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IMPROVED EPHEMERAL SEARCH AND NEPENTHES ALGORITHMS FOR DIMINUTION OF TRUE POWER LOSS

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Abstract

In this paper Improved Ephemeral Search Algorithm and Nepenthes Algorithm are used for solving the power loss lessening problem. Ephemeral Search Algorithm is physics-based algorithm that mimics the ephemeral actions of switching circuits which made by one or more intermediary switching expedients (like inductor and capacitor circuits). Actions of inductor and capacitor circuits are mathematically formulated to design the algorithm. To improve the convergence rate of the algorithm and Improved Ephemeral Search Algorithm has been designed by integrating chaotic opposition learning approach (to engender superior preliminary populations). Logistic chaos possesses arbitrary, ergodic, and systematic characteristics and chaotic variables used for optimization exploration which features the algorithm to evade local optimum, endorse the population multiplicity. Subsequently an adaptive inertia weighting approach is used (to balance exploration and exploitation capability with good convergence speed) then a neighbour learning (dimension) approach is utilized (to uphold the population assortment with every iteration of weight pursuing). Learning between neighbours (dimensional), modernizing the coordinates of the present entity by means of some data (dimensional) of adjacent entities and the data (dimensional) of an entity is arbitrarily chosen from the total population. Then in this paper Nepenthes Algorithm for solving power loss lessening problem. Nepenthes Algorithm is moulded based on the deeds of Nepenthes plant. Certain plants enthral the prey for reproduction deprived of killing them and quite a few restrain or kill the intruders for protection obstinacies conversely do not digest the physical bodies. Although several plants do engross the nutrients from the numb faunas,

Keywords

Optimal, reactive power, transmission loss, Ephemeral search, chaotic, adaptive weight, neighbourhood learning, Nepenthes

hitherto they do not have the competence to kill it. They simply eat the physical bodies found in the topsoil or on the surface of leaf. Every entity is structured rendering to its fitness value in uphill order mode. The highest *p* Nepenthes plant solutions of the systematized population are measured as the "*p Nepenthes plant*" plants, NP; however, the left-over solutions (*p prey*) are the victim (*prey*). The method of combination is obligatory to simulate the atmosphere of each Nepenthes plant and its victim (prey). In the course of the combination method, the Victim (prey) with the outstanding fitness is allotted to the Rank one Nepenthes plant. In the same way, the consequent preys are allotted to consecutive Nepenthes plants, consistently. When fascination rate is mediocre to the produced capricious value, the prey is successful to spurt from the ploy and Nepenthes plant withstands to propagate. Authenticity of the Ephemeral Search Algorithm, Improved Ephemeral Search Algorithm and Nepenthes Algorithm are substantiated in IEEE 30 bus system. Actual power loss lessening is reached. Proportion of actual power loss lessening is augmented

