ORIGINAL ARTICLE

Real Power Loss Reduction by Extreme Learning Machine based - Xiphias and Gilt-head bream Optimization Algorithms

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Abstract: In this paper Extreme Learning Machine based - Xiphias Optimization Algorithm (ELMXOA) and Gilt-head bream Optimization Algorithm (ELMGHO) applied to solve the problem. Entrant solutions in the proposed procedure are Xiphias and populace in the exploration zone, capriciously created. Gilt-head bream Optimization Algorithm designed by imitating the actions of Gilt-head bream's supportive stalking physiognomies. In cluster mode, the Gilt-head bream hunt the victim, it is entitled as key cluster (population), and additional cluster is termed as sub – population. Proposed ELM based - Xiphias Optimization Algorithm (ELMXOA) and Gilt-head bream Optimization Algorithm (ELMGHO) corroborated in IEEE 300 and 220 KV systems.

Keywords: Extreme Learning Machine; Xiphias; Gilt-head bream

Introduction

Real power loss reduction forecasted as one of the farfetched circumstances for safe and fiscal action of system [4-6]. In this paper ELM based - Xiphias Optimization Algorithm (ELMXOA) and Gilt-head bream Optimization Algorithm (ELMGHO). Naturally, Xiphias moves in cluster mode in the direction of Alewife for hunting. Drive of Xiphias is extraordinary, it spasm the Alewife energetically. Xiphias normal actions emulated to design the algorithm. Entrant solutions in the proposed procedure are Xiphias and populace in the exploration zone capriciously created. Gilt-head bream Optimization Algorithm designed by imitating the actions of Gilt-head bream's supportive stalking physiognomies. In cluster mode, the Gilt-head bream hunt the victim, it is entitled as key cluster (population), and additional cluster is termed as sub – population. Once the victim touches, the clogged Gilt-head bream at that time routinely it will converted into turn as fresh tracker. At any period tracker will become clogged and vice versa rendering to victim location and circumstances. Exploration region designed on the root of stalking zone.

Problem Formulation

Power loss minimization defined by

$$\text{Min } \tilde{F}(\bar{d}, \bar{e}) \quad (1)$$

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

$$F_2 = \text{Minimize}\left[\sum_{i=1}^{N_{LB}} \left|V_{Lk} - V_{Lk}^{\text{desired}}\right|^2 + \sum_{i=1}^{Ng} \left|Q_{GK} - Q_{KG}^{\text{Lim}}\right|^2\right] \quad (3)$$

$$F_3 = \text{Minimize } L_{\text{MaxImum}} \quad (4)$$

Parity constraints

$$0 = PG_i - PD_i - V_i \sum_{j \in N_B} V_j \left[G_{ij}\cos[\text{Ø}_i - \text{Ø}_j] + B_{ij}\sin[\text{Ø}_i - \text{Ø}_j]\right] \quad (5)$$

$$0 = QG_i - QD_i - V_i \sum_{j \in N_B} V_j \left[G_{ij}\sin[\text{Ø}_i - \text{Ø}_j] + B_{ij}\cos[\text{Ø}_i - \text{Ø}_j]\right] \quad (6)$$

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Disparity constraints

$$P_{gslack}^{minimum} \leq P_{gslack} \leq P_{gslack}^{maximum} \tag{7}$$

$$Q_{gi}^{minimum} \leq Q_{gi} \leq Q_{gi}^{maximum} \quad , i \in N_g \tag{8}$$

$$VL_i^{minimum} \leq VL_i \leq VL_i^{maximum} \quad , i \in NL \tag{9}$$

$$T_i^{minimum} \leq T_i \leq T_i^{maximum} \quad , i \in N_T \tag{10}$$

$$Q_c^{minimum} \leq Q_c \leq Q_C^{maximum} \quad , i \in N_C \tag{11}$$

$$|SL_i| \leq S_{L_i}^{maximum} \quad , i \in N_{TL} \tag{12}$$

$$VG_i^{minimum} \leq VG_i \leq VG_i^{maximum} \quad , i \in N_g \tag{13}$$

$$MOF = F_1 + r_i F_2 + uF_3 = F_1 + \left[\sum_{i=1}^{NL} x_v \left[VL_i - VL_i^{min}\right]^2 + \sum_{i=1}^{NG} r_g \left[QG_i - QG_i^{min}\right]^2\right] + r_f F_3 \tag{14}$$

