

NOVEL ENRICHED TEACHING - LEARNING INSPIRED OPTIMISATION AND QUANTUM OPPONENT PROCESS THEORY-BASED ALGORITHM FOR POWER LOSS DIMINUTION

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Abstract

The enriched teaching-learning-inspired optimization algorithm (ETLO) and quantum opponent process theory-based (QOPT) algorithm are applied to solve the problem of reducing power loss. In this procedure, each learner in the population acts as a searcher and serves as a potential solution. During the course phases and statistics delivery, learners are trained to improve their skills in order to provide better solutions. The teacher will explore various methods to solve the problem as soon as possible. The environment of the human mind is ambiguous. In the exploitation period, learners of the procedure populations examine locally to discover improved solutions. The QOPT algorithm is based on how individuals observe changes in color and sensation over time. The opponent process theory explains how an individual experiences different color images in the time period following their exposure to the original image's color. The algorithm observes an individual's color over a specific time period as the original image appears and disappears. In the retina of the eye, the photochemical effect will be there for a certain period. The size of the object signifies the present rate of the candidate solution, and the distance of the object characterizes the extent from the finest solution. Enriched teaching - learning inspired optimization algorithm (ETLO) and Quantum Opponent process theory based (QOPT) algorithm validated in 7 benchmark functions and IEEE 118, 300 bus systems.

Keywords: Teaching; Learning; Teacher; Students

Introduction

Enriched teaching - learning inspired optimization algorithm (ETLO) and Quantum Opponent process theory-based (QOPT) algorithm are applied to solve the power loss diminution problem (Yapıcı and Çetinkaya, 2017; Lian, 2022; Sahli *et al.*, 2022; Shaheen *et al.*, 2023; Varan *et al.*, 2023; In *et al.*, 2024; Kanagasabai *et al.*, 2024; Rao *et al.*, 2024). In the procedure, each learner of the population is a searcher and acts as a contender solution. Recognized on the course phases and statistics conveyance, learners are skilled to advance their condition to provide grander solutions. The requirement of the procedure populations acquaints

the technique with unequivocal affiliations, such as the outstanding learner and the deprived learner of the populations, might avoid the process from searching comprehensively in the problem area. These conditions may lead to the speedy convergence of the procedure in the course of the local optimal solution. In the algorithm, teaching - learning is affiliated to acquaint and guide each learner of the progression of citizens in the exploration area. Teaching - learning (Cedeño-Rivadeneira and mendoza-Loor, 2024; Kandau *et al.*, 2024; Lin *et al.*, 2024) is created based on foremost learner, one changeable learner, and the

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dependable learner. In the exploration segment, the learner of the procedure searches the divergent regions of the examination area to find the exclusive optimum region. Great buoyancy on unambiguous learners of the populace (distinguished learners) in the process of evaluating the procedure, population location avoids the global exploration of the progression in the exploration planetary and diminishes the procedure's ability to discover. This requirement in the appraisal procedure can lead to primary convergence of the process to the narrowed optimum, and as a result, the process founders to identify the principal optimal region in the exploration area. In the exploitation period, learners of the procedure populations examine locally to discover improved solutions. Subsequently, in the algorithm, a neighbourhood around each learner of the citizens is measured, and it causes the learner to change its location by searching in the neighbourhood and determining a position with an enhanced value for the objective function. The teacher will explore ways to solve the problem as early as possible. The environment of the human mind is ambiguous. Many beliefs and faiths are explored in the mind of the students. The teacher will explore ways to solve the problem as early as possible. The environment of the human mind is ambiguous. In the exploration segment identification of feasible solution for the problem is defined. Quantum Opponent process theory based (QOPT) algorithm is based on, how the individuals observe color and sensations transformation over time period. The Opponent process theory (Eastman, 1986; Conway *et al.*, 2023; Hagihara and Lüthi, 2024) explains how the individual experiences different colour images in subsequent epochs of revelation to the original image colour. If the people see red colour images but the entity experiences green colour in a certain period of time after the original image disappears. Opponent process theory deals about vision on the color, afterimages, clone cells, change of emotions and behavioral patterns. In this paper, the defined algorithm is grounded on the observed colour of the individuals over a certain time period in the presence and disappearance of the original image. In the retina of the eye, the photochemical effect will be there for a certain period. When an individual looks at an object and afterwards the individual moves away from the object, but the individual's eye continues to see the object for a short period of time. Then the individual experiences different colour images in subsequent epochs of revelation to the original image colour. Each individual undergoes a sensation transformation over a time period. The size of the object signifies the present rate of the candidate

solution, and the distance of the object characterizes the extent from the finest solution. Based on the angle of the visual and intuition-based object size, new-fangled standards of the candidate solutions of the populace are rationalized around the finest solution. A poor solution indicates the opposite of the actual image colour in the occurrence of visualization.

