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Real Power Loss Reduction by Melon Fly Optimization and Spontaneous Process Algorithm's

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HIGHLIGHTS

- Melon Fly algorithm based on the innate events of Melon fly
- By smell and vision the Melon fly will move to the best location
- Spontaneous Process Algorithm based onnuclear fission and fusion
- Nucleus symbolizes the variables and potential solution

Abstract: In this work Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) is designed to reduce the Real power loss, voltage stability enhancement and reducing the Voltage deviation. In this work real power loss measured and how much loss has been reduced is also identified by suitable comparison with standard algorithms. In this society from common consumer to industry needs better quality of power continuously and constantly without much variation. One way to improve the quality of the power is to reduce the power loss. Also reduction of power loss will improve the economic conditions of the nation indirectly and it improves the productivity of the nation with any hurdles. Around the world all nations sequentially identifying the method to reduce the power loss in the transmission and subsequently it improve the quality of power. MFO algorithm has been formed based on the innate events of Melon fly. Due their very excellent eyesight and mutual supportive behaviour Melon fly will find the food without difficulty. By smell and vision the Melon fly will move to the best location form the current location. In the preliminary level Melon flies will search the food in multiple directions and they may be far away from the food source, it like scattering in the plane. Then Spontaneous Process Algorithm (SPA) is designed to solve the optimal reactive power problem Formulation of the projected algorithm is done by imitating the process done during nuclear fission and fusion. Every item of a nucleus attribute symbolizes each solution variable. Sequence of operators directs the nucleus and in order to avoid the local optimum it will imitate the dissimilar condition of reaction. In the exploration space nucleus symbolizes the variables and potential solution. Levy flight has been intermingled in the procedure to enhance the diversification and intensification in the search. Evaluation of validity of the Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) is done in IEEE 30-bus system by considering voltage stability (L-index) and also devoid of L-index criterion. Minimization of voltage deviation, voltage stability enhancement and power loss minimization has been achieved.

Keywords: Optimal Reactive Power; Transmission Loss;Melon Fly Optimization Algorithm; Spontaneous Process Algorithm.

INTRODUCTION

Power loss minimization, voltage stability enhancement and deviation of voltage minimization are multiple objectives of this work. Many countries are trying to identify the way to improve the quality of power. Yet many technical obstacles are found in the process. Reduction of power loss is key factor to improve the quality of power in the network. Since from common (small) consumers to high capacity consumers need better quality of power continuously. It will improve the productivity of the nation and economically it will augment the financial strength of the nation. So in this work two algorithms defined and designed for power loss reduction with voltage stability enhancement. Different conventional methods [1-6] and various Evolutionary algorithms [7-10] are utilized to solve the Science and Engineering problems. Main concern is reaching the optimal solution [22-25]. In the conventional methods due to the constraints many techniques failed to reach the better solution. In the swarm and other evolutionary algorithms the major problem is balancing the exploration and exploitation. Since when both are not balanced then reaching the optimal solution will not be possible. In this work Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) has been designed to balance the exploration and exploitation sequentially. At first in this paper Melon Fly Optimization (MFO) Algorithm applied to solve the optimal reactive power problem. Proposed algorithm has been modelled based on the natural actions of Melon fly. Every Melon fly maintain pathway from its position and keep the attention towards food. Dissimilar types of Smell are compared, and the largest food region will be chosen. After the completion of definite number of iterations' the melon fly will not fly arbitrarily with the obtained memory so a memory move or progress direction has been applied in the algorithm. Proposed MFO algorithm improves the search to reach the global optimal solution and also evade the local optima. Then in this paper Spontaneous Process Algorithm (SPA) a physics-based algorithm which has been inspired by nuclear reaction is applied to solve the optimal reactive power problem. Process of Nuclear fission and fusion are utilized to formulate the algorithm. In order to explore the nearby area positions and also to control the capability of exploration and exploitation "β" decay will be emulated by Gaussian walk. Getting trapped in Local optimal solution is avoided by applying the Levy flight. In ionization phase, all nucleuses are categorized through fitness values. With and without considering L-index Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) evaluated in IEEE 30 bus system. Deviation of voltage minimization, power loss reduction and voltage stability augmentation achieved. With other reported standard algorithms - Hybrid PSO-Tabu search, Ant lion, quasi-oppositional teaching learning based, improved stochastic fractal search optimization algorithm, harmony search, improved pseudo-gradient search particle swarm optimization, cuckoo search algorithm, Evolutionary programming and self - adaptive real coded genetic algorithm. Projected algorithms MFO and SPA minimized the power loss in both with and without considering voltage stability. Then the percentage of power loss reduction also improved substantially.

Problem Formulation

In recent years, the problem of voltage stability and voltage collapse has become a major concern in power system planning and operation. To enhance the voltage stability, voltage magnitudes alone will not be a reliable indicator of how far an operating point is from the collapse point. Voltage stability evaluation using modal analysis is used as the indicator of voltage stability.

Objective function of the problem is mathematically defined in general mode by,

$$Minimization\ \tilde{F}(\bar{x},\bar{y}) \quad (1)$$

Subject to

$$E(\bar{x},\bar{y}) = 0 \quad (2)$$

$$I(\bar{x},\bar{y}) = 0 \quad (3)$$

Minimization of the Objective function is the key and it defined by "F". Both E and I indicate the control and dependent variables of the optimal reactive power problem (ORPD). "x" consist of control variables which are reactive power compensators (Q_c), dynamic tap setting of transformers –dynamic (T), level of the voltage in the generation units (V_g).

$$x = [VG_1,..,VG_{Ng}; QC_1,..,QC_{Nc}; T_1,..,T_{N_T}] \quad (4)$$

"y" consist of dependent variables which has slack generator PG_{slack} , level of voltage on transmission lines V_L , generation units reactive power Q_G , apparent power S_L .

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

Then the single objective problem formulation is defined as follows.

The fitness function (OF_1) is defined to reduce the power loss (MW) in the system is written as,

$$OF_1 = P_{Min} = Min\left[\sum_m^{NTL} G_m \left[V_i^2 + V_j^2 - 2 * V_i V_j cos\emptyset_{ij}\right]\right] \quad (6)$$

Number of transmission line indicated by “NTL”, conductance of the transmission line between the $i^{th}\ and\ j^{th}$ buses, phase angle between buses i and j is indicated by $\emptyset_{ij}$.

