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Real Power Loss Reduction by Extreme Learning Machine, Chaotic, Quantum and Opposition based California Condor Optimization Algorithms

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Abstract

In this paper Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms are applied to solve the power loss lessening problem. California condor Optimization (CO) algorithm is modelled based on the deeds of California condor. In normal environs, numerous California condors can be substantially alienated into dual clusters, in which the procedure principally computes the fitness rate for elucidations to split California condor's into classes. In the design period, in order to alleviate hunger, presumptuous that the poorest solution in the populace is the feeblest and ravenous, the California condor's attempt to preserve their expanse from the poor and emanated up with the preeminent solution. In California condor Optimization (CO) algorithm, twofold of the preeminent solutions are measured as the robust and preeminent California condor's, and the other California condor's attempt to approach the preeminent one. In iterations, the complete population is recomputed. In the proposed Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm, CO approach enhances Extreme Learning Machine features to determine an optimal skeleton of Extreme Learning Machine for enhanced canons. In ELMCO Algorithm principally all elements don't own any info about the explication area. Chaotic sequences are integrated into the California condor Optimization (CO) algorithm and it called as - Chaotic based California condor Optimization (CCO) algorithm. This integration will augment the Exploration and Exploitation. Tinkerbell chaotic map engendering standards are implemented. Quantum mechanics has been combined with California condor Optimization (CO) algorithm and it entitled as Quantum based California condor Optimization (QCO) algorithm. In quantum method, features emulate the analogous performance with the certain stage as they route in a credible powdered of median. California condor Optimization (CO) 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 California condor Optimization (OCO) algorithm employs Laplace distribution to enhance the exploration skill. Proposed Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms are corroborated in IEEE 30 bus system and IEEE 14, 30, 57, 118, 300 bus test systems without considering the voltage constancy index. True power loss lessening, voltage divergence curtailing, and voltage constancy index augmentation has been attained.

Keywords: Optimal Reactive Power, Transmission loss, California condor, Extreme Learning Machine, Chaotic, Quantum, Opposition

1. Introduction

Endorsing a satisfactory quantity of reactive power is spirited for the reliable operation of power transmission systems, as the reactive power insufficiency may lead to severe voltage collapse and primary power disruptions. Covering numerous directive measures, reactive power planning has become a mystifying issue that supports to the safe and economic growth of power systems.

1.1. Literature survey

Zhu et al [1] solved the problem by adapted interior point technique. Quintana et al [2] solve the problem by successive quadratic programming. Jan et al [3] used fast N-R for solving the optimal power flow. Terra et al [4] did Security constrained power dispatch. Grudinin [5] solved the problem by successive quadratic programming. Mohamed Ebeed et al [6] used Marine Predators Algorithm to solve the problem. Zahir Sahli et al [7] applied Hybrid Algorithm. Davoodi et al [8] used semidefinite programming-based approach. Bingane et al [9] applied Tight-and-cheap conic method. Sahli et al [10] applied Hybridized PSO-Tabu. Mouassa et al [11] applied Ant lion algorithm.

Mandal et al [12] solved the problem by using quasi-oppositional teaching. Khazali et al [13] solved the problem by harmony search procedure. Tran et al [14] solved problem by innovative enhanced stochastic fractal search procedure. Polprasert et al [15] solved the problem by using enhanced pseudo-gradient pursuit particle swarm optimization. Thanh et al [16] solved the problem by an Operative Metaheuristic Procedure. Muhammad et al solved the problem by using FACTS. Lin et al [17] solved by using chaotic Lévy flight bat algorithm. Hakli et al [18] did a novel particle swarm optimization algorithm with Levy flight. Nagarajan et al [20] used Interior Search Algorithm. Dai et al [21] used Seeker optimization. Subbaraj et al [22] used self-adaptive real coded Genetic procedure. Pandya et al [23] applied Particle swarm optimization. Ali Nasser Hussain et al [24] applied Amended Particle Swarm Optimization.

Vishnu et al [25] applied an Enhanced Particle Swarm Optimization. Vodchits Angelina et al [26] did Development of a Design Algorithm. Vodchits Angelina et al [27] did the

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work on organization of logistic systems of scientific constructions. Vodchits Angelina et al [28] solved the Problems and organizational and technical solutions. Mei, et al [29] used moth-flame optimization technique. Li et al [30] did Multiobjective Discrete Artificial Bee Colony Algorithm for Multiobjective Permutation Flow Shop Scheduling Problem with Sequence Dependent Setup. Kanata et al [31] did Non-dominated Sorting Genetic Algorithm III for Multi-objective Optimal Reactive Power Dispatch Problem in Electrical Power System.

1.2. Proposed methodology

In this paper Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms are applied for solving the power loss lessening problem. Important goals of the paper are Voltage stability enrichment, voltage deviation minimization and Tangible power loss lessening. California condor Optimization (CO) algorithm is modelled based on the deeds of California condor. Mature California condor is an identical dark with the exemption of big trilateral spots of gray on the underneath of the wings. It has ashen limbs and bottoms, an ivory dyed beak, an embellishment of dark quills contiguous to the base of the neckline with red eyes. The infantile is habitually a dappled black brunette with blackish pattern on the pate. It has dappled somber as a replacement for of snowy on the underneath of its flying quills.

The California condor's cranium and neckline have little quills, and the membrane of the cranium and neckline is accomplished of reddening strikingly in reaction to emotive phase, a competence that can assist as message between entities. The membrane pigment diverges from yellow to radiant roseate orange. The California condor does not possess exact syrinx communications. California condor can create a little groaning sound solitary heard once very nearby. It is considered N California condor's in an environs. It defines the equivalent amount of population in the metaheuristic procedure. And in normal environs, numerous California condors can be substantially alienated into dual clusters, in which the procedure principally computes the fitness rate for elucidations (preliminary populace) to split California condor's into classes.

The finest response is assumed as the preeminent as chief California condor and the succeeding solution as the subsequent finest California condo. Remaining create a population that passages or substitutes one of the twofold preeminent California condor's in every activity. The motive for splitting clusters in this procedure is that California condor's' utmost vital normal task can be articulated: cluster living to discover nutrition.

Every cluster of California condor's is a dissimilar helplessness to discover nutrition and consume. The propensity to consume in California condor's and seeing for nutrition for periods sources them to seepage from the starving ruse. At the design period, in order to alleviate hunger, presumptuous that the poorest solution in the populace is the feeblest and ravenous, the California condor's attempt to preserve their expanse from the poor and emanated up with the preeminent solution.

In California condor Optimization (CO) algorithm, twofold of the preeminent solutions are measured as the robust and preeminent California condor's, and the other California condor's attempt to approach the preeminent one. Subsequent to the formation of preliminary population, the aptness or fitness rate of all solutions is computed, and the preeminent solution is designated as the preeminent California condor of the chief cluster and the subsequent preeminent solution as the best California condor of the succeeding cluster, and remaining solutions will passage in the direction of the preeminent solutions for the chief and succeeding clusters.

In iterations, the complete population is recomputed. California condors are frequently eyeing for nutrition and possess great vigor when they are slaked, which creates them go extended expanses to quest for nutrition, nonetheless when California condors are starving, they do not possess vigor to fly lengthy and gaze for nutrition subsequent to the robust California condor and converted belligerent while ravenous. This aspect has been utilized for transferal activity from the exploration to the exploitation segment, which is stimulated by the degree at which the California condors are slaked or ravenous.

In the proposed Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm, CO approach enhances Extreme Learning Machine features to determine an optimal skeleton of Extreme Learning Machine for enhanced canons. In Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm principally all elements don't own any info about the explication area. In initial stages of iteration, the California condor contestants are assorted in milieu and exponential skimp generates boundless unpremeditated amounts which contribute the rudiments to lodging the entire explication zone. Congruently, all over end stage of iterations, rudiments are surrounded by California condor contestants and all an optimal situation with similar pattern.

Chaotic sequences are integrated into the California condor Optimization (CO) algorithm and it called as - Chaotic based California condor Optimization (CCO) algorithm. This integration will augment the Exploration and Exploitation. Tinkerbell chaotic map engendering standards are implemented. Quantum mechanics has been combined with California condor Optimization (CO) algorithm and it entitled as Quantum based California condor Optimization (QCO) algorithm. In quantum method, features emulate the analogous performance with the certain stage as they route in a credible powdered of median. California condor Optimization (CO) 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 California condor Optimization (OCO) 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 California condor Optimization (CO) 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. Proposed Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms are corroborated in IEEE 30 bus system and IEEE 14, 30, 57, 118, 300 bus test systems without considering the voltage constancy index. True power loss lessening, voltage divergence curtailing, and voltage constancy index augmentation has been attained.

