

PATU DIGUA, QUASI-OPPOSITIONAL BASED TEACHER ACTIONS IN THE SOCIETY AND QUANTUM MONASTERY CHIEF SELECTION INSPIRED OPTIMIZATION ALGORITHMS

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Abstract

Patu digua search (BKS) optimization algorithm, Quasi-Oppositional based Teacher Actions in the Society - inspired Optimization (SGS) Algorithm, Quantum Monastery chief selection Inspired Optimization (QRMCSO) Algorithm are designed and applied to solve the Electrical loss reduction problem. Patu digua search optimization algorithm is designed based on the stalking deeds of Patu digua. The stalking approaches are deliberated by oppression, examination, and hurdling on the prey. Lévy flights are engaged as an ancillary of persistent irrational engagements to emulate the fudging performance. Chaotic sequences are integrated in Patu digua search optimization algorithm. In Quasi-Oppositional based Teacher Actions in the Society - inspired Optimization Algorithm, exploration region is envisaged as a synchronize organization with a quantity of axes equivalent to the decision parameters. Quasi-Opposition approach integrated into the approach to enhance the search and quality of the solution. In QRMCSO, before picking a successor Head of the monastery will do various analyses and these standards are imitated in the design through Chebyshev serviceable connexion system.

Keywords: Monastery; Optimization; Patu digua; Teacher

Introduction

Various authors had solved the optimal reactive power problem (Jia *et al.*, 2023; Zou *et al.*, 2023; Mourtzis *et al.*, 2023). These decades swarm and evolutionary based algorithms are sequentially applied to solve the problem. In this paper Patu digua search (BKS) optimization algorithm, Quasi-Oppositional based Teacher Actions in the Society - inspired Optimization (SGS) Algorithm, Quantum Monastery chief selection Inspired Optimization

(QRMCSO) Algorithm is applied for solving the electrical power loss reduction problem. Patu digua search optimization algorithm is designed based on the stalking deeds of Patu digua. Patu digua is a flamboyant, and male Patu digua owns tawny limbs, a murky prosoma, possess a green tinge in the higher area adjacent the forward-facing, and a willowy magenta tummy with emerald transversal outlines. Once the Patu digua is not inside an expanse

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wherever it can clasp its prey by hurdling, Patu digua will transfer nearer by undertaking certain furtive actions up until it is at an attainable space where Patu digua can hurdle and clasp the prey. The oppression approach can be characterized by the consistently augmented straight-lined wave mode. Patu digua transfers laterally in the direct affiliation and the swiftness upsurges or declines linearly rendering to the phase in continuous acceleration conditions.

Balm is biochemical constituents created and concealed to the outer by a specific, they are olfactory supposed by added entities of the similar classes, and they root a performance alteration. In the Patu digua the enticing coupling is grounded on its conspicuous ensigns.

Opposition based learning integrated in the Patu digua search optimization algorithm and Laplace distribution applied to augment the exploration dexterity. Dissecting the outlook to stretch the exploration, it motivates impulsive information which used in creation of phase controller feature. In the projected technique, the exchange of precipitate figures is done with the specious figures which incited by Laplace distribution to expand the support of the prospect of design period in the exploration region.

Quasi-Optimizational based Teacher Actions in the Society - inspired Optimization (SGS) Algorithm is designed. People in the society position themselves as good and bad rendering to the actions in their life span. Certain people do good actions to the society and assist others such that burden of deprived people will get reduced. Some people may do harmful things to the society in order to earn money and attain the foremost power of domination in the society. Few people may walk along in the path of divinity and opt to stay live alone in the mountain and forest regions. Very few in the population with good thoughts will create ashram, mutt and do service to the society by staying along with the people in the same society. In the projected optimization problem solutions are located in the exploration region. Good people in the population as considered as preeminent population and bad people in the population are considered as poorest population. The Teacher, his holiness, who guiding the society is considered as paramount member of the population. The exploration region can be envisaged as a synchronize organization with a quantity of axes equivalent to the decision parameters. Projected SGS algorithm is iteration grounded procedure and affiliates of the populace move to the optimal sections. The key notion in planning the projected SGS algorithm is to appraise the location of the populace associates of the procedure which grounded on the regular info, and

deduction of the poorest and preeminent associates of the populace. Quasi-Opposition approach integrated into the approach to enhance the search and quality of the solution.

Quantum Monastery chief selection Inspired Optimization (QRMCSO) Algorithm is designed to solve the problem. Head of the monastery will observe, and uses the basic instincts to train the successor in various levels. Certain times Head of the monastery will do various actions and activities to train the successor. It may not be known to successor or anyone in the monastery. Mind calculation of head of the monastery plays an important role in deciding and training the successor. Quantum features are combined in the procedure.

Problem Formulation

Main Objective function of the problem defined as,

$$\text{Min } \tilde{F}(\bar{g}, \bar{h}) \quad (1)$$

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

$$N(\bar{g}, \bar{h}) \quad (3)$$

$$g = [VLG_1, \dots, VLG_{Ng}; QC_1, \dots, QC_{Nc}; T_1, \dots, T_{N_T}] \quad (4)$$

$$h = [PG_{slack}; VL_1, \dots, VL_{N_{Load}}; QG_1, \dots, QG_{Ng}; SL_1, \dots, SL_{N_T}] \quad (5)$$

where; Q_c reactive power compensator
 T Transformer tap
 Fitness functions defined as follows,

$$F_1 = P_{\text{Min}} = \text{Min} \left[\sum_m^{NTL} G_m [V_i^2 + V_j^2 - 2 * V_i V_j \cos \theta_{ij}] \right] \quad (6)$$

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

$$F_3 = \text{Minimize } L_{\text{Maximum}} \quad (8)$$

$$S_L \rightarrow \text{Apparent power } L_{\text{Max}} = \text{Max}[L_j]; j = 1; N_{LB} \quad (9)$$

