Technology and Economics of Smart Grids and Sustainable Energy (2022) 7:25
https://doi.org/10.1007/s40866-022-00149-8

ORIGINAL PAPER

Novel Extreme Learning Machine and Chaotic in-Built Opposition Based – Quantum Ruddy Turnstone Optimization Algorithms for Real Power Loss Dwindling and Voltage Consistency Enhancement

Lenin Kanagasabai[1]

Received: 20 December 2021 / Accepted: 15 June 2022 / Published online: 29 June 2022

Abstract

This paper proposes Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm for genuine loss lessening. Important goals of the paper are Power fidelity extension, power eccentricity minimization and genuine loss lessening. The leading stimulus is in the sculpting of Repositioning –Peripatetic and argumentative actions of Ruddy turnstone. Ruddy turnstone will guzzle wiretaps, young insect and it subsists in bundling style. The constellation of Ruddy turnstone, which mobile from one place to alternate in the sequence of repositioning and the fresh investigation agent position is to evade the smash amongst their contiguous Ruddy turnstone. In the proposed Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Ruddy turnstone Optimization Algorithm approach enhances Extreme Learning Machine features to determine an optimal skeleton of Extreme Learning Machine for enhanced canons. In Chaotic based Ruddy turnstone optimization (CRTO) algorithm Exploration and Exploitation are augmented. In Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, features emulate the analogous performance with the certain stage as they route in a credible powdered of median. Opposition based Ruddy turnstone optimization (ORTO) Algorithm employs Laplace distribution to enhance the exploration skill. Then examining the prospect to widen the exploration, a new method endorses stimulating capricious statistics used in formation stage regulator factor in Ruddy turnstone Optimization Algorithm. In the projected chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm, the transaction of erratic figures is completed with the irrational digits enthused by Laplace distribution to amplify the support of the probability of formation level inside the exploration zone. Proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm are corroborated in Garver's 6-bus test system, IEEE 30, 57, 118, 300, 354 bus test systems and Practical system - WDN 220 KV (Unified Egyptian Transmission Network (UETN)). Loss lessening, voltage divergence curtailing, and voltage constancy index augmentation has been attained.

Keywords Optimization · Power · Transmission loss · Ruddy turnstone · Extreme learning machine · Chaotic · Quantum · Opposition

Introduction

Loss dripping problem is envisioned as one of the noteworthy circumstances for safe and fiscal operation of system. It is consummate by appropriate organization of the edifice apparatus used to cope up the power flow with the goal of diminishing the true power losses and progress the voltage outline of the structure. Many preceding studies solved the

✉ Lenin Kanagasabai
gklenin@gmail.com

[1] Department of EEE, Prasad V.Potluri Siddhartha Institute of Technology, Kanuru, Vijayawada, Andhra Pradesh 520007, India

power dispatch problem as the optimization of one or two objective functions calculated distinctly. Loss lessening, power variance curtailing, and power reliability expansion has been attained.

Related Study

Zhu et al. [1] solved the problem by modified interior point method. Quintana et al. [2] solved by successive quadratic programming. Jan et al. [3] used Newton-Raphson. Terra et al. [4] did Security-constrained mode. Grudinin [5] used successive quadratic programming. Mohamed Ebeed et al. [6] used Marine Predators Algorithm. Zahir Sahli et al. [7] used Hybrid Algorithm. Davoodi et al. [8] used semidefinite method. Bingane et al. [9] applied Tight-and-cheap conic relaxation approach. Sahli et al. [10] applied Hybridized PSO-Tabu. Mouassa et al. [11] applied Ant lion algorithm for solving the problem. Mandal et al. [12] solved by using quasi-oppositional. Khazali et al. [13] solved the problem by harmony search procedure. Tran et al. [14] solved by fractal search procedure. Polprasert et al. [15] solved the problem by using enhanced pseudo-gradient method. Thanh et al. [16] solved the problem by an Operative Metaheuristic Procedure. Raghuwanshi et al. [17] utilized Bagging based ELM. Yu X et al. [18] applied Dual-Weighted Kernel ELM. Han et al. [19] used kernel ELM. From Illinois Center [20] for a Smarter Electric Grid (ICSEG) IEEE 30 bus system data obtained. Dai et al. [21] used Seeker optimization procedure for solving the problem. Subbaraj et al. [22] used self-adaptive real coded Genetic procedure to solve the problem. Pandya et al. [23] applied Particle swarm optimization to solve the problem. Ali Nasser Hussain et al. [24] applied Amended Particle Swarm Optimization to solve the problem. Vishnu et al. [25] applied an Enhanced Particle Swarm Optimization to solve the problem. Vodchits Angelina et al. [26] did Development of a Design Algorithm for the Logistics. Vodchits Angelina et al. [27] did the work on organization of logistic systems of scientific productions. Vodchits Angelina et al. [28] solved the Problems and organizational and technical solutions. Khunkitti et al. [29] used Slime Mould Algorithm. Diab et al. [30] used Optimization Techniques. Reddy [31, 32] solved the problem by faster and cuckoo search algorithms. Sridhar et al. [33] used ALO method. Suja [34] used moth flame optimization procedure. Darvish [35] applied grasshopper optimization algorithm. Sharma, et al. [36] used hybrid ABC-PSO. Saravanan et al. [37] used dragonfly algorithm. Bentouati, Bet al. [38] applied improved moth-swarm algorithm. Menon, et al. [39] applied OS–DPLL. Saxena, et al. [40] used STATCOM. Kazmi, et al. [41] Worked on Loop Configuration. Kola Sampangi, et al. [42] worked in EDN. Zaidan, Majeed et al. [43] worked in var. comp.optimal Location. Lakshmi Priya et al. [44] used GWO-BSA. Ahmadnia Sajjad et al. [45] worked in ESR. Azimi, Mohammad et al. [46] worked in Thyristor-controlled Phase Shifting. Juneja Kapil [47] used a Fuzzy-Controlled Differential Evolution to solve the problem. Kien et al. [48] used Discrete Values of Capacitors and Tap Changers. Souhil et al. [49] applied ant lion optimization algorithm. Tudose et al. [50] applied Improved Salp Swarm Algorithm. Nagarajan et al. [51] applied Levy Interior Search Algorithm. Mei et al. [52] applied moth-flame optimization technique. Nuaekaew et al. [53] applied grey wolf optimizer. Khazali et al. [13] applied harmony search algorithm. Gonggui et al. [54] applied enhanced PSO algorithm. From ee. Washington [55] IEEE 57-Bus Test System data obtained. From Power Systems Test Case Archive, University of Washington [56] data obtained. From ee. Washington [57] IEEE 118-Bus Test System data obtained. Lin, et al. [58] did work in chaotic Lévy flight bat algorithm. Hakli et al. [59] did work in particle swarm optimization algorithm Nagarajan, et al. [51] did work in Levy Interior Search Algorithm. Davidchack et al., [60] did work in chaotic systems. Inoue, et al., [61] did work in Application of chaos. Dinkar, et al. [62] did in Opposition Based Laplacian. Gai-gewang et al. [63] did work in Cauchy mutation. Tizhoosh [64] did the work in Opposition-based learning. Verma et al. [65] done in Modified Artificial Bee. Romero et al. [66] worked in AC Model. Mahmoudabadi, et al., [67] worked in Deregulated Environment. Asadamongkol, et al. [68] worked in Generalized Benders Decomposition. Mohamed eta l [69] worked in binary bat algorithm. Abou et al. [70] worked in System Expansion Planning. Emad M. Ahmed et al. [77] did work in modern distribution networks. Almalaq et al. [78] did work towards Increasing Hosting Capacity of Modern Power Systems. Ismael et al. [79] applied Hybrid PSOGSA Optimization Algorithm. Mahmoud, et al. [80] worked in Real Egyptian Distribution System. Muhyaddin Rawa et al. [81] applied improved grey wolf algorithm.

Proposed Methodology

This paper proposes Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm for solving the loss dripping problem. The leading stimulus is in the sculpting of Repositioning –Peripatetic and argumentative actions of Ruddy turnstone. Ruddy turnstone will guzzle wiretaps, young insect and it subsists in bundling style. The constellation of Ruddy turnstone, which mobile from one place to alternate in the sequence of repositioning and the fresh investigation agent position is to evade the smash amongst their contiguous Ruddy turnstone.

In the proposed Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Ruddy turnstone Optimization approach enhances Extreme Learning Machine features to determine an optimal carcass of Extreme Learning Machine for enhanced standards. In principally all elements don't own any info about the explication area. In preliminary phases of iteration, the Ruddy turnstone contestants are multifarious in milieu and exponential spare generates boundless unpremeditated amounts which contribute the rudiments to lodging the entire explication zone. Disparately, all over end stage of iterations, rudiments are surrounded by Ruddy turnstone contestants and all an optimal situation with similar pattern.

Chaotic sequences are combined into Ruddy turnstone Optimization and it termed as - Chaotic based Ruddy turnstone optimization (CRTO) algorithm. This integration will augment the Exploration and Exploitation. Tinkerbell chaotic map engendering standards are implemented.

Quantum mechanics has been combined with Ruddy turnstone Optimization Algorithm and it titled as Quantum based Ruddy turnstone Optimization (QRTO) Algorithm. In quantum method, features emulate the analogous performance with the certain stage as they route in a credible powdered of median.

Ruddy turnstone Optimization Algorithm, even though the initiative of contestant explications slants to touch an optimal solution, yet several are get entombed and not adept of emotive in the route of the dominant solution. It significances to snare in local optima and it accordingly enforces into primary and slow convergence. Subsequently Opposition based Ruddy turnstone optimization (ORTO) Algorithm employs Laplace distribution to enhance the exploration skill. Then examining the prospect to widen the exploration, a new method endorses stimulating capricious statistics used in formation stage regulator factor in Ruddy turnstone Optimization Algorithm. In the proposed procedure, the exchanging of capricious statistics is done with the illogical numbers stimulated by Laplace distribution to enlarge the assistance of the probability of formation stage in the exploration zone.

In the projected chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm, the transaction of erratic figures is completed with the irrational digits enthused by Laplace distribution to amplify the support of the probability of formation level inside the exploration zone. Chaotic sequences will augment the Exploration and Exploitation. Quantum features emulate the analogous performance with the certain stage as they route in a credible powdered of median.

Important aspects of the Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm

- In Ruddy turnstone optimization algorithm the constellation of Ruddy turnstone, which mobile from one place to alternate in the sequence of repositioning and the fresh investigation agent position is to evade the smash amongst their contiguous Ruddy turnstone.
- In the proposed Extreme Learning Machine based Ruddy turnstone Optimization Algorithm, Ruddy turnstone Optimization approach enhances Extreme Learning Machine features to determine an optimal carcass of Extreme Learning Machine for enhanced standards.
- In Chaotic based Ruddy turnstone optimization algorithm Exploration and Exploitation are augmented. In Quantum based Ruddy turnstone Optimization Algorithm, features emulate the analogous performance with the certain stage as they route in a credible powdered of median.
- Opposition based Ruddy turnstone optimization Algorithm employs Laplace distribution to enhance the exploration skill. Then examining the prospect to widen the exploration, a new method endorses stimulating capricious statistics used in formation stage regulator factor in Ruddy turnstone Optimization Algorithm.
- In the projected chaotic in-built Opposition based – Quantum Ruddy turnstone optimization algorithm, the transaction of erratic figures is completed with the irrational digits enthused by Laplace distribution to amplify the support of the probability of formation level inside the exploration zone.

Critical Outcome of the Work

Significant goals of the paper are Voltage constancy augmentation, voltage deviance minimization and Actual power loss lessening. Proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm is corroborated in Garver's 6-bus test system, IEEE 30, 57, 118, 300, 354 bus test systems and Practical system - WDN 220 KV (Unified Egyptian Transmission Network (UETN)). Loss lessening, power divergence curtailing, and power fidelity augmentation has been attained.

Problem Formulation

Loss minimization [13, 52–54] is demarcated by

$$\text{Min } \tilde{F}\left(\overline{g}, \overline{h}\right) \tag{1}$$

$$M\left(\overline{g},\overline{h}\right)=0 \tag{2}$$

$$N\left(\overline{g},\overline{h}\right)=0 \tag{3}$$

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

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

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

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

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

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

And

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

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

Parity constraints

$$0=PG_i-PD_i-V_i\sum_{j\in N_B}V_j\left[G_{ijcos}\left[\varnothing_i-\varnothing_j\right]+B_{ijsin}\left[\varnothing_i-\varnothing_j\right]\right] \tag{12}$$

$$0=QG_i-QD_i-V_i\sum_{j\in N_B}V_j\left[G_{ijsin}\left[\varnothing_i-\varnothing_j\right]+B_{ijcos}\left[\varnothing_i-\varnothing_j\right]\right] \tag{13}$$

Disparity constraints

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

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

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

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

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

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

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

$$\begin{aligned}&Multi\ objective\ fitness\ (MOF)=F_1+r_iF_2+uF_3=F_1\\&+\left[\sum_{i=1}^{NL}x_v\left[VL_i-VL_i^{min}\right]^2+\sum_{i=1}^{NG}r_g\left[QG_i-QG_i^{min}\right]^2\right]+r_fF_3\end{aligned} \tag{21}$$

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

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

Ruddy Turnstone Optimization Algorithm

In this paper Ruddy turnstone Optimization (RTO) Algorithm is applied to solve the loss lessening problem. The leading stimulus is in the sculpting of Repositioning –Peripatetic and argumentative actions of Ruddy turnstone. Ruddy turnstone will guzzle wiretaps, young insect and it subsists in bundling style. The constellation of Ruddy turnstone, which mobile from one place to alternate in the sequence of repositioning and the fresh investigation agent position is to evade the smash amongst their contiguous Ruddy turnstone.

$$\overrightarrow{Rt_S}=Rt_M+\overrightarrow{Q_P}(t) \tag{24}$$

$$\begin{gathered}where\overrightarrow{Rt_S}\ is\ position\ without\ any\ \text{Hindrance between each other}\\Rt_M\ is\ \text{Mobility of the Ruddy turnstone}\\\overrightarrow{Q_P}(t) is\ present\ location\ and\ t\ indiate\ the\ present\ iteraion\\Rt_M=Rt_F-\left(t\times\frac{Rt_F}{\text{max}.iter}\right)\end{gathered} \tag{25}$$

$$\begin{gathered}where\ t=0,1,2,3,..,\text{max}.iter\\Rt_F\ is\ the\ regulating\ frequency\\when\ Rt_M=2\ then\ Rt_F\ \ gradually\ decrease\ 2\ to\ 0\end{gathered}$$

Examination mediator’s passage in the direction of the dominant representative,

$$\overrightarrow{L_S}=Rt_R\times\left(\overrightarrow{Q_{Best}}(t)-\overrightarrow{Q_P}(t)\right) \tag{26}$$

$$Rt_R=0.5\times R \tag{27}$$

$$\begin{gathered}where\ Rt_R\ is\ random\ parameter\ for\ controlling\ the\ exploration\\\overrightarrow{Q_{Best}}(t)\ specify\ the\ best\ position\\\overrightarrow{L_S}\ is\ location\ of\ the\ examination\ agent\end{gathered}$$