Minimization of Voltage deviation fitness function (OF_2) is given by,

$$OF_2 = Min\left[\sum_{i=1}^{N_{LB}} \left|V_{Lk} - V_{Lk}^{desired}\right|^2 + \sum_{i=1}^{Ng} \left|Q_{GK} - Q_{KG}^{Lim}\right|^2\right] \quad (7)$$

Load voltage in k^{th} load bus is indicated by V_{Lk} , voltage desired at the k^{th} load bus is denoted by $V_{Lk}^{desired}$, reactive power generated at k^{th} load bus generators is symbolized by Q_{GK}, then the reactive power limitation is given by Q_{KG}^{Lim} , then the number load and generating units are indicated by N_{LB} and Ng.

Then the voltage stability index (L-index) fitness function $(OF_3)$is given by,

$$OF_3 = Min\, L_{Max} \quad (8)$$

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

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

Such that

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

The objectives of the reactive power dispatch problem considered here is to diminish the system real power loss and maximize the static voltage stability margins (SVSM). This objective is accomplished by appropriate alteration of reactive power variables like generator voltage magnitude, reactive power generation of capacitor bank, and transformer tap setting. Power flow equations are the equality constraints of the problem, while the inequality constraints comprise of the limits on real and reactive power generation, bus voltage magnitudes, transformer tap positions and line flows.

Then the equality constraints are

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

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

Where, *nb*is the number of buses, P_G and Q_G are the real and reactive power of the generator, $P_D$and$Q_D$are the real and reactive load of the generator, and $G_{ij}$and $B_{ij}$are the mutual conductance and susceptance between bus *i*and bus *j*.

Inequality constraints

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

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

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

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

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

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

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

Multi objective fitness (MOF) function has been defined by,

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

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

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

Where, nc, ng and nt are numbers of the switchable reactive power sources, generators and transformers.The equality constraints are satisfied by running the power flow program. The active power generation (P_{gi}), generator terminal bus voltages (V_{gi}) and transformer tap settings (t_k) are the control variables and they are self-restricted by the optimization algorithm. The active power generation at slack bus (P_{sl}), load bus voltage (V_{load}) and reactive power generation (Q_{gi}) are the state variables and are restricted by adding a quadratic penalty term to the objective function.

Melon Fly Optimization Algorithm

In this work Melon Fly Optimization (MFO) Algorithm has been modelled based on the normal events of Melon fly. Because of outstanding eyesight and reciprocated helpful behaviour Melon fly will find the food devoid of complicatedness. Each Melon fly preserve a lane from its position and concentration will be towards the food. Dissimilar types of Smell are evaluated, and the major food region will be preferred. Subsequently the key concentration is indicated as the most excellent present location. By smell and vision the Melon fly will move to the most excellent location form the existing location. Proposed MFO algorithm perk up the search to attain the global optimal solution and also avoid the local optima.

$$Minimum\ fitness\ (Q)\ s.t\ y_j \in \left[Lower\ bound_j, Upper\ bound_j\right]\ , j = 1,2.,3,..,n \quad (24)$$

Concentration of smell in the Melon fly optimization is the reciprocal of the objective function $fitness\ (Q)$; $Q = (q_1, q_2, .., q_n)$ is the vector of the melon flies.

Parameters are initialized then the preliminary location of the swarm is defined by,

$$\begin{cases} Q_{initial} = Lower\ bound + (Upper\ bound - Lower\ bound) * \text{arbitrary ( )} \\ P_{initial} = Lower\ bound + (Upper\ bound - Lower\ bound) * \text{arbitrary ( )} \end{cases} \quad (25)$$

By the property of smell Melon fly explore the food and it will share the information with co- melon flies. New-fangled location of the Melon fly is engendered by,

$$\begin{cases} Q_i = Q_{initial} + \text{arbitrary ( )} \\ P_i = P_{initial} + \text{arbitrary ( )} \end{cases} \quad (26)$$

Distance is computed from the preliminary location

$$Distance_i = \sqrt{Q_i^2 + P_i^2} \quad (27)$$

Judgment value (Jv_i) of the smell concentration in Melon fly is reciprocal of the distance. Smell concentration ($smell\ \text{concentration}_i$) is obtained by,

$$\begin{cases} Jv_i = 1/Distance_i \\ smell\ \text{concentration}_i = fitness(J_i) \end{cases} \quad (28)$$

Pick the minimum smell concentration value from melon flies and movement with respect to location defined by,

$$\begin{cases} [\,Top\ smell, Top\ index] = Minimum\ (smell) \\ \begin{cases} Q_{initial} = Q(Top\ index) \\ P_{initial} = P(Top\ index) \end{cases} \end{cases} \quad (29)$$

Searching the food in several directions in the early stages and sometimes melon fly may move away from the food source, (scattering in the plane) and it defined by,

$$\begin{cases} \begin{cases} Q_{initial} = \text{arbitrary}(domain) \\ P_{initial} = \text{arbitrary}(domain) \end{cases} \\ Location_{initial\ stage} = \begin{cases} \sqrt{Q_i^2 + P_i^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} > 0 \\ -\sqrt{Q_i^2 + P_i^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} < 0 \end{cases} \\ Top\ smell_{\ initial\ stage} = Fitness\left(Location_{initial\ stage}\right) \end{cases} \quad (30)$$

In beginning phase the food source may be small,

$$\begin{cases} \begin{cases} Q_t(i) = Q_{initial}(i) + \omega_Q(i) \cdot \text{arbitrary}(\,) \\ P_t(i) = P_{initial}(i) + \omega_P(i) \cdot \text{arbitrary}\ (\,) \end{cases} \\ Location_t = \begin{cases} \sqrt{Q_t^2 + P_t^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} > 0 \\ -\sqrt{Y_t^2 + Z_t^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} < 0 \end{cases} \end{cases} \quad (31)$$