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

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

$$0 = PG_i - PD_i - V_i \sum_{j \in N_B} V_j [G_{ij} \cos[\theta_i - \theta_j] + B_{ij} \sin[\theta_i - \theta_j]] \quad (12)$$

$$0 = QG_i - QD_i - V_i \sum_{j \in N_B} V_j [G_{ij} \sin[\theta_i - \theta_j] + B_{ij} \cos[\theta_i - \theta_j]] \quad (13)$$

$$P_{gsi}^{\text{min}} \leq P_{gsi} \leq P_{gsi}^{\text{max}} \quad (14)$$

$$Q_{gi}^{\min} \leq Q_{gi} \leq Q_{gi}^{\max}, i \in N_g \quad (15)$$

$$VL_i^{\min} \leq VL_i \leq VL_i^{\max}, i \in NL \quad (16)$$

$$T_i^{\min} \leq T_i \leq T_i^{\max}, i \in N_T \quad (17)$$

$$Q_c^{\min} \leq Q_c \leq Q_c^{\max}, i \in N_c \quad (18)$$

$$|SL_i| \leq S_{L_i}^{\max}, i \in N_{TL} \quad (19)$$

$$VG_i^{\min} \leq VG_i \leq VG_i^{\max}, i \in N_g \quad (20)$$

$$\text{Multi objective fitness (MOF)} = F_1 + r_1 F_2 + u F_3 = F_1 + \left[\sum_{i=1}^{NL} x_v [VL_i - VL_i^{\min}]^2 + \sum_{i=1}^{NG} r_g [QG_i - QG_i^{\min}]^2 \right] + r_f F_3 \quad (21)$$

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

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

Patu Digua Search Optimization Algorithm

Patu digua search (BKS) optimization algorithm is designed based on the stalking deeds of Patu digua (Kulkarni *et al.*, 2023). Patu digua is a flamboyant, and male Patu digua owns tawny limbs, a murky prosoma, possess a green tinge in the higher area adjacent the forward-facing, and a willowy magenta tummy with emerald transversal outlines show in Figure 1. Female Patu digua owns tawny anterior limbs are stronger than the other, willowy limbs, which are nimble beige. It has a reddish brown prosoma, with the upper area neighboring the anterior gloomy. Female Patu digua moderately own big stomach and its light russet with murky auburn and green tinge motifs.



Figure 1. Patu digua

Patu digua dwells in Mimosoideae foliage (in specific Fabaceae vegetation), where it eats specialized essential nutrients and also ingest fluid and infrequently snip ant grubs from transitory operative ants for nourishment.

In the face of their random performances of biological interaction, the Patu digua soft tissue have been set up to display isotopic signs distinctive of herbivorous faunae, entailing that maximum of their nourishment originates from floras. The contrivance by which they practice, consume, and digest the Beltian physiquies is still unsearched. The massive preponderance of Patu digua deliquesce their prey by means of peptic enzymes earlier imbibing it inside.

The stalking approaches deliberated are confronting by oppression, examination, and hurdling on the prey. In accumulation, an archetypal is also measured to characterize the balm degree.

Once the Patu digua is not inside an expanse wherever it can clasp its prey by hurdling, Patu digua will transfer nearer by undertaking certain furtive actions up until it is at an attainable space where Patu digua can hurdle and clasp the prey. The oppression approach can be characterized by the consistently augmented straight-lined wave mode. Patu digua transfers laterally in the direct affiliation and the swiftness upsurges or declines linearly rendering to the phase in continuous acceleration conditions.

$$O_i = 1/2 at^2 + \text{velocity}_0 t \quad (24)$$

Where; O_i is the location of the i th Patu digua
 t specify the time

$$\text{acceleration}(a) = \text{velocity}/\text{time} \quad (25)$$

$$\text{velocity} = O - O_0 \quad (26)$$

Rendering to the time,

$$\vec{O}_i(s+1) = 1/2 (\vec{O}_i(s) - \vec{O}_a(s)) \quad (27)$$

Where; $\vec{O}_i(s+1)$ is the fresh position of the examination agent

$\vec{O}_a(s)$ present examination agent

$\vec{O}_a(s)$ search agent Arbitrarily selected

$i \neq a$

$a \in 1$ to max. of examination agents

The hurdling Patu digua trails its prey and bounds on it. The stalking stratagem of hurdling on the prey can be characterized in a missile gesticulation.

$$\vec{a}_i = \text{velocity}_0 \cos(\delta) \vec{t} \quad (28)$$

$$da/dt = \overline{\text{Velocity}}_a = \text{velocity}_0 \cos(\delta) \vec{t} \quad (29)$$

$$\vec{b}_i = (\text{velocity}_0 \sin(\delta) t - 1/2 st^2) \vec{j} \quad (30)$$

$$db/dt = \overrightarrow{\text{Velocity}}_b = (\text{velocity}_0 \sin(\delta) - st)^j \quad (31) \quad \vec{a}_i(s) = \vec{a}_E(s) + \frac{1}{2} (\vec{a}_{n1}(s) - (-1)^\sigma \vec{a}_{n2}(s)) \quad (37)$$

Rendering to the time the motion is defined as,

$$b = a \tan(\delta) - sa^2/2\text{velocity}_0^2 \cos^2(\delta) \quad (32)$$

As a final point, the flight portrayed as,

$$\vec{a}_i(s+1) = \vec{a}_i(s) \tan(\delta) - s\vec{a}_i^2(s)/2\text{velocity}_0^2 \cos^2(\delta) \quad (33)$$

Where; $\delta = \varphi\pi/180$
 $\vec{a}_i(s+1)$ fresh location of the examination agent
 $\vec{a}_i(s)$ is the present location
 velocity_0 is fixed as 100.00 mm seg
 s is the gravitational factor $\in (0,1)$
 $\varphi \in (0,1)$

The Hurdling Patu digua executes an arbitrary exploration nearby the location to discover the prey. Narrow and universal examination, are projected for the moulding of this pursuit method.

$$\vec{a}_i(s+1) = \vec{a}_E(s) + w(1/2 - \varepsilon) \quad (34)$$

Where; $\vec{a}_i(s+1)$ fresh location of the examination agent
 $\vec{a}_E(s)$ is the excellent examination agent
 w is pseudo arbitrary integer $\in (-2,2)$
 $\varepsilon \in (0,1)$

$$\vec{a}_i(s+1) = \vec{a}_E(s) + (\vec{a}_E(s) - \vec{a}_P(s))\Delta \quad (35)$$

Where; $\vec{a}_i(s+1)$ fresh location of the examination agent
 $\vec{a}_E(s)$ and $\vec{a}_P(s)$ are excellent and poor examination agent
 Δ symbolize the cauchy arbitrary integer (0,1)

The balm is biochemical constituents created and concealed to the outer by a specific, they are olfactory supposed by added entities of the similar classes, and they root a performance alteration. In the Patu digua the enticing coupling is grounded on its conspicuous ensigns. However, they similarly create balm and it defined as,

$$\text{Balm}(i) = \frac{F(\text{max}) - F(i)}{F(\text{max}) - F(\text{min})} \quad (36)$$

Where; $F(\text{max}) - F(\text{min})$ max and min fitness
 $F \in (0,1)$
0 and 1-poor and excellent Balm rate

Where; $\vec{a}_i(s)$ is hurdling Patu digua
 $n1$ and $n2$ are arbitrary integers from 1 to max. of examination agents
 $\sigma \in \{0,1\}$