Rendering to premium position, Ruddy turnstone will appraise its location,

$$\overrightarrow{M_S} = \overrightarrow{Rt_S} + \overrightarrow{L_S} \tag{28}$$

where $\overrightarrow{M_S}$ indicate the space between examination and excellent agent

In the course of drive the Ruddy turnstone will execute Whorl action and the cantankerous actions of Ruddy turnstone is scientifically demarcated as,

$$U' = B \times \sin(t) \tag{29}$$

$$V' = B \times \cos(t) \tag{30}$$

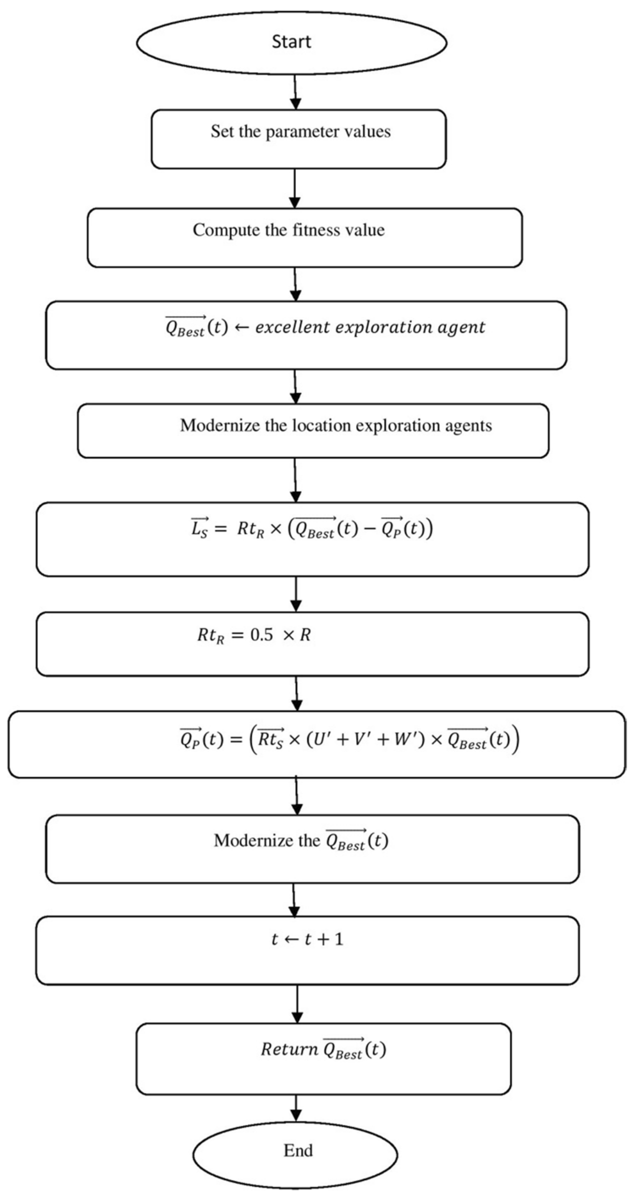


Fig. 1 Schematic diagram of Ruddy turnstone optimization (RTO) algorithm

$$W' = B \times (t) \tag{31}$$

where b specify the radius of Whorl action

$$B = x \times e^{ny} \tag{32}$$

where x and y are the constants to describe the Whorl action

$$n \in [0 \le n \le 2\pi]$$

$$x \text{ and } y = 1$$

Modernizing the Location of the Exploration agents is accomplished by,

$$\overrightarrow{Q_P}(t) = \left(\overrightarrow{Rt_S} \times (U' + V' + W') \times \overrightarrow{Q_{Best}}(t)\right) \tag{34}$$

Figure 1 shows the schematic diagram of Ruddy turnstone optimization (RTO) algorithm.

a. Start
b. Set the Parameters
c. $T = 0$
d. Compute the fitness value
e. $\overrightarrow{Q_{Best}}(t) \leftarrow excellent\ exploration\ agent$
f. $while\ (t < maximum\ number\ of\ Iterations) do$
g. $For\ each\ exploration\ agent\ do$
h. Modernize the location exploration agents
i. $\overrightarrow{L_S} = Rt_R \times (\overrightarrow{Q_{Best}}(t) - \overrightarrow{Q_P}(t))$
j. $Rt_R = 0.5 \times R$
k. $U' = B \times \sin(t)$
l. $V' = B \times \cos(t)$
m. $W' = B \times (t)$
n. $\overrightarrow{Q_P}(t) = \left(\overrightarrow{Rt_S} \times (U' + V' + W') \times \overrightarrow{Q_{Best}}(t)\right)$
o. End for
p. $update\ the\ value\ of\ Rt_M$
q. $update\ the\ value\ of\ Rt_F$
r. Compute the fitness value
s. Modernize the $\overrightarrow{Q_{Best}}(t)$
t. $t \leftarrow t + 1$
u. End while
v. $Return\ \overrightarrow{Q_{Best}}(t)$
w. End

Extreme Learning Machine Based Ruddy Turnstone Optimization Algorithm

In the proposed Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Ruddy turnstone Optimization Algorithm approach enhances Extreme

Learning Machine features to determine an optimal skeleton of Extreme Learning Machine for enhanced canons. ELM is applied and learning speed of feed-forward neural networks is composed of input, hidden and output layer [17–19].

The correlating neurons weight matrix of input to hidden layer is defined as,

$$Weight\ (Wht) = \begin{bmatrix} wht_1^T \\ wht_2^t \\ ; \\ wht_l^T \end{bmatrix} = \begin{bmatrix} wht_{11} & \cdots & wht_{1n} \\ \vdots & \ddots & \vdots \\ wht_{L1} & \cdots & wht_{Ln} \end{bmatrix} \tag{35}$$

$$(nwm.\beta) = \begin{bmatrix} nwm.\beta_1^T \\ nwm.\beta_2^t \\ ; \\ nwm.\beta_l^T \end{bmatrix} = \begin{bmatrix} nwm.\beta_{11} & \cdots & nwm.\beta_{1n} \\ \vdots & \ddots & \vdots \\ nwm.\beta_{L1} & \cdots & nwm.\beta_{Ln} \end{bmatrix} \tag{36}$$

$$\text{Neurons hidden layer bias vector (bsv)} = \begin{bmatrix} bsv_1 \\ bsv_2 \\ \vdots \\ bsv_L \end{bmatrix}_{L\times 1} \tag{37}$$

For N impulsive e (B_i, F_i); $F_i = [F_{i1}, F_{i2}, .., F_{idn}]^E \in MN^{dn}$, $C_i = [C_{i1}, C_{i2}, .., C_{idn}]^E \in MN^{dn}$,

$$(C) = \begin{bmatrix} C_1^T \\ C_2^t \\ ; \\ C_l^T \end{bmatrix} = \begin{bmatrix} C_{11} & \cdots & C_{1n} \\ \vdots & \ddots & \vdots \\ C_{L1} & \cdots & C_{Ln} \end{bmatrix} \tag{38}$$

$$\sum_{i=1}^{N} nwm.\beta_i \cdot k\left(\omega_i F_j + a_i\right) = C_j, j = 1, 2, 3, .., N \tag{39}$$

$$(O) \cdot (nwm.\beta) = C \tag{40}$$

a. Start

b. Input the data

c. Engender the Test and Training set

d. Rendering to the training set - standardize the quantity of (O)

e. $O(F_1, .. F_L; \omega_1, .., \omega_L; a_1, .., a_l) = \begin{bmatrix} k(\omega_1 F_1 + a_1) & \cdots & k(\omega_L F_1 + a_L) \\ \vdots & \ddots & \vdots \\ k(\omega_1 F_N + a_1) & \cdots & k(\omega_L F_N + a_L) \end{bmatrix}$

f. Express the output level of weight

g. $nwm.\beta = O^{-1} \cdot C$

h. Rendering to the test set - estimate the level of (B)

i. $O(F_1, .. F_L; \omega_1, .., \omega_L; a_1, .., a_l) = \begin{bmatrix} k(\omega_1 F_1 + a_1) & \cdots & k(\omega_L F_1 + a_L) \\ \vdots & \ddots & \vdots \\ k(\omega_1 F_N + a_1) & \cdots & k(\omega_L F_N + a_L) \end{bmatrix}$

j. Appraise the genuine level through $nwm.\beta$ and M

k. Computation of error status

l. Assessment of genuine rate with possible level

m. Return the error level

n. End

$$O(F_1,..F_L;\omega_1,..,\omega_L;a_1,..,a_l)=\begin{bmatrix} k(\omega_1 F_1+a_1) & \cdots & k(\omega_L F_1+a_L) \\ \vdots & \ddots & \vdots \\ k(\omega_1 F_N+a_1) & \cdots & k(\omega_L F_N+a_L) \end{bmatrix} \tag{41}$$

$$nwm.\beta = O^{-1}\cdot C \tag{42}$$

In the proposed Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Ruddy turnstone Optimization approach enhances Extreme Learning Machine features to determine an optimal carcass of Extreme Learning Machine for enhanced standards. In principally all elements don't own any info about the explication area. In preliminary phases of iteration, the Ruddy turnstone contestants are multifarious in milieu and exponential spare generates boundless unpremeditated amounts which contribute the rudiments to lodging the entire explication zone. Disparately, all over end stage of iterations, rudiments are surrounded by Ruddy turnstone contestants and all an optimal situation with similar pattern. Figure 2 shows the schematic diagram of Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm.

Chaotic Based Ruddy Turnstone Optimization Algorithm

Chaotic sequences are combined into Ruddy turnstone Optimization and it termed as - Chaotic based Ruddy turnstone optimization (CRTO) algorithm. This integration will augment the Exploration and Exploitation. Tinkerbell chaotic

a. Start
b. Set the Parameters
c. Engender the Test and Training set
d. $T = 0$
e. Compute the fitness value
f. $\overrightarrow{Q_{Best}}(t) \leftarrow excellent\ exploration\ agent$
g. $while\ (t < maximum\ number\ of\ Iterations) do$
h. $For\ each\ exploration\ agent\ do$
i. Modernize the location exploration agents
j. $\overrightarrow{L_S} = Rt_R \times \left(\overrightarrow{Q_{Best}}(t) - \overrightarrow{Q_P}(t)\right)$
k. $Rt_R = 0.5 \times R$
l. $U' = B \times \sin(t)$
m. $V' = B \times \cos(t)$
n. $W' = B \times (t)$
o. $\overrightarrow{Q_P}(t) = \left(\overrightarrow{Rt_S} \times (U' + V' + W') \times \overrightarrow{Q_{Best}}(t)\right)$
p. End for
q. $update\ the\ value\ of\ Rt_M$
r. $update\ the\ value\ of\ Rt_F$
s. Compute the fitness value
t. Modernize the $\overrightarrow{Q_{Best}}(t)$
u. Fix Extreme Learning Machine input weights and hidden bias
v. Extreme Learning Machine testing
w. $t \leftarrow t + 1$
x. End while
y. $Return\ \overrightarrow{Q_{Best}}(t)$
z. End

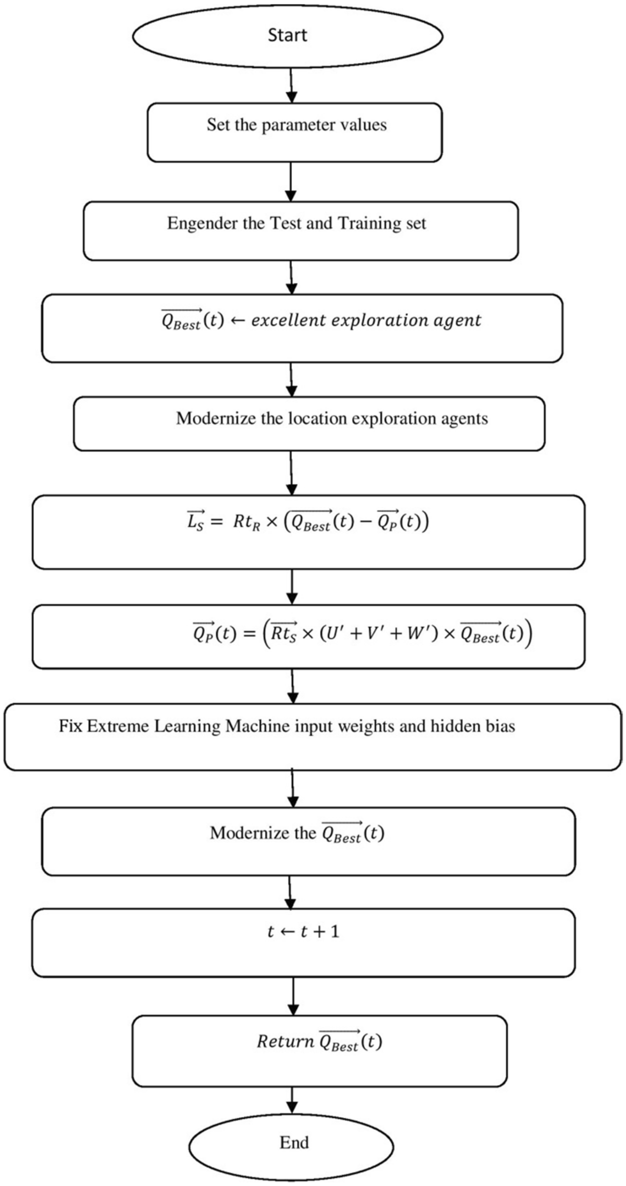


Fig. 2 Schematic diagram of Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm

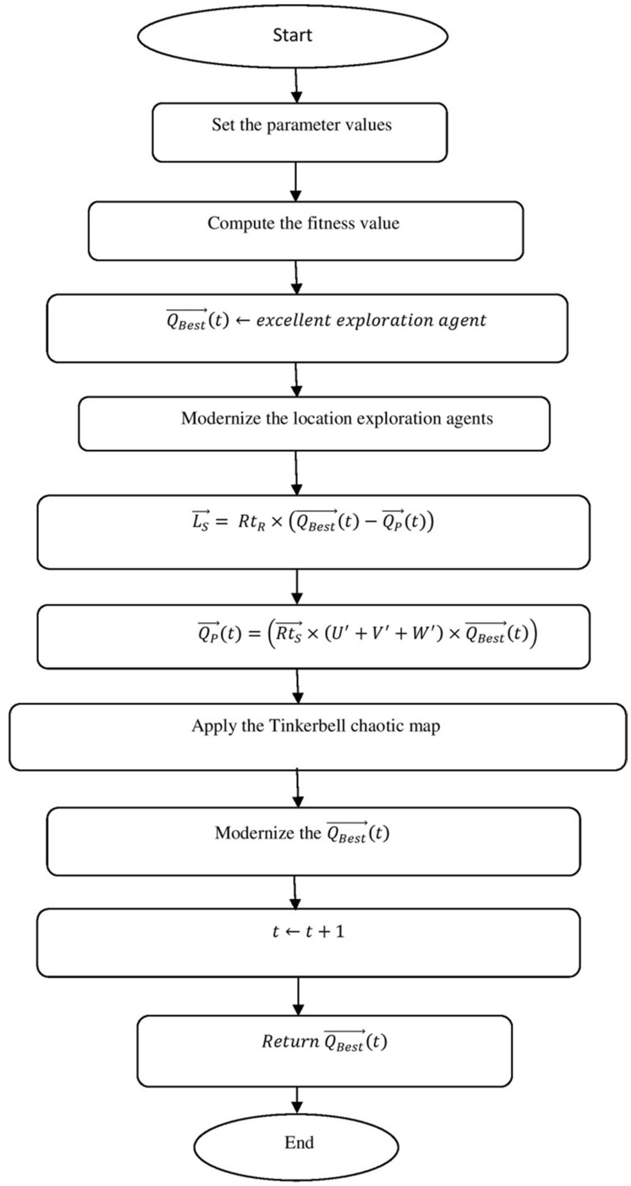


Fig. 3 Schematic diagram of Chaotic based Ruddy turnstone optimization (CRTO) algorithm

map [60, 61] engendering standards are implemented. Figure 3 shows the schematic diagram of Chaotic based Ruddy turnstone optimization (CRTO) algorithm.