Problem Formulation

Power loss diminution is scientifically termed as,

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

$$a = \begin{bmatrix} VLG_1, \dots, VLG_{Ng}; QC_1, \dots, QC_{Nc} \\ ; T_1, \dots, T_{N_T} \end{bmatrix}$$

$$b = \begin{bmatrix} PG_{slack}; VL_1, \dots, VL_{N_{Load}}; QG_1, \dots, QG_{Ng} \\ ; SL_1, \dots, SL_{N_T} \end{bmatrix}$$

Fitness functions are demarcated as,

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

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

$$F_3 = \text{Minimize } L_{Maximum}$$

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

Equality constraints

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

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

Inequality constraints

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

Reactive power generation (QGi)

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

Load bus voltage (VLi)

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

Transformers tap setting (Ti)

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

Switchable reactive power compensations (QCi)

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

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

Generator bus voltage (VGi)

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

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

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

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

Enriched teaching - learning inspired optimization algorithm

Teaching - learning uninterruptedly guides the individuals of humanity to pass in a virtuous manner, like serving others, protecting flora and fauna, valuing the seniors, deeds worthy of humanity and upholding communal harmony.

In the procedure, each learner in the population acts as a searcher and serves as a potential solution. Learners, recognized during the course phases and statistics conveyance, are skilled at adapting their conditions to provide better solutions. The need for the groups involved to understand the method regarding specific connections, like the advanced and struggling learners, could limit the thorough exploration of the problem area. These conditions may lead to the procedure's speedy convergence during the local optimal solution. The algorithm aligns teaching-learning to familiarize and guide each learner with the progression of citizens in the exploration area. This Teaching - learning is created based on foremost learner, one changeable learner, and the dependable learner. The producing populace (citizens) is demarcated as,

$$O = \begin{bmatrix} O_1 \\ \vdots \\ O_i \\ \vdots \\ O_N \end{bmatrix}_{N \times m} = \begin{bmatrix} O_{11} & \cdots & O_{1m} \\ \vdots & \ddots & \vdots \\ O_{N1} & \cdots & O_{Nm} \end{bmatrix}_{N \times m} \quad (12)$$

A → population (inhabitants)

N, m are the size and amount of variables

The condition of every population learner is principally primed intermittently in the assessment of the variables' compressions.

$$o_{i,j} = \text{Low}_j + R(\text{High}_j - \text{Low}_j) \quad (13)$$

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

High_j and Low_j are the limits

The objective function is appraised as follows,

$$U = \begin{bmatrix} U_1 \\ \vdots \\ U_i \\ \vdots \\ U_N \end{bmatrix}_{N \times 1} = \begin{bmatrix} U(O_1) \\ \vdots \\ U(O_i) \\ \vdots \\ U(O_N) \end{bmatrix}_{N \times 1} \quad (14)$$

U → objective function

The learner who achieves the outstanding rate for the objective function is acknowledged as the distinguished learner, and the learner who achieves the lowest rate for the objective function is recognized as the poorest learner.

In the exploration segment, the learner of the procedure searches the divergent regions of the examination area to find the exclusive optimum region. Great buoyancy on unambiguous learners of the populace (distinguished learners) in evaluating the procedure, population location avoids the global exploration of the progression in the exploration planetary. It diminishes the procedure's ability to discover. This requirement in the appraisal procedure can lead to primary convergence of the process to the narrowed optimum, and as a result, the process founders to identify the principal optimal region in the exploration area. Contrariwise, confident learners, like the distinguished learner, have advantageous statistics that must be considered.

Creation of an impulsive head, three learners of the citizens, encompassing a. the consistent learner (the analogous learner to be headed by Teaching - learning), b. the distinguished learner, c. an impulsive learner of the population, is protuberant.

$$V_i = \frac{U_i - U_{\text{poorest}}}{\sum_{j=1}^N (U_j - U_{\text{poorest}})} \quad (15)$$

$$i = 1, 2, 3, \dots, N$$

Aid quantities of each learner are calculated as follows,

$$Wo_i = \frac{v_i}{v_i + v_{preeminent} + v_k} \quad (16)$$

$$Wo_{preeminent} = \frac{v_{preeminent}}{v_i + v_{preeminent} + v_k} \quad (17)$$

$$Wo_k = \frac{v_i}{v_i + v_{preeminent} + v_k} \quad (18)$$

$i = 1, 2, 3, \dots, N$
 $k = 1, 2, 3, \dots, N$
 $U_{poorest} \rightarrow$ value of objective function
 $\rightarrow$ poorest candidate solution
 $Wo_i, Wo_{preeminent}$ and $Wo_k \rightarrow$ ith learner
preeminent learner, kth preeminent learner

Consequently, after determination of the aid quantities, the Teaching - learning is produced for each learner of the citizens (population) as follows,

$$TL_i = Wo_i \cdot O_i + Wo_{preeminent} \cdot O_{preeminent} + Wo_k \cdot O_k \quad (19)$$

$TL_i \rightarrow$ guide the learner

The renewed location for each learner of the citizens (population) in the exploration state under the regulation of the Teaching - learning is calculated as,

$$o_{i,j}^{new,z_1} = \begin{cases} o_{i,j} + \text{random} \cdot \\ (TL_{i,j} + Y \cdot o_{i,j}), Q_{TL_i} < U_i \\ o_{i,j} + \text{random} \cdot \\ (TL_i - TL_{i,j}), \text{else} \end{cases} \quad (20)$$

$$O_i = \begin{cases} o_{i,j}^{new,z_1}, Q_i^{new,z_1} < Q_i \\ O_i, \text{else} \end{cases}$$