The balm procedure is defined as,

- a. Start
- b. Calculate the balm rate for all Patu digua
- c. $\text{Balm}(i) = \frac{F(\text{max}) - F(i)}{F(\text{max}) - F(\text{min})}$
- d. For $i = 1$ to size pop do
- e. if $\text{balm}(i) \leq 0.30$, then
- f. Modernize the examination agent
- g. $\vec{a}_i(s) = \vec{a}_E(s) + \frac{1}{2} (\vec{a}_{n1}(s) - (-1)^\sigma \vec{a}_{n2}(s))$
- h. End if
- i. End for
- j. Return $\vec{a}$
- k. End

$$Z_i = \frac{a}{|b|^{1/\beta}} \quad (38)$$

Opposition based learning integrated in the Patu digua search optimization algorithm.

$$f(l) = \begin{cases} \frac{1}{2} \exp(-|l - c|/d), b \leq c \\ 1 - \frac{1}{2} \exp(-|l - c|/d), b > c \end{cases} \quad (39)$$

$$f(l; c, d) = 1/2 \exp(-|v - c|/d), -\infty < c < \infty$$

$$S^o = a + b - Z$$

$$S_i^o = a_i + b_i - Z_i$$

$$S_i \in [a_i, b_i], i \rightarrow \{1, 2, 3, \dots, d\}$$

$$S_i(\text{iteration}) = (\text{minimum}_i + \text{maximum}_i - S_e(\text{iteration})) \quad (40)$$

- a. Start
- b. Set the parameters
- c. Arbitrarily engender the preliminary population
- d. while iter < max. No of iter. do
- e. if arbitrary < 0.50, then its spasm or examination
- f. if arbitrary < 0.50, then
- g. Spasm by oppression
- h. $\vec{O}_i(s+1) = 1/2 (\vec{O}_i(s) - \vec{O}_a(s))$
- i. Otherwise
- j. Spasm by hurdling on the prey
- k. $\vec{a}_i(s+1) = \vec{a}_i(s) \tan(\delta) - s\vec{a}_i^2(s)/2\text{velocity}_0^2 \cos^2(\delta)$
- l. End if
- m. Otherwise
- n. if arbitrary < 0.50, then
- o. Examination for the prey by confined exploration
- p. $\vec{a}_i(s+1) = \vec{a}_E(s) + w(1/2 - \varepsilon)$

- q. Otherwise
- r. Examination for the prey by universal exploration
- s. $\vec{a}_i(s+1) = \vec{a}_E(s) + (\vec{a}_E(s) - \vec{a}_P(s))\Delta$
- t. End if
- u. End if
- v. Modernize the examination agents
- w. Start
- x. Calculate the balm rate for all Patu digua
- y. $\text{Balm}(i) = \frac{F(\max) - F(i)}{F(\max) - F(\min)}$
- z. $f(l) = \begin{cases} \frac{1}{2} \exp(-|l - c|/d), b \leq c \\ 1 - \frac{1}{2} \exp(-|l - c|/d), b > c \end{cases}$
- aa. $S_i(\text{iteration}) = X_s * (\text{minimum}_i + \text{maximum}_i - S_e(\text{iteration}))$
- bb. For $i = 1$ to size pop do
- cc. if $\text{balm}(i) \leq 0.30$, then
- dd. Modernize the examination agent
- ee. $\vec{a}_i(s) = \vec{a}_E(s) + \frac{1}{2}(\vec{a}_{n1}(s) - (-1)^{\sigma} \vec{a}_{n2}(s))$
- ff. End if
- gg. End for
- hh. Return $\vec{a}$
- ii. End
- jj. Compute the a_{fresh} fitness standards of the examination agents
- kk. if $a_{\text{fresh}} < a_*$, then
- ll. $a_* = a_{\text{fresh}}$
- mm. End if
- nn. $\text{iter} = \text{iter} + 1$
- oo. Output the a_* (excellent solution)
- pp. End

Quasi-Optpositional Based Teacher Actions In The Society – Inspired Optimization Algorithm

In this paper a Novel Quasi-Optpositional based Teacher Actions in the Society - inspired Optimization (SGS) Algorithm is applied. Good people (rendering to good actions) in the population move towards to the good action oriented places and equally bad people (with reference to bad activities) in the population move towards the worst actions doing places which naturally harm the peace and prosperity of the society. At this juncture the Teacher (Figure 2) (Swamiji *et al.*, 2018) will apply themselves without any sort of intentions to guide the entire category (good and bad) of the population in right path. In the projected optimization problem solutions are located in the exploration region.

Good people in the population as considered as preeminent population and bad people in the population are considered as poorest population. The Teacher, his holiness, who guiding the society is considered as paramount member of the population. The exploration region can be envisaged as a synchronize organization with a quantity of

axes equivalent to the decision parameters. Populace affiliates passage in the exploration region and standards of the assessment parameters are defined by the location of the populations. The procedure grounded on the regular info, and deduction of the poorest and preeminent associates of the populace. Quasi-Optpositional approach integrated into the approach to enhance the search and quality of the solution. In the projected procedure every population affiliate is possible solution to the considered problem and the population is engendered as follows,

$$P = \begin{bmatrix} P_1 \\ \vdots \\ P_i \\ \vdots \\ P_N \end{bmatrix}_{N \times m} = \begin{bmatrix} p_{1,1} & \cdots & p_{1,m} \\ \vdots & \ddots & \vdots \\ p_{N,1} & \cdots & p_{N,m} \end{bmatrix}_{N \times m} \quad (41)$$

$P \rightarrow$ procedure candidate solution

$m \rightarrow$ decision parameter

$N \rightarrow$ SGS population members

Every explorer associate is a possible solution to the specified problem. By engaging the solutions in the assessment parameters, the aim functional value appraised and it gives value as resultant to each member.

$$Z = \begin{bmatrix} Z_1 \\ \vdots \\ Z_i \\ \vdots \\ Z_N \end{bmatrix}_{N \times 1} \quad (42)$$

$Z \rightarrow$ complete value of the objective function

In order to enhance the quality of the solutions three sections are applied in the modernization procedure of the algorithm. In the first section both good and bad associates of the populace are utilized for updating. Secondly location of members in the population is streamlined after classifying and deducting the good and bad population members from entire population. Third the Teacher as