Extreme Learning Machine based - Xiphias Optimization Algorithm and Gilt-head bream Optimization Algorithm

In this paper ELM based - Xiphias Optimization Algorithm (ELMXOA) and Gilt-head bream Optimization Algorithm (ELMGHO) is applied to solve the problem. Entrant solutions in the proposed procedure are Xiphias and populace in the exploration zone capriciously created. Naturally, Xiphias moves in cluster mode in the direction of Alewife for hunting [10-12]. Drive of Xiphias is extraordinary, it spasm the Alewife energetically. Xiphias normal actions emulated to design the algorithm. Entrant solutions in the proposed procedure are Xiphias and populace in the exploration zone capriciously created. Gilt-head bream Optimization Algorithm designed by imitating the actions of Gilt-head bream's supportive stalking physiognomies. In cluster mode, the Gilt-head bream hunt the victim, it is entitled as key cluster (population), and additional cluster is termed as sub – population. In Extreme learning machine [8, 9] the associating input to hidden layer delineated as,

$$Wgt = \begin{bmatrix} wgt_1^T \\ wgt_2^t \\ ; \\ wgt_l^T \end{bmatrix} = \begin{bmatrix} wgt_{11} & \cdots & wgt_{1n} \\ \vdots & \ddots & \vdots \\ wgt_{L1} & \cdots & wgt_{Ln} \end{bmatrix} \tag{15}$$

$$O(D_1, .. D_L; \omega_1, .., \omega_L; a_1, .., a_l) = \begin{bmatrix} k(\omega_1 D_1 + a_1) & \cdots & k(\omega_L D_1 + a_L) \\ \vdots & \ddots & \vdots \\ k(\omega_1 D_N + a_1) & \cdots & k(\omega_L D_N + a_L) \end{bmatrix} \tag{16}$$

In the probing zone existing location of the ith associate is defined as,

$$Xiphias_{i,k} \in R(i = 1,2, .., n) \tag{17}$$

Capricious location and fitness of the $Xiphias_L$ throughout process is defined as,

$$Xiphias_L = \begin{bmatrix} f(Xiphias_{1,1} & Xiphias_{1,2} \cdots Xiphias_{1,d}) \\ f(Xiphias_{2,1} & Xiphias_{2,2} \cdots Xiphias_{2,d}) \\ \vdots & \vdots \quad \ldots \quad \vdots \\ f(Xiphias_{n,1} & Xiphias_{n,2} \cdots Xiphias_{n,d}) \end{bmatrix} = \begin{bmatrix} F_{Xiphias1} \\ F_{Xiphias2} \\ \vdots \\ F_{Xiphiasn} \end{bmatrix} \tag{18}$$

Alewife is intermixed in algorithm and in the exploration area it will be in reeling mode. At that juncture the Alewife location and aptness value is determined by,

$$\text{Alewife}_L = \begin{bmatrix} f(Alewife_{1,1} & Alewife_{1,2} \cdots Alewife_{1,d}) \\ f(Alewife_{2,1} & Alewife_{2,2} \cdots Alewife_{2,d}) \\ \vdots & \vdots \quad \ldots \quad \vdots \\ f(Alewife_{n,1} & Alewife_{n,2} \cdots Alewife_{n,d}) \end{bmatrix} = \begin{bmatrix} F_{Alewife1} \\ F_{Alewife2} \\ \vdots \\ F_{Alewifen} \end{bmatrix} \tag{19}$$

The location of the loftier Xiphias and the wounded Alewife which own the superlative aptness rate in the ith iteration is itemized as $U^i_{Loftier\_Xiphias}$ and $U^i_{wounded\_Alewife}$. In the proposed approach the fresh location of Xiphias designated as,

$$U^{i}_{fresh_{Xiphias}} = U^{i}_{Loftier\_Xiphias} - \lambda_i \times \left(Rand(0,1) \times \left(\frac{U^{i}_{Loftier\_Xiphias} + U^{i}_{wounded\_Alewife}}{2}\right) - U^{i}_{preceding\ \ Xiphias}\right)$$