2. Problem Formulation

Power loss minimization is defined by

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

$where$ min $is\ minimization\ of\ power\ loss$
Subject to the constraints

$$A(\bar{d},\bar{e})=0 \quad (2)$$

$$B(\bar{d},\bar{e})=0 \quad (3)$$

$where$ d , e are control and dependent variables

$$d=\left[VLG_1,..,VLG_{Ng};QC_1,..,QC_{Nc};T_1,..,T_{N_T}\right] \quad (4)$$

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

$$F_1=P_{Minimize}=Minimize\left[\sum_m^{NTL}G_m\left[V_i^2+V_j^2-2*V_iV_jcos\emptyset_{ij}\right]\right] \quad (6)$$

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

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

$$L_{Maximum}=Maximum[L_j];j=1;N_{LB} \quad (9)$$

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

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

Parity constraints

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

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

Disparity constraints

$$\mathrm{P_{gslack}^{minimum}\leq P_{gslack}\leq P_{gslack}^{maximum}} \quad (14)$$

$$\mathrm{Q_{gi}^{minimum}\leq Q_{gi}\leq Q_{gi}^{maximum}, i\in N_g} \quad (15)$$

$$\mathrm{VL_i^{minimum}\leq VL_i\leq VL_i^{maximum}, i\in NL} \quad (16)$$

$$\mathrm{T_i^{minimum}\leq T_i\leq T_i^{maximum}, i\in N_T} \quad (17)$$

$$\mathrm{Q_c^{minimum}\leq Q_c\leq Q_C^{maximum}, i\in N_C} \quad (18)$$

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

$$\mathrm{VG_i^{minimum}\leq VG_i\leq VG_i^{maximum}, i\in N_g} \quad (20)$$

$Multi\ objective\ fitness\ (MOF)=F\_1+r\_i\ F\_2+uF\_3=F\_1+[\sum\_(i=1)^NL\ 〖x\_v\ [\ 〖VL〗\_i-\ 〖VL〗\_i^min\ ]^2\ 〗+\sum\_(i=1)^NG\ 〖r\_g\ [\ 〖QG〗\_i-〖QG〗\_i^min\ ]^2\ 〗]+r\_f\ F\_3$ (21)

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

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

3. California condor Optimization Algorithm

California condor Optimization (CO) algorithm is modelled based on the deeds of California condor. It is considered N California condor's in an environs. It defines the equivalent amount of population in the metaheuristic procedure. And in normal environs, numerous California condors can be substantially alienated into dual clusters, in which the procedure principally computes the fitness rate for elucidations (preliminary populace) to split California condor's into classes. The finest response is assumed as the preeminent as chief California condor and the succeeding solution as the subsequent finest California condo. Remaining create a population that passages or substitutes one of the twofold preeminent California condor's in every activity. Subsequent to the formation of preliminary population, the aptness or fitness rate of all solutions is computed, and the preeminent solution is designated as the preeminent California condor of the chief cluster and the subsequent preeminent solution as the best California condor of the succeeding cluster, and remaining solutions will passage in the direction of the preeminent solutions for the chief and succeeding clusters. In iterations, the complete population is recomputed.

$$O(i)=\begin{cases}\text{Preeminent California condor}_1\ if\ q_i=C_1\\ \text{Preeminent California condor}_2\ if\ q_i=C_2\end{cases} \quad (24)$$

$where\ C_1, C_2\in[0,1]$

The prospect of selecting the preeminent solution is expanded by Roulette wheel to select every preeminent solution for each one cluster as follows,

$$q_i=\frac{H_i}{\sum_{i=1}^{n}H_i} \quad (25)$$

California condors are frequently eyeing for nutrition and possess great vigor when they are slaked, which creates them go extended expanses to quest for nutrition, nonetheless when California condors are starving, they do not possess vigor to fly lengthy and gaze for nutrition subsequent to the robust California condor and converted belligerent while ravenous. This aspect has been utilized for transferal activity from the exploration to the exploitation segment, which is stimulated by the degree at which the California condors are slaked or ravenous. The degree of being slaked possess diminishing trend and it defined as,

$$t=g\times\left(sin^R\left(\frac{\pi}{2}\times\frac{iter_i}{\max iter}\right)+cos\left(\frac{\pi}{2}\times\frac{iter_i}{\max iter}\right)-1\right) \quad (26)$$

$$H = (2 \times Random_1 + 1) \times y \times \left(1 - \frac{iter_i}{\max iter}\right) + t \quad (27)$$

$where\ y \in [-1,1],$
$g \in [-2,2],$
$Random_1 \in [0,1]$

When the value of y is decreases below to zero value then California condor is in ravenous phase and if the value of y increases to zero then the California condor is slaked. The motive for splitting clusters in this procedure is that California condor's' utmost vital normal task can be articulated: cluster living to discover nutrition. Every cluster of California condor's is a dissimilar helplessness to discover nutrition and consume. The propensity to consume in California condor's and seeing for nutrition for periods sources them to seepage from the starving ruse. At the design period, in order to alleviate hunger, presumptuous that the poorest solution in the populace is the feeblest and ravenous, the California condor's attempt to preserve their expanse from the poor and emanated up with the preeminent solution. In California condor Optimization (CO) algorithm, twofold of the preeminent solutions are measured as the robust and preeminent California condor's, and the other California condor's attempt to approach the preeminent one.

In resolving perplexing optimization complications, there is no assurance that the concluding populace will comprise precise approximations for the global optimal solution at the completion of the exploration segment. Aimed at this purpose, it grounds early convergence in local solution. To escape from the escape from local optimal solutions $t = g \times \left(sin^R\left(\frac{\pi}{2} \times \frac{iter_i}{\max iter}\right) + cos\left(\frac{\pi}{2} \times \frac{iter_i}{\max iter}\right) - 1\right)$ is employed. The concluding iterations of the California condor Optimization (CO) algorithm execute the exploitation segment and do exploration processes in concluding iterations. Through this stratagem's complete aim is to amend $t = g \times \left(sin^R\left(\frac{\pi}{2} \times \frac{iter_i}{\max iter}\right) + cos\left(\frac{\pi}{2} \times \frac{iter_i}{\max iter}\right) - 1\right)$ to alter exploration and exploitation segments so that California condor Optimization (CO) algorithm can upsurge the possibility of arriving the exploration segment at certain period in the process. R Specifies the process disorders the exploration and operation segments and when R upsurges, the possibility of arrive to the exploration segment in the concluding phase's upsurges, nevertheless, by lessening R, the possibility of arrive to the exploration segment diminishes.

$when\ H > 1\ then$ California condor explore the nutrition in various places
$when\ H < 1\ then$ California condor optimization (CO)algorithm enters to exploitation segment

$$Q(i+1) = \begin{cases} O(i) - E(i) \times H\ if\ Q_1 \geq Random_{Q1} \\ U \times O(i) - Q(i)\ if\ Q_1 < Random_{Q1} \end{cases} \quad (28)$$

$$Q(i+1) = O(i) - E(i) \times H \quad (29)$$

$$E(i) = |U \times O(i) - Q(i)\ | \quad (30)$$

$$U = 2 \times Random \quad (31)$$

In the exploration segment California condor will search nutrition in different zones.

$Random_{Q1}\ \in [0,1]$
$where\ Q(i+1)\ signify\ the\ position\ in\ the$ Subsequent iteration $H\ indicate\ the\ Rate\ of\ the\ California\ condor\ Optimization\ slaked\ O(i)\ is\ most\ excellent$ California condor $U\ is\ coefficient\ vector$

$$Q(i+1) = O(i) - H + Random_2 * \left((UB - LB) * (Random_3) + LB\right) \quad (32)$$

$where\ UB, LB\ is\ Upper\ and\ lower\ bound$

When
$H\ is\ between$ 0.5 and 1 $then$ California condor optimization (CO) algorithm enters to exploitation segment

$$Q(i+1) = \begin{cases} E(i) \times (H + Random_4) - d(t) if\ Q_2 \geq Random_{Q2} \\ O(i) - (J_1 + J_2)\ if\ Q_2 < Random_{Q2} \end{cases} \quad (33)$$

$when\ H \geq 0.5\ then\ the\ California\ condor\ Optimization\ slaked$

Many times the fragile California condors will rim the robust California condors which possess the nutrition and it defined as,

$$Q(i+1) = E(i) \times (H + Random_4) - d(t) \quad (34)$$

$$d(t) = O(i) - Q(i) \quad (35)$$

$where\ Random_4 \in [0,1]$
$O(i)\ is\ most\ excellent$ California condor
$Q(i) signify\ the\ present\ position$

The gyratory flying of California condors is articulated as,

$$J_1 = O(i) \times (Random_5 \times Q(i)/2\pi) \times cos(Q(i)) \quad (36)$$

$$J_2 = O(i) \times (Random_6 \times Q(i)/2\pi) \times sin(Q(i)) \quad (37)$$

$$Q(i+1) = O(i) - (J_1 + J_2) \quad (38)$$

$where\ J_1, J_2\ specify\ the$ gyratory flying
$Random_5, Random_6 \in [0,1]$

In the subsequent segment of exploitation, the dual California condor's activities accrue numerous categories of California condors over the nutrition source and this period $H < 0.5$,

$$Q(i+1) = \begin{cases} M_1 + M_2/2\ if\ Q_3 \geq Random_{Q3} \\ O(i) - |d(t)| \times H \times Levy(d) if\ Q_3 < Random_{Q3} \end{cases} \quad (39)$$