$o_{i,j}^{new,z_1} \rightarrow$ new location of the ith learner
 $U_i^{new,z_1} \rightarrow$ objective functional value in primary phase
 $Y \in [1, 2]$

$Q_{TL_i} \rightarrow$ value of the objective function obtained
In the exploitation period, learners of the procedure populations examine locally to discover improved solutions. Subsequently, in the algorithm, a neighbourhood around each learner of the citizens is measured, and it causes the learner to change its location by searching in the neighbourhood and determining a position with an enhanced value for the objective function. This local examination is designed to advance and increase the ability to exploit algorithms.

$$o_{i,j}^{new,z_2} = o_{i,j} + (1 - 2R) \cdot X \cdot \left(1 - \frac{t}{T}\right) \cdot o_{i,j} \quad (21)$$

$O_i = \begin{cases} o_{i,j}^{new,z_2}, U_i^{new,z_2} < U_i \\ O_i, \text{else} \end{cases}$
 $o_{i,j}^{new,z_2} \rightarrow$ new location of the ith learner
 $U_i^{new,z_2} \rightarrow$ objective functional value in second phase
 $X = 0.2$

$t, T \rightarrow$ current and maximum iterations

The teacher will explore ways to solve the problem as early as possible. The environment of the human mind is ambiguous (Greubel *et al.*, 2024; Salinas-Navarro *et al.*, 2024; Tzimas and Demetriadis, 2024). In the exploration segment, the feasible solution for the problem is identified.

$$H_i^{t+1} = \gamma \cdot \left(1 - \frac{t}{\max_{iter}}\right) \cdot \left(\frac{H_i^t}{-H_{best}^t}\right) \cdot L(D) + H_{best}^t \cdot \left(1 - \frac{t}{\max_{iter}}\right) + \left(\frac{H_{mean}^t}{-H_{best}^t}\right) \cdot f\left(\frac{R}{f_i}\right) \cdot f_j \quad (22)$$

$H_i^{t+1} \rightarrow$ new state of the student H_i^t
 $\rightarrow$ present state of the student
 $H_{best} \rightarrow$ best position of the student H_{mean}^t
 $\rightarrow$ Mean status of student
 $R \in [0, 1]$

$$H_{mean}^t = \frac{1}{N} \sum_{k=1}^N H_k^t \quad (23)$$

$$\gamma = 0.2 \left(1 - \frac{t}{\max_{iter}}\right) \cdot (H_{mean}^t - H_{best}^t)$$

$$H_i^{t+1} = \begin{cases} \omega \cdot H_i^t \cdot \exp\left(\frac{-t}{R \cdot \max_{iter}}\right), R < E \\ \omega \cdot H_i^t + R \cdot O(1, d), R > E \end{cases}$$

$$E = 0.60$$

$$\omega = 0.2 \cos\left(\frac{\pi}{2} \left(1 - \frac{t}{R \cdot \max_{iter}}\right)\right)$$

The teacher explores more possible ways for obtaining a better solution to the problem, under various conditions,

$$H_i^{t+1} = R \cdot \exp\left(\frac{H_p^t - H_i^t}{i^2}\right) \quad (24)$$

$H_p^t \rightarrow$ quality of the solutions
 $H_i^{t+1} = H_i^t + \omega \cdot R \cdot (H_{best}^t - H_i^t)$
 $H_i^{t+1} = H_{best}^t + (H_{best}^t - H_i^t) \cdot R$

The teacher's search for the solution is defined as

$$H_{i,j}^{t+1} = \begin{cases} H_{i,j}^t \cdot \exp\left(\frac{i^2}{|2\alpha-1| \cdot T_{max}}\right), R_1 < SR \\ H_{i,j}^t + \exp\left(-\frac{2i}{T_{max}}\right) \cdot Q \cdot M, R_1 \geq SR \end{cases} \quad (25)$$

$$\begin{aligned}
 &H_{ij}^{t+1} \rightarrow \text{new location in the search; } \alpha \\
 &\quad \in (0,1]; Q \in [-1,1]; R_1 \in (0,1] \\
 &\quad SR \rightarrow \text{search region; } SR \in [0.7, 1.0] \\
 &H_{ij}^{t+1} = \begin{cases} H_{best\ S}^{t+1} + E \cdot \begin{pmatrix} H_{ij}^t \\ -H_{best\ S}^{t+1} \end{pmatrix}, i < PS/2 \\ H_{ij}^t + E \cdot \begin{pmatrix} H_{ij}^t \\ -H_{ij,k}^{t+1} \end{pmatrix}, i \geq PS/2 \end{cases} \quad (26)
 \end{aligned}$$