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Introduction. In power system subsiding of factual power loss is a substantial facet. Ample numeric procedures (Fuel-cost minimization, revised linear programming approach, Newton's optimal power flow, interior point method, successive quadratic programming method, Distributed control method) [1–6] and evolutionary approaches (Moth-flame optimization technique, Improved GSA-based algorithm, a novel fuzzy adaptive configuration of particle swarm optimization, Gaussian bare-bones based water cycle algorithm, Ant lion optimizer, quasi-oppositional teaching learning based optimization, Harmony search algorithm, a novel improved stochastic fractal search optimization algorithm, Improved pseudo-gradient search based particle swarm optimization, Effective Metaheuristic Algorithm) [7–16] are applied for solving Factual power loss lessening problem. Yet many approaches failed to reach the global optimal solution. In this paper Improved Ephemeral Search Algorithm (IESO) and Nepenthes Algorithm (NA) are applied to solve the Factual power loss lessening problem. In Ephemeral Search Algorithm (ESO), first-order circuits are solo storage component capacitor or inductor. Circuits are unable to change suddenly towards stable mode switching, since capacitor or inductor requires time (for charging or discharging) to touch its stable mode value. To engender superior preliminary populations, the data in the solution zone is completely pull out and seized by chaotic mapping. Logistic chaos mapping is used at this point. Arbitrary, ergodic, and systematic physiognomies of chaotic variables for optimization exploration countenances the algorithm to dodge local optimum, uphold the population multiplicity, and expand the global exploration competence. Even though chaotic classifications can produce the populations, which are sumptuous in diversity and impartially well spread, it is indisputable that there may be enriched exploration agents on the conflicting side of the exploration space; then, the matching number of opposite populations is created. In the primary iterations large inertia adaptive weight will expand the global exploration competence and consecutively in following phases smaller inertia adaptive weight will augment the exploitation (local) competency with speeding up of convergence rate. Population multiplicity acts as a significant role in the convergence speed and precision of the procedure. Population multiplicity increasingly reduces when iterations increasing and this will lead to trap in local optimal solution. Then in this paper NA is applied to solve the factual power loss lessening problem. Nepenthes Algorithm is modelled based on the behaviour of Nepenthes plant. For enthralling the prey, Nepenthes plant's exterior surfaces own radiant colours and tantalizing fragrance. Nepenthes plant holds digestive enzymes inside for dissection of the prey to extract the nutrients for the body of the prey. But the Nepenthes plant's inmost surface is lubricious, which impedes the knotted prey from absconding. Fascination, enmeshing, ingestion and reproduction of the Nepenthes plant have been imitated in the sculpting of the NA methodology. Nepenthes Algorithm starts with priming a set of solutions capriciously. At that point the solutions are regarded as Nepenthes plant and victim (prey), and subsequently gathered for the growing and reproduction developments. Due to the nutrient dispossessed soil, Nepenthes plants enthral, gambit and consume the victim (prey) for growing. Prey is drawn to the Nepenthes plant by its high cologne; conversely the prey might meritoriously spurt from the grabs of the Nepenthes plants fitfully. At this point, a fascination rate (0.81) is applied. For every group, a victim (prey) is capriciously nominated. If the fascination rate is greater than a capriciously produced number, then the prey is apprehended and consumed by the Nepenthes plant. Superior growth rate, will broader the exploration capability and if not, there will be a greater possibility to slip the global optimal solution. Nepenthes plant assimilates the nutrients from the victim (prey) for growth and reproduction. Only the top (rank) Nepenthes plant is used for reproduction. This method will make the exploitation to focus on distinguished solution. Too much exploitation on additional solutions can be dodged and subsequently computational cost will be abridged. Sagacity of ESO, IESO and NA is confirmed by corroborated in IEEE 30 bus system. Factual power loss lessening is achieved. Proportion of factual power loss reduction is amplified.

Problem formulation. The objective of the reactive power problem [21–25] is to minimize the active power loss and can be defined in equations as follows:

$$F = P_L = \sum_{k \in N_{br}} g_k \left(V_i^2 + V_j^2 - 2V_i V_j \cos \theta_{ij} \right),$$

where F is objective function; P_L is power loss; g_k is conductance of branch; V_i, V_j are voltages at buses *i*, *j*; N_{br} is total number of transmission lines in power systems.

To minimize the voltage deviation in PQ buses, the objective function can be written as

$$F = P_L + \omega_v VD.$$

Here ω_v is a weighting factor of voltage deviation; *VD* is voltage deviation,

$$VD = \sum_{i=1}^{N_{PQ}} \left| V_i - 1 \right|,$$

where N_{PQ} is number of load buses.

The equality constraint of the problem is indicated by the power balance equation as follows: $P_G = P_D + P_L$, where P_G is total power generation; P_D is total power demand.

The inequality constraint implies the limits on components in the power system in addition to the limits created to make sure system security. Upper and lower bounds on the active power of slack bus (P_G), and reactive power of generators (Q_G) are written as follows:

$$P_{G\,slack}^{\min} \le P_{G\,slack} \le P_{G\,slack}^{\max};$$

$$Q_{G\,i}^{\min} \le Q_{G\,i} \le Q_{G\,i}^{\max}, \quad i \in N_G.$$

Upper and lower bounds on the bus voltage magnitudes (V_i) are given by

$$V_i^{\min} \le V_i \le V_i^{\max}, \; i \in N. \tag{1}$$

Upper and lower bounds on the transformers tap ratios (T_i) are given by

$$T_i^{\min} \le T_i \le T_i^{\max}, \quad i \in N_T. \tag{2}$$

Upper and lower bounds on the compensators (Q_C) are given by

$$Q_C^{\min} \le Q_C \le Q_C^{\max}, \quad i \in N_C. \tag{3}$$

In (1)–(3), N_G is the total number of generators; N is the total number of buses; N_T is the total number of transformers; N_C is the total number of shunt reactive compensators.