$M\_1 =$ 〖Preeminent California condor〗_1 (i) − (〖Preeminent California condor〗_1 $(i) \times Q(i)$) / (〖Preeminent California condor〗_1 $(i) \times$ 〖$Q(i)$〗^2) ×
(40)

$M\_2 =$ 〖Preeminent California condor〗_2 (i) − (〖Preeminent California condor〗_2 $(i) \times Q(i)$) / (

〖Preeminent California condor〗_2 $(i) \times$ 〖$Q(i)$〗^2) $\times H$ (41)

$where\ Q(i+1)\ signify\ the\ position\ in\ the$ Subsequent iteration

$$Q(i+1) = M_1 + M_2/2 \quad (42)$$

Then the movement of the robust California condor's in search of nutrition with reference to Levy flight [17-19] is mathematically articulated as,

$$Q(i+1) = O(i) - |d(t)| \times H \times Levy(d) \quad (43)$$

$$L(s) \sim |s| - 1 - \beta \ where\ 0 < ß < 2 \quad (44)$$

$$L(s, \gamma, \mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} & \exp\left[-\frac{\gamma}{2(s-\mu)}\right]\frac{1}{(s-\mu)^{3/2}} \quad \text{if } 0 < \mu < s < \infty \\ 0 & \text{if } s \le 0 \end{cases} \quad (45)$$

$$F(k) = \exp\left[-\alpha|k|^{\beta}\right] \ 0 < \beta \le 2, \quad (46)$$

$where\ \alpha \in [-1,1]$
$\beta \in [0,2]$

$$Z^{t+1} = Z^t + \alpha \oplus \text{Levy}(\beta) \quad (47)$$

$$Z^{t+1} = Z^t + R\left(\text{size}(D)\right) \oplus \text{Levy}(\beta) \quad (48)$$

$$Z^{t+1} = Z^t + R\left(\text{size}(D)\right) \oplus \text{Levy}(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}}\left(Z_j^t - gb\right) \quad (49)$$

$$u \sim N(0, \sigma_u^2) \quad v \sim N(0, \sigma_v^2) \quad (50)$$

$$\sigma_u = \left\{\frac{\Gamma(1+\beta)\sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\right\}^{1/\beta}, \sigma_v = 1 \quad (51)$$

$where\ R\ specify\ the\ random$
$\Gamma\ indicate\ the\ Gamma\ function$

$$\Gamma(Z_G^t) = (Z_G^t - 1)! \quad (52)$$

Fig 1 shows the Flow chart of California condor Optimization (CO) algorithm.

a. Start
b. Fix the parameter values
c. Initialize the population arbitrarily
d. $while\ (end\ condition\ is\ not\ met) do$
e. Compute the fitness rate of the California condor
f. Fix preeminent as chief California condor (〖Preeminent California condor〗_1)
g. $Fix\ next\ best$ California condor (〖Preeminent California condor〗_2)
h. $For\ (every$ California condor $(Q_i))\ do$
i. $Pick\ O(i)$
j. $O(i) = \begin{cases} \text{Preeminent California condor}_1 \ if\ q_i = C_1 \\ \text{Preeminent California condor}_2 \ if\ q_i = C_2 \end{cases}$
k. $streamline\ H(i)$
l. $H = (2 \times$ 〖$Random$〗_1 $+ 1) \times y \times (1 -$ 〖$iter$〗_i/max $iter) + t$
m. $if(|H| > 1)\ then$
n. $if\ (Q_1 \ge Random_{Q1})\ then$
o. Streamline the position of the California condor
p. $Q(i+1) = O(i) - E(i) \times H$
q. Otherwise
r. Modernize the spot of California condor
s. $Q(i+1) = O(i) - H + Random_2 * ((UB - LB) * (Random_3) + LB)$
t. $if(|H| < 1)\ then$
u. $if(|H| \ge 0.5)\ then$
v. $if\ (Q_2 \ge Random_{Q2})\ then$
w. Streamline the position of the California condor
x. $Q(i+1) = E(i) \times (H + Random_4) - d(t)$
y. $otherwise$
z. Modernize the spot of California condor
aa. $Q(i+1) = O(i) - (J_1 + J_2)$
bb. $otherwise$
cc. $if\ (Q_3 \ge Random_{Q3})\ then$
dd. Streamline the position of the California condor
ee. $Q(i+1) = M_1 + M_2/2$
ff. Otherwise
gg. $Q(i+1) = O(i) - |d(t)| \times H \times Levy(d)$
hh. $Return\ the$ Preeminent California condor $_1$
ii. End

4. Extreme Learning Machine based California condor Optimization Algorithm

In the proposed Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm, CO approach enhances Extreme Learning Machine features to determine an optimal skeleton of Extreme Learning Machine for enhanced canons. Extreme learning machine (ELM) is applied and learning speed of feed-forward neural networks is composed of input, hidden and output layer [34-16].

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

$$Weight\ (Wht) = \begin{bmatrix} wht_1^T \\ wht_2^t \\ ; \\ wht_l^T \end{bmatrix} = \begin{bmatrix} wht_{11} & \cdots & wht_{1n} \\ \vdots & \ddots & \vdots \\ wht_{L1} & \cdots & wht_{Ln} \end{bmatrix} \quad (53)$$

$$(nwm.\beta) = \begin{bmatrix} nwm.\beta_1^T \\ nwm.\beta_2^t \\ ; \\ nwm.\beta_l^T \end{bmatrix} = \begin{bmatrix} nwm.\beta_{11} & \cdots & nwm.\beta_{1n} \\ \vdots & \ddots & \vdots \\ nwm.\beta_{L1} & \cdots & nwm.\beta_{Ln} \end{bmatrix} \quad (54)$$

$$\text{Neurons hidden layer bias vector (bsv)} = \begin{bmatrix} bsv_1 \\ bsv_2 \\ \vdots \\ bsv_L \end{bmatrix}_{L\times 1} \quad (55)$$

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

$$(C) = \begin{bmatrix} C_1^T \\ C_2^t \\ ; \\ C_l^T \end{bmatrix} = \begin{bmatrix} C_{11} & \cdots & C_{1n} \\ \vdots & \ddots & \vdots \\ C_{L1} & \cdots & C_{Ln} \end{bmatrix} \quad (56)$$

$$\sum_{i=1}^{N} nwm.\beta_i \cdot k(\omega_i F_j + a_i) = C_j, j = 1,2,3, .., N \quad (57)$$

$$(O) \cdot (nwm.\beta) = C \quad (58)$$

$$O(F_1, ..F_L; \omega_1, .., \omega_L; a_1, .., a_l) = \begin{bmatrix} k(\omega_1 F_1 + a_1) & \cdots & k(\omega_L F_1 + a_L) \\ \vdots & \ddots & \vdots \\ k(\omega_1 F_N + a_1) & \cdots & k(\omega_L F_N + a_L) \end{bmatrix} \quad (59)$$

$$nwm.\beta = O^{-1} \cdot C \quad (60)$$

Method of the Extreme Learning Machine (ELM)

1) Start
2) Input the data
3) Engender the Test and Training set
4) Rendering to the training set - standardize the quantity of (O)
5) $O(F_1, .. F_L; \omega_1, .., \omega_L; a_1, .., a_l) = \begin{bmatrix} k(\omega_1 F_1 + a_1) & \cdots & k(\omega_L F_1 + a_L) \\ \vdots & \ddots & \vdots \\ k(\omega_1 F_N + a_1) & \cdots & k(\omega_L F_N + a_L) \end{bmatrix}$
6) Express the output level of weight
7) $nwm.\beta = O^{-1} \cdot C$
8) Rendering to the test set - estimate the level of (B)
9) $O(F_1, .. F_L; \omega_1, .., \omega_L; a_1, .., a_l) = \begin{bmatrix} k(\omega_1 F_1 + a_1) & \cdots & k(\omega_L F_1 + a_L) \\ \vdots & \ddots & \vdots \\ k(\omega_1 F_N + a_1) & \cdots & k(\omega_L F_N + a_L) \end{bmatrix}$
10) Appraise the genuine level through $nwm.\beta$ and M
11) Computation of error status
12) Assessment of genuine rate with possible level
13) Return the error level
14) End