(20)

$$\lambda_i = 2 \times Rand(0,1) \times \text{victim compactness} - \text{victim compactness}$$

$$\text{victim compactness} = 1 - \left(\frac{\text{Sum } of \ Xiphias}{\text{Sum of } Xiphias + amount \ of \ \text{Alewife}}\right) \quad (21)$$

$$U^{i}_{fresh\_P} = Rand \times \left(U^{i}_{Loftier\_Xiphias} - U^{i}_{preceding\ \ Xiphias} + Xiphias \ \text{spasm control}\right) \quad (22)$$

$$\text{spasm control} = l \times (2 \times iter \times \varepsilon)$$

$$\alpha = amount \ of \ \text{Alewife} \times \text{spasm control}$$

$$\beta = parameters \times \text{spasm control}$$

Probabilities of Xiphias to quest fresh Alewife is demarcated as,

$$U^{i}_{Xiphias} = U^{i}_{\text{Alewife}} \ \ if$$

$$f(\text{Alewife}_i) < f(Xiphias_i) \quad (23)$$

i. Start

ii. Input the data

iii. Engender the Test and Training set

iv. Create the Xiphias population capriciously

v. Engender the Alewife population

vi. Factor spasm control values are chosen

vii. Compute the Fitness rate of Xiphias,

viii. Calculi the fitness value of Alewife

ix. Premium Xiphias, is selected as loftier Xiphias and Designate the wounded Alewife

x. $while \ stop \ condition \ not \ satisfied$

xi. Compute the λ_i value

xii. $\lambda_i = 2 \times Rand(0,1) \times \text{victim compactness} - \text{victim compactness}$

xiii. Streamline the location of Xiphias

xiv. $U^{i}_{fresh_{Xiphias}} = U^{i}_{Loftier\_Xiphias} - \lambda_i \times \left(Rand(0,1) \times \left(\frac{U^{i}_{Loftier\_Xiphias} + U^{i}_{wounded\_Alewife}}{2}\right) - U^{i}_{preceding\ \ Xiphias}\right)$

xv. End for

xvi. Calculate the rate of spasm control

xvii. $\text{spasm control} = l \times (2 \times iter \times \varepsilon)$

xviii. if spasm control < 0.5 , then compute

xix. $\alpha = amount \ of \ \text{Alewife} \times \text{spasm control}$

xx. $\beta = parameters \times \text{spasm control}$

xxi. Grounded on the rate of α, β ; elect the set of Alewife and Location of elected Alewife is rationalised

xxii. $U^{i}_{fresh\_P} = Rand \times \left(U^{i}_{Loftier\_Xiphias} - U^{i}_{preceding\ \ Xiphias} + Xiphias \ \text{spasm control}\right)$

xxiii. $Y^{i}_{new\_P} = random \ number \times \left(Y^{i}_{superior\_Xiphias} - Y^{i}_{previous\_P} + Xiphias \ attack \ power\right)$

xxiv. End if

xxv. Calculate fitness rate of all Alewife

xxvi. If better Alewife population found at that moment exchange a Alewife with wounded Alewife

xxvii. $U_{Xiphias}^{i} = U_{\text{Alewife}}^{i}$ if $f(\text{Alewife}_i) < f(Xiphias_i)$

xxviii. Fix Extreme Learning Machine input weights and hidden bias

xxix. Extreme Learning Machine testing

xxx. Abolish the startled Alewife from the population and Streamline the premium Xiphias and Alewife

xxxi. End if

xxxii. End while

xxxiii. Return preeminent Xiphias

xxxiv. End

Contingent to spatial distribution of the entity's population and sub clusters are designed. Populace of "n" Gilt-head breams (individuals) is $\{\text{Gilt}-\text{head bream}_1, \text{Gilt}-\text{head bream}_2, .., \text{Gilt}-\text{head bream}_n\}$ has been capriciously created in the exploration region with stated limitations; $\text{L}^{\max}$ and $\text{L}^{\min}$. Rendering to resolution factors,

$$Gilt-head\ \ bream_i \in Gilt-head\ \ bream\ \ ;\ \ Gilt-head\ \ bream_i = \{Gilt-head\ \ bream_i^1, Gilt-head\ \ bream_i^2, .., Gilt-head\ \ bream_i^n\} \tag{24}$$

$$Gilt-head\ \ bream_i^j = Rand \cdot (L_j^{max} - L_j^{min}) + L_j^{min}\ \ ; i = 1,2, .., m\ \ ; j = 1,2.., n \tag{25}$$