Improved Ephemeral Search Algorithm. Ephemeral Search Algorithm is physics-based algorithm that mimics the ephemeral actions of switching circuits which made by one or more intermediary switching expedients. First-order circuits are solo storage component capacitor or inductor. Circuits are unable to change suddenly towards stable mode switching, since capacitor or inductor requires time (for charging or discharging) to touch its stable mode value. The ephemeral reaction of a first-order circuit can be computed as follows:

$$\frac{d}{dt} y(t) + \frac{y(t)}{\varphi} = G,$$

where t is present condition; φ is time constant of circuit and $\varphi = RC$ or L / R; G is constant value; $y(t)$ symbolize the capacitive voltage or inductive current,

$$y(t) = y(\infty) + (y(0) - y(\infty)) e^{t/\varphi}.$$

Here $y(0)$, $y(\infty)$ indicates initial and final reactions.

Under damped reactions of second-order circuits are defined with reference to ephemeral reactions as follows:

$$\frac{d^2}{dt^2} y(t) + 2\alpha \frac{d}{dt} y(t) + \omega_0^2 y(t) = f(t),$$

where $y(t) = e^{-\alpha t} (H_1 \cos(2\pi f_{DR} t) + H_2 \sin(2\pi f_{DR} t)) + y(\infty)$, H_1, H_2 are constants; f_{DR} indicates the damped resonant frequency; α, ω_0 symbolizes tamping factor and resonant frequency.

Preliminary population is engendered as follows:

$$Y_{ij} = Lower\,bound(LB) + rand(R)(Upper\,bound(UB) - LB),$$
$$i = 0, 1, 2, \ldots, N, \quad j = 0, 1, \ldots, d. \tag{4}$$

Here Y_{ij} symbolize the variables of i-th population in j-th dimension.

Search for the best solution is termed as exploration and it is stirred by second-order (neighbouring to zero point) RLC circuit as follows:

$$Y(t+1) = Y^*(t) + e^{-T} [\cos(2\pi L) + \sin(2\pi L)] \left| X(t) - M_1 Y^*(t) \right|, \tag{5}$$

where $Y(t+1)$ symbolize the position of current agent; $Y^*(t)$ indicate the position of present most excellent agent; $X(t)$ signifies the present position; L, M_1 are random coefficients,

$$L = 2Q\, rand_1 - k; \tag{6}$$

$$M_1 = kQ\, rand_2 + 1. \tag{7}$$

Here Q linearly decreases from 2.0 to 0 and $rand_1, rand_2 \in [0,1]$:

$$Q = 2.0 - 2.0\frac{t}{maximum\ iteration}.$$

At this juncture the exploitation is the procedure of pretending the exponential waning of the main discharge

$$Y(t+1) = Y^*(t) + \left[Y(t) - M_1 Y^*(t+1)\right]e^L. \tag{8}$$

Ephemeral Search Algorithm

a. Start
b. Engender the preliminary population (4)
c. Fitness value of the population is computed
d. Position of the most excellent fitness value exploration agent is identified
e. while t < maximum iteration
f. Compute the value of L (6) and M_1 (7)
g. when σ > 0.5; then modernize the position of exploration agent by (5)
h. otherwise, if $\sigma \le 0.5$; then modernize the position of exploration agent by (8)
i. End if
j. Fitness value of the population is computed
k. Optimal search agent fitness and position are modernized
l. $t = t + 1$
m. End while

In the IESO at first, preliminary population are arbitrarily engendered with intense distribution. To avoid the premature convergence a chaotic logistic learning approach is integrated for engendering an excellent preliminary population. Additionally, adaptive inertia weights are used to augment the exploration and exploitation capability of the procedure. A neighbour learning (dimension) approach is combined in the procedure and it makes the population as diversity one during the course of the iterative procedure. This activity will avoid the local optima.

To engender superior preliminary populations, the data in the solution zone is completely pull out and seized by chaotic mapping [17]. Logistic chaos mapping is used at this point. Arbitrary, ergodic, and systematic characteristics of chaotic variables for optimization exploration countenances the algorithm to evade local optimum, uphold the population multiplicity, and expand the global exploration capability:

$$\lambda_{t+1} = \mu\lambda_t\left(1-\lambda_t\right),\ \lambda_t \in \left[0,1\right],\ t = 0,\ 1,\ldots,\ T. \tag{9}$$

With respect to engendered chaotic variables mapping will be done as follows:

$$Y_i^j = LB + \lambda_j\left(UB - LB\right). \tag{10}$$

Even though chaotic categorizations can yield the populations, which are opulent in multiplicity and equitably well dispersed, it is irrefutable that there may be improved exploration agents on the contradictory side of the exploration space; then, the identical number of opposite populations is engendered once more:

$$Y_{opposite\ position} = Y_{\max} + Y_{\min} - Y_i. \tag{11}$$

In the preliminary iterations big inertia adaptive weight [18] will augment the global exploration capability and sequentially in next stages lesser inertia adaptive weight will enrich the exploitation (local) capability with speeding up of convergence rate:

$$\omega\left(t\right) = u\,\cos^{\nu}\left(\ln\left(1+e^{t/T_{\max}}\right)\right) + x, \tag{12}$$

where u, v and x are parameters used in choice mode.