Then the t_{th} iterations steps are $step_Q^t\ and\ step_P^t$, then

$$step_Q^t(i) = Q_t(i) - Q_{t-1}(i)(i = 1,2,..,N) \quad (32)$$

Small steps $\left(small_{steps}\right)$ and large steps $\left(large_{steps}\right)$ are recorded in N- dimensional plane

$$\omega_t(i) = \left(large_{steps_t}(i) - small_{steps_t}(i)\right) * \left[e^{\frac{step_{t-1}-(i)-small_{steps_t}(i)}{large_{steps_t}(i)-small_{steps_t}(i)}-1}\right] + small_{steps_t}(i) \quad (33)$$

A normal distribution [42-46] is utilized to augment the spread of ω_t,

$$f(q) = \frac{1}{\sqrt{2\pi}}\ exp(-(q - \omega_t)^2) \quad (34)$$

Gradient compressed progressively by,

$$Gradient_t(i) = \frac{Number\ of\ Melon\ flies * \|Q_t(i) - Q_{t-1}(i)\|}{\sum_i \|Q_t(i)\|} \quad (35)$$

Sub swarm (SS) is described as,

$$SS(i) = \frac{Gradient(i)}{\sum_i Gradient(i)} \quad (36)$$

After the completion of definite number of iterations' the melon fly will not fly arbitrarily with the obtained memory so a memory move or progress direction has been applied in the algorithm.

$$Memory\ step_t = Q_t - Q_{t-1} \quad (37)$$

Then the exploration process is given by,

$$\begin{cases} Q_{t+1} = Q_t + \lambda \cdot Memory\ step_t \cdot \text{arbitrary}\ (\,) \\ P_{t+1} = P_t + \lambda \cdot Memory\ step_t \cdot \text{arbitrary}\ (\,) \end{cases} (38)$$

$$\lambda = \lambda_{maximum} \cdot exp\left(log\left(\frac{\lambda_{minimum}}{\lambda_{maximum}}\right) \cdot \frac{t}{t_{maximum}}\right) 39)$$

Previous to iteration(φ), the Melon flies will go for collaborative exploration and when iteration number reached the φ then Memory move or progress direction will be turned on.

$$f(q) = \begin{cases} 0 & q < \varphi \\ \left\lceil Memory \cdot 2 \cdot \left(\frac{1}{1+e^{-\frac{y-\varphi}{\varphi}}} - \frac{1}{2}\right)\right\rceil & q \geq \varphi \end{cases} \quad (40)$$

Begin
Parameters are initialized
Swarm location initialized by

$$\begin{cases} \begin{cases} Q_{initial} = \text{arbitrary}(domain) \\ P_{initial} = \text{arbitrary}(domain) \end{cases} \\ Location_{initial\ stage} = \begin{cases} \sqrt{Q_i^2 + P_i^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} > 0 \\ -\sqrt{Q_i^2 + P_i^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} < 0 \end{cases} \\ Top\ smell\ _{initial\ stage} = Fitness\left(Location_{initial\ stage}\right) \end{cases}$$

Iteration =0

$$Top\ smell = Fitness\left(Jv_{initial\ stage}\right)$$

Repeat

$$while\ iteration < \varphi$$

$$step_Q^t(i) = Q_t(i) - Q_{t-1}(i)(i = 1,2,..,N)$$

$$\omega_t(i) = \left(large_{steps_t}(i) - small_{steps_t}(i)\right) * \left[e^{\frac{step_{t-1}-(i)-small_{steps_t}(i)}{large_{steps_t}(i)-small_{steps_t}(i)}-1}\right] + small_{steps_t}(i)$$

$$\begin{cases} \begin{cases} Q_t(i) = Q_{initial}(i) + \omega_Q(i) \cdot \text{arbitrary}(\,) \\ P_t(i) = P_{initial}(i) + \omega_P(i) \cdot \text{arbitrary}\,(\,) \end{cases} \\ Location_t = \begin{cases} \sqrt{Q_t^2 + P_t^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} > 0 \\ -\sqrt{Y_t^2 + Z_t^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} < 0 \end{cases} \end{cases}$$

$$[Top\ smell, Top\ index] = Fitness(Location_{iteration})$$
$$if\ Top\ smell < Top\ index\ then\ top\ smell = top\ index$$
$$Then\ Q_{initial} = Q(\ Top\ index)\ ; Q_{initial} = P(\ Top\ index)$$

End if

$$Gradient_t(i) = \frac{Number\ of\ Melon\ flies\ *\ \|Q_t(i) - Q_{t-1}(i)\|}{\sum_i \|Q_t(i)\|}$$

$$P(i) = \frac{Gradient(i)}{\sum_i Gradient(i)}$$

$$if\ \text{arbitrary} < SS(i)\ then\ Q(i) = \text{arbitrary}\ (domain)$$

End if
End

$$while\ iteration < \varphi$$

$$\begin{cases} \begin{cases} Q_{initial} = \text{arbitrary}(domain) \\ P_{initial} = \text{arbitrary}(domain) \end{cases} \\ Location_{initial\ stage} = \begin{cases} \sqrt{Q_i^2 + P_i^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} > 0 \\ -\sqrt{Q_i^2 + P_i^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} < 0 \end{cases} \\ Top\ smell\ _{initial\ stage} = Fitness\left(Location_{initial\ stage}\right) \end{cases}$$

$$Memory\ step_t = Q_t - Q_{t-1}$$
$$Q_t(i) = Q_{initial}(i) + \lambda \cdot Memory\ step_t \cdot \text{arbitrary}(\,)\ i = 1,2,3,..,f(y)$$
$$Q_t(i) = Q_{initial}(i) + \omega_y(i) \cdot \text{arbitrary}(\ )\ i = f(Q) + 1,..,N$$

$$Location_{initial\ stage} = \begin{cases} \sqrt{Q_i^2 + P_i^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} > 0 \\ -\sqrt{Q_i^2 + P_i^2} \text{ if } \mathrm{Q_i} + \mathrm{P_i} < 0 \end{cases}$$

$$\begin{cases} [\,Top\ smell, Top\ index] = Minimum\ (smell) \\ \begin{cases} Q_{initial} = Q(Top\ index) \\ P_{initial} = P(Top\ index) \end{cases} \end{cases}$$