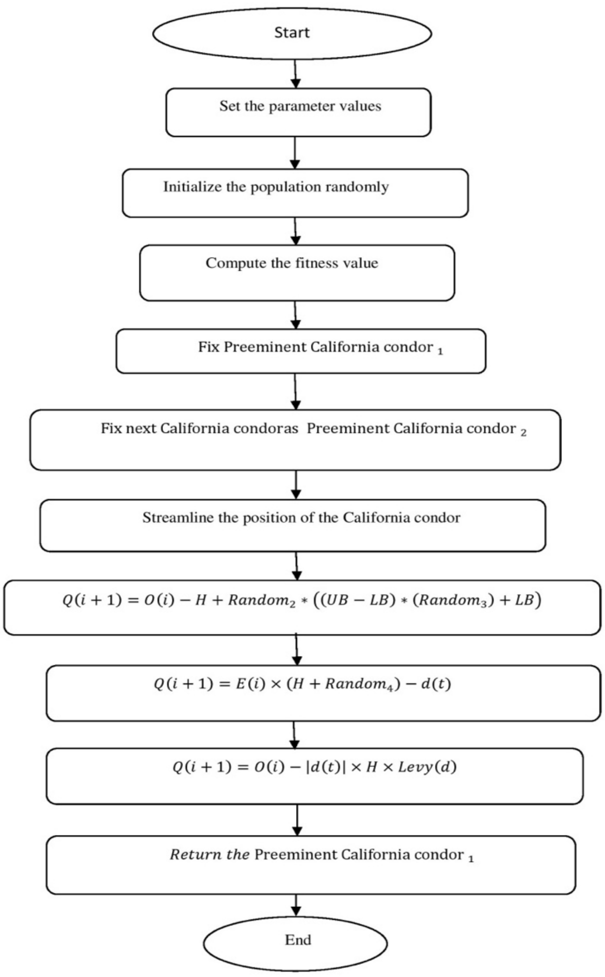

Fig 1. Flow chart of California condor Optimization (CO) algorithm.

In the proposed Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm, CO approach enhances Extreme Learning Machine features to determine an optimal skeleton of Extreme Learning Machine for enhanced canons. In Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm principally all elements don't own any info about the explication area. In initial stages of iteration, the California condor contestants are assorted in milieu and exponential skimp generates boundless unpremeditated amounts which contribute the rudiments to lodging the entire explication zone. Congruently, all over end stage of iterations, rudiments are surrounded by California condor contestants and all an optimal situation with similar pattern. Fig 2 shows the schematic diagram of Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm.

a. Start
b. Input the data
c. Engender the Test and Training set
d. Engender the population
a. $while\ (end\ condition\ is\ not\ met) do$
b. Compute the fitness rate of the California condor
c. Fix preeminent as chief California condor (Preeminent California condor $_1$)
d. $Fix\ next\ best$ California condor (Preeminent California condor $_2$)
e. $For\ (every$ California condor $(Q_i))\ do$
f. $Pick\ O(i)$
g. $O(i) = \begin{cases} \text{Preeminent California condor}_1 & if\ q_i = C_1 \\ \text{Preeminent California condor}_2 & if\ q_i = C_2 \end{cases}$
h. $streamline\ H(i)$
i. $H = (2 \times Random_1 + 1) \times y \times \left(1 - \frac{iter_i}{\max iter}\right) + t$
j. $if(|H| > 1)\ then$
k. $if\ (Q_1 \geq Random_{Q1})\ then$
l. Streamline the position of the California condor
m. $Q(i+1) = O(i) - E(i) \times H$
n. Otherwise
o. Modernize the spot of California condor
p. $Q(i+1) = O(i) - H + Random_2 * ((UB - LB) * (Random_3) + LB)$
q. $if(|H| < 1)\ then$
r. $if(|H| \geq 0.5)\ then$
s. $if\ (Q_2 \geq Random_{Q2})\ then$
t. Streamline the position of the California condor
u. $Q(i+1) = E(i) \times (H + Random_4) - d(t)$
v. $otherwise$
w. Modernize the spot of California condor
x. $Q(i+1) = O(i) - (J_1 + J_2)$
y. $otherwise$
z. $if\ (Q_3 \geq Random_{Q3})\ then$
aa. Streamline the position of the California condor
bb. $Q(i+1) = M_1 + M_2/2$
cc. Otherwise
dd. $Q(i+1) = O(i) - |d(t)| \times H \times Levy(d)$
ee. Fix Extreme Learning Machine input weights and hidden bias
ff. Extreme Learning Machine testing
gg. $Return\ the$ Preeminent California condor $_1$
hh. End

5. Chaotic based California condor Optimization Algorithm

Chaotic sequences are integrated into the California condor Optimization (CO) algorithm and it called as - Chaotic based California condor Optimization (CCO) algorithm. This integration will augment the Exploration and Exploitation. Tinkerbell chaotic map [37, 38] engendering standards are implemented. Fig 3 shows the schematic diagram of Chaotic based California condor Optimization (CCO) algorithm.

$$u_{t+1} = u_t^2 - v_t^2 + a \cdot u_t + b \cdot v_t \quad (61)$$

$$v_{t+1} = 2u_t v_t + c \cdot u_t + d \cdot v_t \quad (62)$$

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

The functional value by linear scaling in Tinkerbell chaotic map [33, 34] is demarcated as,

$$u_{t+1}^* = u_{t+1} - minimum(u)/maximum(u) - minimum(u) \quad (63)$$

a. Start
b. Fix the parameter values
c. Initialize the population arbitrarily
d. $while\ (end\ condition\ is\ not\ met) do$
e. Compute the fitness rate of the California condor
f. Fix preeminent as chief California condor (Preeminent California condor $_1$)
g. $Fix\ next\ best$ California condor (Preeminent California condor $_2$)
h. $For\ \big(every$ California condor $(Q_i)\big)\ do$
i. $Pick\ O(i)$
j. $O(i) = \begin{cases} \text{Preeminent California condor}_1 & if\ q_i = C_1 \\ \text{Preeminent California condor}_2 & if\ q_i = C_2 \end{cases}$
k. $streamline\ H(i)$
l. $H = (2 \times Random_1 + 1) \times y \times \left(1 - \frac{iter_i}{\max iter}\right) + t$
m. $if(|H| > 1)\ then$
n. $if\ \left(Q_1 \geq Random_{Q1}\right)\ then$
o. Streamline the position of the California condor
p. $Q(i+1) = O(i) - E(i) \times H$
q. Otherwise
r. Modernize the spot of California condor
s. $Q(i+1) = O(i) - H + Random_2 * \big((UB - LB) * (Random_3) + LB\big)$
t. $if(|H| < 1)\ then$
u. $if(|H| \geq 0.5)\ then$
v. $if\ \left(Q_2 \geq Random_{Q2}\right)\ then$
w. Streamline the position of the California condor
x. $Q(i+1) = E(i) \times (H + Random_4) - d(t)$
y. $otherwise$
z. Modernize the spot of California condor
aa. $Q(i+1) = O(i) - (J_1 + J_2)$
bb. $otherwise$
cc. $if\ \left(Q_3 \geq Random_{Q3}\right)$
dd. Smear the Tinkerbell chaotic map
ee. $\mathrm{u_{t+1} = u_t^2 - v_t^2 + a \cdot u_t + b \cdot v_t}$
ff. $\mathrm{v_{t+1} = 2u_t v_t + c \cdot u_t + d \cdot v_t}$
gg. $u_{t+1}^* = u_{t+1} - minimum(u)/maximum(u) - minimum(u)$
a. Streamline the position of the California condor
b. $Q(i+1) = M_1 + M_2/2$
c. Otherwise
d. $Q(i+1) = O(i) - |d(t)| \times H \times L(d)$
e. $Return\ the$ Preeminent California condor $_1$
f. End

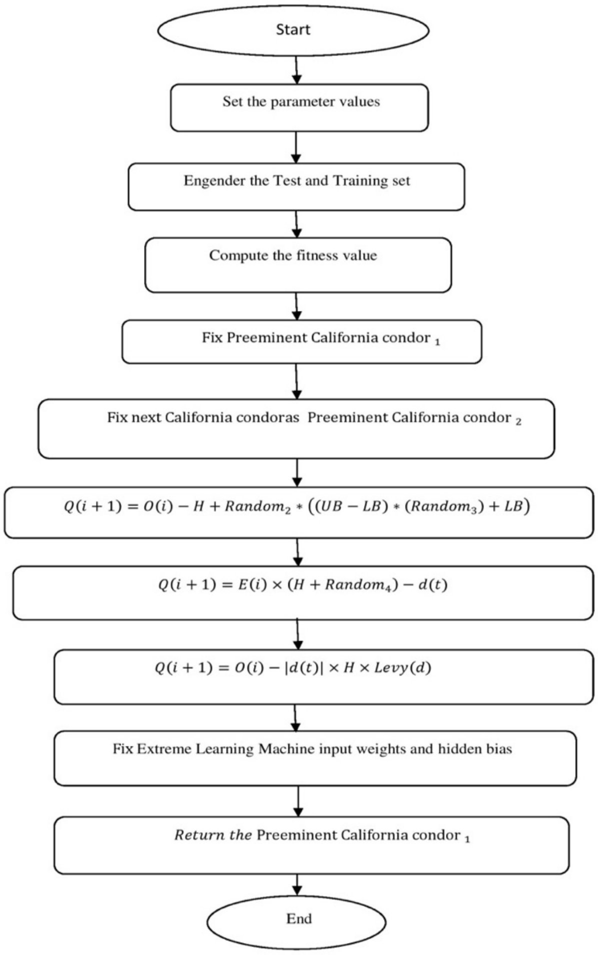

Fig 2. Schematic diagram of Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm.