After applying the adaptive weights exploration and exploitation distribution is defined as:

$$Y\left(t+1\right) = \omega\left(t\right)Y^*\left(t\right) + e^{-T}\left[\cos\left(2\pi L\right)+\sin\left(2\pi L\right)\right]\left|X\left(t\right) - M_1Y^*\left(t\right)\right|;$$

$$Y\left(t+1\right) = \omega\left(t\right)Y^*\left(t\right) + \left[Y\left(t\right) - M_1\,Y^*\left(t+1\right)\right]e^L.$$

Population multiplicity acts as an important role in the convergence speed and precision of the procedure. Population multiplicity progressively reduces when iterations increasing and this will lead to trap in local optimal solution. Consequently, to guarantee that the populations endure rich in multiplicity throughout iterations, a neighbour learning (dimension) approach [19] is applied in the procedure:

$$\vec{Y}_{CP\,i} = \begin{cases} \omega\vec{Y}^*\left(t\right) + 2\left(R-0.5\right)\left(UB-LBR+LB\right)\ \sigma > 0.5; \\ \omega\vec{Y}_i\left(t\right) + 2\left(R-0.5\right)\left(UB-LBR+LB\right)\ \sigma \le 0.5, \end{cases} \tag{13}$$

where $\vec{Y}_{CP\,i}$ is the candidate population (i-th individual); $\vec{Y}^{*}(t)$ indicate the position vector of most excellent individual; $\vec{Y}_i(t)$ symbolize the i-th explore agent position; σ is random variable probability.

Based on the Euclidean distance radius of the neighbourhood is computed as follows:

$$Radius_i\left(t\right)=\vec{Y}_i\left(t\right)-\vec{Y}_{CP\,i}\left(t+1\right). \quad (14)$$

Subsequently i-th entity (individual) of the neighbourhood is defined as

$$Neighbourhood_i\left(t\right)=\left\{Y_j\left(t\right)\middle|ED_i\left(Y_i\left(t\right),Y_j\left(t\right)\right)\le Radius_i\left(t\right),Y_j\left(t\right)\in Y\middle|\right\}. \quad (15)$$

Here ED_i symbolize the process of Euclidean distance.

The subsequent stage executes learning between neighbours (dimensional), modernizing the coordinates of the present entity by means of some data (dimensional) of adjacent entities and the data (dimensional) of an entity is arbitrarily chosen from the total population as follows:

$$Y_{NL\_i,d}\left(t+1\right)=Y_{i,d}\left(t\right)+\mathrm{sign}\left(R-0.5\right)\left(Y_{n,d}\left(t\right)-Y_{R,d}\left(t\right)\right), \quad (16)$$

where $Y_{NL\_i,d}\left(t+1\right)$ indicate the fresh data from d-dimension; $Y_{i,d}(t)$ symbolize the i-the explore agent d-dimension information; $Y_{n,d}(t)$ indicate the neighboring entities d-dimension information; $Y_{R,d}(t)$ signify the randomly chosen d-dimension information.

Then the fitness value is computed for modernizing the data as follows:

$$Y_i\left(t+1\right)=\begin{cases} Y_{CP\_i}\left(t+1\right)\ if\ f\left(Y_{CP\_i}\left(t+1\right)<f\left(Y_{NL\_i,d}\left(t+1\right)\right)\right); \\ Y_{NL\_i,d}\left(t+1\right) if\ f\left(Y_{CP\_i}\left(t+1\right)\ge f\left(Y_{NL\_i,d}\left(t+1\right)\right)\right). \end{cases} \quad (17)$$