$$u_{t+1} = u_t^2 - v_t^2 + a \cdot u_t + b \cdot v_t \tag{43}$$

$$v_{t+1} = 2u_t v_t + c \cdot u_t + d \cdot v_t \tag{44}$$

$$\begin{aligned} &where\ a, b, c\ and\ d\ are\ non-zero\ parameters \\ &a = 0.900 \\ &b = -0.600 \\ &c = 2.000 \\ &d = 0.500 \\ &At\ primary\ stage\ \ u_o and\ v_o = 0.10 \end{aligned}$$

The functional value by linear scaling in Tinkerbell chaotic map [60, 61] is demarcated as,

$$u^*_{t+1} = u_{t+1} - minimum(u)/maximum(u) - minimum(u) \tag{45}$$

a. Start
b. Set the Parameters
c. $T = 0$
d. Compute the fitness value
e. $\overrightarrow{Q_{Best}}(t) \leftarrow excellent\ exploration\ agent$
f. $while\ (t < maximum\ number\ of\ Iterations) do$
g. $For\ each\ exploration\ agent\ do$
h. Modernize the location exploration agents
i. $\overrightarrow{L_S} = Rt_R \times \left(\overrightarrow{Q_{Best}}(t) - \overrightarrow{Q_P}(t)\right)$
j. $Rt_R = 0.5 \times R$
k. $U' = B \times \sin(t)$
l. $V' = B \times \cos(t)$
m. $W' = B \times (t)$
n. $\overrightarrow{Q_P}(t) = \left(\overrightarrow{Rt_S} \times (U' + V' + W') \times \overrightarrow{Q_{Best}}(t)\right)$
o. End for
p. Smear the Tinkerbell chaotic map
q. $u_{t+1} = u_t^2 - v_t^2 + a \cdot u_t + b \cdot v_t$
r. $v_{t+1} = 2u_t v_t + c \cdot u_t + d \cdot v_t$
s. $u_{t+1}^* = u_{t+1} - minimum(u)/maximum(u) - minimum(u)$
t. $update\ the\ value\ of\ Rt_M$
u. $update\ the\ value\ of\ Rt_F$
v. Compute the fitness value
w. Modernize the $\overrightarrow{Q_{Best}}(t)$
x. $t \leftarrow t + 1$
y. End while
z. $Return\ \overrightarrow{Q_{Best}}(t)$
aa. End

Quantum Based Ruddy Turnstone Optimization Algorithm

Quantum mechanics [71–76] has been combined with Ruddy turnstone Optimization Algorithm and it titled as Quantum based Ruddy turnstone Optimization (QRTO) Algorithm. In quantum method, features emulate the analogous performance with the certain stage as they route in a credible powdered of median. The wave utility in the Quantum mechanics [71–76] is demarcated as,

$$|\Psi|^2 \cdot dx \cdot dy \cdot dz = Quantum \cdot dx \cdot dy \cdot dz \tag{46}$$

where Ψ indicate probability density functional value

The time contingent Schrodinger equation [71–76] is smeared to evaluate the wave utility is demarcated as,

$$ih \bullet \partial/\partial t \bullet \Psi(x,t) = Hor \bullet \Psi(x,t) \tag{47}$$

where Hor specify the Hamiltonian operator

$$Hor = -h^2/2m \cdot \Delta^2 + V(x) \tag{48}$$

In the quantum pattern ΔFit consecutively achieve as particle and it successively passages in delta potential in the direction of center. Figure 4 shows the schematic diagram of Quantum based Ruddy turnstone Optimization (QRTO) Algorithm.

a. Start
b. Set the Parameters
c. $T = 0$
d. Compute the fitness value
e. $\overrightarrow{Q_{Best}}(t) \leftarrow excellent\ exploration\ agent$
f. $while\ (t < maximum\ number\ of\ Iterations) do$
g. $For\ each\ exploration\ agent\ do$
h. Modernize the location exploration agents
i. $\overrightarrow{L_S} = Rt_R \times \left(\overrightarrow{Q_{Best}}(t) - \overrightarrow{Q_P}(t)\right)$
j. $|\Psi|^2 \cdot dx \cdot dy \cdot dz = Quantum \cdot dx \cdot dy \cdot dz$
k. $Hor = -h^2/2m \cdot \Delta^2 + V(x)$
l. $Rt_R = 0.5 \times R$
m. $U' = B \times \sin(t)$
n. $V' = B \times \cos(t)$
o. $W' = B \times (t)$
p. $\overrightarrow{Q_P}(t) = \left(\overrightarrow{Rt_S} \times (U' + V' + W') \times \overrightarrow{Q_{Best}}(t)\right)$
q. End for
r. $update\ the\ value\ of\ Rt_M$
s. $update\ the\ value\ of\ Rt_F$
t. Compute the fitness value
u. Modernize the $\overrightarrow{Q_{Best}}(t)$
v. $t \leftarrow t + 1$
w. End while
x. $Return\ \overrightarrow{Q_{Best}}(t)$
y. End

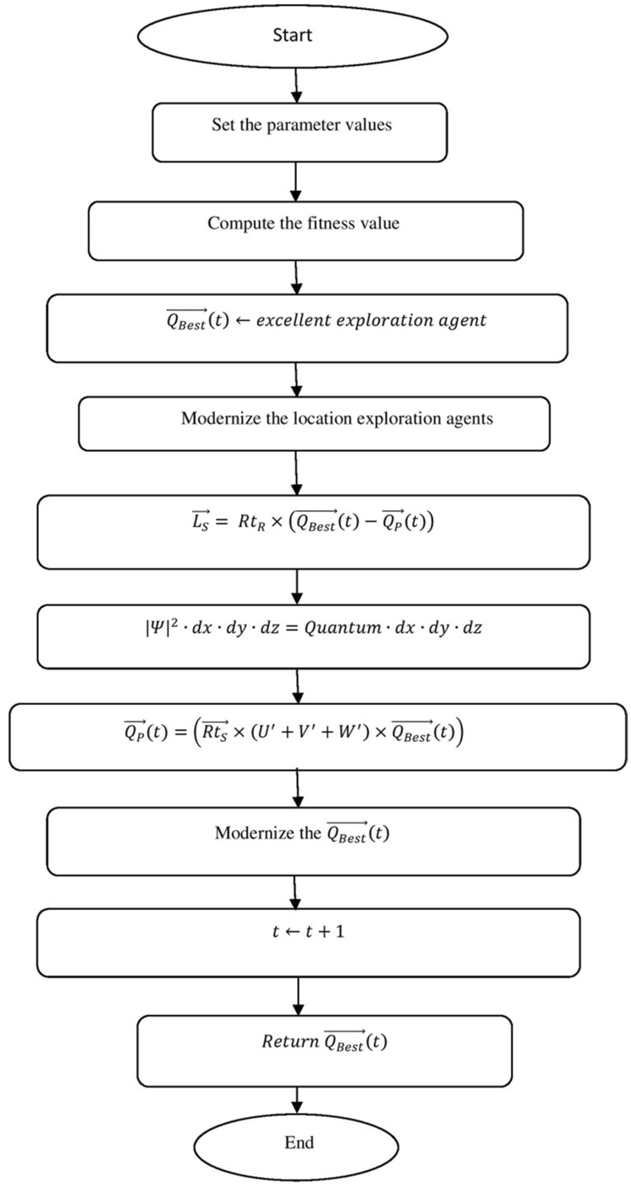


Fig. 4 Schematic diagram of Quantum based Ruddy turnstone Optimization (QRTO) Algorithm

$$\text{Schrodinger(Time}-\text{independent)}is\ \frac{d^2\Psi}{dz^2} + \frac{2m}{h^2}[G + \gamma\delta(z)]\Psi = 0 \tag{49}$$

$$\Psi(z) = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}} \tag{50}$$

$$Quantum(z) = |\Psi(z)|^2 = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}} \tag{51}$$

$$z = \pm \frac{L}{2} In(1/g) \tag{52}$$

Opposition Based Ruddy Turnstone Optimization Algorithm

Ruddy turnstone Optimization Algorithm, even though the initiative of contestant explications slants to touch an optimal solution, yet several are get entombed and not adept of emotive in the route of the dominant solution. It significances to snare in local optima and it accordingly enforces into primary and slow convergence. Subsequently Opposition based Ruddy turnstone optimization (ORTO) Algorithm employs Laplace distribution to enhance the exploration skill. Then examining the prospect to widen the exploration, a new method endorses stimulating capricious statistics used in formation stage regulator factor in Ruddy turnstone Optimization Algorithm. In the proposed procedure, the exchanging of capricious statistics is done with the illogical numbers stimulated by Laplace distribution [62–64] to enlarge the assistance of the probability of formation stage in the exploration zone.

$$function(v) = \begin{cases} \frac{1}{2}\exp(-|v-c|/d), b \le c \\ 1-\frac{1}{2}\exp(-|v-c|/d), b > c \end{cases} \tag{53}$$

The probability propagation function of Laplace dispersal is,

$$function(v;c,d) = 1/2v\exp(-|v-c|/d), -\infty < c < \infty \tag{54}$$

where $c \in (-\infty, \infty)$

Opposition based learning (OBL) is one of the influential approaches to improve the convergence quickness of procedures [62–64]. The flourishing use of the Opposition based learning includes evaluation of opposite populace and dominant populace in the analogous generation to regulate the superior contestant explication. The perception of opposite number requirements is to be delineated to explicate Opposition based learning. Figure 5 shows the schematic diagram of Opposition based Ruddy turnstone optimization (ORTO) Algorithm.

Let O ($Z \in [c, d]$) be a palpable figure and the O^o (opposite figure) can be delineated as,

$$O^o = c + d - U \tag{55}$$

In the exploration area it has been protracted as,

$$O_i^o = c_i + d_i - U_i \tag{56}$$

Where $\left(O_1, O_2, ..O_d\right)$ *indicate dimensional exploration zone* $O_i \in \left[c_i, d_i\right], i \rightarrow \{1, 2, 3, ..d\}$

The perception of Opposition based learning is employed in the initialization procedure and in iterations by means of the cohort vaulting level.

a. $Min\, f$
b. $if\, f(O^*) \le f(O)$; *then* $O = O^*$
c. *Or else*
d. Sustain with O in successive generations

An opposite component is assimilated after streamlining and produced the distinguished component

$$Rt_i(iter) = \left(LB_i + UB_i - Rt_e(iter)\right) \tag{57}$$

where LB, UB *are lower and upper bound*

a. Start
b. Set the Parameters
c. Apply opposition points
d. Compute the fitness value
e. $\overrightarrow{Q_{Best}}(t) \leftarrow excellent\ exploration\ agent$
f. $while\ (t < maximum\ number\ of\ Iterations) do$
g. $For\ each\ exploration\ agent\ do$
h. Modernize the location exploration agents
i. $\overrightarrow{L_S} = Rt_R \times \left(\overrightarrow{Q_{Best}}(t) - \overrightarrow{Q_P}(t)\right)$
j. $Rt_R = 0.5 \times R$
k. $U' = B \times \sin(t)$
l. $V' = B \times \cos(t)$
m. $W' = B \times (t)$
n. $\overrightarrow{Q_P}(t) = \left(\overrightarrow{Rt_S} \times (U' + V' + W') \times \overrightarrow{Q_{Best}}(t)\right)$
o. End for
p. $Rt_i(iter) = \left(LB_i + UB_i - Rt_e(iter)\right)$
q. $F_s = F_{max} - iter_p \cdot F_{max} - F_{min}/iter_{max}$
r. $Rt_i(iter) = F_s * \left(LB_i + UB_i - Rt_e(iter)\right)$
s. $update\ the\ value\ of\ Rt_M$
t. $update\ the\ value\ of\ Rt_F$
u. Compute the fitness value
v. Modernize the $\overrightarrow{Q_{Best}}(t)$
w. $t \leftarrow t + 1$
x. End while
y. $Return\ \overrightarrow{Q_{Best}}(t)$
z. End

At that moment the Flexible speeding up factor (F_s) balance the exploration and exploitation and scientifically demarcated as,

$$F_s = F_{max} - iter_p \cdot F_{max} - F_{min}/iter_{max} \tag{58}$$

The Opposition based learning method engaged round the distinguished component and it demarcated as,

$$Rt_i(iter) = F_s * \left(LB_i + UB_i - Rt_e(iter)\right) \tag{59}$$

a. Start
b. Set the Parameters
c. Apply opposition points
d. Compute the fitness value
e. $\overrightarrow{Q_{Best}}(t) \leftarrow excellent\ exploration\ agent$
f. $while\ (t < maximum\ number\ of\ Iterations) do$
g. $For\ each\ exploration\ agent\ do$
h. Modernize the location exploration agents
i. $\overrightarrow{L_S} = Rt_R \times \left(\overrightarrow{Q_{Best}}(t) - \overrightarrow{Q_P}(t)\right)$
j. $|\Psi|^2 \cdot dx \cdot dy \cdot dz = Quantum \cdot dx \cdot dy \cdot dz$
k. $Hor = -h^2/2m \cdot \Delta^2 + V(x)$
l. $Rt_R = 0.5 \times R$
m. $U' = B \times \sin(t)$
n. $V' = B \times \cos(t)$
o. $W' = B \times (t)$
p. $\overrightarrow{Q_P}(t) = \left(\overrightarrow{Rt_S} \times (U' + V' + W') \times \overrightarrow{Q_{Best}}(t)\right)$
q. End for
r. $Rt_i(iter) = \left(LB_i + UB_i - Rt_e(iter)\right)$
s. $F_s = F_{max} - iter_p \cdot F_{max} - F_{min}/iter_{max}$
t. $Rt_i(iter) = F_s * \left(LB_i + UB_i - Rt_e(iter)\right)$
u. Smear the Tinkerbell chaotic map
v. $\mathrm{u_{t+1} = u_t^2 - v_t^2 + a \cdot u_t + b \cdot v_t}$
w. $\mathrm{v_{t+1} = 2u_tv_t + c \cdot u_t + d \cdot v_t}$
x. $u^*_{t+1} = u_{t+1} - minimum(u)/maximum(u) - minimum(u)$
y. $update\ the\ value\ of\ Rt_M$
z. $update\ the\ value\ of\ Rt_F$
aa. Compute the fitness value
bb. Modernize the $\overrightarrow{Q_{Best}}(t)$
cc. $t \leftarrow t + 1$
dd. End while
ee. $Return\ \overrightarrow{Q_{Best}}(t)$
ff. End

Chaotic in-Built Opposition Based – Quantum Ruddy Turnstone Optimization Algorithm

In the projected chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm, the transaction of erratic figures is completed with the irrational digits enthused by Laplace distribution to amplify the support of the probability of formation level inside the exploration zone. Chaotic sequences will augment the Exploration and Exploitation. Quantum features emulate the analogous performance with the certain stage as they route in a credible powdered of median. Figure 6 shows the schematic diagram of chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm.