6. Quantum based California condor Optimization Algorithm

Quantum mechanics [39-43] has been combined with California condor Optimization (CO) algorithm and it entitled as Quantum based California condor Optimization (QCO) 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 [39-43] is demarcated as,

$$|\Psi|^2 \cdot dx \cdot dy \cdot dz = Quantum \cdot dx \cdot dy \cdot dz \quad (64)$$

$where\ \Psi\ indicate\ probability\ density\ functional\ value$

The time contingent Schrodinger equation [39-43] is smeared to evaluate the wave utility is demarcated as,

$$ih \cdot \partial/\partial t \cdot \Psi(x,t) = Hor \cdot \Psi(x,t) \quad (65)$$

$where\ Hor\ specify\ the$ Hamiltonian operator$[39 - 43]$

$$Hor = -h^2/2m \cdot \Delta^2 + V(x) \quad (66)$$

In the quantum pattern ΔFit consecutively achieve as particle and it successively passages in delta potential in the direction of center. Fig 4 shows the schematic diagram of Quantum based California condor Optimization (QCO) algorithm.

$$\text{Schrodinger(Time} - \text{independent)} is\ \frac{d^2\Psi}{dz^2} + \frac{2m}{h^2}[G + \gamma\delta(z)]\Psi = 0 \quad (67)$$

$$\Psi(z) = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}} \quad (68)$$

$$Quantum(z) = |\Psi(z)|^2 = \frac{1}{\sqrt{L}} e^{-\frac{|z|}{L}} \quad (69)$$

$$z = \pm\frac{L}{2} In(1/g) \quad (70)$$

$where\ u \in [0,1]$

a. Start
b. Fix the parameter values
c. Initialize the population arbitrarily
d. $while\ (end\ condition\ is\ not\ met) do$
e. Compute the fitness rate of the California condor
f. Fix preeminent as chief California condor (Preeminent California condor $_1$)
g. $Fix\ next\ best$ California condor (Preeminent California condor $_2$)
h. $For\ (every$ California condor $(Q_i))\ do$
i. $Pick\ O(i)$
j. $O(i) = \begin{cases} \text{Preeminent California condor}_1\ if\ q_i = C_1 \\ \text{Preeminent California condor}_2\ if\ q_i = C_2 \end{cases}$
k. $streamline\ H(i)$
l. $H = (2 \times Random_1 + 1) \times y \times \left(1 - \frac{iter_i}{\max iter}\right) + t$
m. $if(|H| > 1)\ then$
n. $if\ (Q_1 \geq Random_{Q1})$
o. $|\Psi|^2 \cdot dx \cdot dy \cdot dz = Quantum \cdot dx \cdot dy \cdot dz$
p. $Hor = -h^2/2m \cdot \Delta^2 + V(x)$
q. Streamline the position of the California condor
r. $Q(i+1) = O(i) - E(i) \times H$
s. Otherwise
t. Modernize the spot of California condor
u. $Q(i+1) = O(i) - H + Random_2 * ((UB - LB) * (Random_3) + LB)$
v. $if(|H| < 1)\ then$
w. $if(|H| \geq 0.5)\ then$
x. $if\ (Q_2 \geq Random_{Q2})\ then$
y. Streamline the position of the California condor
z. $Q(i+1) = E(i) \times (H + Random_4) - d(t)$
aa. $otherwise$
bb. Modernize the spot of California condor
cc. $Q(i+1) = O(i) - (J_1 + J_2)$
dd. $otherwise$
ee. $if\ (Q_3 \geq Random_{Q3})\ then$
ff. Streamline the position of the California condor
gg. $Q(i+1) = M_1 + M_2/2$
hh. Otherwise
ii. $Q(i+1) = O(i) - |d(t)| \times H \times Levy(d)$
jj. $Return\ the$ Preeminent California condor $_1$
kk. End

7. Opposition based California condor Optimization Algorithm

California condor Optimization (CO) 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 California condor Optimization (OCO) 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 California condor Optimization (CO) algorithm. In the proposed procedure, the exchanging of capricious statistics is done with the illogical numbers stimulated by Laplace distribution [44-46] to enlarge the assistance of the probability of formation stage in the exploration zone. The propagation of Laplace dispersal [44-46] is scientifically demarcated as,

$$function(v) = \begin{cases} \frac{1}{2}\ exp(-|v-c|/d), b \leq c \\ 1 - \frac{1}{2}\ exp(-|v-c|/d), b > c \end{cases} \quad (71)$$

The probability propagation function of Laplace dispersal is,

$$function(v; c, d) = 1/2v\ exp(-|v-c|/d), -\infty < c < \infty \quad (72$$

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

Opposition based learning (OBL) is one of the influential approaches to improve the convergence quickness of procedures [44-46]. 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. Fig 5 shows the schematic diagram of Opposition based California condor Optimization (OCO) algorithm.

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

$$O^o = c + d - U \quad (73)$$

In the exploration area it has been protracted as,

$$O_i^o = c_i + d_i - U_i \quad (74)$$

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

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. $if\ f\ (O^*) \leq f(O); then\ O = O^*$
c. $Or\ else$
d. Sustain with O in successive generations

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

$$CC_i(iter) = (LB_i + UB_i - CC_e(iter)) \quad (75)$$

$where\ LB\ , UB\ are\ lower\ and\ upper\ bound$

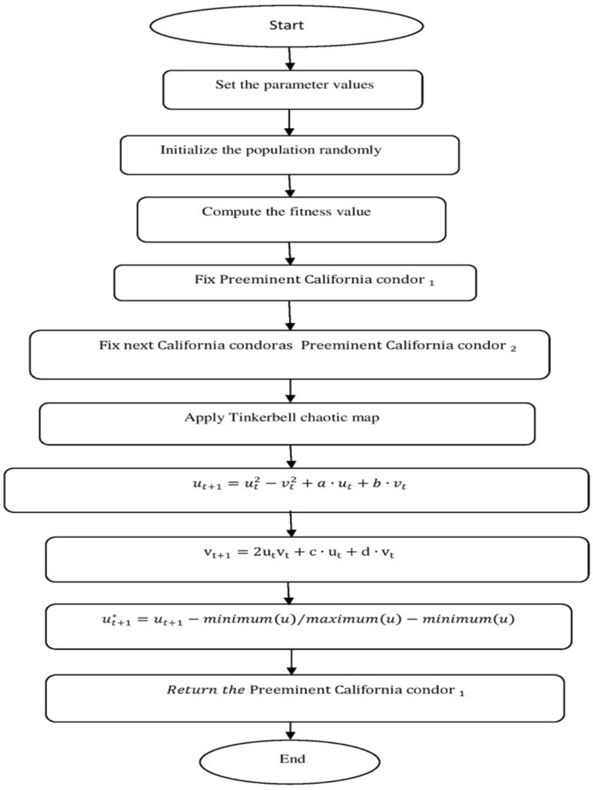

Fig 3. Schematic diagram of Chaotic based California condor Optimization (CCO) algorithm.

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

$$V_s = V_{max} - iter_p \cdot V_{max} - V_{min}/iter_{max} \quad (76)$$

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

$$CC_i(iter) = V_s * \left(LB_i + UB_i - CC_e(iter)\right) \quad (77)$$

a. Start
b. Fix the parameter values
c. Employ opposition based learning approach
d. $while\ (end\ condition\ is\ not\ met) do$
e. Compute the fitness rate of the California condor
f. Fix preeminent as chief California condor (Preeminent California condor $_1$)
g. $Fix\ next\ best$ California condor ($^{\text{Preeminent}}_{\text{California condor } 2}$)
h. $For\ (every$ California condor $(Q_i))\ do$
i. $Pick\ O(i)$
j. $O(i) = \begin{cases} \text{Preeminent California condor}_1 & if\ q_i = C_1 \\ \text{Preeminent California condor}_2 & if\ q_i = C_2 \end{cases}$
k. $streamline\ H(i)$
l. $H = (2 \times Random_1 + 1) \times y \times \left(1 - \frac{iter_i}{\max iter}\right) + t$
m. $if(|H| > 1)\ then$
n. $if\ (\ Q_1 \geq Random_{Q1})\ then$
o. Streamline the position of the California condor
p. $Q(i+1) = O(i) - E(i) \times H$
q. Otherwise
r. Modernize the spot of California condor
s. $Q(i+1) = O(i) - H + Random_2 * \left((UB - LB) * (Random_3) + LB\right)$
t. $if(|H| < 1)\ then$
u. $if(|H| \geq 0.5)\ then$
v. $if\ (\ Q_2 \geq Random_{Q2})\ then$
w. Streamline the position of the California condor
x. $Q(i+1) = E(i) \times (H + Random_4) - d(t)$
y. $otherwise$
z. Modernize the spot of California condor
aa. $Q(i+1) = O(i) - (J_1 + J_2)$
bb. $otherwise$
cc. $if\ (\ Q_3 \geq Random_{Q3})$
dd. $Employ\ the$ Opposition based learning approach to modernize the component
ee. $CC_i(iter) = \left(LB_i + UB_i - CC_e(iter)\right)$
ff. $Integrate\ the$ Opposition based learning approach with Variable speeding up factor (V_s)
gg. $V_s = V_{max} - iter_p \cdot V_{max} - V_{min}/iter_{max}$
hh. $CC_i(iter) = V_s * \left(LB_i + UB_i - CC_e(iter)\right)$
ii. Streamline the position of the California condor
jj. $Q(i+1) = M_1 + M_2/2$
kk. Otherwise
ll. $Q(i+1) = O(i) - |d(t)| \times H \times L(d)$
mm. $Return\ the$ Preeminent California condor $_1$
nn. End