Improved Ephemeral Search Algorithm

a. Start
b. Engender chaotic mapping sequence (9)
c. Population created (10)
d. Engender the opposite populations (11)
e. Alternate population's fitness values are computed
f. Preliminary population (most excellent fitness value) are chosen
g. while t < maximum iteration
h. Adaptive inertia weights are computed (12)
i. Compute the value of L (6) and M_1 (7)
j. when $\sigma > 0.5$; then modernize the position of exploration agent by (5)
k. otherwise, if $\sigma \le 0.5$; then modernize the position of exploration agent by (8)

l. End if
m. Candidate populations are engendered (13)
n. Euclidean distance radius of the neighbourhood is computed (14)
o. Neighbourhood population calculated (15)
p. Compute the Neighbourhood individual population (16)
q. Modernize the population by calculating fitness value (17)
r. Optimal search agent fitness and position are modernized
s. $t = t + 1$
t. End while

Nepenthes Algorithm. Nepenthes Algorithm is modelled based on the behaviour of Nepenthes plant. Certain plants fascinate the prey for reproduction deprived of carnage them and several restrain or assassinate the invaders for protection tenacities however do not digest the physical bodies. Whereas various plants do captivate the nutrients from the numb faunas, yet, they do not have the capability to assassinate it. They simply eat the physical bodies found in the topsoil or on the surface of leaf. Nepenthes plant possesses digestive enzymes inside for itemization of the prey to extract the nutrients for the body of the prey. For fascinating the prey, Nepenthes plant's external surface possess glowing colours and tempting aroma. Nepenthes plant possesses digestive enzymes inside for itemization of the prey to extract the nutrients for the body of the prey. But the Nepenthes plant's innermost surface is slick, which precludes the entangled prey from escaping. Fascination, enmeshing, ingestion and reproduction of the Nepenthes plant has been imitated in the modelling of the NA approach. Nepenthes Algorithm starts with priming a set of solutions arbitrarily, which characterized as Nepenthes plant and victim (prey), and consequently congregated for the growing and reproduction developments. Fitness values are rationalized and uniting of the solution will be done. This procedure endures until the end criterion is achieved.

Nepenthes Algorithm starts with initialization of population with prospective solutions. To begin with, a population of "*P*" entities (*E*), entailing of Nepenthes plants and preys, are arbitrarily initialized. Then the sum of Nepenthes plants and preys are represented as "*p Nepenthes plant*" and "*p prey*" correspondingly. The location of each entity is epitomized in a matrix as follows:

$$Nepenthes\,population = \begin{bmatrix} E_{1,1} & \dots & E_{1,d} \\ \dots & \dots & \dots \\ E_{p,1} & \dots & E_{p,d} \end{bmatrix},$$

where *p* is the sum of "*p Nepenthes plant*" and "*p prey*"; *d* symbolize the dimension.

By arbitrarily each entity is initialized as follows:

$$Entity_{i,j} = Lower\,bound\left(LB\right)_j + \left(Upper\,bound\left(UB\right)_j - \left(LB\right)_j\right) random\left(R\right),$$

where $i = 1, 2, 3, \ldots, n;\ j = 1, 2, 3, \ldots, d;\ R \in \left[0,1\right]$.

From each *i*-th entity, fitness value is estimated by replacing each *i*-th entity to the preconceived fitness function. Subsequently the obtained fitness value is stockpiled as follows:

$$Fitness = \begin{bmatrix} F\left(E_{1,1}E_{1,2}\ldots E_{1,d}\right) \\ F\left(E_{2,1}E_{2,2}\ldots E_{2,d}\right) \\ \cdots \\ \cdots \\ \cdots \\ F\left(E_{p,1}E_{p,2}\ldots E_{p,d}\right) \end{bmatrix}.$$

Subsequently, every entity is organised rendering to its fitness value in uphill order. The highest *p Nepenthes plant solutions* of the organized population are measured as the *p Nepenthes plant* plants, *NP*, whereas the left-over solutions (*p prey*) are the victim (prey). Organized fitness values matrix and arranged population is defined as follows:

$$Organized\,Fitness\,value = \begin{bmatrix} F_{NP(1)} \\ F_{NP(2)} \\ \vdots \\ F_{NP(p\,Nepenthes\,plant)} \\ F_{prey(p\,Nepenthes\,plant\,+\,1)} \\ F_{prey(p\,Nepenthes\,plant\,+\,2)} \\ \vdots \\ F_{prey(p\,Nepenthes\,plant + p\,\,prey)} \end{bmatrix},$$

$$Organized\,Population =$$

$$= \begin{bmatrix} NP_{1,1} & \cdots & NP_{1,d} \\ \vdots & \ddots & \vdots \\ prey_{p\,Nepenthes\,plant+p\,\,prey,1} & \cdots & prey_{p\,Nepenthes\,plant+p\,\,prey,d} \end{bmatrix}.$$