End if

$$Gradient_t(i) = \frac{Number\ of\ Melon\ flies\ *\ \|Q_t(i) - Q_{t-1}(i)\|}{\sum_i \|Q_t(i)\|}$$

$$SS(i) = \frac{Gradient(i)}{\sum_i Gradient(i)}$$

$$if \text{ arbitrary} < SS(i)\ then\ Q(i) = \text{arbitrary } (domain)$$

End if
End
Until iteration = maximum generation
End

Spontaneous Process Algorithm

Process of nuclear reaction has been imitated to design Spontaneous Process Algorithm (SPA). In a preserved pot Exploration space is defined and it represents a nucleus which has mass number, charge, location, potential and kinetic energy [11]. Order of operators induce the nucleus (quality of dissimilar condition of reaction) in order to keep away from the local optimum. In exploration space each nucleus signifies variable and solution. Population of i-th nucleus is created by following equation,

$$H_{i,d} = lower\ bound_d + \text{arbitrary} \cdot (upper\ bound_d - lowerbound_d) \quad (41)$$

Through nuclear fusion neutrons in heated state is produced,

$$neutron \text{ heated state i} - \text{th}(he_i) = \frac{(i{-}th\ nucleus(H_i) + j{-}th\ nucleus(H_j))}{2} \quad (42)$$

Secondary Fission advocates the discrepancy between existing solution and neutron in heated state to compose in same range. Once $\text{arbitrary} \leq probability\ of\ \beta \text{ decay}$ then the development process of Secondary fission, is defined by

$$H_i^{fission} = Gaussian(H_{best}, \sigma_1) + (\text{arbitrary}\ n \cdot H_{best} - Mutation\ factor\ (MF) \cdot he_i) \quad (43)$$

$$\sigma_1 = \left(\frac{\log(existing\ generation)}{existing\ generation}\right) \cdot |H_i - H_{best}| \quad (44)$$

$$MF = round(\text{arbitrary} + 1) \quad (45)$$

Prime fission is formed by,

$$H_i^{fission} = Gaussian(H_i, \sigma_2) + (\text{arbitrary}\ n \cdot H_{best} - Mutation\ factor \cdot he_i) \quad (46)$$

$$\sigma_2 = \left(\frac{\log(existing\ generation)}{existing\ generation}\right) \cdot \left|H_{\text{arbitrary}} - H_{best}\right| \quad (47)$$

$$MF = round(\text{arbitrary} + 2) \quad (48)$$

Gaussian walk described as,

$$H_i^{fission} = gaussian\ (H_i \cdot \sigma_2) \quad (49)$$

With respect to fitness values various types of nucleus are categorized in appropriate mode in the ionization section. Through uniform distribution probability (Py_i) i-th nucleus defined as,

$$Py_i = \frac{Level\left(fitness\ Y_i^{fitness}\right)}{entire\ number\ of\ nuclei} \quad (50)$$

$\mathrm{d-th\ variable}\ ionization\ \ H_i^{fitness}$ described as,

$$H_{i,d}^{ion} = H_{r1,d}^{fitness} + \ \mathrm{arbitrary} \cdot \left(H_{r2,d}^{fitness} - H_{i,d}^{fitness}\right), \mathrm{arbitrary} \le 0.50 \quad (51)$$

$$H_{i,d}^{ion} = H_{r1,d}^{fitness} - \ \mathrm{arbitrary} \cdot \left(H_{r2,d}^{fitness} - H_{i,d}^{fitness}\right), \mathrm{arbitrary} > 0.50 \quad (52)$$

Slender disturbance in $H_{r1,d}^{fitness}$ is included to improve the exploitation as shown below,

$$H_{i,d}^{ion} = H_{i,d}^{fitness} + round\ (\mathrm{arbitrary}) \cdot \left(H_{worst,d}^{fitness} - H_{best,d}^{fitness}\right) \quad (53)$$

i-th ion probability value found by,

$$py_i = \frac{level\left(fitnessY_i^{ion}\right)}{whole\ \ nuclei} \quad (54)$$

Exploration is enhanced by various operators and it replicates the collision and fusion;

$$H_i^{fusion} = H_i^{ion} + \mathrm{arbitrary}\ \cdot \left(H_{r1}^{ion} - H_{best}^{ion}\right) + \mathrm{arbitrary}\ \cdot \left(H_{r2}^{ion} - H_{best}^{ion}\right) - e^{-normal\left(H_{r1}^{ion} - H_{r2}^{ion}\right)} . \left(H_{r1}^{ion} - H_{r2}^{ion}\right) \quad (55)$$

Velocity will be decreased whenever fusion does not happened with reference to Coulomb force [47-50] and it defined as,

$$H_i^{fusion} = H_i^{ion} - 0.50 \cdot \left(sin(2\pi.frequency \cdot g + \pi) \cdot \frac{maximum\ generation - existing\ generation}{maximum\ generation} + 1\right) . \left(H_{r1}^{ion} - H_{r2}^{ion}\right) \mathrm{arbitrary} > 0.50 \quad (56)$$

$$H_i^{fusion} = H_i^{ion} - 0.50 \cdot \left(sin(2\pi.frequency \cdot g + \pi) \cdot \frac{existing\ generation}{maximum\ generation} + 1\right) . \left(H_{r1}^{ion} - H_{r2}^{ion}\right) \mathrm{arbitrary} \le 0.50 \quad (57)$$

Levy flight is a rank of non-Gaussian random procedure [42-46] and allocation by *L(s)* ~ $|s|^{-1-\beta}$ where $0 < \beta < 2$ is an index. Scientifically defined as,

$$Ly(s, \gamma, \mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} \quad exp\left[-\frac{\gamma}{2(s-\mu)}\right] \frac{1}{(s-\mu)^{3/2}} & if\ 0 \ < \mu < s < \infty \\ 0 \quad if\ s \le 0 & \end{cases} \quad (58)$$

$$Fy(k) = exp\left[-\alpha |k|^{\beta}\right], 0 < \beta \le 2, \quad (59)$$

$$sy = \frac{u}{|v|^{\frac{1}{\beta}}} \quad (29)$$

$$H^{t+1} = H^t + \mathrm{arbitrary}\big(size(D)\big) \oplus Levy(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}} \left(H_j^t - gb\right) \quad (60)$$