$$\begin{aligned}
 &H_{best\ S}^{t+1} \rightarrow \text{optimized position} \\
 &\quad E = \exp\left(\frac{t}{t_{max}}\right) \cdot Q \cdot M \\
 &\quad H_{ij}^t = \frac{1}{3} \cdot (H_{best\ S}^{t+1} + H_{best\ O}^{t+1} + H_{ij}^t) \\
 &H_{best\ S}^{t+1} \rightarrow \text{best position in the search} \\
 &\quad H_{best\ O}^{t+1} \rightarrow \text{successful solution} \\
 &\quad H_{ij}^{t+1} = \beta \cdot H_{ij}^t + \gamma \cdot H_{ij}^t \\
 &\quad H_{ij}^{t+1} \rightarrow \text{teacher's evaluation} \\
 &\quad \beta = \begin{cases} \exp(-t/T_{max}), t < T_{max}/2 \\ \exp(-(T_{max} - t)/T_{max}), t \geq T_{max}/2 \end{cases} \\
 &\text{Problems of the students are defined as} \\
 &\quad ER = \{ER_1, ER_2, ER_3, \dots, ER_N\} \\
 &\quad ER_i(t) = (H_i(t), F_i(t)) \\
 &\quad H_i(t) = [H_{i1}, H_{i2}, H_{i3}, \dots, H_{iD}] \\
 &\quad H_i(t) \rightarrow \text{solutions} \\
 &\quad F_i(t) \rightarrow \text{Fitness value of the solutions} \\
 &\quad pop_{dp} = \log(t + M) / \log(\text{maximum iteration}) * 2 \\
 &\quad H_i(t + 1) = H_G(t) + U_1(x) * (H_{O_i}(t) - H_O(t)) \\
 &\quad pop_{dp} \rightarrow \text{divided population} \\
 &\quad H_G(t) \rightarrow \text{solution steps} \\
 &\quad H_{O_i}(t) \rightarrow \text{excellent solutions} \\
 &\quad H_O(t) \rightarrow \text{randomly choosen form the population} \\
 &\quad U_1(x) \rightarrow \text{dividing factor}
 \end{aligned}$$

The dividing factor is utilised to uphold the population multiplicity, which is grounded on the quantum mode.

$$\begin{aligned}
 &U_1(x) = (\delta/2^n * n! * \pi^{1/2})^{\frac{1}{2}} \\
 &HP_n(\delta * x) \cdot e^{-0.5 * \delta^2 * x^2} \quad (27)
 \end{aligned}$$

$$\begin{aligned}
 &\delta = \left(\frac{\text{particle}}{\text{mass} * \text{strength} / \text{constant}} \right) \\
 &HP_n \rightarrow \text{Hermite polynomial} \\
 &\text{Effervescent prominent actions of the teacher are defined as,} \\
 &\quad ERF(t) = \{ERF_1, ERF_2, \dots, ERF_i, \dots, ERF_{N'}\} \\
 &\quad N' = N - pop_{dp} \\
 &\quad ERF_i \rightarrow \text{fitness value of the decisions} \\
 &\text{From end to end, dividing every element of evocative set} \\
 &\quad V = \{V_1, V_2, \dots, V_k\} \text{ is allocated as the principal component of solutions.}
 \end{aligned}$$

$$\begin{aligned}
 &ERF(t) = \{ER_i(t) \in ER | ER_i(t) \leq ER_{i+1}(t)\} \\
 &\quad i = 1, 2, 3, \dots, N'
 \end{aligned}$$

$$\begin{aligned}
 &V(t) = \{ER_i(t) \in ER(t)\} \\
 &\quad i = 1, 2, 3, \dots, k \\
 &\quad \text{Section } (S) = ER - V \\
 &\quad \text{Each cluster consists of } n \text{ decisions,} \\
 &\quad n(ER) = \frac{N'}{k} \\
 &G_w, V_w \text{ and } S_w \\
 &\quad \rightarrow \text{cluster, representative set and section} \\
 &\text{Cluster excellence is mathematically designed as,} \\
 &\quad U_w(t) = \sum_{i=1}^k \frac{1}{2} \sum_{j=1}^n ERF_{ij}(t) / \left(\frac{1}{2} \sum_{i=1}^k \frac{1}{2} ERF_{wj}(t) \right) \\
 &ERF_{ij} \rightarrow \text{fitness value of } i\text{th solution in the subpopulation}
 \end{aligned}$$

$$H_i(t + 1) = \begin{cases} \text{problems of the students} \\ \text{if } U_w(t) \leq \varphi_U(t) \\ \text{updated solutions o} \\ \text{if } U_w(t) > \varphi_U(t) \\ \text{else} \end{cases} \quad (28)$$

Enriched teaching - learning inspired Optimization Algorithm (ETLO)