The procedure of combination is compulsory to simulate the atmosphere of each Nepenthes plant and its victim (prey). In the course of the combination procedure, the victim (prey) with the pre-eminent fitness is allotted to the Rank one Nepenthes plant. Equally, the succeeding preys are allotted to consecutive Nepenthes plants, correspondingly. This procedure is repetitive until the victim (prey) is distributed to the Nepenthes plant. At that point, the $p\,Nepenthes\,plant+1$ prey is allotted to the 1 rank Nepenthes plant. The combining attribute is vital to decrease the probability of having numerous deprived worth preys and this will subsidize to the growing of Nepenthes plants, which is significant to progress the endurance of the Nepenthes plants. Owing to the nutrient deprived soil, Nepenthes plants fascinate, ploy and ingest the victim (prey) for growing. Prey is tempted to the Nepenthes plant by its high fragrance; however, the prey might effectively spurt from the grabs of the Nepenthes plants spasmodically. At this point, a fascination rate (0.81) is applied. For every group, a victim (prey) is arbitrarily selected. If the fascination rate is greater than an arbitrary engendered number, then the prey is seized and consumed by the Nepenthes plant. New-fangled Nepenthes plant growth is mathematically defined as follows:

$$\begin{gathered}New\text{-}fangled\,Nepenthes\,plant\left(NP_{i,j}\right)=\\=NP\,Growth\,NP_{i,j}+\left(1-NP\,Growth\right)prey_{a,j};\\NP\,Growth=Growth\,\_rate\,random_{i,j},\end{gathered}\quad(18)$$

where $NP_{i,j}$ indicate the i-th rank of Nepenthes plant; $prey_{a,\,j}$ symbolizes the randomly selected prey.

The exploration of the NA is prejudiced by the growth percentage. The greater the growth rate, the broader the exploration is and in turn, the greater probability to slip the global optimal solution. Therefore, an appropriate growth rate has to be carefully chosen. When fascination rate is inferior to the engendered arbitrary value, the prey succeeds to spurt from the ploy and Nepenthes plant endures to propagate as follows:

$$New\text{-}fangled\,prey_{i,j}=NP\,Growth\,prey_{b,j}+\left(1-NP\,Growth\right)prey_{a,j};\ a\neq b;\quad(19)$$

$$NP\ Growth=\begin{cases}Growth\_rate\,random_{i,j}\,F\left(prey_a\right)>F\left(prey_b\right);\\1-Growth\_rate\,random_{i,j}\,F\left(prey_a\right)<F\left(prey_b\right).\end{cases}$$

Here $prey_{b,\,j}$ is arbitrarily selected in the i-th group (rank).

Nepenthes plant integrates the nutrients from the victim (prey) for growth and reproduction. Only the top (rank) Nepenthes plant is utilized for reproduction. This procedure will make the exploitation to focus on pre-eminent solution. Excessive exploitation on additional solutions can be circumvented and consequently computational cost will be reduced. The reproduction procedure (RR) is mathematically defined as follows:

$$\textit{New-fangled Nepenthes plant}\left(NP_{i,j}\right) = NP_{1,j} + RR\,random_{i,j}\,mate_{i,j}; \quad (20)$$

$$\textit{Nepenthes plant}\_mate_{i,j} = \begin{cases} NP_{a,j} - NP_{i,j}\; F\left(NP_i\right) > F\left(NP_a\right); \\ NP_{i,j} - NP_{a,j}\; F\left(NP_i\right) < F\left(NP_a\right), \end{cases}$$

$$i \neq a \neq 1,$$

where $NP_{i,j}$ is most excellent solution; $NP_{a,j}$ is randomly picked Nepenthes plant.

The freshly engendered Nepenthes plants and preys are united with the preceding population, which ensuing in a new-fangled group:

$$\textit{New-fangled group} = \left[p + pNP\left(\textit{Combined iteration}\right) + pNP\right]d.$$

Nepenthes Algorithm

a. Start
b. Define the parameters
c. Initialization of population
d. Each entity fitness function computed
e. Based on the fitness value classify the entities
f. Recognize the most excellent entity $\left(G_{Best}\right)$ top ranked Nepenthes plant
g. Repeat until the End Criterion met
h. Categorize the top *p NP* entities as Nepenthes plants
i. Categorize the remaining *p prey* entities as victim (prey)
j. Combine the Nepenthes plants and prey