Computational Complexity

The off line incorrectness is computed as,

$$off - line \text{ erroneousness} = \frac{1}{\max iter} \sum_{t=1}^{\max iter} Present \text{ erroneousness}_t$$

Categories of computation complication of $O(nlogn)$ *and* $O(n^2)$ in the finest and least case correspondingly. The generalized total calculation of complexity is apportioned as follows:

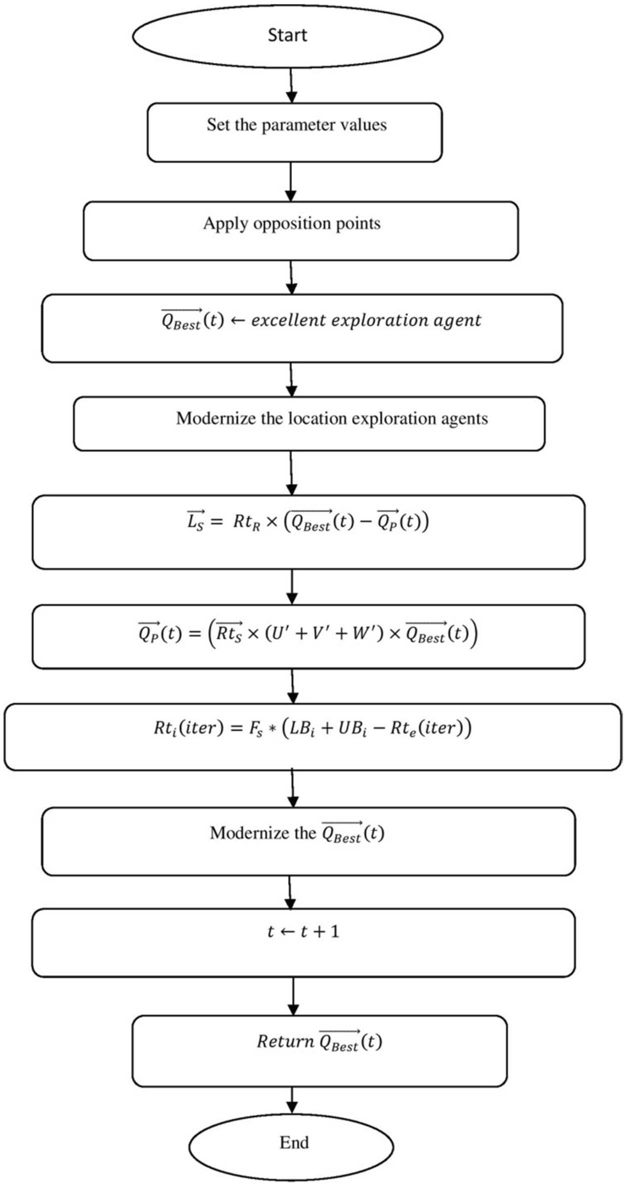


Fig. 5 Schematic diagram of Opposition based Ruddy turnstone optimization (ORTO) Algorithm

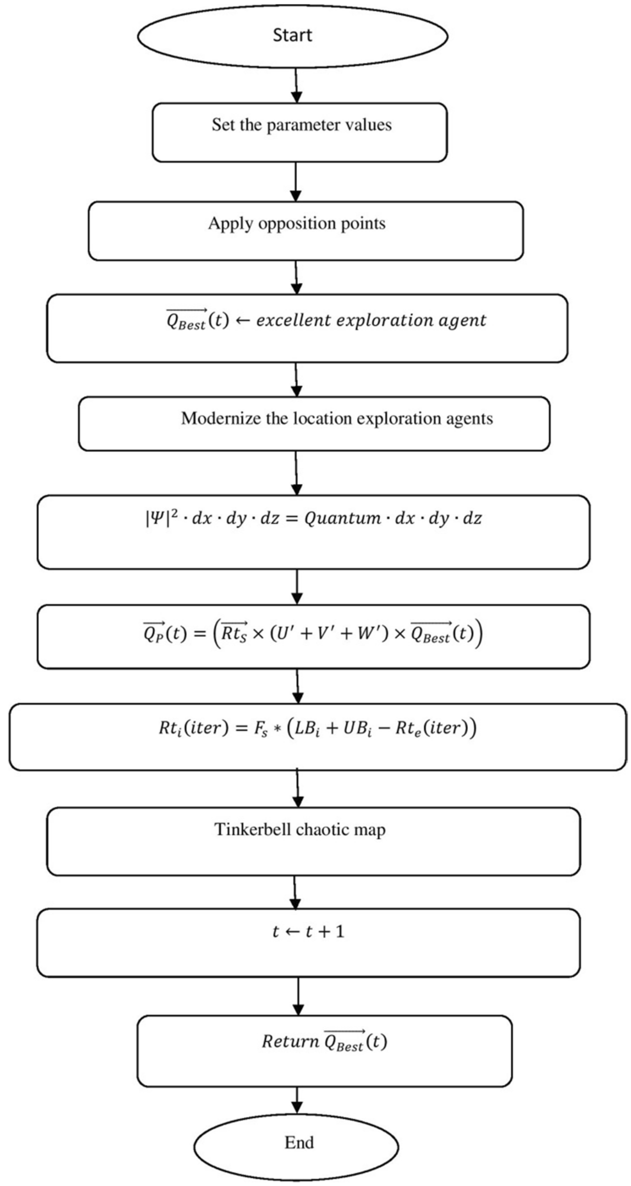


Fig. 6 Schematic diagram of chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm

$$O(Q\ )O(nlogn) = O(T(O(s) + O(p\ )))$$
$$O(n^2) = O\left(t\left(n^2 + n \times d\right)\right) = O\left(tn^2 + tnd\right)$$
$$O\left(\text{Max } iter * N^2 * D\right) * O(obj.fun) + O(\text{Max } iter * t * N) + O(\text{Max } iter * N * D)$$

Simulation Results

Proposed Extreme Learning Machine based Ruddy turnstone optimization (RTO) algorithm, Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm are corroborated in Garver's 6-bus test system, IEEE 30, 57, 118, 300, 354 bus test systems and Practical system - WDN 220 KV (Unified Egyptian Transmission Network (UETN)). At first proposed algorithm is reviewed in Garver's 6-bus test system [65]. It has six buses and lines, three generators and five loads [65] at buses. Table 1 shows the loss appraisal and Table 2 shows the voltage aberration evaluation. Figures 7 and 8 give the graphical appraisal between the methods.

Comparison of real power loss done between the standard methods and proposed Ruddy turnstone optimization (RTO)

Table 1 Loss appraisal

Method	Power loss (MW)
BCHA [66]	14.880
BGA [67]	14.150
SBD [68]	13.640
BBBA [69]	12.794
IMBBA [69]	12.768
RTO	11. 123
ELMRTO	11. 054
CRTO	11. 108
QRTO	11. 096
ORTO	11. 084
COQRTO	11. 049

Table 2 Power aberration analysis

Method	VD (PU)
BCHA [66]	NA
BGA [67]	NA
SBD [68]	NA
BBBA [69]	0.5191
IMBBA [69]	0.2208
RTO	0.2092
ELMRTO	0.2064
CRTO	0.2081
QRTO	0.2073
ORTO	0.2070
COQRTO	0.2060

algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm reduced the power loss efficiently. Real power Loss (MW) obtained by RTO-11. 123, ELMRTO-11. 054, CRTO-11. 108, QRTO-11. 096, ORTO-11. 084 and COQRTO-11. 049.

Comparison of voltage deviation done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Projected Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm are corroborated in IEEE 30 bus system [20]. In Table 3 shows the loss appraisal, Table 4 shows the voltage aberration evaluation and Table 5 gives the power permanence assessment. Figs. 9, 10 and 11 gives the graphical assessment between the approaches.

Comparison of real power loss done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone

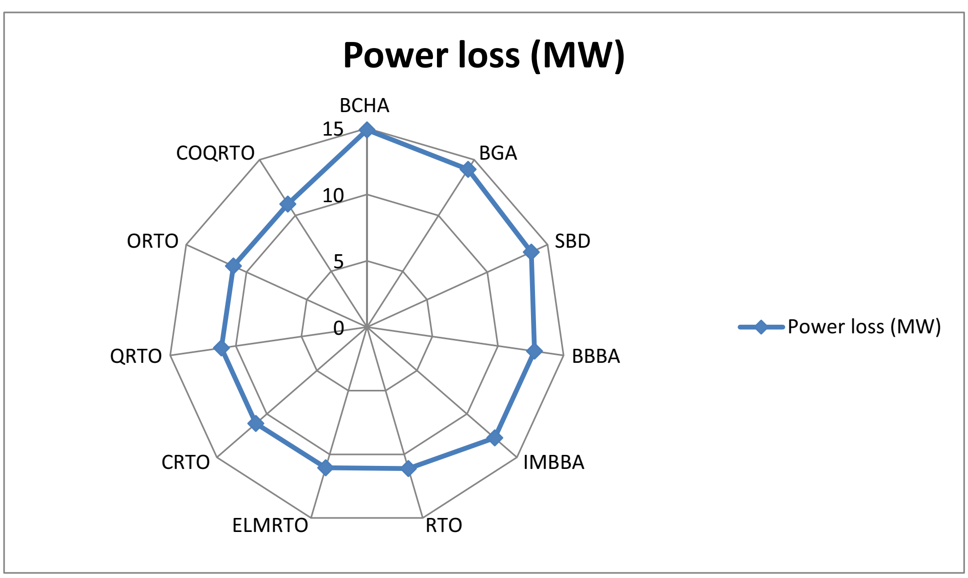


Fig. 7 Assessment of loss

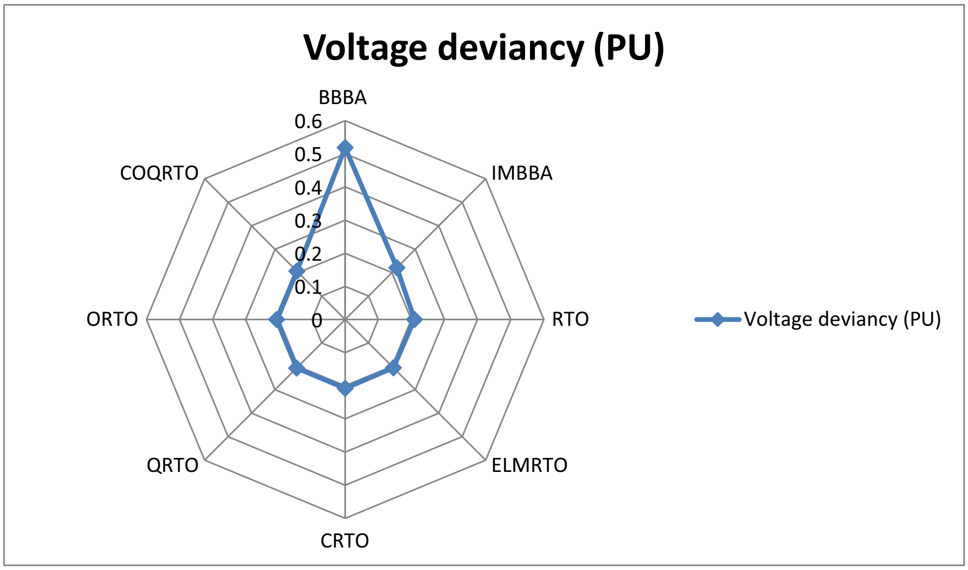


Fig. 8 Appraisal of Voltage aberration

optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm reduced the power loss efficiently. Real power Loss (MW) obtained by RTO- 4.2119, ELMRTO- 4.2075, CRTO-4.2109, QRTO-4.2081, ORTO-4.2092 and COQRTO- 4.2069.