Figure 2. Teacher pontiff SGS with followers

paramount member will guide the population in order to attain the better solutions. At first both good and bad members of the population are utilized to modernize the population as follows,

$$A^{o_1} = \frac{P_g + P_b}{2} \quad (43)$$

$A^{o_1} \rightarrow$ average of good and bad members

$P_g \rightarrow$ good members of the population

$P_b \rightarrow$ bad members of the population

$$p_{i,d}^{new,o_1} = \begin{cases} p_{i,d} + E \cdot (A_d^{o_1} - H \cdot p_{i,d}), Z^{o_1} < Z_i \\ p_{i,d} + E \cdot (p_{i,d} - A_d^{o_1}) \text{ otherwise} \end{cases} \quad (44)$$

$H = [1, 2]$

$E = [0, 1]$

$P_i = \begin{cases} p_i^{new,o_1}, Z_i^{new,o_1} < Z_i \\ P_i, \text{otherwise} \end{cases}$

$p_i^{new,o_1} \rightarrow$ new location of ith population

member in first section

Z_i^{new,o_1} objective functional

value in first section

Secondly the location of the members in the population is streamlined after classifying and deducting the good and bad population members from entire population as follows,

$$A^{o_2} = P_g - P_b \quad (45)$$

$$p_{i,d}^{new,o_2} = p_{i,d} + E \cdot A_d^{o_2} \quad (46)$$

$$P_i = \begin{cases} p_i^{new,o_2}, Z_i^{new,o_2} < Z_i \\ P_i, \text{otherwise} \end{cases} \quad (47)$$

$A^{o_2} \rightarrow$ deduction the good and bad

population members from entire population

$p_i^{new,o_2} \rightarrow$ new location of ith population member

in second section

Z_i^{new,o_2} objective functional value in second section

Third the Teacher as paramount member will guide the population in order to attain the better solutions as follows,

$$p_{i,d}^{new,o_3} = p_{i,d} + E \cdot (p_{i,d} - H \cdot p_{g,b}) \quad (48)$$

$$P_i = \begin{cases} p_i^{new,o_3}, Z_i^{new,o_3} < Z_i \\ P_i, \text{otherwise} \end{cases} \quad (49)$$

$p_i^{new,o_3} \rightarrow$ new location of ith population member in third section

Z_i^{new,o_3} objective functional value in third section

Quasi opposition-based learning (Lenin, 2023) integrated in the process

$$O_{OBL}(t+1) = \text{Min} + \text{Max} - O(t) \quad (50)$$

$$O_{QSOBL}(t+1) = \begin{cases} \frac{\text{Min} + \text{Max}}{2} + R \times \left((\text{Min} + \text{Max} - O(t)) - \frac{\text{Min} + \text{Max}}{2} \right) & \text{if } (\text{Min} + \text{Max} - O(t)) > \frac{\text{Min} + \text{Max}}{2} \\ (\text{Min} + \text{Max} - O(t)) + R \times \left(\frac{\text{Min} + \text{Max}}{2} - (\text{Min} + \text{Max} - O(t)) \right) & \text{otherwise} \end{cases} \quad (51)$$

$$O(t+1) = \begin{cases} O_{OBL}(t), & \text{if } R < 0.1 \\ O_{QSOBL}(t), & \text{otherwise} \end{cases} \quad (52)$$

- a. Begin
- b. Create primary population
- c. Fix the Quasi opposition points
- d. Assess the objective function
- e. For $t = 1$ to T
- f. Update the good members of the population
- g. Modernize the bad members of the population
- h. For $i = 1$ to N
- i. $O_{OBL}(t+1) = \text{Min} + \text{Max} - O(t)$
- j. Execute the first section
- k. Compute A^{o_1}
- l. $A^{o_1} = \frac{P_g + P_b}{2}$
- m. Update P_i
- n. $p_{i,d}^{new,o_1} = \begin{cases} p_{i,d} + E \cdot (A_d^{o_1} - H \cdot p_{i,d}), Z^{o_1} < Z_i \\ p_{i,d} + E \cdot (p_{i,d} - A_d^{o_1}) \text{ otherwise} \end{cases}$
- o. $P_i = \begin{cases} p_i^{new,o_1}, Z_i^{new,o_1} < Z_i \\ P_i, \text{otherwise} \end{cases}$
- p. Execute the second section
- q. Compute A^{o_2}
- r. $A^{o_2} = P_g - P_b$
- s. Update P_i
- t. $p_{i,d}^{new,o_2} = p_{i,d} + E \cdot A_d^{o_2}$
- u. $P_i = \begin{cases} p_i^{new,o_2}, Z_i^{new,o_2} < Z_i \\ P_i, \text{otherwise} \end{cases}$
- v. Execute the third section
- w. $p_{i,d}^{new,o_3} = p_{i,d} + E \cdot (p_{i,d} - H \cdot p_{g,b})$
- x. $P_i = \begin{cases} p_i^{new,o_3}, Z_i^{new,o_3} < Z_i \\ P_i, \text{otherwise} \end{cases}$
- y. End for
- z. $t = t + 1$
- aa. Output the best solution

End

Quantum Monastery Chief Selection Inspired Optimization Algorithm

In this paper Quantum Monastery chief selection Inspired Optimization (QRMCSSO) Algorithm is designed to solve the Active power loss diminishing problem. The head of the monastery will produce specific physiognomies by means of observing,

version, basic instincts as feelings. Before picking a successor, head of the monastery will do various analyses and these standards are imitated in the design through Chebyshev serviceable connexion system. Mind calculation of head of the monastery plays an important role in deciding and training the successor. Few times after section also head of the monastery may change another one; it's all depend on the how the designated successor acquire the knowledge for running the monastery without any sort of problems. Figure 3 shows the monastery head Sri Ganapathy Sachchidananda Swamiji - Avadhoota Datta monastery (Avadhoota Datta Peetham 2024) (Dr Sri Ganapathy Sachchidananda Swamiji *et al.*, 2018).



Figure 3. Monastery head Sri Ganapathy Sachchidananda Swamiji - Avadhoota Datta monastery (Avadhoota Datta Peetham 2024)

The head of the monastery search and activities are defined with boundaries as follows,

$$M_j^i = LB + U_j \times (UB - LB) \quad (53)$$

Where; LB is lower bound
UB is upper bound
 $U_j \in [0,1]$

Population is signified in the matrix as follows,

$$Z = \begin{bmatrix} z_1^1 & \dots & z_n^1 \\ \vdots & \ddots & \vdots \\ z_1^N & \dots & z_n^N \end{bmatrix}_{N \times n} \quad (54)$$

Fitness rate of the probable successors is calculated by exploiting the physiognomies (choice parameters) in the customary appropriateness utility and the calculated standards are stockpiled in matrix as follows,

$$f(Z) = \begin{bmatrix} f_1[z_1^1, \dots, z_n^1] \\ f_2[z_1^2, \dots, z_n^2] \\ \vdots \\ f_N[z_1^N, \dots, z_n^N] \end{bmatrix}_{N \times n} \quad (55)$$