In the proposed procedure in each bunch $_r$ will own $\forall_{\text{tr}}$ (tracker Gilt-head bream) and $\forall_{\text{cd}}$ (clogged Gilt-head bream). File set will be designed on the foundation of the populace of Gilt-head bream and file points $\{Gilt-head\ \ bream_1, Gilt-head\ \ bream_2, .., Gilt-head\ \ bream_n\}$ and aligned inaccuracy ϑ_r in the bunch b_r is defined as,

$$e(b_r) = \sum_{Gilt-head\ \ bream\ \ _b \in b_r} \|Gilt-head\ \ bream\ \ _b - \vartheta_r\|^2\ \ \ \ ;\ \ b = 1,2, .., h\ \ ; \vartheta_r = 1,2, .., k \tag{26}$$

$$E(b) = \sum_{r=1}^{k} e(b_r) \tag{27}$$

At that point the fresh position of the tracker Gilt-head bream is specified as,

$$Fresh\ \ Location\ \ (\forall_{tr}^{t+1}) = Present\ \ location\ \ (\forall_{tr}^{t}) + \alpha \oplus L(\beta) \tag{28}$$

For harmonizing the exploration and exploitation-levy flights, β will be employed in suitable method to boost the examination in the exploration region [13, 14].

$$\beta = 2.00 + \frac{0.001t}{t_{max}/10} \tag{29}$$

$$R(SS) = \alpha \oplus L(\beta) \sim \alpha \left(\frac{u}{|v|^{1/\beta}}\right) \cdot (\forall_{lr}^{t} - \forall_{best}^{t}) \tag{30}$$

Fresh location of the tracker Gilt-head bream rendering to Levy is specified as,

$$fresh(\forall_{tr}^{t+1}) = \forall_{tr}^{t} + Rand\ \ (SS) \tag{31}$$

Rendering to global best the fresh location of tracker Gilt-head bream is specified as,

$$\forall_{best}^{t+1} = \forall_{best}^{t} + SS' \tag{32}$$

$$SS' = \alpha \left(\frac{u}{|v|^{1/\beta}}\right) \tag{33}$$

Rendering to the location of the victim, the Fresh location of the $\forall_{\text{cd}}^{\text{t+1}}$ (clogged Gilt-head bream) is demarcated as,

$$\forall_{cd}^{t+1} = Dis_{cd} \cdot e^{bp} \cdot \cos 2\pi\rho + \forall_{tr} \tag{34}$$

Contemporary expanse between clogged and tracker Gilt-head bream is demarcated as,

$$Dist_{cd} = |rand \cdot \forall_{tr} - \forall_{cd}^{t}| \tag{35}$$

$$\{\forall_{tr}, \forall_{cd}^{t}\} \in b_r \tag{36}$$

Exploration region is designed on the root of stalking zone and change of zone is defined as,

$$Gilt-head\ \ bream_n^{t+1} = \frac{\forall_{best} + Gilt-head\ \ bream_n^{t}}{2} \tag{37}$$

a. Start

b. Input the data

c. Engender the Test and Training set

d. Set the parameter values

e. Engender the population

f. $Gilt - head\ \ bream_i = \{Gilt - head\ \ bream_i^1, Gilt - head\ \ bream_i^2, .., Gilt - head\ \ bream_i^n\}$

g. Compute the Fitness value of each entity

h. Identify the $\forall_{best}$

i. Form the bunch $\{bunch_1, bunch_2, .. bunch_r\}$

j. For every bunch identify $\forall_{tr}$ (tracker Gilt-head bream) and $\forall_{cd}$ (clogged Gilt-head bream)