Where H_j^t is the H^t solution vector at iteration "t", "u" is an arbitrary parameter which kowtow to a uniform distribution, ⊕ is the dot product for entry wise multiplications. And it takes three values 1, 0, and -1. And in Equation (60) the combination is to say, to get rid of local minima and perk up global search ability are guaranteed by means of this combination.

$$u \sim N(0, \sigma_u^2) \quad v \sim N(0, \sigma_v^2) \quad (61)$$

$$\sigma_u = \left\{\frac{\Gamma(1+\beta) sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\right\}^{1/\beta}, \sigma_v = 1 \quad (62)$$

$$Levy(H) = 0.01 \times \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}} \quad (63)$$

$$H_{i,d}^{ion} = H_{i,d}^{Fission} + (\alpha \oplus Levy\ (\beta))_d \cdot \left(H_{i,d}^{fission} - H_{best,d}^{fission}\right) \quad (64)$$

$$H_{i,d}^{ion} = H_{i,d}^{Fission} + (\alpha \oplus Levy\ (\beta))_d \cdot (upper\ bound_d - lowerbound_d) \quad (65)$$

$$H_i^{fusion} = H_i^{ion} + (\alpha \oplus Levy\ (\beta)) \oplus \cdot \left(H_i^{ion} - H_{best}^{ion}\right) \quad (66)$$

Periphery management done by,

$$H_{i,d} = lowerbound_d + \text{arbitrary } \cdot (upper\ bound_d - lowerbound_d) \quad (67)$$

a. Begin
b. Creation of Population by $H_{i,d} = lower\ bound_d + \text{arbitrary} \cdot (upper\ bound_d - lowerbound_d)$
c. Fitness function of the population is created by
d. While $(existing\ generation < maximum\ iteration)\ do$
e. existing generation = existing generation+1
f. $For\ i = 1\ to\ N\ do$
g. Computation of neutron in heated status is done by

$$neutron \text{ heated state i} - \text{th}(he_i) = \frac{\left(i - th\ nucleus(H_i) + j - th\ nucleus(H_j)\right)}{2}$$

h. Population updated by

$$H_i^{fission} = Gaussian(H_{best}, \sigma_1) + (\text{arbitrary}\ n \cdot H_{best} - Mutation\ factor\ (MF) \cdot he_i)$$

$$\sigma_1 = \left(\frac{\log(existing\ generation)}{existing\ generation}\right) \cdot |H_i - H_{best}|$$

$$MF = round(\text{arbitrary} + 1)$$

i. Fitness value is calculated for $H_i^{fitness}$, then frontier conditions are verified
j. $H_i^{fitness}\ and\ H_i^{generation}\ are\ updated$
k. Computed $Probability_i = \frac{level\left(fitness\ H_i^{fitness}\right)}{entire\ \ nuclei}$
l. $For\ i = 1\ to\ N\ do$
m. $For\ d = 1\ to\ N\ do$
n. levy flight applied by
o. $H_{i,d}^{ion} = H_{i,d}^{Fission} + (\alpha \oplus Levy\ (\beta))_d \cdot \left(H_{i,d}^{fission} - H_{best,d}^{fission}\right)$
p. $H_{i,d}^{ion} = H_{i,d}^{Fission} + (\alpha \oplus Levy\ (\beta))_d \cdot (upper\ bound_d - lowerbound_d)$
q. $H_i^{fusion} = H_i^{ion} + (\alpha \oplus Levy\ (\beta)) \oplus \cdot \left(H_i^{ion} - H_{best}^{ion}\right)$
r. Updating of Ion states is done through,

$$H_{i,d}^{ion} = H_{r1,d}^{fitness} + \text{ arbitrary} \cdot \left(H_{r2,d}^{fitness} - H_{i,d}^{fitness}\right), \text{arbitrary} \leq 0.50$$

$$H_{i,d}^{ion} = H_{r1,d}^{fitness} - \text{ arbitrary} \cdot \left(H_{r2,d}^{fitness} - H_{i,d}^{fitness}\right), \text{arbitrary} > 0.50$$

s. Slender disturbance in $\mathrm{Y}_{\mathrm{r1,d}}^{\mathrm{fitness}}$ is included to improve the exploitation as shown below,

$$H_{i,d}^{ion} = H_{i,d}^{fitness} + round\ (\text{arbitrary}) \cdot \left(H_{worst,d}^{fitness} - H_{best,d}^{fitness}\right)$$

t. End for
u. fitness value of H_i^{ion} compute the calculated and frontier conditions are verified
v. $H_i^{fitness} and\ H_i^{ion}$ are updated
w. End for
x. calculate probability

$$py_i = \frac{level\left(fitnessH_i^{ion}\right)}{entire\ nuclei}$$

y. $For\ i = 1\ to\ N\ do$
z. levy flight applied by

$$H_i^{fusion} = H_i^{ion} + (\alpha \oplus Levy\ (\beta)) \oplus \cdot \left(H_i^{ion} - H_{best}^{ion}\right)$$

aa. population of fusion updated by,

$$H_i^{fusion} = H_i^{ion} + \text{arbitrary } \cdot \left(H_{r1}^{ion} - H_{best}^{ion}\right) + \text{arbitrary } \cdot \left(H_{r2}^{ion} - H_{best}^{ion}\right) - e^{-normal\left(H_{r1}^{ion} - H_{r2}^{ion}\right)} . \left(H_{r1}^{ion} - H_{r2}^{ion}\right)$$

$$H_i^{fusion} = H_i^{ion} - 0.50 \cdot \left(sin(2\pi. frequency \cdot g + \pi) \cdot \frac{maximum\ generation - existing\ generation}{maximum\ generation} + 1 \right). \left(H_{r1}^{ion} - H_{r2}^{ion} \right) \text{arbitrary} > 0.50$$

$$H_i^{fusion} = H_i^{ion} - 0.50 \cdot \left(sin(2\pi. frequency \cdot g + \pi) \cdot \frac{existing\ generation}{maximum\ generation} + 1 \right). \left(H_{r1}^{ion} - H_{r2}^{ion} \right) \text{arbitrary} \leq 0.50$$

bb. fitness value of H_i^{fusion} compute the calculated and frontier conditions are verified
cc. $H_i^{fusion} and\ H_i^{ion}$ are updated
dd. End while
ee. Output; most excellent solution