- Start
- Produce the population
- $V_i = \frac{U_i - U_{poorest}}{\sum_{j=1}^N (U_j - U_{poorest})}$
- Streamline the i th learner
- $O_i = \begin{cases} O_i^{new, z_1}, Q_i^{new, z_1} < Q_i \\ O_i, \text{ else} \end{cases}$
- Compute the new-fangled location of the i th learner
- $O_{ij}^{new, 2} = O_{ij} + (1 - 2R) \cdot X \cdot \left(1 - \frac{t}{T}\right) \cdot O_{ij}$
- Streamline the i th learner
- $O_i = \begin{cases} O_i^{new, z_2}, U_i^{new, 2} < U_i \\ O_i, \text{ else} \end{cases}$
- $H_i^{t+1} = \gamma \cdot \left(-\frac{1}{\max_{iter}}\right) \cdot (H_i^t - H_{best})$
 $\cdot L(D) + H_{best} \cdot \left(-\frac{1}{\max_{iter}}\right)$
 $+ \left(\frac{H_{mean}^t}{-H_{best}^t}\right) \cdot f\left(\frac{R}{f_j}\right) \cdot f_j$
- $H_i^{t+1} = \begin{cases} \omega \cdot H_i^t \cdot \exp\left(\frac{-t}{R \cdot \max_{iter}}\right), R < E \\ \omega \cdot H_i^t + R \cdot O(1, d), R > E \end{cases}$
- $H_i^{t+1} = H_i^t + \omega \cdot R \cdot (H_{best}^t - H_i^t)$
- Define the search for the solution
- $H_{ij}^{t+1} = \begin{cases} H_{ij}^t \cdot \exp\left(\frac{i^2}{|2\alpha - 1| \cdot T_{max}}\right), R_1 < SR \\ H_{ij}^t + \exp\left(-\frac{2i}{T_{max}}\right) \cdot Q \cdot M, R_1 \geq SR \end{cases}$
- $H_{ij}^{t+1} = \begin{cases} H_{best\ S}^{t+1} + E \cdot \begin{pmatrix} H_{ij}^t \\ -H_{best\ S}^{t+1} \end{pmatrix}, i < PS/2 \\ H_{ij}^t + E \cdot \begin{pmatrix} H_{ij}^t \\ -H_{ij,k}^{t+1} \end{pmatrix}, i \geq PS/2 \end{cases}$
- $H_{ij}^t = \frac{1}{3} \cdot (H_{best\ S}^{t+1} + H_{best\ O}^{t+1} + H_{ij}^t)$
- $H_{ij}^{t+1} = \beta \cdot H_{ij}^t + \gamma \cdot H_{ij}^t$

- r. $\text{pop}_{dp} = \log(t + M) / \log(\text{maximum iteration}) * 2$
- s. $H_i(t + 1) = H_G(t) + U_1(x) * \begin{pmatrix} H_{oi}(t) \\ -H_o(t) \end{pmatrix}$
- t. Define the dividing factor
- u. $U_1(x) = \left(\delta / \left(2^n * n! \right)^{\frac{1}{2}} * \pi^{1/2} \right) \cdot \text{HP}_n(\delta * x) \cdot e^{-.05 * \delta^2 * x^2}$
- v. Define Effervescent, prominent actions of teacher
- w. $t = t + 1$
- x. End

Quantum Opponent Process Theory-Based Algorithm

Quantum Opponent process theory based (QOPT) algorithm is based on, how the individuals observe color and sensations transformation over period. The Opponent process theory explains how the individual experiences different colour images in subsequent epochs of revelation to the original image colour. If the people see red colour images but the entity experiences green colour in a specific period after the original image disappears. Opponent process theory deals about vision on the color, afterimages, clone cells, change of emotions and behavioral patterns. In this paper, the defined algorithm is grounded on the observed colour of the individuals over a specific period in the presence and disappearance of the original image. The photochemical effect will be there in the eye's retina in a particular period. When an individual looks at an object and afterwards moves away from the object, the individual's eye continues to see the object for a short period. Then the individual experiences different colour images in subsequent epochs of revelation to the original image colour. Each undergoes a sensation transformation over some time.

The theory explains how the individual's eye perceives an object. Based on the angle of the visual towards the object, the retina will reflect the size of the image.

$$AoV = 2 \cdot \arctan\left(\frac{SoB}{2 \cdot DoB}\right) \quad (29)$$

$AoV \rightarrow \text{angle of visual}$
 $SoB \rightarrow \text{size of the object}$
 $DoB \rightarrow \text{distance of the object}$

The size of the object observed by the individual is defined as,

$$Oi = AoV \cdot D \quad (30)$$

$Oi \rightarrow \text{object observed by the individual}$

The distance of the object is measured by the Manhattan distance measurement (Xu *et al.*, 2023) as follows,

$$MDM(x, y) = \sum_{i=1}^n |x_i - y_i| \quad (31)$$

$MDM \rightarrow \text{Manhattan distance measurement}$

The size of the object signifies the present rate of the candidate solution, and the distance of the object characterizes the expanse from the finest solution. Based on the angle of the visual and intuition-based object size, new-fangled standards of the populace's candidate solutions are rationalized around the finest solution. A poor solution indicates the opposite of the color of the actual image color in the visualization.

$$AoV = 2 * Q \left(\frac{P_{i,j}}{2 \cdot P_{i,j} - b_{1,j}} \right) \quad (32)$$

$$Oi,j = AoV \cdot (P_{i,j} - b_{1,j}) \quad (33)$$

$$\text{New } P_{i,j} = Oi,j + \left(\left| - \left(b_{i,j} - \left| \frac{w_{i,j}}{-p_{i,j}} \right| \right) \right| \right) \cdot \text{rand} \quad (34)$$