k. $While\ \ (t\ <\ tmax)$

l. For every $bunch_r\ \ do$

m. Apply stalking plan for tracker Gilt-head bream

n. Apply clogged plan for clogged Gilt-head bream

o. Compute the fitness value for all Gilt-head bream

p. If $\forall_{cd}$ (clogged Gilt-head bream) has improved fitness than $\forall_{tr}$ (tracker Gilt-head bream), at that moment exchange the protagonists by streamlining $\forall_{tr}$ (tracker Gilt-head bream)

q. End If

r. If $\forall_{tr}$ (tracker Gilt-head bream) has superior fitness value than $\forall_{best}$

s. Streamline $\forall_{best}$

t. End If

u. If $\forall_{tr}$ (tracker Gilt-head bream) fitness value not enhanced then ,

v. $u \leftarrow u + 1$

w. End If

x. Fix Extreme Learning Machine input weights and hidden bias

y. Extreme Learning Machine testing

z. If $u > \lambda$

aa. Apply a plan for shifting the zone

bb. $u \leftarrow 0$

cc. End If

dd. End For

ee. $t \leftarrow t + 1$

ff. End While

gg. Return the $\forall_{best}$

hh. End

Simulation Results

Projected ELM based - Xiphias Optimization Algorithm (ELMXOA) and Gilt-head bream Optimization Algorithm (ELMGHO) substantiated in IEEE 300 bus system [3]. Table I shows assessment. IEEE 300-bus system encompasses 69-generators, 60-LTCs, 304- transmission lines, and 195- loads.

Table I. Review of tangible loss

Technique	Loss (MW)	POD (PU)
IMPAI [1]	396.9830	5.93240
IMPAII [1]	397.2360	5.94160
IMPSA [1]	397.9020	5.96130
IMPALO [2]	398.8530	6.01690
ELMXOA	390.8970	5.81540
ELMGHO	390.7860	5.80990

Projected ELM based - Xiphias Optimization Algorithm (ELMXOA) and Gilt-head bream Optimization Algorithm (ELMGHO) verified in 220 KV (UETN) [5]. Table II shows the tangible power loss and deviancy review.

Table II. Valuation of tangible loss

Method	Loss (MW)	POD (PU)
IMPPSO[4]	32.314	0.5800
IMPBBA [4]	33.875	0.6327
MPBBA [4]	30.786	0.6751
ELMXOA	27. 108	0.5793
ELMGHO	27. 092	0.5776

Projected ELM based - Xiphias Optimization Algorithm (ELMXOA) and Gilt-head bream Optimization Algorithm (ELMGHO) compared with other standard algorithms; IMPAI [1], IMPAII [1], IMPSA [1], IMPALO [2]. Projected ELMXOA and ELMGHO algorithms reduced the power loss effectively. Power oddness also reduced to minimum level by Projected ELMXOA and ELMGHO algorithms proficiently while equated to other indicated procedures.

Conclusion

In this paper Extreme Learning Machine based - Xiphias Optimization Algorithm (ELMXOA) and Gilt-head bream Optimization Algorithm (ELMGHO) has been successfully solved the power loss lessening problem. Entrant solutions in the proposed procedure are Xiphias and populace in the exploration zone capriciously created. In cluster mode, the Gilt-head bream hunt the victim, it is entitled as key cluster (population), and additional cluster is termed as sub – population. Once the victim touches, the clogged Gilt-head bream at that time routinely it will converted into turn as fresh tracker. Proposed ELM based - Xiphias Optimization Algorithm (ELMXOA) and Gilt-head bream Optimization Algorithm (ELMGHO) authenticated in IEEE 300 and 220 KV systems. Projected ELMXOA and ELMGHO algorithms reduced the power loss effectively.