Where; $f(Z)$ specify the Existing population's fitness rate

By Least Squares Guesstimate the projected scheme is optimized. Chebyshev serviceable polynomial is stimulated as follows,

$$O_k(z) := \begin{cases} 1. & ; \text{if } p = 1 \\ z. & ; \text{if } p = 1 \\ 2zT_{p-1}(z) - O_{p-2}(z). & ; \text{if } p \geq 2 \end{cases} \quad (56)$$

Standardized rate of the physiognomies are demarcated as,

$$\hat{z}_j^i = 2 * \frac{(z_j^i - LB)}{(UB - LB)} - 1 \quad (57)$$

Where; LB is lower bound
UB is upper bound
 $i = 1, 2, 3, \dots, N$
 $j = 1, 2, 3, \dots, n$

The matrix for the standardized value of the physiognomies is demarcated as,

$$\hat{Z} = \begin{bmatrix} \hat{z}_1^1 & \dots & \hat{z}_n^1 \\ \vdots & \ddots & \vdots \\ \hat{z}_1^N & \dots & \hat{z}_n^N \end{bmatrix}_{N \times n} \quad (58)$$

For each input component in the matrix the retrogression and sub- retrogression is defined as,

$$\mathfrak{A} = \begin{bmatrix} O_1(\hat{z}_1^1) & \dots & O_p(\hat{z}_n^1) \\ \vdots & \ddots & \vdots \\ O_1(\hat{z}_1^N) & \dots & O_p(\hat{z}_n^N) \end{bmatrix}_{N \times (n \times k)} = \begin{bmatrix} \mathfrak{R}_1^1 & \dots & \mathfrak{R}_n^1 \\ \vdots & \ddots & \vdots \\ \mathfrak{R}_1^N & \dots & \mathfrak{R}_n^N \end{bmatrix} \quad (59)$$

Where; $\mathfrak{A}$ is retrogression
 $\mathfrak{R}$ is sub - retrogression

Least Squares Assessment increment dynamics are attained as follows,

$$\begin{aligned} \widehat{\varphi}f &= (\mathfrak{A}^T \mathfrak{A})^{-1} \mathfrak{A}^T f \\ (\widehat{\varphi}f) &= [\varphi f_1^1 \dots \dots \varphi f_n^1]_{1 \times (n \times p)} \\ &= [\varphi f^1 \dots \dots \varphi f^n]^T \end{aligned} \quad (60)$$

Fractional fitness rate is attained by,

$$\widehat{Vf}_j^i = \mathfrak{A}_j^i \varphi^i \quad (61)$$

$$\widehat{VF} = \begin{bmatrix} \widehat{vf}_1^1 & \dots & \widehat{vf}_n^1 \\ \vdots & \ddots & \vdots \\ \widehat{vf}_1^N & \dots & \widehat{vf}_n^N \end{bmatrix}_{N \times n} \quad (62)$$

Premium physiognomies of current populace is demarcated by,

$$z_j^* = z_j^{\text{minimum}^j} \quad (62)$$

$$\text{minimum}^j = \arg \min_{i=1,2,3,\dots,N} \{\hat{v}_{ij}^d | i=1,2,3,\dots,N\}, \forall j \quad (63)$$

Fresh physiognomies are found by,

$$z_{\text{new}}^i = z^i - R_1(z^i - z^*) \quad (64)$$

$R_1 \in [0,1]$

Ideal will be chosen based on the personal basic instincts of the whom own the premium fitness rate and rendering to this fresh physiognomies as follows,

$$z_{\text{new}}^i = z^i - R_2(z^{\text{vth Head}} - v^{\text{ideal}}) \quad (65)$$

$R_2 \in [0,1]$

Head of the monastery will sort out options in his mind and picks four or five disciples in the top level of the monastery and by conducting various analyses; out of which one will be announced as successor of the monastery.

$$z_{\text{new}}^i = z^i - R_3(z^i - z^{\text{analyses}}) \quad (66)$$

$$R_3 \in [0,1] \quad (67)$$

$$z^{\text{analyses}} = [z^g \quad z^g \quad z^g]^T_{1 \times n}$$

Head of the monastery will observe, and uses the basic instincts to train the successor in various levels.

$$z_{\text{new}}^i = \begin{cases} z^i - R_1(z^i - z^*), & R_4 \leq 1/3 \\ z^i - R_2(z^{\text{vth Head}} - v^{\text{ideal}}), & 1/3 < R_4 < 2/3 \\ z_{\text{new}}^i = z^i - R_3(z^i - z^{\text{analyses}}), & 2/3 < R_4 \end{cases} \quad (68)$$

$R_4 \in [0,1]$

The situations (S) during the process of choosing successor is defined as,

$$S = \exp(-n/N) \quad (69)$$

Where; n is existing iteration
 N specify the is maximum iteration

Test and analysis (TA) in the process is defined as,

$$TA = B_1 \times \exp(n - N/N) \quad (70)$$

$B_1 = 0.5$

Head of the monastery will have own mind calculations and conditions,
 $W < \text{Origin rate}$
 $\text{Origin rate} = 0.25$

Capriciously the position is selected and mathematically it defined as,

$$Z_{i,m}(n+1) = Z_{R,m}(n) \pm B_2 \times K_m \times ((Z_{UB} - Z_{LB}) \times R + Z_{LB}) \quad (71)$$

$Z_{i,m}(n+1)$ specify Head of the monastery position
 $R \in [0,1]$
 K_m is the Head of the monastery actions in the process of choosing

$$K_m = \exp(-F_{R,f}/F_{i,m}) \quad (72)$$

Where; $F_{R,f}$ is the fitness value of $Z_{R,f}$
 $F_{i,f}$ fitness value of the successor

$$Z_{i,f}(n+1) = Z_{R,f}(n) \pm B_2 \times K_f \times ((Z_{UB} - Z_{LB}) \times R + Z_{LB}) \quad (73)$$

$$K_f = \exp(-F_{R,f}/F_{i,f})$$

In the phase of exploitation the origin rate is demarcated as,

$W > \text{origin rate}$
 $\text{origin rate} = 0.6$

$$Z_{i,j}(n+1) = Z_{i,q}(n) \pm b_3 \times W \times R \times ((Z_{E,f} - Z_{i,m}(n))) \quad (74)$$

Where; $Z_{i,j}(n+1)$ define the position of the individual
 $B_3 = 2.0$
 $W < \text{origin rate}$
 $\text{origin rate} = 0.60$

Certain times four or more will be initially picked by the Head of the monastery and from that one will be selected as successor based on the outcome of the analysis.