$P \rightarrow \text{population}$
 $b \rightarrow \text{best solution}$
 $w \rightarrow \text{poor solution}$
 $\text{rand} \in [0,1]$

In the Opponent process theory-based algorithm, Quantum computing (Golec *et al.*, 2024) has been amalgamated as follows,

$$|\Psi|^2 \cdot da \cdot db \cdot dc = Q \cdot da \cdot db \cdot dc \quad (35)$$

$\Psi \rightarrow \text{probability density}$

$$ih \cdot \partial / \partial t \cdot \Psi(a, t) = H \cdot \Psi(a, t) \quad (36)$$

$H \rightarrow \text{Hamiltonian operator}$

$$H = -\hbar^2 / 2m \cdot \Delta^2 + V(xa) \quad (37)$$

$$S(T) \frac{d^2 \Psi}{dz^2} + \frac{2m}{\hbar^2} [G + \gamma \delta(z)] \Psi = 0 \quad (38)$$

$$\begin{aligned} \psi(z) &= \frac{1}{\sqrt{L}} e^{-\frac{|a|}{L}} \\ V(z) &= |\psi(z)|^2 = \frac{1}{\sqrt{L}} e^{-\frac{|a|}{L}} \\ z &= \pm \frac{L}{2} \ln(1/g) \\ u &\in [0,1] \end{aligned}$$

$$|\Psi(t + 1, X_i)\rangle = QOD = |\Psi(V_D)\rangle - \left| \frac{\Psi^D(X_i)}{(|\Psi(X_i)\rangle - |\Psi(X_o)\rangle)} \right| \quad (39)$$

QOB → quantum bounding in descending mode

$$|\Psi(t+1, X_i)\rangle = QOA = |\Psi(V_D)\rangle - \frac{\Psi^A(X_i)}{|\Psi(X_i)\rangle - |\Psi(X_j)\rangle + |\Psi(\Delta_1)\rangle} \quad (40)$$

QOA → Quantum bounding in ascending mode

$$QB = \begin{cases} QOA, & \text{if } |\Psi^A(X_i)| > |\Psi^D(X_i)| \\ QOD, & \text{if } |\Psi^A(X_i)| \leq |\Psi^D(X_i)| \end{cases} \quad (41)$$

$$\begin{aligned} |\Psi^A(X_i)\rangle &= e^{i\theta} \cos \theta * |\Psi(\Delta_2)\rangle + e^{i\theta} \sin \theta * |\Psi(\Delta_2)\rangle \\ |\Psi^D(X_i)\rangle &= -e^{-i\theta} \sin \theta * |\Psi(\Delta_2)\rangle + e^{-i\theta} \cos \theta * |\Psi(\Delta_2)\rangle \\ |\Psi(\Delta_2)\rangle &= \sqrt{\frac{\tau}{2 * \pi * x^3}} * e \left[-\frac{\tau(x-\varphi)}{2 * \varphi^2 * x} \right] \end{aligned}$$

1. Begin
2. Define the angle of the visual
3. $AoV = 2 \cdot \arctan\left(\frac{SoB}{2 \cdot DoB}\right)$
4. Define the size of the object
5. $Oi = AoV \cdot D$
6. Determine the distance of the object
7. $MDM(x, y) = \sum_{i=1}^n |x_i - y_i|$
8. $AoV = 2 * Q \left(\frac{P_{i,j}}{2 \cdot P_{i,j} - b_{1,j}} \right)$
9. $Oi, j = AoV \cdot (P_{i,j} - b_{1,j})$
10. New $P_{i,j} = Oi, j + (|Oi, j - (b_{i,j} - |w_{i,j} - p_{i,j}|)|) \cdot rand$
11. Apply quantum computing
12. $|\Psi|^2 \cdot da \cdot db \cdot dc = Q \cdot da \cdot db \cdot dc$
13. $ih \cdot \partial / \partial t \cdot \Psi(a, t) = H \cdot \Psi(a, t)$
14. $H = -\hbar^2 / 2m \cdot \Delta^2 + V(xa)$
15. $S(T) \frac{d^2 \Psi}{dz^2} + \frac{2m}{\hbar^2} [G + \gamma \delta(z)] \Psi = 0$
16. $\Psi(z) = \frac{1}{\sqrt{L}} e^{-\frac{|a|}{L}}$
17. $V(z) = |\Psi(z)|^2 = \frac{1}{\sqrt{L}} e^{-\frac{|a|}{L}}$
18. $z = \pm \frac{L}{2} \ln(1/g)$
19. $|\Psi(t+1, X_i)\rangle = QOD = |\Psi(V_D)\rangle - \frac{\Psi^D(X_i)}{|\Psi(X_i)\rangle - |\Psi(X_o)\rangle}$
20. $|\Psi(t+1, X_i)\rangle = QOA = |\Psi(V_D)\rangle - \frac{\Psi^A(X_i)}{|\Psi(X_i)\rangle - |\Psi(X_j)\rangle + |\Psi(\Delta_1)\rangle}$
21. $QB = \begin{cases} QOA, & \text{if } |\Psi^A(X_i)| > |\Psi^D(X_i)| \\ QOD, & \text{if } |\Psi^A(X_i)| \leq |\Psi^D(X_i)| \end{cases}$
22. $|\Psi^A(X_i)\rangle = e^{i\theta} \cos \theta * |\Psi(\Delta_2)\rangle + e^{i\theta} \sin \theta * |\Psi(\Delta_2)\rangle$

