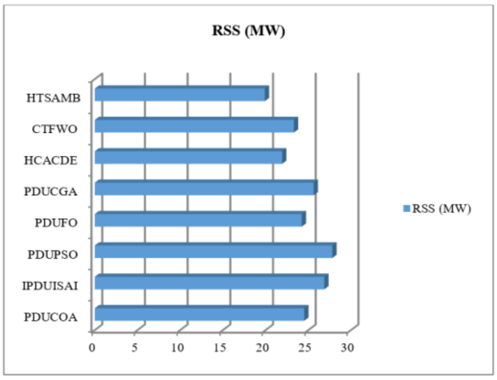


**Figure 1. Real Loss (RSS (MW)) (IEEE 57 bus)**

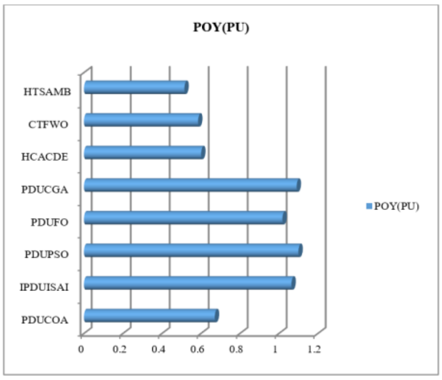


**Figure 2. Power incongruity (POY (PU)) (IEEE 57 bus)**

Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite and Barbary Falcon Search (HTSAMB) Algorithm endorsed in IEEE 354 bus system. Table 2 and Figures 4 and 5 shows the real loss reduction and Power irregularity estimation.

Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite and Barbary Falcon Search (HTSAMB) Algorithm is appraised in WDN Grid 220 KV (El-Ela *et al*., 2019). Table 3 and Figures 6 and 7 shows the Real loss estimate and Power anomaly estimate.

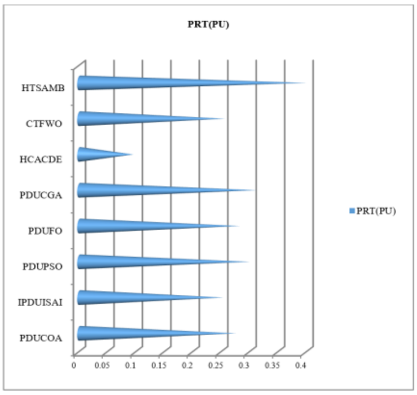


**Figure 3. Power forte (PRT (PU)) (IEEE 57 bus)**

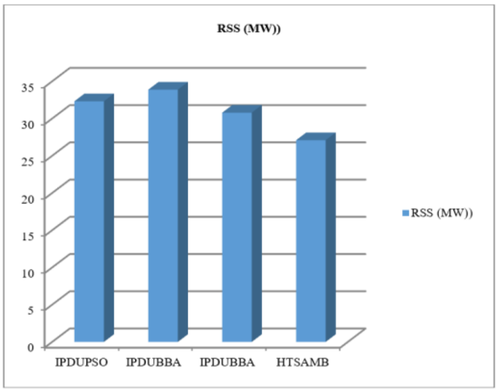


**Figure 6. Real Loss (RSS (MW)) (WDN GRID 220KV)**

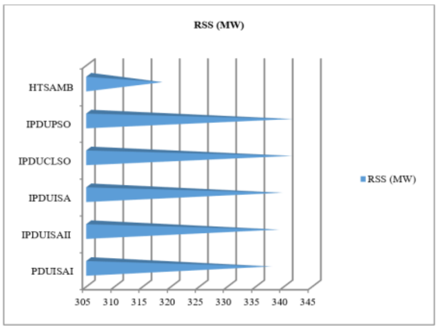


**Figure 4. Real Loss (RSS (MW)) (IEEE 354 bus)**

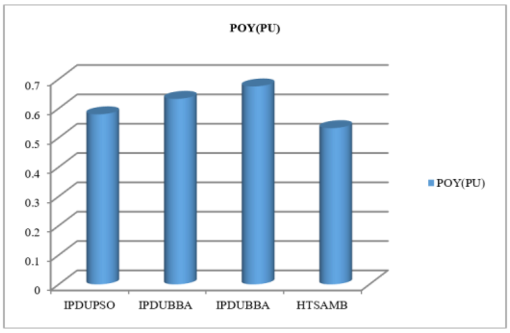


**Figure 7. Power incongruity (POY (PU)) (WDN GRID 220KV)**

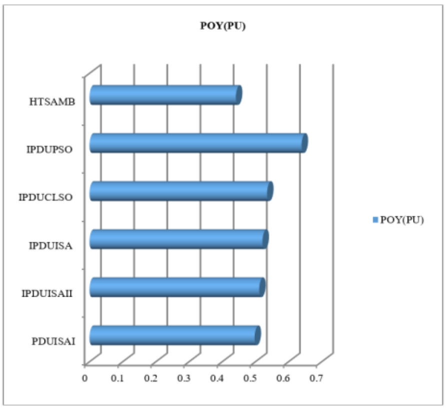


**Figure 5. Power incongruity (POY (PU)) (IEEE 354 bus)**

Comparison of Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite and Barbary Falcon Search (HTSAMB) Algorithm done with all proposed methods has been done. From this examination it is found that HTSAMB performed well in real power loss reduction. Table 4 show the time taken by HTSAMB

Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite and Barbary Falcon Search Algorithm (HTSAMB) solved the problem effectively.

## Conclusions

Hybrid Tayberry, Self-Help Regime, Adam's Ale Sequence, Metoza Appetite and Barbary Falcon Search (HTSAMB) Algorithm proficiently solved the real loss diminishing problem. In Tayberry algorithm exploitation is smeared by dissemination of voluminous elfin runners by Tayberrys in good acnes, and exploration is pragmatic by dispersal of diminutive runners by Tayberrys in flimsy acnes. In planned process of Self-help regime optimization algorithm, rendering to the private familiarities, constellation understandings, and sequential involvements of each entity chooses the succeeding place. Drive strategy and fresh locus of the affiliate will be demarcated with orientation to the premeditated appropriateness rate and in assessment. Grounded on the contemporary location first crusade dogma for the ith affiliate is engaged up. Adam's ale Sequence procedure starts with presupposition of water flow and oceanic is designated as the finest entity. In Metoza Appetite, divergence and binary forms are hypothetical to accomplish sound if castoff correspondingly in the meantime the exploration zone is limited to twofold standards for each facet. Transfer utility requisite be castoff to allocate the Appetite standards to the possibilities of famishments so that the location can be rationalized. In Barbary Falcon method, stalking progression is alienated as, pick and penetrating the zone. Choosing the examination zone in the preceding phase, the Barbary Falcon starts the exploration for prey in this zone by stirring in a helix silhouette to accelerate the exploration. Projected HTSAMB algorithm has been validated in IEEE 57, 354 and 220 KV systems.

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