Comparison of voltage deviation done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built

Table 3 Assessment of loss

Method	loss (MW)
BAPSOTS [10]	4.5213
SITS [10]	4.6862
SIPSO [10]	4.6862
ANTLOA [11]	4.5900
HYQOTLBO [12]	4.5594
BATLBO [12]	4.5629
SIGA [13]	4.9408
SSPSO [13]	4.9239
HYAS [13]	4.9059
SIFS [14]	4.5777
HYIFS [14]	4.5142
SIFS [16]	4.5275
LISA-I [51]	4.8193
LISA-II [51]	4.8547
SSA [50]	4.5317
ISSA [50]	4.5269
RTO	4.2119
ELMRTO	4.2075
CRTO	4.2109
QRTO	4.2081
ORTO	4.2092
COQRTO	4.2069

Table 4 Assessment of power eccentricity

Method	Power deviancy (PU)
SIPSOTVIW [15]	0.1038
BAPSOTVAC [15]	0.2064
BSPSOTVAC [15]	0.1354
HYPSOCF [15]	0.1287
HPGPSO [15]	0.1202
HYSWTPSO [15]	0.1614
HPGSWTPSO [15]	0.1539
HYMPGPSO [15]	0.0892
HQOTLBO [12]	0.0856
SITLBO [12]	0.0913
SIFS [14]	0.1220
HYISFS [14]	0.0890
SIFS [16]	0.0877
LISA-I [51]	0.374
LISA-II [51]	0.377
SSA [50]	0.0854
ISSA [50]	0.0831
RTO	0.0828
ELMRTO	0.0814
CRTO	0.0823
QRTO	0.0821
ORTO	0.0820
COQRTO	0.0812

Table 5 Appraisal of Voltage constancy

Method	Voltage constancy (PU)
SIPSOTVIW [15]	0.1258
BAPSOTVAC [15]	0.1499
BSPSOTVAC [15]	0.1271
HYPSOCF [15]	0.1261
HPGPSO [15]	0.1264
HYSWTPSO [15]	0.1488
HPGSWTPSO [15]	0.1394
HYMPGPSO [15]	0.1241
HQOTLBO [12]	0.1191
SITLBO [12]	0.1180
SIALO [11]	0.1161
BAABC [11]	0.1161
SIGWO [11]	0.1242
BBA [11]	0.1252
SIFS [14]	0.1252
HYISFS [14]	0.1245
SIBFS [16]	0.1007
RTO	0.1564
ELMRTO	0.1581
CRTO	0.1569
QRTO	0.1573
ORTO	0.1579
COQRTO	0.1589

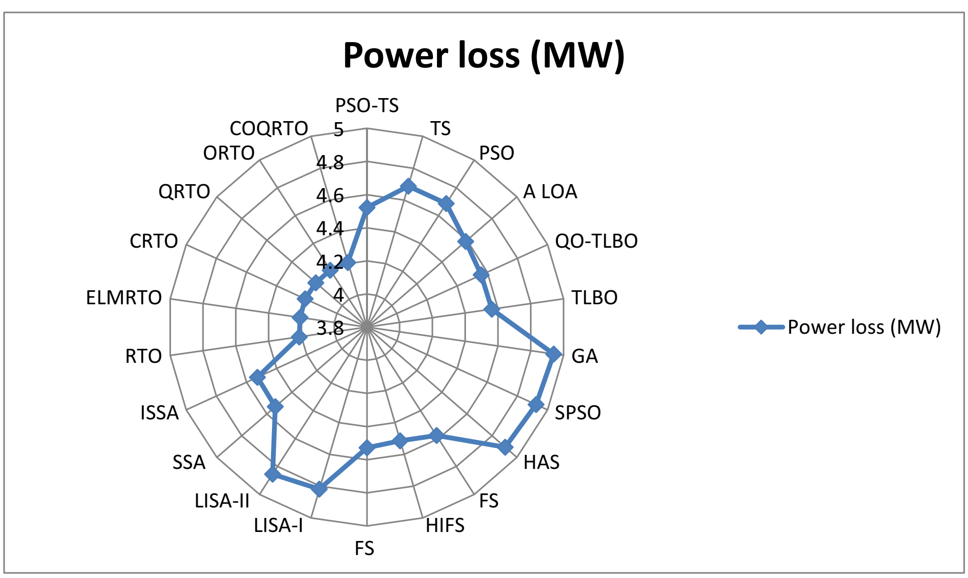
Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Comparison of voltage constancy done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm are corroborated in IEEE 57 bus system [55]. Table 6 shows the loss appraisal, Table 7 shows the voltage aberration evaluation and Table 8 gives the power constancy assessment. Figures 12, 13 and 14 give the graphical appraisal between the methods.

Comparison of real power loss done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm reduced the power loss efficiently. Real power Loss (MW) obtained

Fig. 9 Assessment of loss



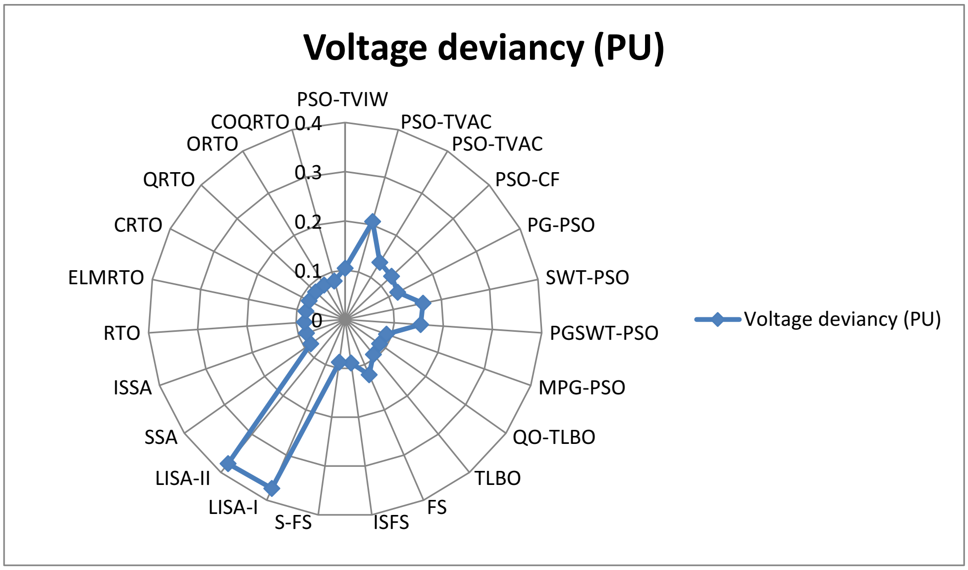


Fig. 10 Appraisal of Voltage aberration

by RTO-20.35, ELMRTO- 20.11, CRTO-20.32, QRTO-20.29, ORTO-20.22 and COQRTO-20.06.

Comparison of voltage deviation done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Comparison of voltage constancy done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Projected Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based

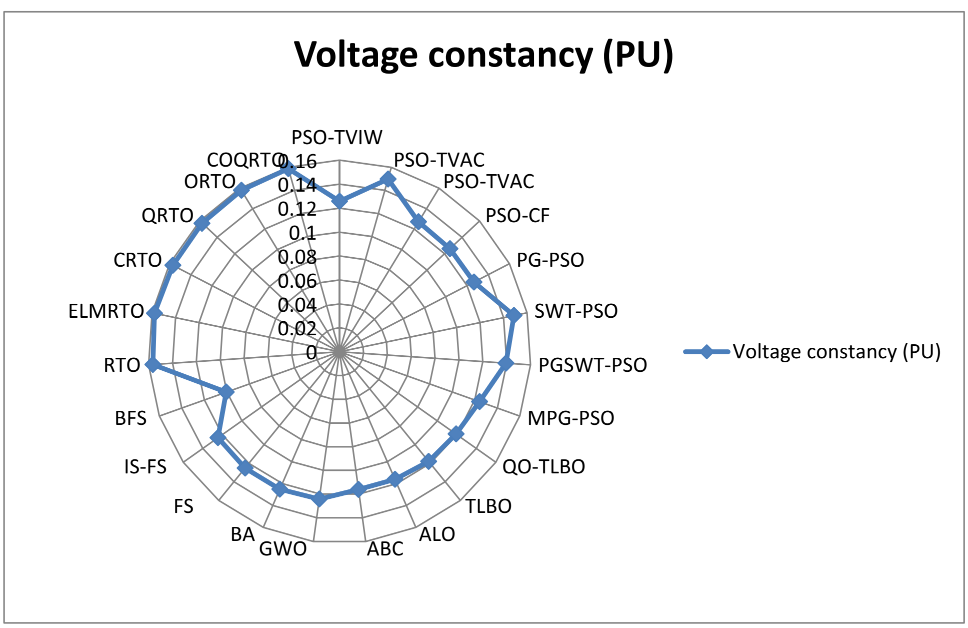


Fig. 11 Assessment of voltage constancy

Table 6 Appraisal of power loss

Method	Power loss (MW)
ICOA [48]	22.376
ICOA1 [48]	22.383
WCA [48]	26.0402
SSA [48]	25.3854
SFOA [48]	26.6541
COA [48]	24.5358
LISA-I [51]	26.88
LISA-II [51]	26.92
ISA [51]	26.97
MOPSO [49]	27.83
MOEPSO [49]	27.42
MFO [52]	24.25
MOGWA [53]	21.171
SGA [13]	25.64
PSO [13]	25.03
HAS [13]	24.90
RTO	20.35
ELMRTO	20.11
CRTO	20.32
QRTO	20.29
ORTO	20.22
COQRTO	20.06

Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based

Table 7 Voltage aberration evaluation

Method	VD (PU)
ICOA [48]	0.6051
ICOA1 [48]	0.6155
WCA [48]	0.7309
SSA [48]	0.94
SFOA [48]	0.7913
COA [48]	0.6711
LISA-I [51]	1.0642
LISA-II [51]	1.072
ISA [51]	1.0912
MOPSO [49]	1.10
MOEPSO [49]	0.896
RTO	0.616
ELMRTO	0.598
CRTO	0.610
QRTO	0.607
ORTO	0.601
COQRTO	0.590

Table 8 power constancy assessment

Method	Voltage stability index
ICOA [48]	0.25169
ICOA1 [48]	0.2583
WCA [48]	0.2789
SSA [48]	0.29
SFOA [48]	0.2831
COA [48]	0.2757
RTO	0.2958
ELMRTO	0.2989
CRTO	0.2964
QRTO	0.2969
ORTO	0.2973
COQRTO	0.2995

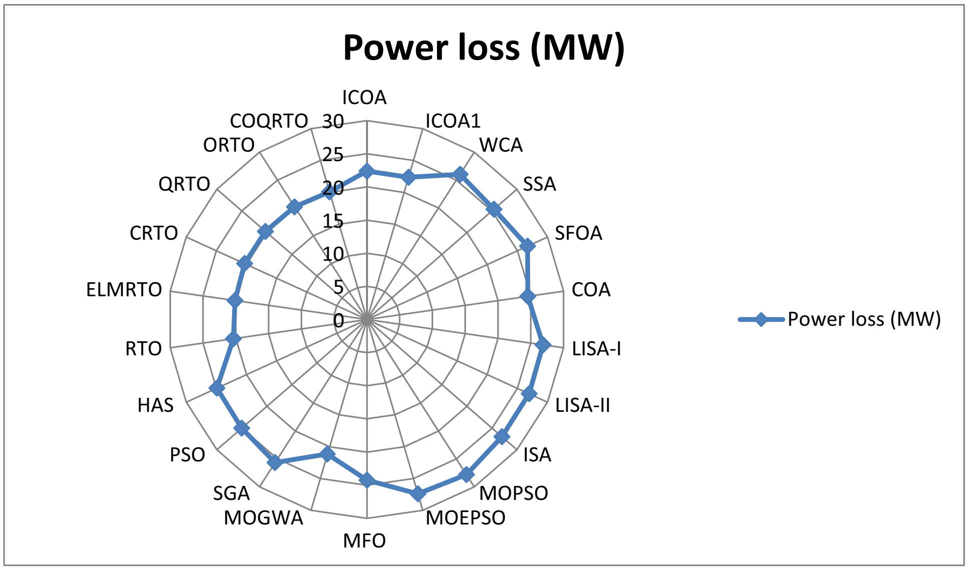
– Quantum Ruddy turnstone optimization (COQRTO) algorithm are corroborated in IEEE 118 bus system [57]. Table 9 shows the loss appraisal, Table 10 shows the voltage aberration evaluation and Table 11 gives the power constancy assessment. Figs. 15, 16 and 17 give the graphical appraisal between the methods.

Comparison of real power loss done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm reduced the power loss efficiently. Real power Loss (MW) obtained by RTO-113.92, ELMRTO-113.31, CRTO-113.80, QRTO-113.69, ORTO-113.48 and COQRTO-113.24.

Comparison of voltage deviation done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Comparison of voltage constancy done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization

Fig. 12 Appraisal of loss

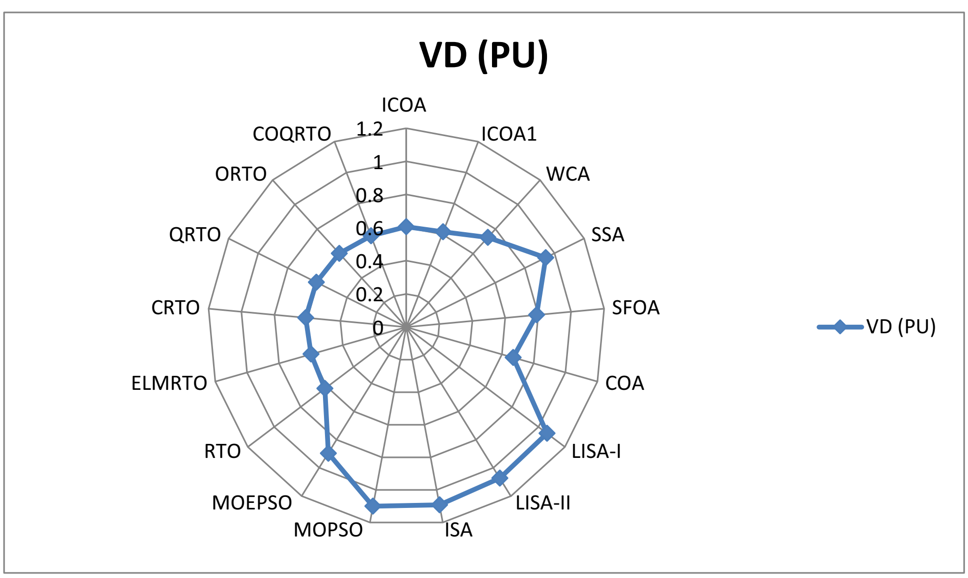


(ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Projected Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm are corroborated in IEEE 300 bus system [56]. Table 12 shows the loss appraisal and Table 13 shows the voltage aberration evaluation. Figures 18 and 19 give the graphical appraisal between the methods.

Comparison of real power loss done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm reduced the power loss efficiently. Real power Loss (MW) obtained by RTO-390.156, ELMRTO-390.108,

Fig. 13 Appraisal of power deviance



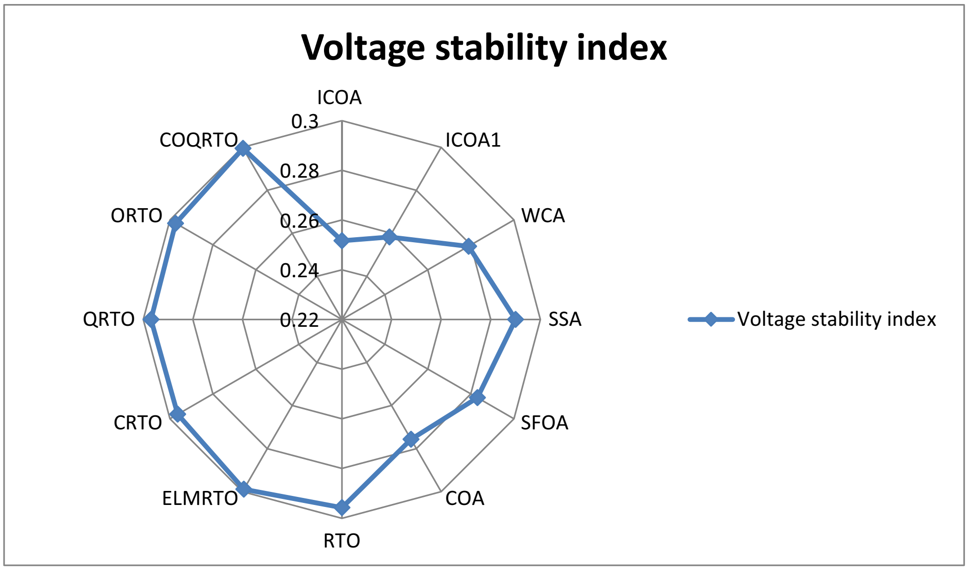


Fig. 14 Appraisal of power permanence

CRTO-390.137, QRTO-390.126, ORTO-390.118 and COQRTO-390.090.