$$23. |\Psi^D(X_i)\rangle = -e^{-i\theta} \sin \theta * |\Psi(\Delta_2)\rangle + e^{-i\theta} \cos \theta * |\Psi(\Delta_2)\rangle$$

$$24. |\Psi(\Delta_2)\rangle = \sqrt{\frac{\tau}{2 * \pi * x^3}} * e \left[-\frac{\tau(x-\varphi)}{2 * \varphi^2 * x} \right]$$

25. Obtain the best value

26. End

Results

The validity of the Enriched teaching-learning-inspired optimization algorithm (ETLO) and the Quantum-Opponent process theory-based (QOPT) algorithm is verified in 7 benchmark functions (Yapıcı *et al.*, 2017).

$$\begin{aligned} f_1 &= \sum_{i=1}^D x_i^2 \\ f_2 &= -20 \exp \left\{ -0.2 \sqrt{\frac{1}{D} \sum_{i=1}^D x_i^2} \right\} \\ &\quad - \exp \left\{ \frac{1}{D} \sum_{i=1}^D \cos(2\pi x_i) \right\} + 20 + e \\ f_3 &= \sum_{i=1}^{D-1} \{100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2\} \\ f_4 &= \frac{1}{4000} \sum_{i=1}^D x_i^2 - \prod_{i=1}^D \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1 \\ f_5 &= -\sum_{i=1}^4 c_i \exp \left[-\sum_{j=1}^3 a_{ij}(x_j - p_{ij})^2 \right] \\ f_6 &= 4x_1^2 - 2.1x_1^4 + \frac{1}{3}x_1^6 + x_1x_2 - 4x_2^2 + 4x_2^3 \\ f_7 &= \{1 \\ &\quad + (x_1 + x_2 + 1)^2(19 - 14x_1 + x_1^2 - 14x_2 + 6x_1x_2 \\ &\quad + 3x_2^2)\} \\ &\quad \times \left\{ \frac{30 + (2x_1 - 3x_2)^2}{(18 - 32x_1 + 12x_1^2 + 48x_2 - 36x_1x_2 + 27x_2^2)} \right\} \\ &\quad FNC \rightarrow function \end{aligned}$$

Results are displayed in Table 1 and Figure 1. The performance of the Enhanced teaching-learning inspired optimization algorithm (ETLO) and the Quantum Opposition process theory-based (QOPT) algorithm in 7 benchmark functions is better, and the algorithms are compared with the stated reported algorithms.

Enriched teaching - learning inspired optimization algorithm (ETLO) and Quantum Opponent process theory-based (QOPT) algorithm are validated in the IEEE 118 bus system. PLE (MW) - Power loss, DEI (PU) - Deviation of voltage.

Table 1. Etlo Result Of In 7 Benchmark Functions

FC	HS (Yapıcı <i>et al.</i> , 2017)	EO (Yapıcı <i>et al.</i> , 2017)	ETLO	QOPT
FC1	0.8874	0.0026	0.0091	0.0091
FC2	0.0918	0.0125	0.0181	0.0181
FC3	22.9814	16.5622	16.489	16.489
FC4	1.1092 e-2	3.459 e-4	3.82 e-4	3.82 e-4
FC5	-3.8629	-3.8629	-3.8629	-3.8629
FC6	-1.0318	-1.0316	-1.0319	-1.0319
FC7	3.0280	3.0130	3.0135	3.0135

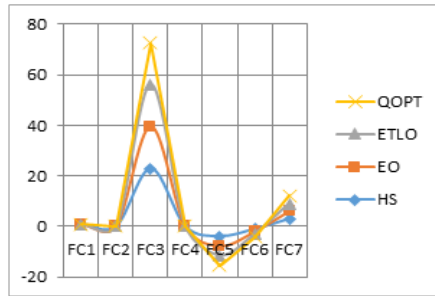
**Figure 1. ETLO valuation in 7 benchmark functions**

Table 2, Figure 2 and Figure 3 shows the estimation of outcomes in the 118 bus system. The enhanced teaching-learning-inspired optimization algorithm (ETLO) and the Quantum - Opponent process theory-based (QOPT) algorithm effectively reduced the power loss, and voltage deviation was minimized. Comparisons with other standard algorithms were done.