$$Z_{i,m}(n+1) = Z_{i,m}(n) \pm b_3 \times CGC \times R \times ((Z_{E,f} - Z_{i,m}(n))) \quad (75)$$

Where; CGC define the contending capability
 $Z_{i,m}(n)$ – position of Head monastery
 $Z_{E,f}$ define the position of the eminent sucssor with the Head of the monastery

Few time all may fail in the test and procedures conducted by Head of the monastery and again another set of disciples will be picked by the Head of the monastery to identify the successor.

$$Z_{i,f}(n+1) = Z_{i,f}(n) \pm B_3 \times OGA \times R \times ((Z_{E,m} - Z_{i,f}(n+1))) \quad (76)$$

Where; OGA define the various set of disciples
 $Z_{i,f}(n)$ – position of disciples as contenders
 $Z_{E,m}$ define the contender picked as sucssor
 $CGC = \exp(-F_{E,f}/F_i)$
 $OGA = \exp(-F_{E,m}/F_i)$

Coherent actions of Head of the monastery and designated successor is delineated scientifically,

$$Z_{i,m}(n+1) = Z_{i,m}(n) \pm B_3 \times EA_M \times R \times (W \times (Z_{E,fe} - Z_{i,m}(n))) \quad (77)$$

$$Z_{i,f}(n+1) = Z_{i,f}(n) \pm B_3 \times EA_F \times R \times (W \times (Z_{E,m} - Z_{i,f}(n+1))) \quad (78)$$

Where; EA_M define the actions of Head of the monastery
 EA_F define the actions of designated successor
 $EA_M = \exp(-F_{i,f}/F_{i,m})$
 $EA_F = \exp(-F_{i,m}/F_{i,f})$

Quantum features are combined in the procedure.

$$|\Psi|^2 \cdot dx \cdot dy \cdot dz = Q \cdot dx \cdot dy \cdot dz \quad (79)$$

Ψ is probability density

$ih \cdot \partial/\partial t \cdot \Psi(x, t) = H_p \cdot \Psi(x, t)$

H_p is Hamiltonian operator

$H_p = -h^2/2m \cdot \Delta^2 + V(x)$

$$Si(Ti)is \frac{d^2\Psi}{dz^2} + \frac{2m}{h^2} [G + \gamma\delta(z)]\Psi = 0$$

$$\Psi(z) = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}}$$

$$Q(z) = |\Psi(z)|^2 = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}}$$

$$z = \pm \frac{L}{2} \ln(1/g)$$

- Start
- Initial populace is created
- $Z_j^i = LB + U_j \times (UB - LB)$
- Fitness rate is computed
- while end ccondition is not sastisfied do
- Calculated standards are stockpiled in matrix

$$g. (f(Z)) = \begin{bmatrix} f_1[z_1^1, \dots, z_n^1] \\ f_2[z_1^2, \dots, z_n^2] \\ \vdots \\ f_N[z_1^N, \dots, z_n^N] \end{bmatrix}_{N \times n}$$

h. Chebyshev serviceable polynomial is stimulated

$$i. O_k(z) := \begin{cases} 1. & ; \text{if } p = 1 \\ z. & ; \text{if } p = 1 \\ 2zT_{p-1}(z) - O_{p-2}(z). & ; \text{if } p \geq 2 \end{cases}$$

$$j. \hat{z}_j^i = 2 * \frac{(z_j^i - LB)}{(UB - LB)} - 1$$

k. Generate matrix for the standardized value of the physiognomies

$$l. \hat{Z} = \begin{bmatrix} \hat{Z}_1^1 & \dots & \hat{Z}_n^1 \\ \vdots & \ddots & \vdots \\ \hat{Z}_1^N & \dots & \hat{Z}_n^N \end{bmatrix}_{N \times n}$$

m. For each input component in the matrix the retrogression and sub- retrogression is defined

$$n. \mathfrak{A} = \begin{bmatrix} O_1(\hat{Z}_1^1) & \dots & O_p(\hat{Z}_n^1) \\ \vdots & \ddots & \vdots \\ O_1(\hat{Z}_1^N) & \dots & O_p(\hat{Z}_n^N) \end{bmatrix}_{N \times (n \times k)} =$$

$$\begin{bmatrix} \mathfrak{N}_1^1 & \dots & \mathfrak{N}_n^1 \\ \vdots & \ddots & \vdots \\ \mathfrak{N}_1^N & \dots & \mathfrak{N}_n^N \end{bmatrix}$$

o. Least Squares Assessment increment parameter is premeditated

$$\widehat{\varphi f} = (\mathfrak{A}^T \mathfrak{A})^{-1} \mathfrak{A}^T f$$

$$p. (\widehat{\varphi f}) = [\varphi f_1^1 \dots \dots \varphi f_n^1]_{1 \times (n \times p)}^T = [\varphi f^1 \dots \dots \varphi f^n]^T$$

q. Fractional fitness rate is attained

$$r. \widehat{Vf}_j^i = \mathfrak{A}_j^i \varphi^i$$

$$s. \widehat{VF} = \begin{bmatrix} \widehat{Vf}_1^1 & \dots & \widehat{Vf}_n^1 \\ \vdots & \ddots & \vdots \\ \widehat{Vf}_1^N & \dots & \widehat{Vf}_n^N \end{bmatrix}_{N \times n}$$

$$t. Sch(Ti)is \frac{d^2\Psi}{dz^2} + \frac{2m}{h^2} [G + \gamma\delta(z)]\Psi = 0$$

$$u. \Psi(z) = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}}$$

$$v. Q(z) = |\Psi(z)|^2 = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}}$$

w. Premium physiognomies of current populace is demarcated

$$x. z_j^* = z_j^{\text{minimum}^j}$$

$$y. \text{minimum}^j = \arg \min_{l=1,2,3,\dots,N} \{\widehat{Vf}_l^j\}_{\forall j}$$

z. Fresh physiognomies are found

$$aa. z_{\text{new}}^i = z^i - R_1(z^i - z^*)$$

bb. Ideal will be selected

$$cc. z_{\text{new}}^i = z^i - R_2(z^{\text{vth Head}} - v^{\text{ideal}})$$

dd. Analysis done by Head of the monastery

$$ee. z_{\text{new}}^i = z^i - R_3(z^i - z^{\text{analyses}})$$

$$ff. z^{\text{analyses}} = [z^g \quad z^g \quad z^g]_{1 \times n}^T$$

gg. Head of the monastery will observe, and uses the basic instincts to train the successor in various levels.