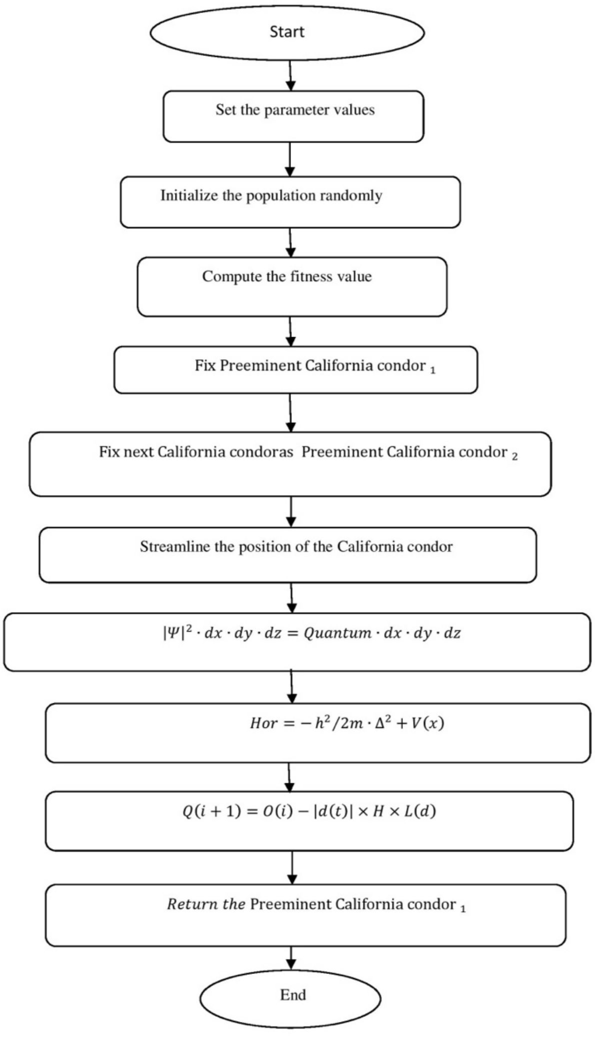

Fig 4. Schematic diagram of Quantum based California condor Optimization (QCO) algorithm.

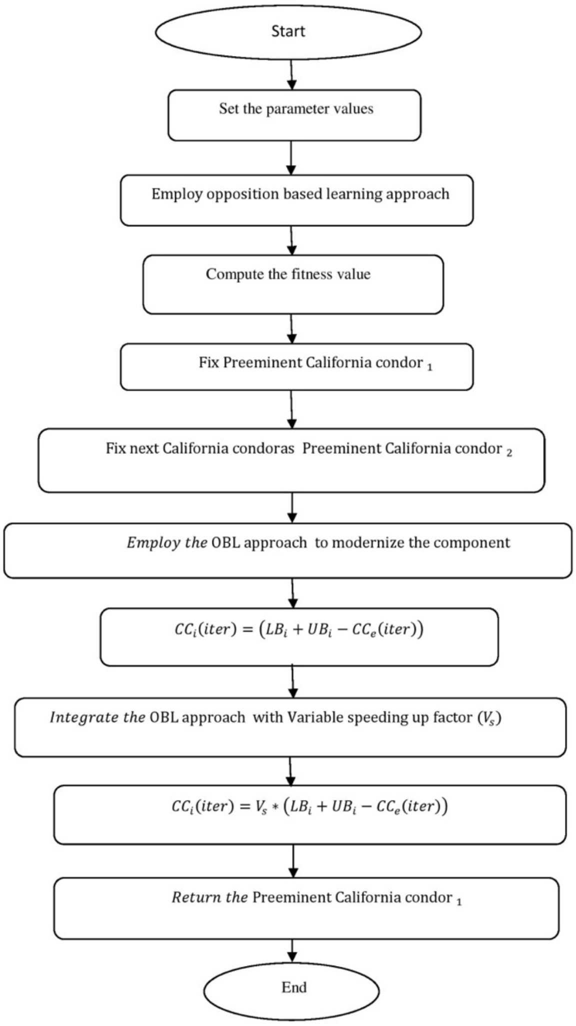

Fig 5. Schematic diagram of Opposition based California condor Optimization (OCO) algorithm.

The computational complexity of Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms are contingent on initialization, aptness assessment, and appraisal of the California condor. Specified N California condor, the computational complication in the initialization procedure is equivalent to $O(M)$. Likewise, the computational complication in the modernizing procedure is based on examining for the preeminent position and modernizing the position of all designed California condor's is,

$$O(T \times M) + O(T \times M \times E)$$

where T is max iter
E is dim
Then the computation complexity of Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms is,

$$O(N \times (T + TE))$$

8. Simulation Results and Discussion

Projected Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms are corroborated in IEEE 30 bus system [20]. In Table 1 shows the loss appraisal, Table 2 shows the voltage aberration evaluation and Table 3 gives the Voltage constancy assessment. Figures 6 to 8 gives the graphical appraisal between the methods.

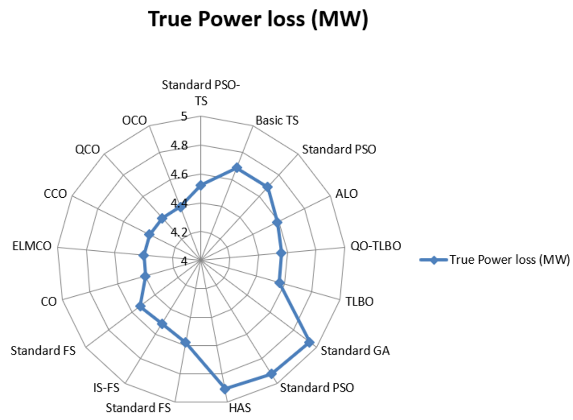

Fig 6. Assessment of real power loss

Appraisal of loss has been done with Particle swarm optimization, adapted Particle swarm optimization, enriched Particle swarm optimization, comprehensive learning Particle swarm optimization, Adaptive genetic algorithm, Canonical genetic algorithm, enhanced genetic algorithm, Hybrid Particle swarm optimization -Tabu search , Ant lion approach, quasi-oppositional teaching learning based algorithm, enriched stochastic fractal search optimization algorithm , harmony search , advanced pseudo-gradient search particle swarm optimization and cuckoo search algorithm. Power loss abridged competently and proportion of the power loss lessening has been enhanced. Predominantly voltage constancy augmentation attained with minimized voltage deviancy.

Table 2. Comparison of voltage aberration

Technique	Voltage deviancy (PU)
Hybrid-PSOTVIW [15]	0.1038
Hybrid-PSOTVAC [15]	0.2064
Hybrid-PSOTVAC [15]	0.1354
Hybrid-PSOCF [15]	0.1287
Hybrid-PGPSO [15]	0.1202
Hybrid-SWTPSO [15]	0.1614
Hybrid-PGSWTPSO [15]	0.1539
Hybrid-MPGPSO [15]	0.0892
Hybrid-QOTLBO [12]	0.0856
B-TLBO [12]	0.0913
B-FS [14]	0.1220
Hybrid-ISFS [14]	0.0890
B-FS [16]	0.0877
CO	0.0830
ELMCO	0.0828
CCO	0.0826
QCO	0.0825
OCO	0.0821

Table 3. Appraisal of Voltage constancy.