Comparison of voltage deviation done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Projected Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm are corroborated in IEEE 354 bus system [56]. In Table 14 shows the loss appraisal and Table 15 shows

Table 9 loss appraisal

Method	Power loss (MW)
ICOA [48]	114.8036
ICOA1 [48]	114.8623
WCA [48]	118.3207
SSA [48]	125.7288
SFOA [48]	125.6801
COA [48]	132.3341
COA1 [48]	123.6867
COA2 [48]	126.0426
LISA-I [51]	119.79
LISA-II [51]	120.15
ISA [51]	120.67
ALCPSO [54]	121.53
CLPSO [54]	130.96
RTO	113.92
ELMRTO	113.31
CRTO	113.80
QRTO	113.69
ORTO	113.48
COQRTO	113.24

Table 10 Voltage aberration evaluation

Method	VD (PU)
ICOA [48]	0.1605
ICOA1 [48]	0.1608
WCA [48]	0.2315
SSA [48]	0.4883
SFOA [48]	0.6061
COA [48]	0.2034
COA1 [48]	0.1928
COA2 [48]	0.1936
LISA-I [51]	0.2819
LISA-II [51]	0.2876
ISA [51]	0.2948
RTO	0.1592
ELMRTO	0.1551
CRTO	0.1583
QRTO	0.1579
ORTO	0.1571
COQRTO	0.1542

Table 11 Power constancy assessment

Method	Voltage stability index
ICOA [48]	0.06061
ICOA1 [48]	0.06064
WCA [48]	0.060731
SSA [48]	0.0639
SFOA [48]	0.0619
COA [48]	0.06123
COA1 [48]	0.06072
COA2 [48]	0.06077
RTO	0.06470
ELMRTO	0.06492
CRTO	0.06476
QRTO	0.06479
ORTO	0.06481
COQRTO	0.06502

the voltage aberration evaluation. Figures 20 and 21 give the graphical appraisal between the methods.

Comparison of real power loss done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm reduced the power loss efficiently. Real power Loss (MW) obtained by RTO-336.099, ELMRTO-336.047, CRTO-336.081, QRTO-336.076, ORTO-336.064 and COQRTO-336.039.

Comparison of voltage deviation done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm are reviewed in practical system - WDN 220 KV (Unified Egyptian Transmission Network (UETN)) [70] - 21 buses and 49 lines). Table 16 shows the loss appraisal and Table 17 shows the voltage aberration evaluation. Figures 22 and 23 give the graphical appraisal between the methods.

Comparison of real power loss done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and

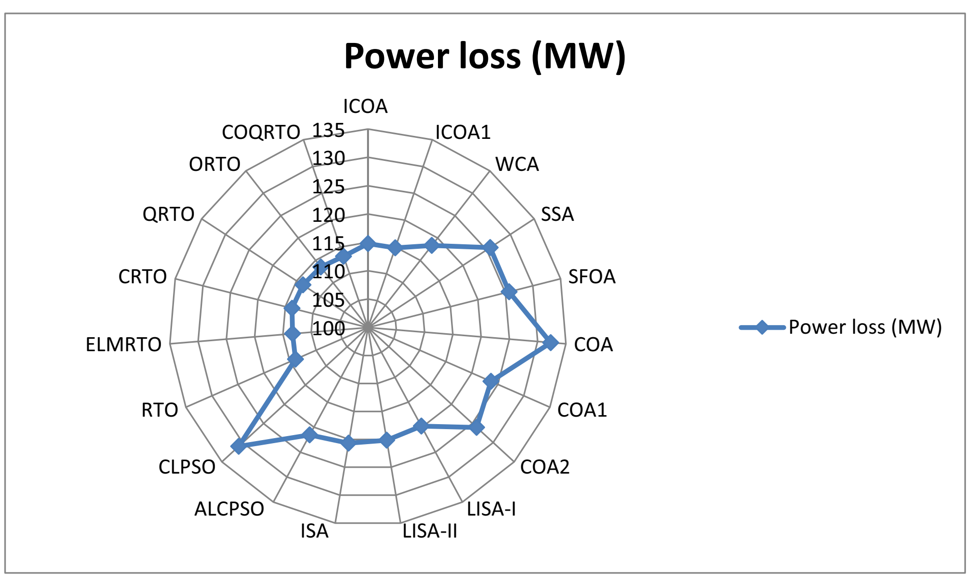


Fig. 15 Appraisal of loss

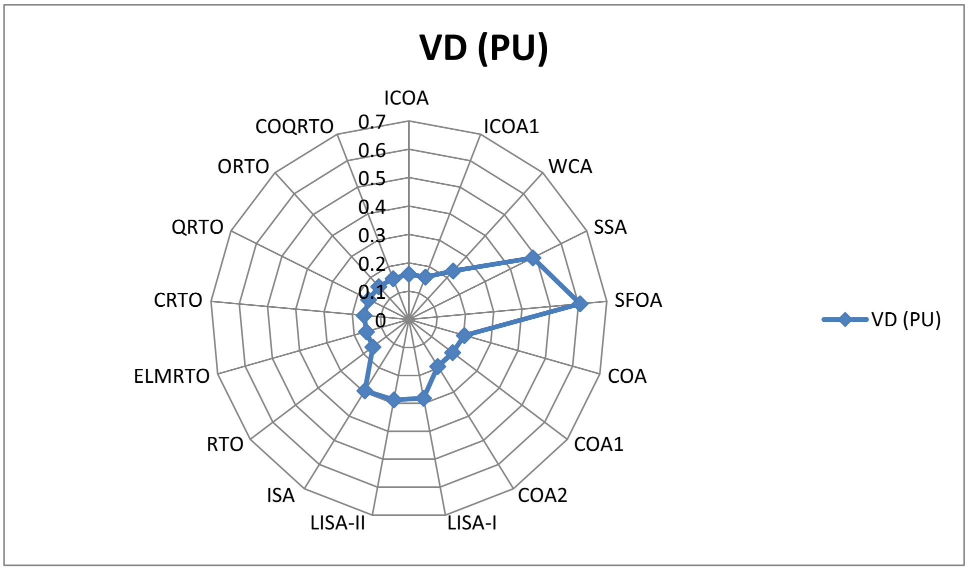


Fig. 16 Appraisal of power deviance

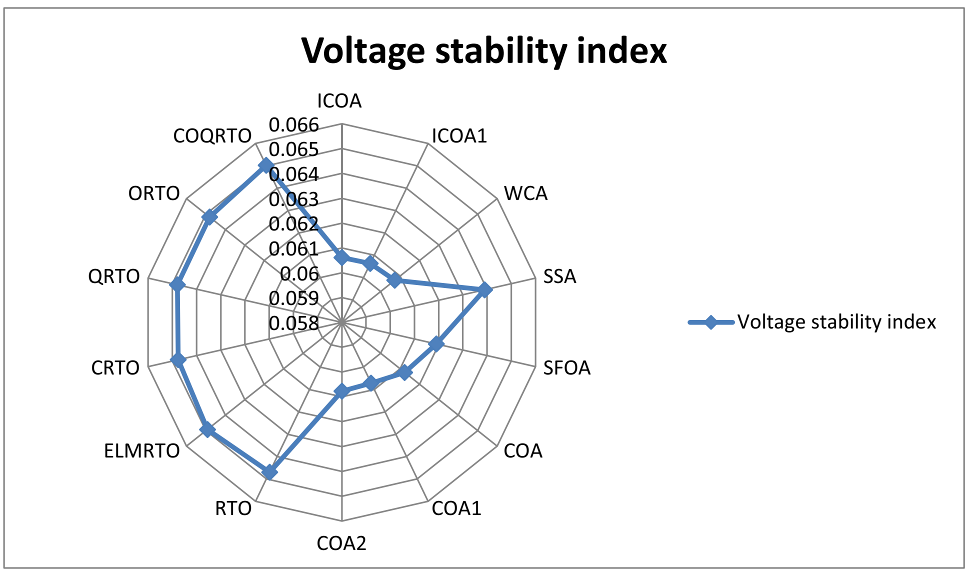


Fig. 17 Appraisal of power permanence

chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm reduced the power loss efficiently. Real power Loss (MW) obtained by RTO-29. 352, ELMRTO-29. 329, CRTO-29. 344, QRTO-29. 340, ORTO-29. 336 and COQRTO-29. 322.

Comparison of voltage deviation done between the standard methods and proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm performed well.

Table 12 Loss appraisal

Method	Power Loss (MW)
LISA-I [51]	396.983
LISA-II [51]	397.236
ISA [51]	397.902
MOALO [49]	398.853
RTO	390.156
ELMRTO	390.108
CRTO	390.137
QRTO	390.126
ORTO	390.118
COQRTO	390.090

Table 13 Voltage aberration evaluation

Method	VD (PU)
LISA-I [51]	5.9324
LISA-II [51]	5.9416
ISA [51]	5.9613
MOALO [49]	6.0169
RTO	5.7412
ELMRTO	5.7360
CRTO	5.7408
QRTO	5.7399
ORTO	5.7378
COQRTO	5.7335

Table 18 and Fig. 24 show the time taken for Proposed Ruddy turnstone optimization (RTO) algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm are corroborated in Garver's 6-bus test system, IEEE 30, 57, 118, 300, 354 bus test systems and Practical system - WDN 220 KV (Unified Egyptian Transmission Network (UETN)).

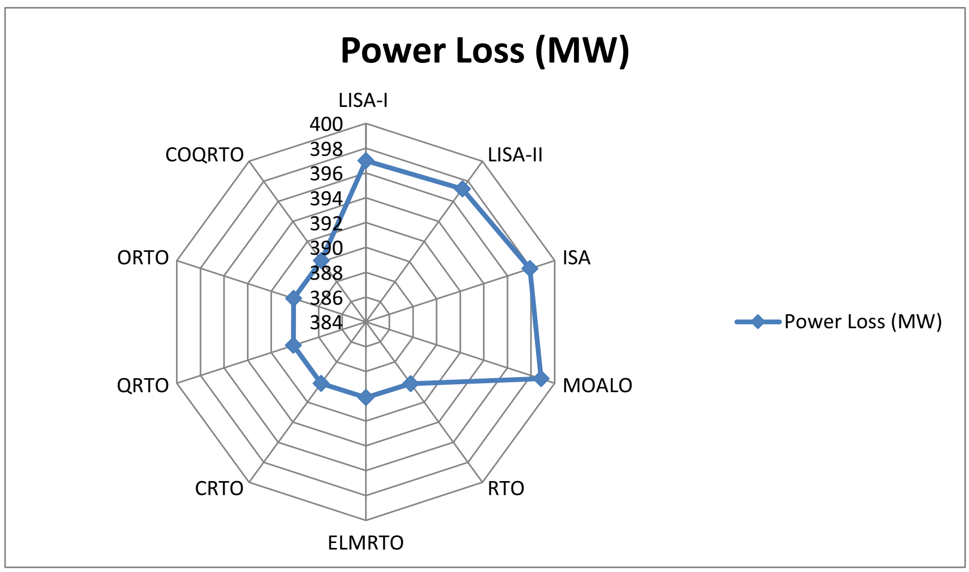


Fig. 18 Appraisal of power loss

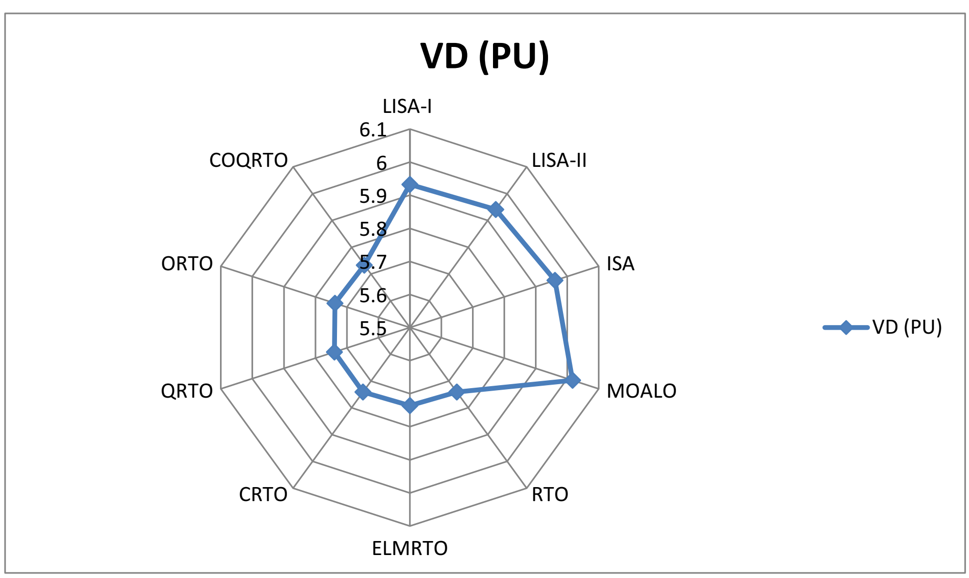


Fig. 19 Appraisal of power deviance

Table 14 Loss appraisal

Method	Power Loss (MW)
LISA-I [51]	337.374
LISA-II [51]	338.715
ISA [51]	339.325
FAHCLSO [49]	341.001
PSO [49]	341.123
RTO	336.099
ELMRTO	336.047
CRTO	336.081
QRTO	336.076
ORTO	336.064
COQRTO	336.039

Table 15 Voltage aberration

Method	VD(PU)
LISA-I [51]	0.4978
LISA-II [51]	0.5117
ISA [51]	0.5216
FAHCLSO [49]	0.5354
PSO [49]	0.6395
RTO	0.4148
ELMRTO	0.4127
CRTO	0.4142
QRTO	0.4139
ORTO	0.4130
COQRTO	0.4121

Conclusion

Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm truncated the loss competently. Important goals of the paper are Power fidelity extension, power eccentricity minimization and genuine loss lessening.

- In Ruddy turnstone optimization algorithm the constellation of Ruddy turnstone, which mobile from one place to alternate in the sequence of repositioning and the fresh investigation agent position is to evade the smash amongst their contiguous Ruddy turnstone.
- In the proposed Extreme Learning Machine based Ruddy turnstone Optimization Algorithm, Ruddy turnstone Optimization approach enhances Extreme Learning Machine features to determine an optimal carcass of Extreme Learning Machine for enhanced standards.
- In Chaotic based Ruddy turnstone optimization algorithm Exploration and Exploitation are augmented. In Quantum based Ruddy turnstone Optimization Algorithm, features emulate the analogous performance with the certain stage as they route in a credible powdered of median.