$$hh. z_{\text{new}}^i = \begin{cases} z^i - R_1(z^i - z^*) , \\ R_4 \leq 1/3 \\ z^i - R_2(z^{\text{vth Head}} - v^{\text{ideal}}), \\ 1/3 < R_4 < 2/3 \\ z_{\text{new}}^i = z^i - R_3(z^i - z^{\text{analyses}}), \\ 2/3 < R_4 \end{cases}$$

ii. Situations (S) during the process of choosing successor is defined

$$jj. S = \exp(-n/N)$$

kk. Test and analysis (TA) in the process is defined

$$ll. TA = B_1 \times \exp(n - N/N)$$

$$mm. Atmosphere = \exp(-n/N)$$

nn. Head of the monastery apply various actions in the process of selection

oo. Capriciously the position is selected

$$pp. Z_{i,m}(n+1) = Z_{R,m}(n) \pm B_2 \times K_m \times ((Z_{UB} - Z_{LB}) \times R + Z_{LB})$$

$$qq. Z_{i,f}(n+1) = Z_{R,f}(n) \pm B_2 \times K_f \times ((Z_{UB} - Z_{LB}) \times R + Z_{LB})$$

rr. In the phase of exploitation the origin rate is demarcated

$$ss. Z_{i,j}(n+1) = Z_{i,q}(n) \pm b_3 \times W \times R \times ((Z_{E,f} - Z_{i,m}(n)))$$

tt. Head of the monastery will select a successor based on the outcome of the analysis

$$uu. Z_{i,m}(n+1) = Z_{i,m}(n) \pm b_3 \times CGC \times R \times ((Z_{E,f} - Z_{i,m}(n)))$$

- vv. If first set of contenders fail, another set of disciples will be picked by the Head of the monastery to identify the successor.
- ww. $Z_{i,f}(n+1) = Z_{i,f}(n) \pm B_3 \times OGA \times R \times (Z_{E,m} - Z_{i,f}(n+1))$
- xx. $CGC = \exp(-F_{E,fe}/F_i)$
- yy. $OGA = \exp(-F_{E,m}/F_i)$
- zz. Coherent actions of Head of the monastery and designated successor is delineated
- aaa. $Z_{i,m}(n+1) = Z_{i,m}(n) \pm B_3 \times EA_M \times R \times (W \times (Z_{E,fe} - Z_{i,m}(n)))$
- bbb. $Z_{i,f}(n+1) = Z_{i,f}(n) \pm B_3 \times EA_F \times R \times (W \times (Z_{E,m} - Z_{i,f}(n+1)))$
- ccc. $EA_M = \exp(-F_{i,f}/F_{i,m})$
- ddd. $EA_F = \exp(-F_{i,m}/F_{i,f})$
- eee. $n = n + 1$
- fff. Return the most excellent optimal solution
- ggg. End

Simulation Study

Validity of Patu digua search (BKS) optimization algorithm, Quasi-Optpositional based Teacher

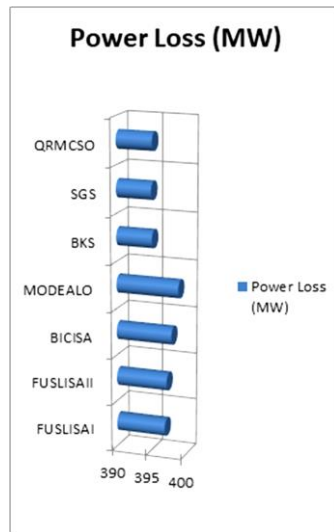


Figure 4. Appraisal of power loss (IEEE 300 bus)

Actions in the Society - inspired Optimization (SGS) Algorithm, Quantum Monastery chief selection Inspired Optimization (QRMCSO) Algorithm are tested in IEEE 300 bus system. Tables1, 2 and Figures 4, 5 give the evaluation.

Table 1. Loss (MW) appraisal- IEEE 300 bus

Method	Power Loss (MW)
FUSLISAI (Nagarajan <i>et al.</i> , 2020)	396.983
FUSLISAI (Nagarajan <i>et al.</i> , 2020)	397.236
BICISA (Nagarajan <i>et al.</i> , 2020)	397.902
MODEALO (Mei <i>et al.</i> , 2017)	398.853
BKS	395.110
SGS	394.992
QRMCSO	395.109

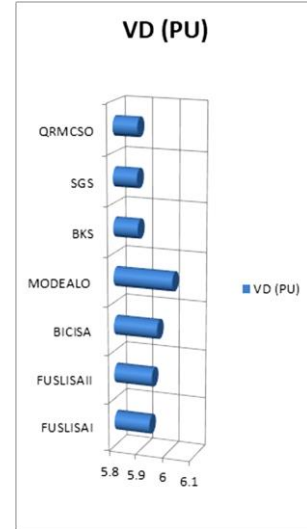


Figure 5. Assessment of power deviance (IEEE 300 bus)

Table 2. Power aberration (PU) - IEEE 300 bus

Method	Power aberration (PU)
FUSLISAI (Nagarajan <i>et al.</i> , 2020)	5.9324
FUSLISAI (Nagarajan <i>et al.</i> , 2020)	5.9416
BICISA (Nagarajan <i>et al.</i> , 2020)	5.9613
MODEALO (Mei <i>et al.</i> , 2017)	6.0169
BKS	5.8910
SGS	5.8884
QRMCSO	5.8905

Then validity of Patu digua search (BKS) optimization algorithm, Quasi-Optpositional based Teacher Actions in the Society - inspired Optimization (SGS) Algorithm, Quantum Monastery chief selection Inspired Optimization (QRMCSO) Algorithm tested in IEEE 354 bus system. Tables 3, 4 and Figures 6, 7 show the valuation.

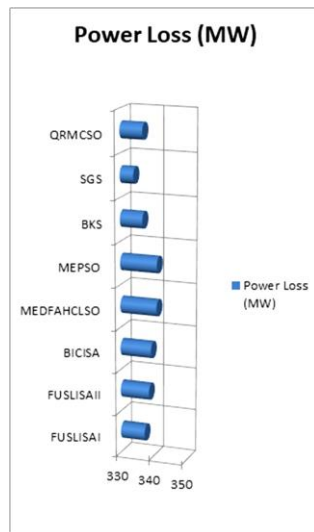


Figure 6. Appraisal of power loss (IEEE 354 bus)

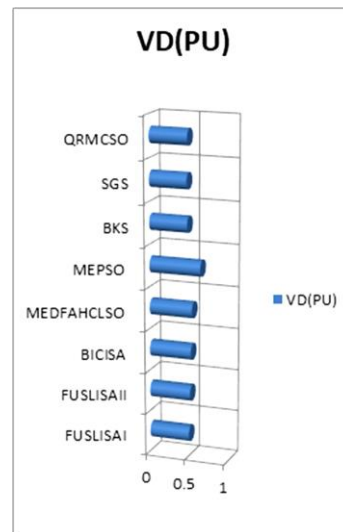


Figure 7. Appraisal of power deviance (IEEE 354 bus)