// Nepenthes plants and prey growth //

i. For *i* = 1 : *p* Nepenthes plant
ii. For Combining cycle = 1: Combined iteration
iii. if Fascination rate > Engendered random number
iv. Then the prey is seized and ingested
v. Engender new Nepenthes plants (18)
vi. Otherwise
vii. Prey Spurt out from the ploy
viii. Engender new prey (20)

k. End for
l. End for

// Top rank Nepenthes plant reproduction procedure //

i. For *i* = 1 : *p* Nepenthes plant

ii. Engender new Nepenthes plants based on top rank Nepenthes plant (20)

m. End for

n. For new-fangled Nepenthes plant and prey compute the fitness value

o. The freshly engendered Nepenthes plants and preys are united with the preceding one

p. Classify the entities

q. Choose the top ranked *p* entities for subsequent generation

r. Recognize the most excellent entity (G_{Best}) top ranked Nepenthes plant

s. End while

t. Output the (G_{Best}) solution

u. End

Simulation results. Ephemeral Search Algorithm, IESO and NA are corroborated in IEEE 30 bus system [20]. Appraisal of loss has been done amended PSO, standard PSO, standard evolutionary programming, standard genetic algorithm, basic particle swarm optimization, Differential evolution combined with particle swarm optimization and JAYA algorithm. Power loss abridged competently and proportion of the power loss lessening has been enriched. Predominantly voltage constancy enrichment achieved with minimized voltage deviancy. Table 1 shows the real power loss assessment and Table 2 shows the convergence characteristics. Figures 1 and 2 show the comparison of loss and convergence characteristics of ESO, IESO and NA. Simulation was carried out on a personal computer with an *Intel® Core™2 Duo* processor working at 2.24 GHz and 2 GB of RAM memory. The simulation has been performed using codes written in *MATLAB R2014a* for the specific algorithms in conjunction with *MATPOWER 3.2*. Proportional power loss reduction attained for ESO, IESO and NA are 20.2222, 20.3988, and 19.658. Figure 1 shows the better performance of the proposed ESO, IESO and NA in reduction of real power loss. Very importantly proportion of power loss reduction has been improved. Figure 2 shows the convergence characteristics of ESO, IESO and NA. All three algorithms performed well with respect to real power loss reduction.

Table 1

Assessment of true power loss

Algorithm	Factual power loss, MW	Proportion of lessening in power loss, %
Base case value [24]	17.5500	0
Amended PSO [24]	16.0700	8.40000
Standard PSO [23]	16.2500	7.40000
Standard EP [21]	16.3800	6.60000

End of the Table 1

Algorithm	Factual power loss, MW	Proportion of lessening in power loss, %
Standard GA [22]	16.0900	8.30000
Basic PSO [25]	17.5246	0.14472
DEPSO [25]	17.5200	0.17094
JAYA [25]	17.5360	0.07977
ESO	14.0010	20.2222
IESO	13.9700	20.3988
NA	14.1000	19.6580

Table 2

Convergence characteristics

Algorithms	Factual power loss with / without L-index, MW	Proportion of lessening in power loss, %	Time with / without L-index, s	Number of iterations with / without L-index
ESO	4.5007 / 14.001	20.2222	18.47 / 15.49	29 / 26
IESO	4.5002 / 13.970	20.3988	18.36 / 15.35	27 / 23
NA	4.5007 / 14.10	19.658	20.06 / 16.18	32 / 27

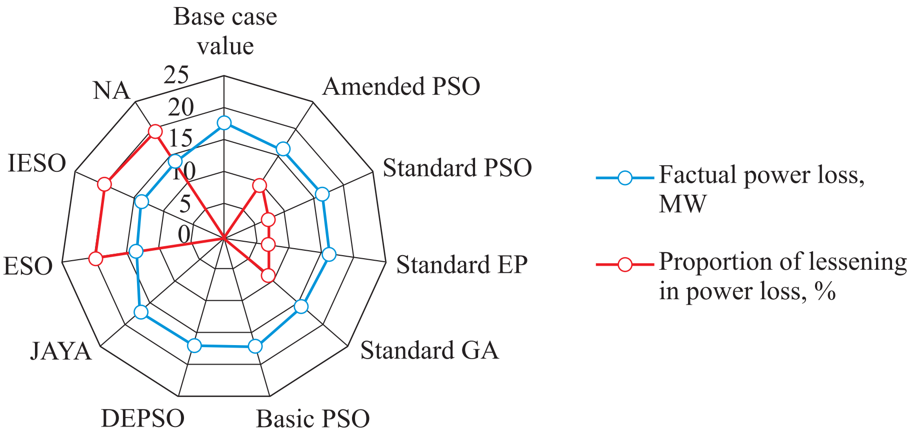

Fig. 1. Comparison of true power loss

Conclusion. Ephemeral Search Algorithm, IESO and NA abridged the factual power loss ingeniously. Ephemeral Search Algorithm, IESO and NA corroborated in IEEE 30 bus test system. In the IESO at first, primary population are capriciously produced with intense distribution. To dodge the premature convergence a chaotic logistic learning approach is integrated for engendering an excellent preliminary population. To engender superior