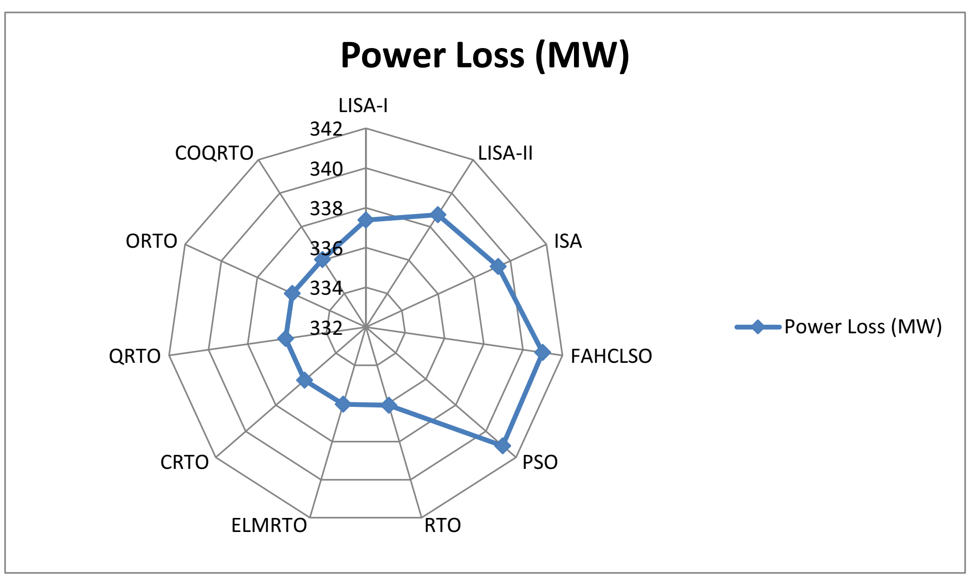


Fig. 20 Appraisal of power loss

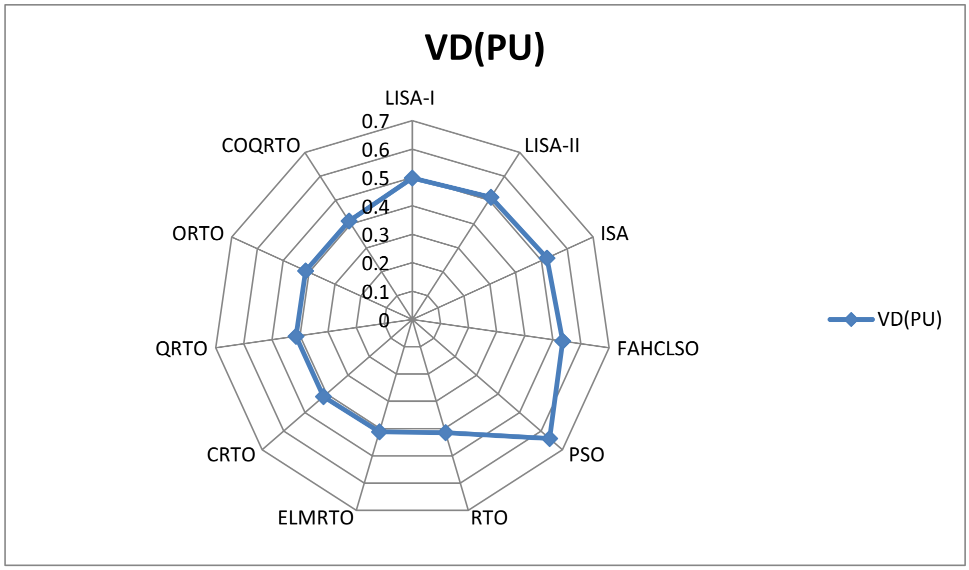


Fig. 21 Appraisal of power deviance

Table 16 Loss appraisal

Method	Power loss (MW)
BSPSO [69]	32.314
BBBA [69]	33.875
IMBBA [69]	30.786
RTO	29. 352
ELMRTO	29. 329
CRTO	29. 344
QRTO	29. 340
ORTO	29. 336
COQRTO	29. 322

Table 17 Power aberration analysis

Method	VD (PU)
BSPSO [69]	0.5800
BBBA [69]	0.6327
IMBBA [69]	0.6751
RTO	0.5446
ELMRTO	0.5429
CRTO	0.5441
QRTO	0.5438
ORTO	0.5431
COQRTO	0.5420

- Opposition based Ruddy turnstone optimization Algorithm employs Laplace distribution to enhance the exploration skill. Then examining the prospect to widen the exploration, a new method endorses stimulating capricious statistics used in formation stage regulator factor in Ruddy turnstone Optimization Algorithm.
- In the projected chaotic in-built Opposition based – Quantum Ruddy turnstone optimization algorithm, the transaction of erratic figures is completed with the irrational digits enthused by Laplace distribution to amplify the support of the probability of formation level inside the exploration zone.

Proposed Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm is corroborated in Garver's 6-bus test system, IEEE 30, 57, 118, 300, 354 bus test systems and Practical system - WDN 220 KV (Unified Egyptian Transmission Network (UETN)). Power loss weakening, power inconsistency curbing, and power reliability escalation has been accomplished.

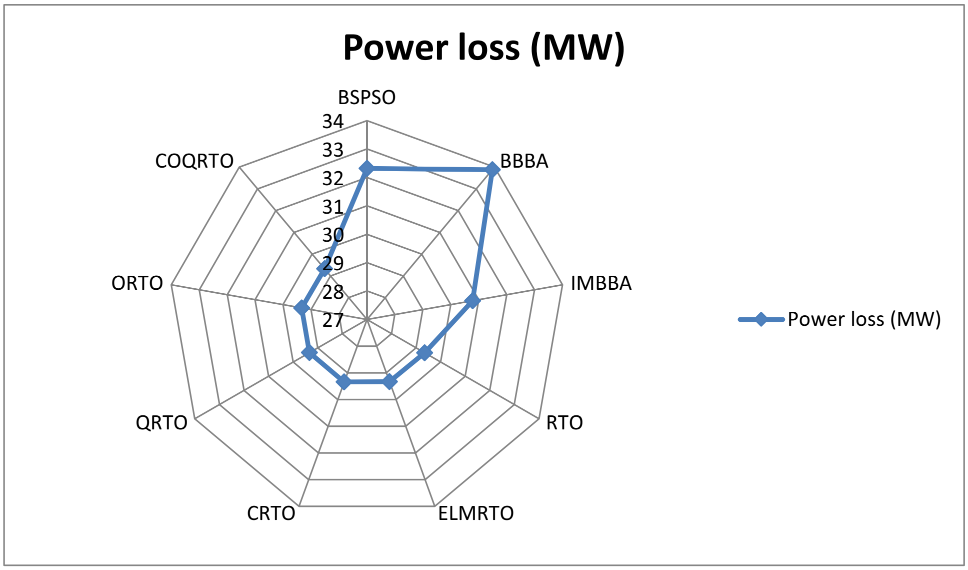


Fig. 22 Assessment of loss

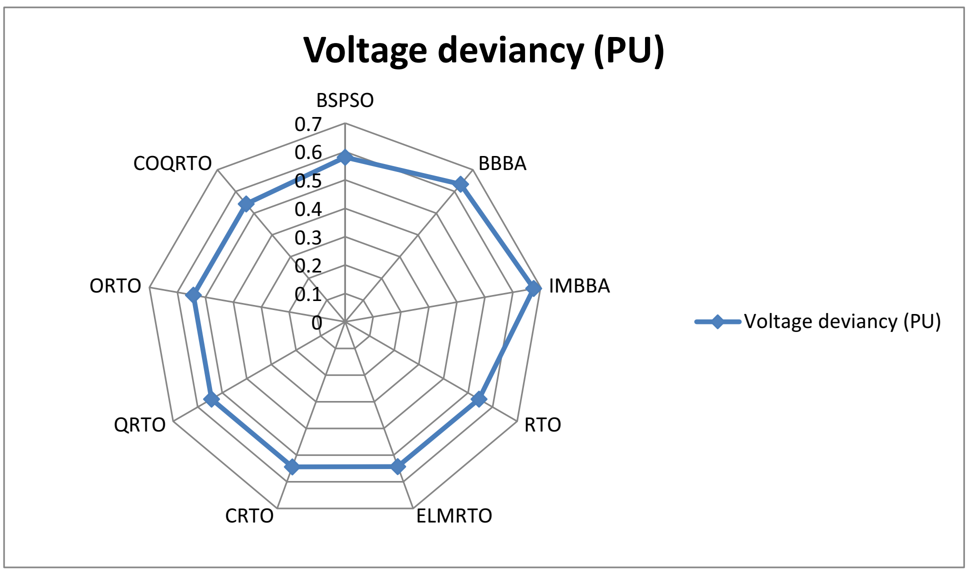


Fig. 23 Appraisal of Voltage aberration

Table 18 Time taken for Ruddy turnstone optimization (RTO) algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm

Method	Garver's 6-bus Time (S)	IEEE 30 bus Time (S)	IEEE 57 bus Time (S)	IEEE 118 bus Time (S)	IEEE 300 bus Time (S)	IEEE 354 bus Time (S)	WDN 220 KV Time (S)
RTO	8.99	22.85	29.91	39.90	75.82	85.87	24.97
CRTO	8.92	22.98	29.95	39.93	75.89	85.92	24.90
QRTO	8.90	22.95	29.91	39.89	75.88	85.89	24.88
ORTO	8.87	22.92	29.89	39.83	75.84	85.85	24.83
COQRTO	8.82	22.52	29.67	39.84	75.76	85.86	24.80

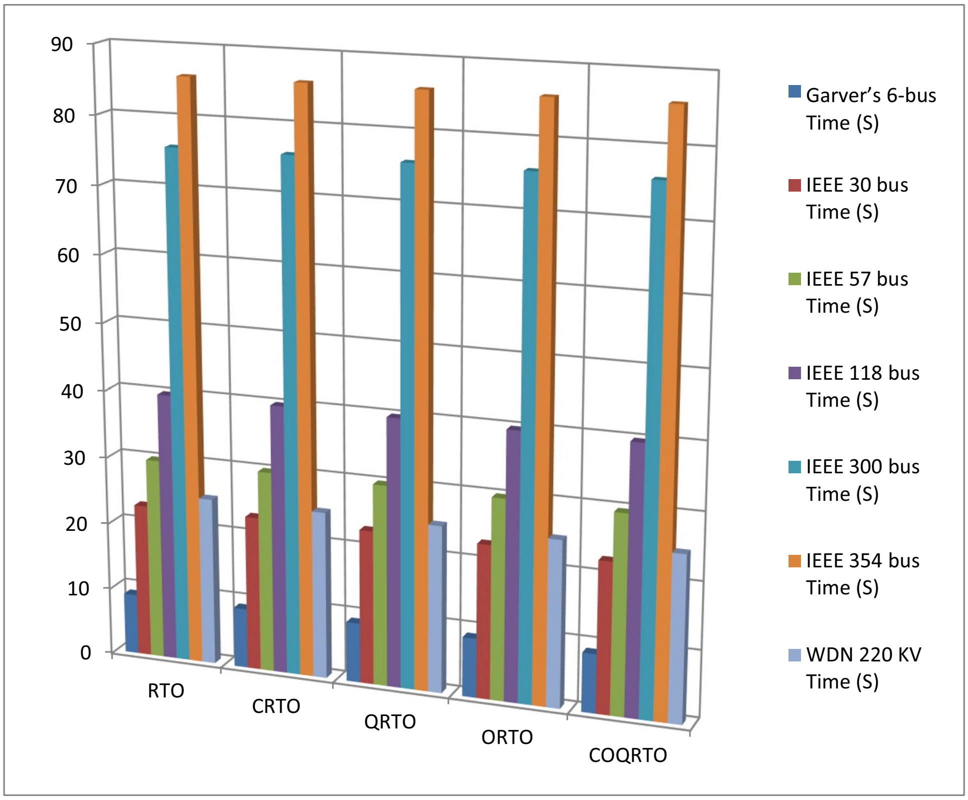


Fig. 24 Time taken for Ruddy turnstone optimization (RTO) algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm

Scope of Future Work

In future Ruddy turnstone optimization (RTO) algorithm, Extreme Learning Machine based Ruddy turnstone Optimization (ELMRTO) Algorithm, Chaotic based Ruddy turnstone optimization (CRTO) algorithm, Quantum based Ruddy turnstone Optimization (QRTO) Algorithm, Opposition based Ruddy turnstone optimization (ORTO) Algorithm and chaotic in-built Opposition based – Quantum Ruddy turnstone optimization (COQRTO) algorithm can be extended to apply for other areas of power system problems. Mainly in the area of medical diagnosis it can be applied for enhancing the identification and treatment of the disease. Sequentially the algorithm can be tuned further to solve the large problems in complex systems.

Authorship Contribution Statement I. Single author - Dr. Lenin Kanagasabai

II. Conception or design of the work. - yes
III. Data collection. - yes
IV. Data analysis and interpretation.- yes
V. Drafting the article.- yes
VI. Critical revision of the article.- yes
VII. Final approval of the version to be published.- yes

Data Availability Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

Declarations

Ethical Approval All the ethics are followed and no human and animal are involved in the research.

Conflict of Interest No conflict of interest for the author.

Informed Consent Single author- And the author has full consent to submit the paper for possible publication.