RESULTS

With considering L – index Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) evaluated in IEEE 30 bus system [21]. Table 1 shows the optimized values. Tables 2 to 4 give the comparison of parameters. Figure 1 shows the real power loss comparison. Figures 2 and 3 show the voltage deviation and stability index. Figure 4 shows the power loss evaluation and Figure 5 shows the convergence characteristics

Table 1. Optimal solutions of the proposed algorithms

Parameter	Real Power loss (MFO)	Real Power loss (SPA)	Voltage Deviation (MFO)	Voltage Deviation (SPA)	Voltage Stability Index (MFO)	Voltage Stability Index (SPA)
VG1	1.1002	1.1003	1.0056	1.0057	1.0804	1.0801
VG2	1.0953	1.0952	1.0014	1.0013	1.0532	1.0530
VG5	1.0753	1.0751	1.0170	1.0173	1.0731	1.0730
VG8	1.0762	1.0753	1.0125	1.0127	1.0089	1.0086
VG11	1.0870	1.0872	1.0323	1.0324	1.0800	1.0803
VG13	1.0990	1.0991	1.0234	1.0230	1.0855	1.0857
T1	1.0500	1.0501	1.0500	1.0500	0.9000	0.9000
T2	0.9200	0.9201	0.9000	0.9000	0.9000	0.9000
T3	1.0100	1.0102	1.0000	1.0001	0.9000	0.9000
T4	0.9800	0.9803	0.9700	0.9701	0.9000	0.9000
Qc1	5.0000	5.0000	4.0000	4.0000	5.0000	5.0000
Qc2	5.0000	5.0000	2.0000	2.0000	5.0000	5.0000
Qc3	5.0000	5.0000	4.0000	4.0000	0.0000	0.0000
Qc4	5.0000	5.0000	3.0000	3.0000	0.0000	0.0000
Qc5	3.0000	3.0000	5.0000	5.0000	5.0000	5.0000
Qc6	5.0000	5.0000	3.0000	3.0000	3.0000	3.0000
Qc7	3.0000	3.0000	5.0000	5.0000	5.0000	5.0000
Qc8	4.0000	4.0000	5.0000	5.0000	5.0000	5.0000
Qc9	2.0000	2.0000	3.0000	3.0000	1.0000	1.0000

Table 2. Comparison of total power loss for IEEE 30 bus system

Method	Power loss (MW)
Hybrid PSO-TS [14]	4.5213
TS [14]	4.6862
Basic PSO [14]	4.6862
ALO [15]	4.5900
QO-TLBO [15]	4.5594
TLBO [15]	4.5629
Standard GA [16]	4.9408
S.PSO [16]	4.9239
HAS [16]	4.9059
S-FS [17]	4.5777
IS-FS [17]	4.5142
SFS [19]	4.5275
MFO	4.5082
SPA	4.5094

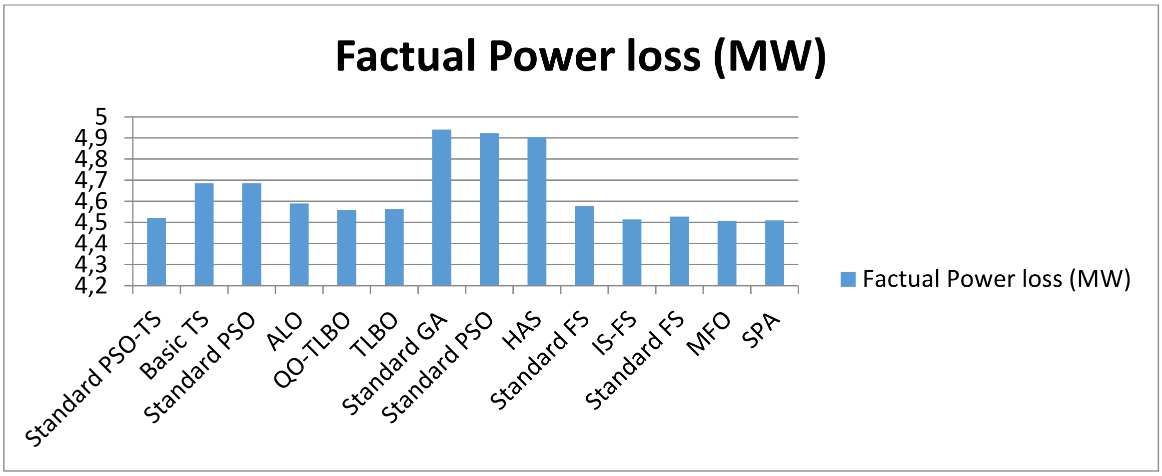

Figure 1. Comparison of real power loss

Table 3. Comparison of voltage deviation for IEEE 30 bus system.

Method	Voltage deviation (PU)
BPSO-TVIW [18]	0.1038
BPSO-TVAC [18]	0.2064
SPSO-TVAC [18]	0.1354
BPSO-CF [18]	0.1287
PG-PSO [18]	0.1202
SWT-PSO [18]	0.1614
PGSWT-PSO [18]	0.1539
MPG-PSO [18]	0.0892
QO-TLBO [15]	0.0856
TLBO [15]	0.0913
S-FS [17]	0.1220
ISFS [17]	0.0890
SFS [19]	0.0877
MFO	0.0873
SPA	0.0870