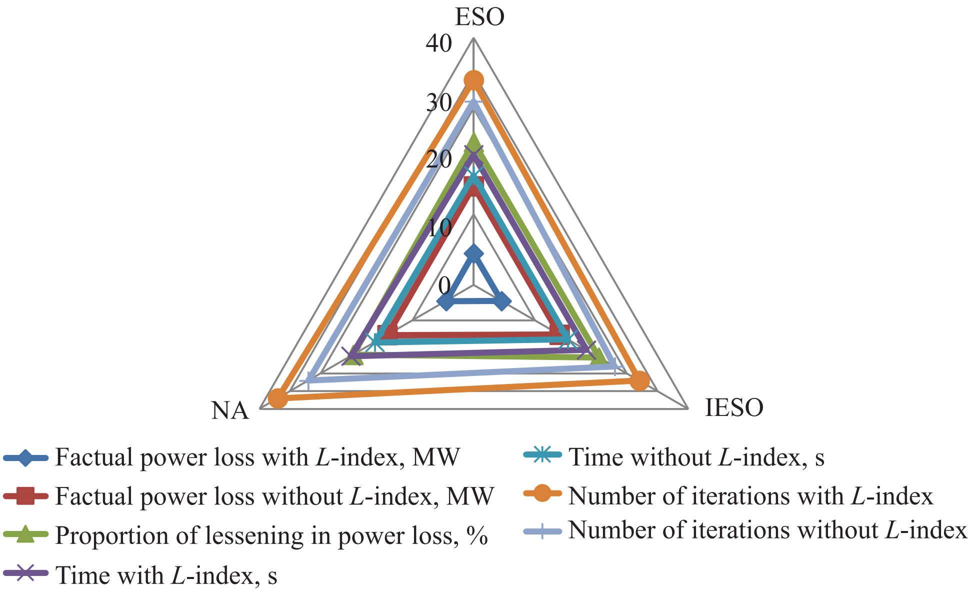

Fig. 2. Convergence characteristics

preliminary populations, the data in the solution zone is completely pull out and seized by chaotic mapping. Logistic chaos mapping is used at this point. Arbitrary, ergodic, and systematic physiognomies of chaotic variables for optimization exploration countenances the algorithm to dodge local optimum, uphold the population multiplicity, and expand the global exploration competence. Even though chaotic classifications can produce the populations, which are sumptuous in diversity and impartially well spread, it is indisputable that there may be enriched exploration agents on the conflicting side of the exploration space; then, the matching number of opposite populations is created. Additionally, adaptive inertia weights are used to augment the exploration and exploitation capability of the procedure. A neighbour learning (dimension) approach is combined which make the population as diversity one during the course of the iterative procedure in order to avoid the local optima. Nepenthes Algorithm started with priming a set of solutions arbitrarily. Then the solutions are then characterized as Nepenthes plant and victim (prey), and consequently congregated for the growing and reproduction developments. Fitness values are rationalized and uniting of the solution has been done. This procedure endures until the end criterion is achieved. The exploration of the NA is prejudiced by the growth percentage. The greater the growth rate, the broader the exploration is and in turn, the greater probability to slip the global optimal solution. Therefore, an appropriate growth rate has to be carefully chosen. When fascination rate is inferior to the engendered arbitrary value, the prey succeeds to spurt from the ploy and Nepenthes plant endures to propagate. Nepenthes plant integrates the nutrients from the victim (prey) for growth and reproduction. Only the top (rank) Nepenthes plant is utilized for reproduction. This procedure will make the exploitation to focus on pre-eminent solution. Excessive exploitation on additional solutions can be circumvented and consequently computational cost is reduced. Ephemeral Search Algorithm, IESO and NA creditably condensed the power loss and proportion of factual power loss lessening has been upgraded. Convergence characteristics show the better performance of the proposed ESO, IESO and NA. Assessment of power loss has been done with other customary reported algorithms.

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