References

1. Zhu JZ, Xiong XF (2003) Optimal reactive power control using modified interior point method. Electr Power Syst Res 66(2):187–192
2. V.H. Quintana, M. Santos-Nieto reactive-power dispatch by successive quadratic programming IEEE trans. Energy Convers., 4 (3) (1989), pp. 425–435
3. Jan R-M, N. (1995) Chen application of the fast Newton-Raphson economic dispatch and reactive power/voltage dispatch by sensitivity factors to optimal power flow. IEEE Trans Energy Convers 10(2):293–301
4. Terra LDB, Short MJ (1991) Security-constrained reactive power dispatch. IEEE Trans Power Syst 6(1):109–117
5. Grudinin N (1998) Reactive power optimization using successive quadratic programming method. IEEE Transactions on Power System, vol/issue 13(4):1219–1225. https://doi.org/10.1109/59.736232

6. Ebeed M, Alhejji A, Kamel S, Jurado F (2020) Solving the optimal reactive power dispatch using marine predators algorithm considering the uncertainties in load and wind-solar generation systems. Energies MDPI Open Access J 13(17):1–19
7. Sahli Z, Hamouda A, Bekrar A, Trentesaux D (2018) Reactive power dispatch optimization with voltage profile improvement using an efficient hybrid algorithm. Energies MDPI Open Access J 11(8):1–21
8. Davoodi E, Babaei E, Mohammadi-Ivatloo B, Rasouli M (2019) A novel fast semidefinite programming-based approach for optimal reactive power dispatch. IEEE Transactions on Industrial Informatics 16(1):288–298
9. Bingane C, Anjos MF, Le Digabel S (2019) Tight-and-cheap conic relaxation for the optimal reactive power dispatch problem. IEEE Trans Power Syst 34(6):4684–4693
10. Sahli Z, Hamouda A, Bekrar A, Trentesaux D (2014) Hybrid PSO-tabu search for the optimal reactive power dispatch problem, in Proceedings of the IECON 2014-40th Annual Conference of the IEEE Industrial Electronics Society, Dallas
11. Mouassa S, Bouktir T, Salhi A (2017) Ant lion optimizer for solving optimal reactive power dispatch problem in power systems. Engineering Science and Technology, an International Journal 20(3):885–895
12. Mandal B, Roy PK (2013) Optimal reactive power dispatch using quasi-oppositional teaching learning based optimization. Int J Electr Power Energy Syst 53:123–134
13. Khazali H, Kalantar M (2011) Optimal reactive power dispatch based on harmony search algorithm. Int J Electr Power Energy Syst 33(3):684–692
14. Tran HV, Pham TV, Pham LH, Le NT, Nguyen TT (2019) Finding optimal reactive power dispatch solutions by using a novel improved stochastic fractal search optimization algorithm. Telecommunication Computing Electronics and Control 17(5):2517–2526
15. Polprasert J, Ongsakul W, Dieu VN (2016) Optimal reactive power dispatch using improved pseudo-gradient search particle swarm optimization. Electric Power Components and Systems 44(5):518–532
16. Duong TL, Duong MQ, Phan V-D, Nguyen TT (2020, Article ID 6382507) Optimal Reactive Power Flow for Large-Scale Power Systems Using an Effective Metaheuristic Algorithm. Hindawi J Electr Comput Eng:11. https://doi.org/10.1155/2020/6382507
17. Raghuwanshi BS, Shukla S (2019) Class imbalance learning using UnderBagging based kernelized extreme learning machine. Neurocomputing 329:172–187
18. Yu X, Feng Y, Gao Y, Jia Y, Mei S (2021) Dual-weighted kernel extreme learning machine for hyperspectral imagery classification. Remote Sens 13(3):508. https://doi.org/10.3390/rs13030508
19. Lv F, Han M (2019) Hyperspectral image classification based on multiple reduced kernel extreme learning machine. Int J Mach Learn Cybern 10:3397–3405
20. Illinois Center for a Smarter Electric Grid (ICSEG) (2019) Available online: https://icseg.iti.illinois.edu/ieee-30-bussystem/ (accessed on 25 February 2019)
21. Dai C, Chen W, Zhu Y, Zhang X (2009) Seeker optimization algorithm for optimal reactive power dispatch. IEEE T Power Syst 24(3):1218–1231
22. Subbaraj P, Rajnarayan PN (2009) Optimal reactive power dispatch using self-adaptive real coded genetic algorithm. Electr Power Syst Res 79(2):374–338
23. Lin KM, Nilar Aung T, Oo K (2017) Particle swarm optimization based optimal reactive power dispatch for power distribution network with distributed generation. Int J Energy Power Eng 6:54–60. https://doi.org/10.11648/j.ijepe.20170604.12
24. Hussain AN, Abdullah AA, Neda OM (2018) Modified particle swarm optimization for solution of reactive power dispatch. Res J Appl Sci Eng Technol 15(8):316–327. https://doi.org/10.19026/rjaset.15.5917
25. Vishnu MS (2020) An Improved Solution for Reactive Power Dispatch Problem Using Diversity-Enhanced Particle Swarm Optimization. Energies 13(2862):2–21. https://doi.org/10.3390/en13112862
26. Omelchenko IN, Lyakhovich D, Aleksandrov AA, Vodchits A, Kunkov NV (2020) Development of a design algorithm for the logistics system of product distribution of the mechanical engineering Enterprise. Herald of the Bauman Moscow State Technical University. Series. Mech Eng 62-69:10.18698/0236-3941-2020-3-62-69
27. Omelchenko I, Zakharov M, Lyakhovich D, Vodchits A (2020) Organization of logistic systems of scientific productions: scientific research work of the master's student and evaluation of its results. https://doi.org/10.18334/9785912923258.252-256
28. Omelchenko I, Lyakhovich D, Alexandrov A, Vodchits A, Sturua K (2020). Problems and organizational and technical solutions of processing management problems of material and technical resources in a design-oriented organization. https://doi.org/10.18334/9785912923258.257-260
29. Khunkitti S, Siritaratiwat A, Premrudeepreechacharn S (2021) Multi-objective optimal power flow problems based on slime Mould algorithm. Sustainability 13:7448. https://doi.org/10.3390/su13137448
30. Diab H, Abdelsalam M, Abdelbary A (2021) A multi-objective optimal power flow control of electrical transmission networks using intelligent Meta-heuristic optimization techniques. Sustainability 13:4979
31. Surender Reddy S (2017) "Optimal reactive power scheduling using cuckoo search algorithm", international. Journal of Electrical and Computer Engineering 7(5):2349–2356
32. Reddy SS (2014) Faster evolutionary algorithm based optimal power flow using incremental variables. Electr Power Energy Syst 54:198–210
33. Sridhar N, Kowsalya M (2021) Enhancement of power management in micro grid system using adaptive ALO technique. J Ambient Intell Human Comput 12:2163–2182. https://doi.org/10.1007/s12652-020-02313-3
34. Suja KR (2021) Mitigation of power quality issues in smart grid using levy flight based moth flame optimization algorithm. J Ambient Intell Human Comput 12:9209–9228. https://doi.org/10.1007/s12652-020-02626-3
35. Darvish Falehi A (2020) Optimal robust disturbance observer based sliding mode controller using multi-objective grasshopper optimization algorithm to enhance power system stability. J Ambient Intell Human Comput 11:5045–5063. https://doi.org/10.1007/s12652-020-01811-8
36. Sharma S, Ghosh S (2020) FIS and hybrid ABC-PSO based optimal capacitor placement and sizing for radial distribution networks. J Ambient Intell Human Comput 11:901–916. https://doi.org/10.1007/s12652-019-01216-2
37. Saravanan C, Anbalagan P (2021) Multi objective dragonfly algorithm for congestion management in deregulated power systems. J Ambient Intell Human Comput 12:7519–7528. https://doi.org/10.1007/s12652-020-02440-x
38. Bentouati B, Khelifi A, Shaheen AM et al (2021) An enhanced moth-swarm algorithm for efficient energy management based multi dimensions OPF problem. J Ambient Intell Human Comput 12:9499–9519. https://doi.org/10.1007/s12652-020-02692-7
39. Menon P, Rani B, Kumar K, Gupta V (2021) An effective OS–DPLL design for reducing power dissipation in an IoT application. J Ambient Intell Humaniz Comput. https://doi.org/10.1007/s12652-021-03016-z
40. Saxena NK, Kumar A, Gupta V (2021) Enhancement of system performance using STATCOM as dynamic compensator with

squirrel cage induction generator (SCIG) based microgrid. International Journal of Emerging Electric Power Systems 22(2):177–189. https://doi.org/10.1515/ijeeps-2020-0228
41. Kazmi SA, Shahzad M, Shin D (2017) Voltage stability index for distribution network connected in loop configuration. IETE J Res 63:1–13. https://doi.org/10.1080/03772063.2016.1257376
42. Sampangi K, Sambaiah, Jayabarathi T (2020) Optimal modeling and allocation of mixed wind and solar generation Systems in Electric Distribution Networks. IETE J Res:1–13. https://doi.org/10.1080/03772063.2020.1787876
43. Zaidan M, Toos I, Saber (2021) Optimal location of static Var compensator to regulate voltage in power system. IETE J Res. https://doi.org/10.1080/03772063.2021.1886877
44. Lakshmi Priya J, Jaya Christa ST (2021) An effective hybridized GWO-BSA for resolving optimal power flow problem with the inclusion of unified power flow controller. IETE J Res. https://doi.org/10.1080/03772063.2021.1942245
45. Ahmadnia S, Tafehi E, Dastgahian F (2019) Optimal placement and sizing for solar farm with economic evaluation, power line loss and energy consumption reduction. IETE J Res:1–16. https://doi.org/10.1080/03772063.2019.1694450
46. Azimi M, Mohammadi-ivatloo B, Zare K, Abapour M (2015) Probabilistic allocation of Thyristor-controlled phase shifting transformer for transient stability enhancement of electric power system. IETE J Res 61:1–10. https://doi.org/10.1080/03772063.2015.1023743
47. Juneja K (2020) A fuzzy-controlled differential evolution integrated static synchronous series compensator to enhance power system stability. IETE J Res:1–16. https://doi.org/10.1080/03772063.2020.1795936
48. Kien LC, Hien CT, Nguyen TT (2021) Optimal reactive power generation for transmission power systems considering discrete values of capacitors and tap changers. Appl Sci 11(12):5378. https://doi.org/10.3390/app11125378
49. Mouassa S (2018) Tarek 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 35(1):350–372
50. Tudose A, Picioroaga I, Sidea D, Bulac C (2021) Solving single- and multi-objective optimal reactive power dispatch problems using an improved Salp swarm algorithm. Energies 14:1222. https://doi.org/10.3390/en14051222
51. Nagarajan K, Parvathy AK, Arul R (2020) Multi-Objective Optimal Reactive Power Dispatch using Levy Interior Search Algorithm. Int J Electr Eng Inf 12:547–570. https://doi.org/10.15676/ijeei.2020.12.3.8
52. Mei RNS, Sulaiman MH, Mustaffa Z, Daniyal H (2017) Optimal reactive power dispatch solution by loss minimization using moth-flame optimization technique. Appl Soft Comput 59:210–222
53. Nuaekaew K, Artrit P, Pholdee N, Bureerat S (2017) Optimal reactive power dispatch problem using a two-archive multi-objective grey wolf optimizer. Expert Syst Appl 87:79–89
54. Chen G, Liu L, Guo Y (2016) Shanwai Huang, multi-objective enhanced PSO algorithm for optimizing power losses and voltage deviation in power systems. COMPEL: The International Journal for Computation and Mathematics in Electrical and Electronic Engineering 35(1):350–372
55. The IEEE (n.d.) 57-Bus Test System [online], available at http://www.ee.washington.edu/research/pstca/pf57/pg_tca57bus.htm
56. PSTCA, Power Systems test case archive, University of Washington (2016) Available: http://www.ee.washington.edu/research/pstca/
57. The IEEE (n.d.) 118-Bus Test System [online], available at http://www.ee.washington.edu/research/pstca/pf118/pg_tca118bus.htm
58. Lin JH, Chou CW, Yang CH, Tsai HL (2012) Chaotic Lévy flight bat algorithm for parameter estimation in nonlinear dynamic biological systems. J Comput Inf Technol 2(2):56–63
59. Hakli H, Uguz H (2014) A novel particle swarm optimization algorithm with levy flight. Appl Soft Comput 23(1):333–345
60. Davidchack RL, Lai YC, Klebanoff A, Bolt EM (2001) Towards complete detection of unstable periodic orbits in chaotic systems. Phys Lett A 287:99–104
61. Inoue K, M. (2000) Ohya Sato K application of chaos degree to some dynamical systems. Chaos, Solitons Fractals 11:1377–1385
62. Dinkar S, Deep K (2017) Opposition based Laplacian ant lion optimizer. Journal of Computational Science 23. https://doi.org/10.1016/j.jocs.2017.10.007
63. GeWang G, Deb S, Gandomi AH, Alavi AH (2016) Opposition-based krill herd algorithm with Cauchy mutation and position clamping. J Neurocomputing 177:147–157. https://doi.org/10.1016/j.neucom.2015.11.018
64. Tizhoosh HR (n.d.) Opposition-based learning: a new scheme for machinei ntelligence. In: Proceeding of the international conference on computational intelligence for modeling, control and automation, Austria. p. 695–701
65. Das S, Verma A, Bijwe P (2017) Transmission network expansion planning using a modified artificial bee Colony algorithm. Int Trans Electr Energy Syst 27(9):1–23
66. Rider MJ, Garcia AV, Romero R (2007) Power system transmission network expansion planning using AC model. IET Gener Transm Distrib 1(5):731–742
67. Mahmoudabadi A, Rashidinejad M, Maymand MZ (2012) A new model for transmission network expansion and reactive power planning in a deregulated environment. Eng J 4(2):119–125
68. Asadamongkol S, Eua-arporn B (2013) Transmission expansion planning with AC model based on generalized benders decomposition. Int J Electr Power Energy Syst 47:402–407
69. Mouwafi MT, Abou AA, El-Ela RA, El-Sehiemy WK, Al-Zahar (2022) Techno-economic based static and dynamic transmission network expansion planning using improved binary bat algorithm. Alexandria Engineering Journal 61(2):1383–1401
70. Abou El-Ela AA, Mouwafi MT, Al-Zahar WK (2019) Optimal transmission system expansion planning via binary bat algorithm, proc. 21st Int. Middle East Power Systems Conf. (MEPCON), Cairo, pp 238–243
71. Moré JJ (1978) The Levenberg-Marquardt algorithm: implementation and theory, in: Numerical Analysis, Springer, pp. 105–116
72. Hestenes MR, Stiefel E (1952) Methods of conjugate gradients for solving linear systems. NBS, Washington, DC
73. Salajegheh F, Salajegheh E (2019) PSOG: Enhanced particle swarm optimization by a unit vector of first and second order gradient directions. Swarm Evol Comput 46:28–51. https://doi.org/10.1016/j.swevo.2019.01.010
74. Bouwmeester D, Zeilinger A (2000) The physics of quantum information: basic concepts. In: The physics of quantum information. Springer, Berlin
75. Choi V (2018) Minor-embedding in adiabatic quantum computation: I. the parameter setting problem. Quantum Inf Process 193–209
76. Schuld M, Killoran N (2019) Quantum machine learning in feature hilbert spaces. Phys Rev Lett 122:040504. https://doi.org/10.1103/PhysRevLett.122.040504
77. Ahmed E, Rakočević S, Calasan M, Ali Z, Hasanien H, Turky R, Abdel Aleem S (2022) BONMIN solver-based coordination of distributed FACTS compensators and distributed generation units in modern distribution networks. Ain Shams Eng J 13(4):101664. https://doi.org/10.1016/j.asej.2021.101664
78. Almalaq A, Alqunun K, Refaat MM, Farah A, Benabdallah F, Ali ZM, Aleem SHEA (2022) Towards increasing hosting capacity

of modern power systems through generation and transmission expansion planning. Sustainability 14(5):2998
79. Ismael SM, Abdel Aleem SHE, Abdelaziz AY, Zobaa AF (2019) Probabilistic hosting capacity enhancement in non-sinusoidal power distribution systems using a hybrid PSOGSA optimization algorithm. Energies. 12(6):1018. https://doi.org/10.3390/en12061018
80. Mahmoud AM, Ezzat M, Abdelaziz AY, Aleem SHEA (2021) A cost-benefit analysis of optimal active and reactive power compensators and voltage conditioners allocation in a real Egyptian distribution system, 2021 22nd International Middle East Power Systems Conference (MEPCON), pp 116–123. https://doi.org/10.1109/MEPCON50283.2021.9686207
81. Rawa M, Abusorrah A, Bassi H, Mekhilef S, Ali ZM, Abdel Aleem SHE, Hasanien HM, Omar AI (2021) Economical-technical-environmental operation of power networks with wind-solar-hydropower generation using analytic hierarchy process and improved grey wolf algorithm. Ain Shams Eng J 12(3):2717–2734. https://doi.org/10.1016/j.asej.2021.02.004