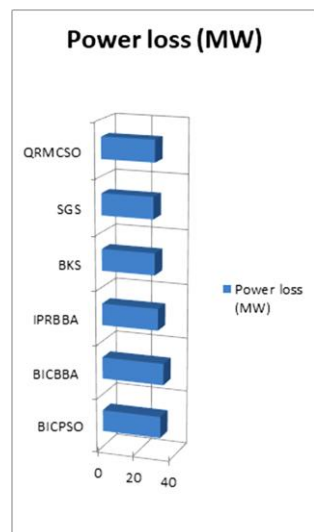


Figure 8. Assessment of loss (220KV)

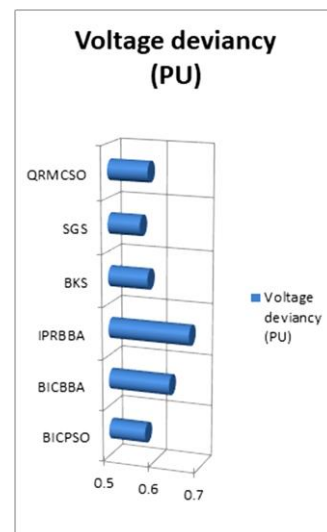


Figure 9. Appraisal of Power aberration (220KV)

Table 3. Loss (MW) appraisal - IEEE 354 bus

Method	Power Loss (MW)
FUSLISAI (Nagarajan <i>et al.</i> , 2020)	337.374
FUSLISAI (Nagarajan <i>et al.</i> , 2020)	338.715
BICISA (Nagarajan <i>et al.</i> , 2020)	339.325
MEDFAHCLSO (Mei <i>et al.</i> , 2017)	341.001
MEPSO (Mei <i>et al.</i> , 2017)	341.123
BKS	336.79
SGS	334.12
QRMCSO	336.81

Table 4. Power aberration (PU) - IEEE 354 bus

Method	Power Loss (MW)
FUSLISAI (Nagarajan <i>et al.</i> , 2020)	0.4978
FUSLISAI (Nagarajan <i>et al.</i> , 2020)	0.5117
BICISA (Nagarajan <i>et al.</i> , 2020)	0.5216
MEDFAHCLSO (Mei <i>et al.</i> , 2017)	0.5354
MEPSO (Mei <i>et al.</i> , 2017)	0.6395
BKS	0.4759
SGS	0.4683
QRMCSO	0.4761

Then validity of Patu digua search (BKS) optimization algorithm, Quasi-Optpositional based Teacher Actions in the Society - inspired Optimization (SGS) Algorithm, Quantum Monastery chief selection Inspired Optimization (QRMCSO) Algorithm is reviewed in 220 KV (Abou El-Ela *et al.*, 2019). Tables 5, 6 and Figures 8, 9 shows the valuation.

Table 5. Loss (MW) appraisal - 220 KV

Method	Power Loss (MW)
BICPSO (Mouwafi <i>et al.</i> , 2022)	32.314
BICBBA (Mouwafi <i>et al.</i> , 2022)	33.875
IPRBBA (Mouwafi <i>et al.</i> , 2022)	30.786
BKS	29.010
SGS	28.216
QRMCSO	29.019

Table 6. Power aberration

Method	Power aberration(PU)
BICPSO (Mouwafi, <i>et al.</i> , 2022)	0.5800
BICBBA (Mouwafi, <i>et al.</i> , 2022)	0.6327
IPRBBA (Mouwafi, <i>et al.</i> , 2022)	0.6751
BKS	0.5859
SGS	0.5697
QRMCSO	0.5865

Table 7 and Figure 10 show the time taken by proposed algorithms

Table 7. Time taken by Patu digua search (BKS) optimization algorithm, Quasi-Optpositional based Teacher Actions in the Society - inspired Optimization (SGS) Algorithm, Quantum Monastery chief selection Inspired Optimization (QRMCSO) Algorithm.

Table 7. Time taken by proposed algorithms

Method	IEEE 300 bus T (S)	IEEE 354 bus T (S)	220 KV T (S)
BKS	75.69	85.76	24.89
SGS	73.14	83.12	22.17
QRMCSO	75.83	85.91	24.93

Figure 10, Time taken by Patu digua search (BKS) optimization algorithm, Quasi-Optpositional based Teacher Actions in the Society - inspired Optimization (SGS) Algorithm, Quantum Monastery chief selection Inspired Optimization (QRMCSO) Algorithm.

Conclusion

Patu digua search (BKS) optimization algorithm, Quasi-Optpositional based Teacher Actions in the Society - inspired Optimization (SGS) Algorithm,

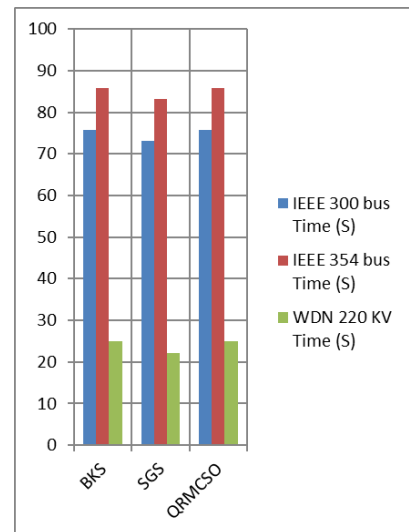


Figure 10. Time taken by algorithms

Quantum Monastery chief selection Inspired Optimization (QRMCSO) Algorithm reduced the electrical power loss adeptly. Key aims of the paper are Power fidelity extension, power eccentricity minimization and electrical power loss lessening. Opposition based learning integrated in the Patu digua search optimization algorithm and Laplace distribution utilized to augment the exploration dexterity. In SGS procedure the exploration region can be envisaged as a synchronize organization with a quantity of axes equivalent to the decision parameters. Each affiliate of the populace delivers info to other associates of the populace about the condition in which they discover themselves. Projected SGS procedure is iteration grounded procedure, affiliates of the populace move to the optimal sections. The key notion in planning the projected SGS algorithm is to appraise the location of the populace associates of the procedure which grounded on the regular info, and deduction of the poorest and preminent associates of the populace. Quasi-Optposition approach integrated into the approach to enhance the search and quality of the solution. In QRMCSO before picking a successor Head of the monastery will do various analyses and these standards are imitated in the design through Chebyshev serviceable connexion system.

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