Enriched teaching - learning - inspired optimization algorithm (ETLO) and Quantum-Opponent process theory-based (QOPT) algorithm are validated in IEEE 300 bus system. Table 3,

Table 2. Result examination - IEEE 118 bus

Method	PLE(MW)	DEI (PU)
GEZ (Shaheen <i>et al.</i> , 2023)	128.137	1.12945
EPO (Varan <i>et al.</i> , 2023)	123.511	1.21790
ETLO	121.063	1.10437
QOPT	121.079	1.10448

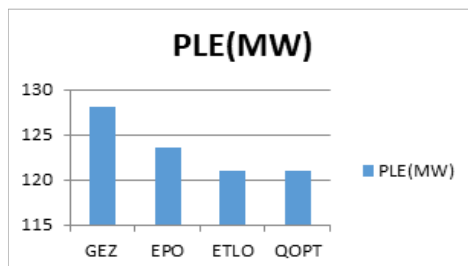
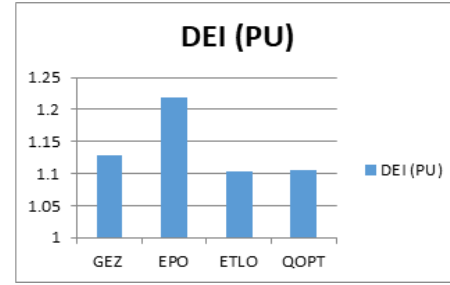
**Figure 2. PLE (MW) Examination - IEEE 118 bus****Figure 3. DEI (PU) Examination - IEEE 118 bus**

Table 3, Figure 4 and Figure 5 shows the estimation of outcomes in the 300 bus system. The enhanced teaching-learning-inspired optimization algorithm (ETLO) and the Quantum-Opponent process theory-based (QOPT) algorithm effectively reduced the power loss, and voltage deviation was minimized. Evaluation has been done with other standard reported algorithms.

Table 3. Result examination - IEEE 300 bus

Method	PLE(MW)	DEI (PU)
IBQI (Lian, 2022)	410.31	1.1276
MQA (Sahli <i>et al.</i> , 2022)	390.60	1.1079
ETLO	384.33	1.0062
QOPT	384.41	1.0069

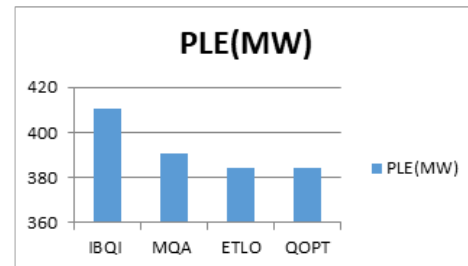
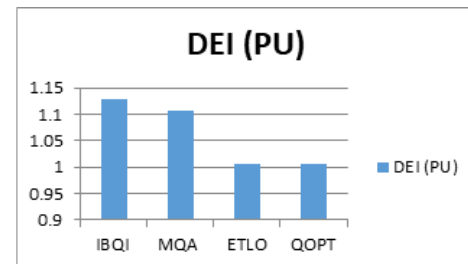
**Figure 4. PLE (MW) Examination - IEEE 300 bus****Figure 5. DEI (PU) Examination - IEEE 300 bus**

Table 4 and Figure 6 display the computation time of the Enriched teaching-learning-inspired optimization algorithm (ETLO) and the Quantum-Opponent process theory-based (QOPT) algorithm.

Table 4. ETLO, QOPT Computation Time

Technique	118 BUS T(S)	300 BUS T(S)
ETLO	33.10	52.76
QOPT	33.13	52.79

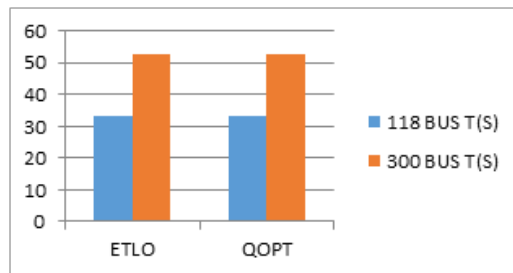


Figure 6. ETLO, QOPT computation time

Conclusions

Enriched teaching - learning inspired optimization algorithm (ETLO) and Quantum Opponent process theory-based (QOPT) algorithm skillfully solved the loss diminishing problem. Teaching - learning procedure is created based on foremost learner, one changeable learner, and the dependable learner. In the exploration segment, the learner of the procedure searches the divergent regions of the examination area to find the exclusive optimum region. Great buoyancy on unambiguous learner of the populace (distinguished learner) in evaluating the procedure populace location avoids the global exploration of the progression in the exploration planetary and diminishes the procedure's ability to discover. In the exploitation period learner of the procedure populations examine locally to find the improved solutions. Teacher will explore the ways for solving the problem as early as possible. Environment of the human mind is ambiguous. Many beliefs, faith are exploring in the mind of the students. Teacher will explore the ways for solving the problem as early as possible. Environment of the human mind is ambiguous. In the exploration segment identification of feasible solution for the problem is defined. The Opponent process theory explains about how the individual's experience different color images subsequent epoch of revelation to the original image color. If the people see red colour images but the entity experience as green color in specific period of the time after the

original image disappears. Each undergoes a sensation transformation over some time. Size of the object signifies the present rate of the candidate solution, and distance of the object characterizes the expanse from the finest solution. Based on the angle of the visual and intuition-based object size new-fangled standards of the candidate solutions of the populace are rationalized around the finest solution. Enriched teaching - learning inspired optimization algorithm (ETLO) and Quantum Opponent process theory based (QOPT) algorithm are validated in 7 benchmark functions and IEEE 118, 300 bus systems.

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