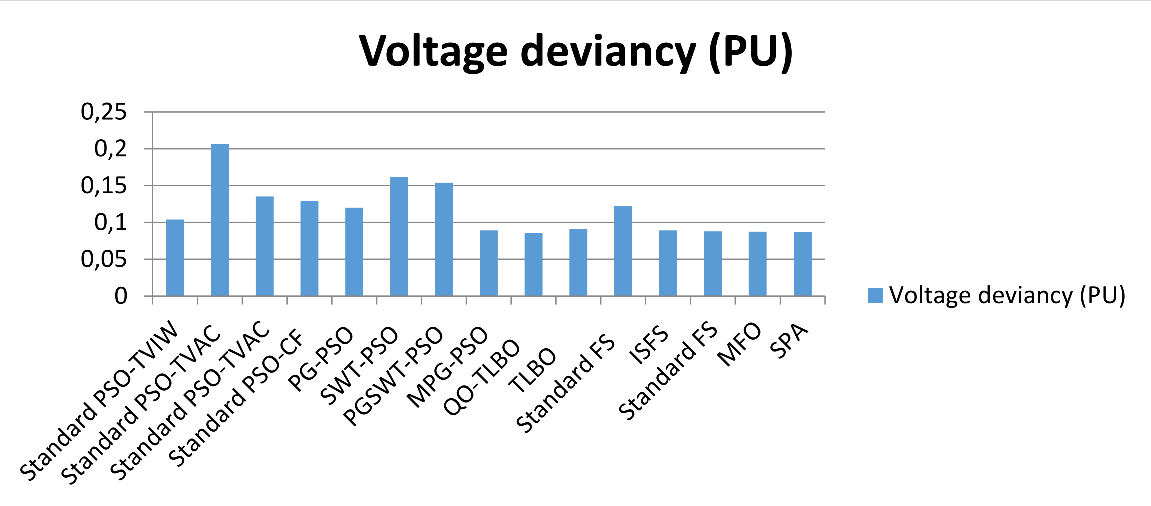

Figure 2. Comparison of Voltage deviation.

Table 4. Comparison of Voltage Stability Index for IEEE 30 bus system.

Method	L-index (PU)
BPSO-TVIW [18]	0.1258
BPSO-TVAC[18]	0.1499
SPSO-TVAC[18]	0.1271
BPSO-CF [18]	0.1261
PG-PSO [18]	0.1264
SWT-PSO [18]	0.1488
PGSW-PSO [18]	0.1394
MPG-PSO [18]	0.1241
QO-TLBO [15]	0.1191
TLBO [15]	0.1180
ALO[14]	0.1161
ABC [14]	0.1161
GWO [14]	0.1242
BA [14]	0.1252
S-FS [17]	0.1252
IS-FS [17]	0.1245
SFS [19]	0.1007
MFO	0.1006
SPA	0.1004

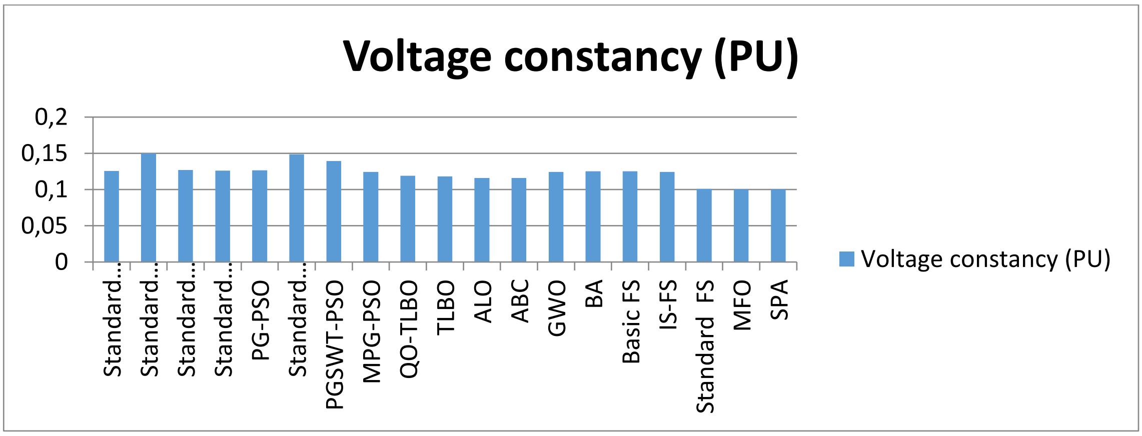

Figure 3. Comparison of voltage stability index

Then Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) verified in IEEE 30, bus system [51] without L-index. Comparisons of results are presented in Table 5. Comparison of loss has been done with other algorithms – particle swarm optimization (PSO), Modified PSO, Evolutionary programming, self -adaptive real coded genetic algorithm. Projected algorithms very effectively reduced the power loss. Percentage of real power loss reduction has been improved.

Table 5. Loss comparison with reference to IEEE −30 system

Parameter	Base case value [25]	Modified Particle swarm optimization [25]	Standard - Particle swarm optimization [23]	Evolutionary Programming [24]	self-adaptive real coded Genetic algorithm [22]	MFO
Percentage of Reduction in real Power loss	0.0000	8.4000	7.4000	6.6000	8.3000	8.85
Real Power Loss in MW	17.5500	16.0700	16.2500	16.3800	16.0900	15.9

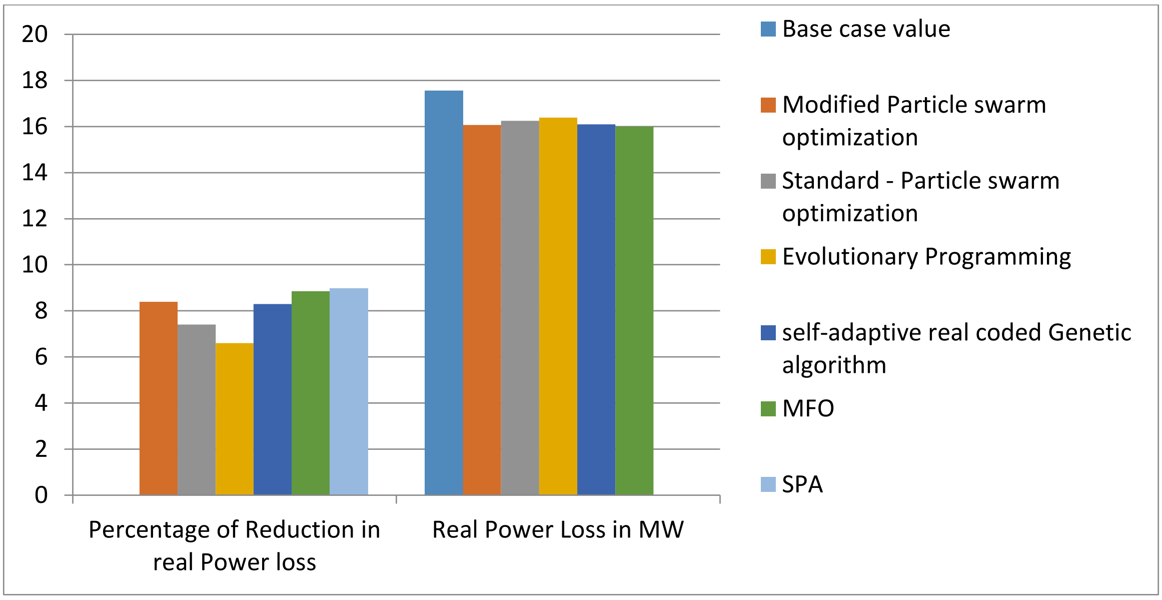

Figure 4. Comparison of Real Power Loss between methodologies (Tested in IEEE 30 bus system)