Technique	(Voltage constancy) L-index (PU)
Hybrid-PSOTVIW [15]	0.1258
Hybrid-PSOTVAC [15]	0.1499
Hybrid-PSOTVAC [15]	0.1271
Hybrid-PSOCF [15]	0.1261

Hybrid-PGPSO [15]	0.1264
Hybrid-SWTPSO [15]	0.1488
Hybrid-PGSWTPSO [15]	0.1394
Hybrid-MPGPSO [15]	0.1241
Hybrid-QOTLBO [12]	0.1191
B-TLBO [12]	0.1180
B-ALO [11]	0.1161
B-ABC [11]	0.1161
B-GWO [11]	0.1242
B-BA [11]	0.1252
B-FS [14]	0.1252
Hybrid-ISFS [14]	0.1245
B-FS [16]	0.1007
CO	0.1003
ELMCO	0.1002
CCO	0.1001
QCO	0.1002
OCO	0.1001

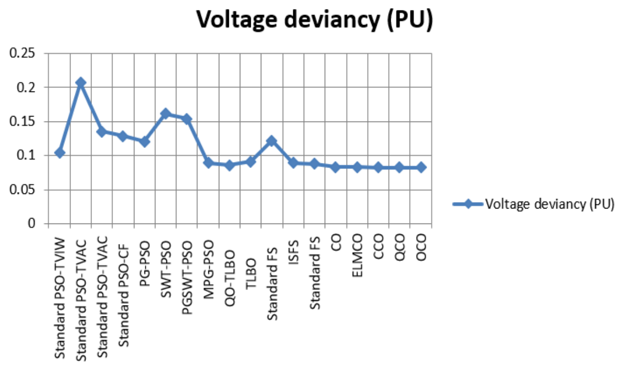

Fig 7. Appraisal of Voltage aberration.

Then the Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms are substantiated in IEEE 14, 30, 57, 118 and 300 bus test systems deprived of Voltage constancy. Loss appraisal is shown in Tables 4 to 8. Figure 9 to 13 gives graphical comparison between the approaches with orientation to power loss.

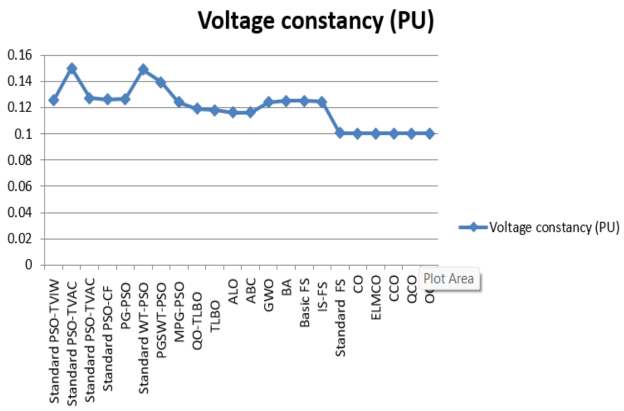

Fig 8. Assessment of voltage constancy index.

Proposed algorithms are compared with Adapted Particle swarm optimization, Particle swarm optimization, Evolutionary Programming, self-adaptive real coded Genetic algorithm, Canonical Genetic Algorithm, Adaptive Genetic Algorithm, Enhanced Particle swarm optimization, Comprehensive Learning Particle swarm optimization, Enhanced Genetic Algorithm, Faster Evolutionary algorithm and Cuckoo search Optimization algorithm.

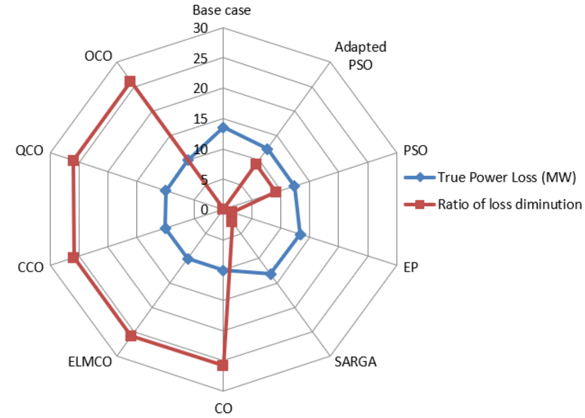

Fig 9. Power Loss appraisal (IEEE 14 bus system).

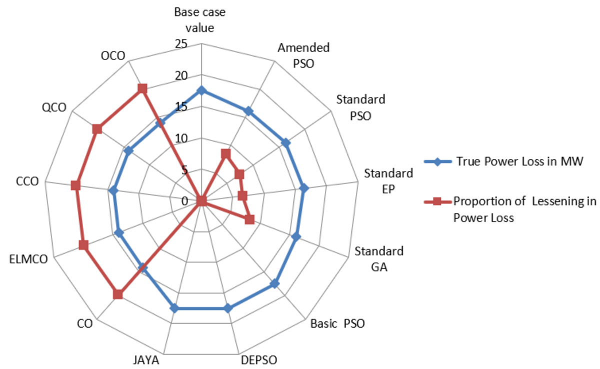

Fig 10. Appraisal of Power Loss (IEEE 30 bus system).

Table 4. Assessment of results (IEEE 14 Bus).

Parameter	**True Loss (MW)**	**Ratio of loss diminution**
Base case [24]	13.550	0.000
Improved PSO [24]	12.293	9.2000
B-PSO [23]	12.315	9.1000
B-EP [23]	13.346	1.500
Hybrid-SARGA [22]	13.216	2.500
CO	10.051	25.8228
ELMCO	10.043	25.8819
CCO	10.039	25.9114
QCO	10.027	26.0000
OCO	10.020	26.0516

Table 5. Appraisal of loss (IEEE 30 bus system)

Parameter	**Actual Power Loss in MW**	**Proportion of Lessening in Power Loss**
Base case value [24]	17.5500	0.0000
Improved PSO[24]	16.0700	8.40000
B -PSO [23]	16.2500	7.4000
B-EP [21]	16.3800	6.60000
B-GA [22]	16.0900	8.30000
S-PSO [25]	17.5246	0.14472
Improved	17.52	0.17094

DEPSO [25]		
B-JAYA [25]	17.536	0.07977
CO	14.064	19.8632
ELMCO	14.051	19.9373
CCO	14.045	19.9715
QCO	14.034	20.0341
OCO	14.029	20.0626

Table 6. Assessment of parameters (IEEE 57 Bus system)

Parameter	True Loss (MW)	Ratio of loss diminution
Base case [24]	27.8	0.00
Improved PSO [24]	23.51	15.400
B-PSO [23]	23.86	14.100
Canonical -GA[22]	25.24	9.200
Adaptive -GA [22]	24.56	11.600
CO	21.087	24.1474
ELMCO	21.076	24.1870
CCO	21.059	24.2482
QCO	21.044	24.3021
OCO	21.029	24.3561

Table 7. Assessment of results (IEEE 118 Bus system).

Parameter	True Loss (MW)	Ratio of loss diminution
Base case [24]	132.8	0.00
Improved PSO [24]	117.19	11.700
B-PSO [23]	119.34	10.100
B-EPSO [21]	131.99	0.600
B-CLPSO [21]	130.96	1.300
CO	112.062	15.6159
ELMCO	112.054	15.6219
CCO	112.042	15.6310
QCO	112.029	15.6408
OCO	112.018	15.6490

Table 8. Power Loss appraisal (IEEE 300 Bus system)

Parameter	True Loss (MW)
Adaptive -GA [33]	646.299800
Faster -EA [33]	650.602700
B-CSO [32]	635.894200
CO	625.109287
ELMCO	625.107452
CCO	625.106009
QCO	625.104135
OCO	625.102428

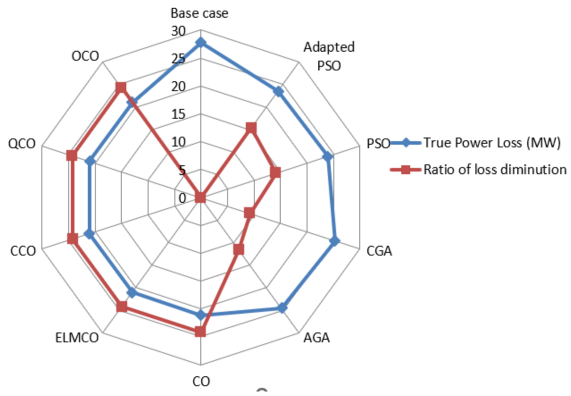

Fig 11. Power Loss appraisal (IEEE 57 bus system).

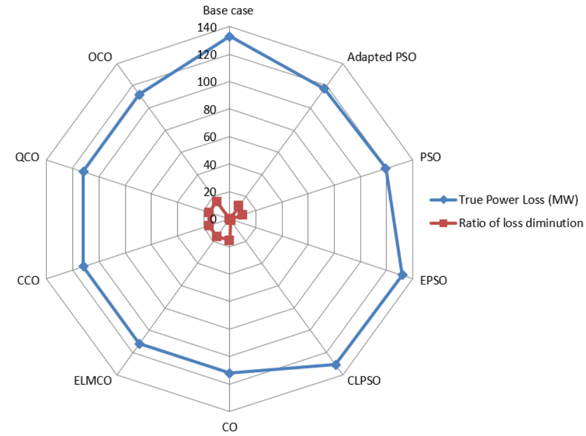

Fig 12. Power Loss appraisal (IEEE 118 bus system).