References

[1] N.Karthik, P.Arul, “Multi-Objective Optimal Reactive Power Dispatch using Levy Interior Search Algorithm”, *International Journal on Electrical Engineering and Informatics*, 12, 547–570, 2020. https://doi.org/10.15676/ijeei.2020.12.3.8

[2] S.Mouassa, T.Bouktir, “Multi-objective ant lion optimization algorithm to solve large-scale multi-objective optimal reactive power dispatch problem”, *COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering*, Vol. 35 No. 1, pp. 350–372, 2018. https://doi.org/10.1108/COMPEL-05-2018-0208

[3] Https://*icseg.iti.illinois.edu/ieee-300-bus* / accessed on 1.02.2023 at 10.11 IST

[4] M. Mouwafi, Adel A. Abou El-Ela, A. El-Sehiemy, K. Al-Zahar, “Techno-economic based static and dynamic transmission network expansion planning using improved binary bat algorithm,” *Alexandria Engineering Journal*, Volume 61, Issue 2, 1383–1401, 2022. https://doi.org/10.1016/j.aej.2021.06.021

[5] A.AbouEl-Ela, M.Mouwafi, W.Al-Zahar, "Optimal Transmission System Expansion Planning Via Binary Bat Algorithm," *2019 21st International Middle East Power Systems Conference (MEPCON)*, Cairo, Egypt, 2019, pp. 238–243. https://doi.org/10.1109/MEPCON47431.2019.9008022

[6] L.Kanagasabai, “Novel Western Jackdaw Search, Antrostomus Swarm and Indian Ethnic Vedic Teaching – Inspired Optimization Algorithms for Real Power Loss Diminishing and Voltage Consistency Growth,” *International Journal of System Assurance Engineering and Management,* 13(6), 2895–2919, 2022. https://doi.org/10.1007/s13198-022-01758-3

[7] M. Rasyid Ridho, H. Nuha, "Application of Extreme Learning Machine (ELM) Classification in Detecting Phishing Sites," *2022 5th International Conference of Computer and Informatics Engineering (IC2IE),"* Jakarta, Indonesia, 2022, pp. 60-64. https://doi.org/10.1109/IC2IE56416.2022.9970191

[8] S.Fan, F.Li, B.Wang, X.Zhang, P.Yan, "ELM Based Improved Layered Ensemble Architecture for Security Situation Prediction," *2022 IEEE 6th Advanced Information Technology, Electronic and Automation Control Conference (IAEAC),* Beijing, China, 2022, pp. 630–634. https://doi.org/10.1109/IAEAC54830.2022.9929487

[9] H.Zhu, Z.Lv, R.Di, H.Gao, K.Hao, W.Peng, "Remaining Useful Life Prediction of Lithium Battery Based on SSA-ELM," *2022 International Conference on Computer Network, Electronic and Automation (ICCNEA), Xi'an, China, 2022,* pp. 307–310. https://doi.org/10.1109/ICCNEA57056.2022.00074

[10] K.Ari, T.Suesut, W.Tangsrirat, G.Schleining, N.Nunak, "Fish Detection and Classification for Automatic Sorting System with an Optimized YOLO Algorithm" *Applied Sciences* 13, no. 6: 3812. 2023. https://doi.org/10.3390/app13063812

[11] V.Ananthan, "Fish Species Detection and Tracking Based on Fusion Intensity Entity Transformation using Optical Flow Algorithm," *2022 International Conference on Edge Computing and Applications (ICECAA), Tamilnadu, India, 2022*, pp. 1711–1716. https://doi.org/10.1109/ICECAA55415.2022.9936540

[12] A.Raihan, M. Monju, M. MehediHasan, M. Tarek Habib, M.S.Uddin, "CNN Modeling for Recognizing Local Fish," *2021 24th International Conference on Computer*

and Information Technology (ICCIT), Dhaka, Bangladesh, 2021, pp. 1–5. https://doi.org/10.1109/ICCIT54785.2021.9689898

[13] C.Xin, X.Han, Z.Zhou , Y.Jin, G. Yu, "Visual Power System based on Artificial Fish Swarm Algorithm," 2022 IEEE 2nd International Conference on Electronic Technology, Communication and Information (ICETCI), Changchun, China, 2022, pp. 927–930. https://doi.org/10.1109/ICETCI55101.2022.9832147

[14] J.Wu, Y.Zhou. H.Yu, Y.Zhang, J.Li, "A Novel Fish Counting Method with Adaptive Weighted Multi-Dilated Convolutional Neural Network," *2021 20th International Conference on Ubiquitous Computing and Communications (IUCC/CIT/DSCI/SmartCNS),* London, United Kingdom, 2021, pp. 178–183. https://doi.org/10.1109/IUCC-CIT-DSCI-SmartCNS55181.2021.00039

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