Table 6 shows the convergence characteristics of the proposed Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA).

Table 6. Convergence characteristics.

IEEE 30 Bus system	Real power Loss in MW(With L-index)	Real power Loss in MW (without L-index)	Time in Sec (with L-index)	Time in sec (without L-index)	Number of iterations (with L-index)	Number of iterations (without L-index)
MFO	4.5082	15.996	18.64	14.80	26	23
SPA	4.5094	15.971	18.69	14.82	28	21

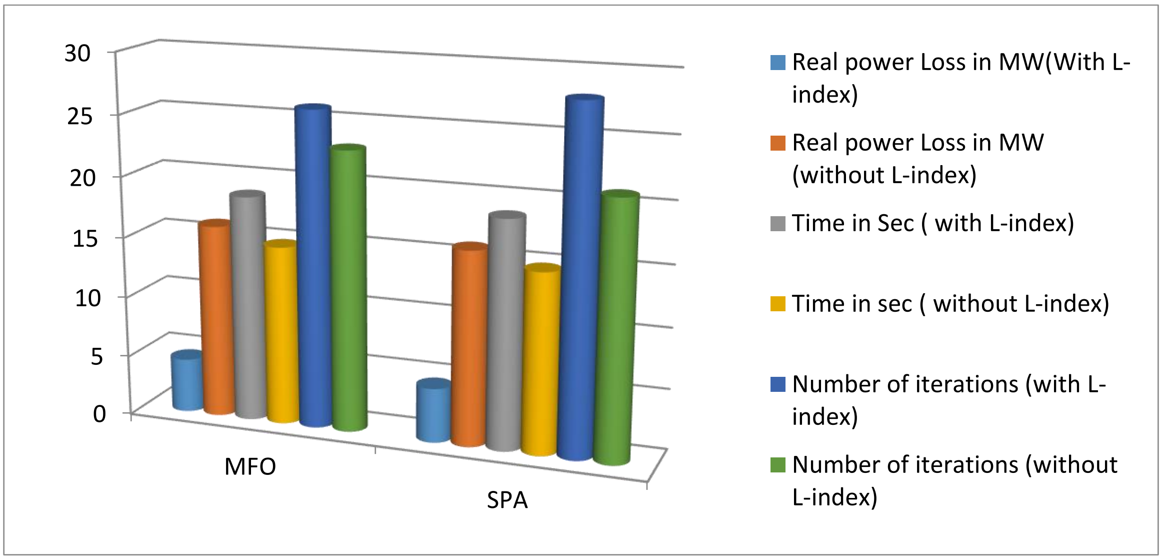

Figure 5. Convergence characteristics of MFO and SPA.

DISCUSSION

Both Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) reduced the power loss efficiently. Voltage stability augmentation with voltage deviation minimization has been achieved. Comparison of results are done with Hybrid PSO-Tabu search, Ant lion, quasi-oppositional teaching learning based, improved stochastic fractal search optimization algorithm, harmony search, improved pseudo-gradient search particle swarm optimization and cuckoo search algorithm.

CONCLUSION

Key aim of this paper is real power loss reduction with voltage stability enhancement. Voltage deviation minimization is additional objective of the paper. Both Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) reduced the power loss effectively. In MFO, after the completion of specific number of iterations' the melon fly will not fly capriciously with the acquired memory, so a memory shift or advancement direction has been applied in the MFO algorithm. In SPA approach with respect to fitness values different types of nucleus are classified in pertinent mode in the ionization section. With considering L - index Proposed Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) evaluated in IEEE 30, bus system with and without considering voltage stability enhancement index. Comparison of simulation results done with Hybrid PSO-Tabu search (PSO-TS), Ant lion (ALO), quasi-oppositional teaching learning based (QOTBO), improved stochastic fractal search optimization algorithm (ISFS), harmony search (HS), improved pseudo-gradient search particle swarm optimization and cuckoo search algorithm. Then for without considering voltage stability the comparison done with particle swarm optimization (PSO), Modified PSO, Evolutionary programming, self - adaptive real coded genetic algorithm. Projected algorithms very effectively reduced the power loss. Percentage of real power loss reduction has been improved. In MFO Real power Loss in MW (With L-index) value obtained is 4.5082 and value of Real power Loss in MW (without L-index) is 15.996. Time (S) required for reaching the solution (with L-index) is 18.64and Time (s) for (without L-index) is14.80. Then number of iterations (with L-index) is 26 and number of iterations (without L-index) is 23. In SPA Real power Loss in MW (With L-index) value obtained is 4.5094 and value of Real power Loss in MW (without L-index) is 15.971. Time (S) required for reaching the solution (with L-index) is 18.69and Time (s) for (without L-index) is 14.82. Then number of iterations (with L-index) is 28 and number of iterations (without L-index) is 21. Percentage of the power loss reduction for MFO is 8.85% and for SPA is 8.99%. So it's well understood that both Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) performed well with respect to the given power loss reduction problem.

Scope of future work

In future Both the Melon Fly Optimization (MFO) Algorithm and Spontaneous Process Algorithm (SPA) can be applied to large system (IEEE 300 bus system). Then sequentially it can be applied to practical systems. Further the algorithms can be enhanced and applied to other power system optimization problems (Real and reactive power dispatch problem, Economic dispatch problem and Unit commitment problem).

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