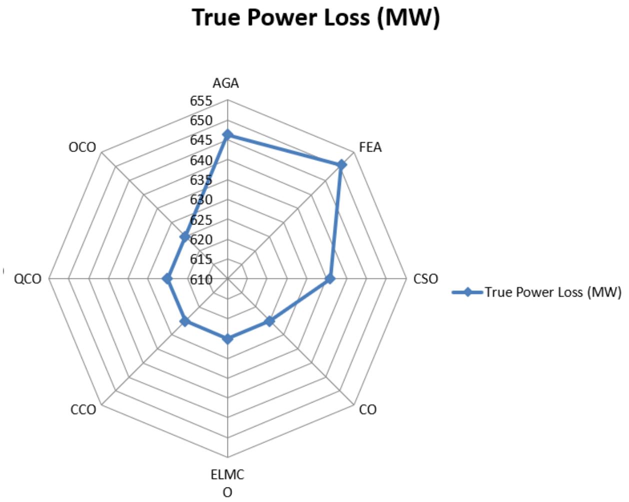

Fig 13. Power Loss appraisal (IEEE 300 bus system).

Table 9 shows the convergence characteristics of Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms are for IEEE 30 bus system. In IEEE 30 bus system, Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms are appraised as Multiobjective and single objective mode. Figure 14 shows the graphical representation of the characteristics.

Table 9. Convergence characteristics

Method	Actual Loss in MW(With Power reliability)	Actual Loss in MW (without Power reliability)	Time (S) (with Power reliability)	Time (S) (without Power reliability)	No. of iter. (with Power reliability)	No. of iter.(without Power reliability)

CO	4.4015	14.064	29.81	27.76	30	28
ELMCO	4.4002	14.051	27.24	25.98	28	25
CCO	4.3987	14.045	28.92	27.82	27	24
QCO	4.3976	14.034	29.09	28.14	29	28
OCO	4.3965	14.029	30.15	28.07	30	29

9. Conclusion

Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms condensed the Actual power loss resourcefully. In normal environs, numerous California condors can be substantially alienated into dual clusters, in which the procedure principally computes the fitness rate for elucidations (preliminary populace) to split California condor's into classes.

The finest response is assumed as the preeminent as chief California condor and the succeeding solution as the subsequent finest California condo. Remaining create a population that passages or substitutes one of the twofold preeminent California condor's in every activity. Subsequent to the formation of preliminary population, the aptness or fitness rate of all solutions is computed, and the preeminent solution is designated as the preeminent California condor of the chief cluster and the subsequent preeminent solution as the best California condor of the succeeding cluster, and remaining solutions will passage in the direction of the preeminent solutions for the chief and succeeding clusters. In iterations, the complete population is recomputed. When the value of y is decreases below to zero value then California condor is in ravenous phase and if the value of y increases to zero then the California condor is slaked. The motive for splitting clusters in this procedure is that California condor's' utmost vital normal task can be articulated: cluster living to discover nutrition.

Every cluster of California condor's is a dissimilar helplessness to discover nutrition and consume. The propensity to consume in California condor's and seeing for nutrition for periods sources them to seepage from the starving ruse. At the design period, in order to alleviate hunger, presumptuous that the poorest solution in the populace is the feeblest and ravenous, the California condor's attempt to preserve their expanse from the poor and emanated up with the preeminent solution.

In California condor Optimization (CO) algorithm, twofold of the preeminent solutions are measured as the robust and preeminent California condor's, and the other California condor's attempt to approach the preeminent one. In resolving perplexing optimization complications, there is no assurance that the concluding populace will comprise precise approximations for the global optimal solution at the completion of the exploration segment. Aimed at this purpose, it grounds early convergence in local solution. To escape from the escape from local optimal solutions $t = g \times \left(sin^R \left(\frac{\pi}{2} \times \frac{iter_i}{\max iter} \right) + cos \left(\frac{\pi}{2} \times \frac{iter_i}{\max iter} \right) - 1 \right)$ is employed. The concluding iterations of the California condor Optimization (CO) algorithm execute the exploitation segment and do exploration processes in concluding iterations. Through this stratagem's complete aim is to amend $t = g \times \left(sin^R \left(\frac{\pi}{2} \times \frac{iter_i}{\max iter} \right) + cos \left(\frac{\pi}{2} \times \frac{iter_i}{\max iter} \right) - 1 \right)$ to alter exploration and exploitation segments so that California condor Optimization (CO) algorithm can upsurge the possibility of arriving the exploration segment at certain period in the process. R Specifies the process disorders the exploration and operation segments and when R upsurges, the possibility of arrive to the exploration segment in the concluding phase's upsurges, nevertheless, by lessening R, the possibility of arrive to the exploration segment diminishes.

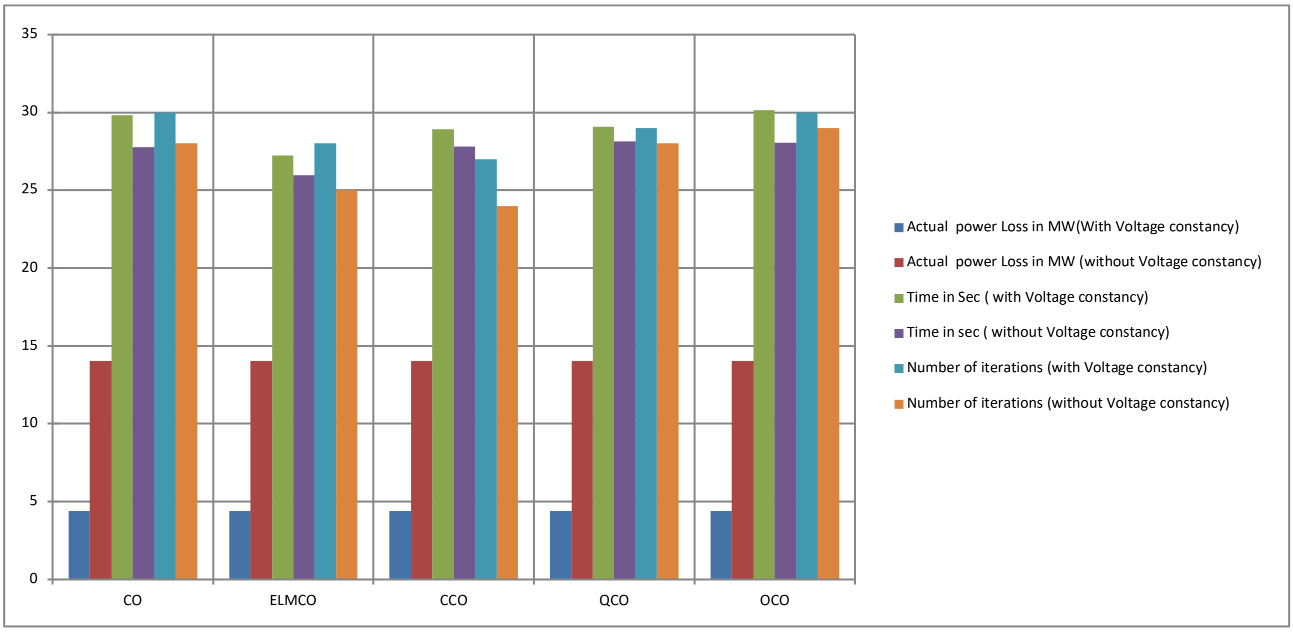

Fig 14. Convergence characteristics.

In the proposed Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm, CO approach enhances Extreme Learning Machine features to determine an optimal skeleton of Extreme Learning Machine for enhanced canons. In Extreme Learning Machine based California condor Optimization (ELMCO) Algorithm principally all elements don't own any info about the explication area.

In initial stages of iteration, the California condor contestants are assorted in milieu and exponential skimp generates boundless unpremeditated amounts which contribute the rudiments to lodging the entire explication zone. Congruently, all over end stage of iterations, rudiments are surrounded by California condor contestants and all an optimal situation with similar pattern. Chaotic sequences are integrated into the California condor Optimization (CO) algorithm and it called as - Chaotic based California condor Optimization (CCO) algorithm. This integration will augment the Exploration and Exploitation. Tinkerbell chaotic map engendering standards are implemented. Quantum mechanics has been combined with California condor Optimization (CO) algorithm and it entitled as Quantum based California condor Optimization (QCO) algorithm.

In quantum method, features emulate the analogous performance with the certain stage as they route in a credible powdered of median. Opposition based California condor Optimization (OCO) 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 California condor Optimization (CO) algorithm. Opposition based learning is one of the influential approaches to improve the convergence quickness of procedures.

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.

Proposed Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms is corroborated in IEEE 30 bus system and IEEE 14, 30, 57, 118, 300 bus test systems without considering the voltage constancy index.

Proposed Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms creditably condensed the power loss and proportion of Tangible power loss lessening has been elevated. Convergence characteristics show the better performance of the proposed Extreme Learning Machine, Chaotic, Quantum and Opposition based California condor Optimization algorithms. Valuation of power loss has been done with other customary reported algorithms.

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