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Optimal Reactive Power Dispatch Using Moth-Flame Optimization Algorithm

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Abstract

This paper describes a newly developed Moth-Flame optimization algorithm to deal with optimal reactive power dispatch problem. The prime intention of reactive power dispatch problem is to curtail the real power loss and control the bus voltages in power system network. The Moth-Flame algorithm is one of the most powerful and robust new global optimization algorithms in engineering. The primary aim of this advanced algorithm is quick convergence rate owing to the roulette wheel election method. This algorithm deals with numerous nonconvex, non-linear, continuous & discrete variable reactive power optimization problems. The Moth-Flame optimization is established by flow of moths in the direction from source to flame. This optimization algorithm employs a standard IEEE-30 bus & 57 bus system to attain the optimal settings of regulating variables from reactive power compensating components. As a result of the regulating variables, the prime intentions for system network can be achieved. The outcome solutions and results are notable in comparison with other well-known algorithms reported in journals.

Keywords: Optimal reactive power dispatch, Moth-Flame optimization algorithm, curtailing the real power loss in transmission lines, controlling the bus voltages in system network.

INTRODUCTION

The optimal power flow and reactive power dispatch are the two major optimization problems in large scale power system network [1-2]. These two major optimization problems are interrelated with respect to the system operation & control in existing power system and restructured electric power system network. The first optimization problem (OPF) is related to regulation of the real power output from the generator, aimed to cut down the fuel cost by satisfying the set of specified operational constraints. The second ORPD optimization problem is related to curtailing the total real power losses in transmission lines and controlling all the bus voltages by satisfying the set of specified operational constraints. Hence, the solution and outcome results of these two optimization problems are necessary for efficient, economical operation and for controlling the system parameters during load variation in large scale power system network. In economical and optimal operation, the system operator's prime intention of reactive power supplies are: (i) Controlling the specified voltage limits in all the buses (ii) maintaining the real power flow limits in transmission lines (iii) Curtailing the total real power loss in transmission lines. Also, the system stability, reliability, quality of power supply and network security are completely dependent on reactive power supply in system network during the load variation and contingency occurs conditions. Therefore, the reactive power supply is assured in large scale power system for healthy operation. In this paper, the reactive power optimization problems for optimal solutions are discussed.

The ORPD problem is a huge constrained, nonlinear, non-convex and global optimization problem in vast power system network. In practical terms, the reactive power dispatch problem may be formulated under typical conditions from reactive power components. The reactive power components such as generator output voltages (continuous variable), regulating transformers and switchable VAR compensating devices (discrete variable) are considered for formulating the reactive power optimization problems. To simulate suitable optimization algorithm techniques in reactive power dispatch problem, the optimal variables can be determined from reactive power components. Hence, the system operators can achieve the prime intentions by setting these control variables in system network.

In the past three decades, researchers and scholars have been engaged in several debates on reactive power optimization algorithm for realizing satisfactory solutions in ORPD problems. So far, the developed optimization algorithms are mainly classified into deterministic & stochastic. The deterministic algorithms include linear & non-linear programming method [3], quadratic programming method [4-5], Interior point method [6], and Newton's method[7] etc…, These algorithms are unsuitable in large scale power system due to equality & inequality constraints in handling, discrete variables, seeking global optimum, suffering convergence and dimensionality in non-linear, nonconvex, mixed integer and a wide range of formulated global optimization problems. Therefore, the new stochastic algorithms are advanced to overcome the optimization problems.

As a result of high flexibility and simplicity, the mathematical derivation model is not mandatory for making numerous random solutions and for raising the solutions during optimization. These stochastic optimization algorithms are popular for their role in realizing the global optimization problem. A few new and popular stochastic algorithm sub-branches which already applied for ORPD problems are: (i) evolutionary techniques such as genetic algorithm [8-9], biogeography-based optimization algorithm [10], differential evolution and evolution strategy [11-17] developed from evolutionary phenomena. (ii) Swarm access techniques such as particle swarm optimization [18-19], Ant colony optimization [20], and Artificial bee colony algorithm [21-23] are developed from creation of collective behavior. (iii) Gravitational search algorithm [24-25], black hole [26], and colliding bodies optimization algorithm [27] are developed from physical rules, and the teaching-learning based optimization algorithm [28] is developed from human imitation. Even though the above algorithms have been reported in large number of publications and their applications in science & industry are common, the No-free-Lunch theorem is motivate to realize moth-flame optimization algorithm. As stated in No-Free-Lunch theorem, all optimization algorithms do not realize all the available optimization problems, whereas the algorithm proposed here attempts to solve a vast range of optimization problems.

The MFA has many advantages & it is dissimilar from other population based meta heuristic algorithms. These differences effect the MFA more powerful. These are revealed in detail in [29]. It has been tested on 19 different level benchmark functions & correlated with other meta heuristic algorithm. The moth-flame optimization algorithm results have been found to be superior solutions by comparing them with the algorithm realized for reactive power dispatch problems in literature.

This paper presents the objective function and ORPD problem in section II, the Moth-Flame optimization algorithm in section III, the Moth-Flame algorithm fulfillment in section IV and the test system descriptions and discussions in section V. Finally, the conclusion is given in section VI.

FORMATION OF OPTIMAL REACTIVE POWER DISPATCH PROBLEM

The optimization of reactive power dispatch problem could be systematized in large scale power system network by

Minimize $F(x,u) = P_L(x, u)$

Subject to $G(x,u) = 0$ and $H(x,u) \leq 0$

Where 'F' is the prime intention that losses in transmission lines. $G(x,u) = 0$, illustrates the equality constraints for real power & reactive power flow equation in system network and $H(x,u) \leq 0$, illustrates the inequality constraints for power flow limits in transmission lines and system parameters in another security limits. In practical cases, 'x' & 'u' stand for vector of dependent variables and control variables respectively.

ie,.. $x = [P_{G1}, V_{L1} \ldots V_{Lnpq}, Q_{G1} \ldots Q_{Gnpv}]^T$

$u = [V_{G1}, \ldots V_{Gnpv}, Qc_1 \ldots Q_{Cnc}, T_1 \ldots T_{nt}]^T$ concerning the the dependent vector variables are voltage at slack bus generator P_G, voltage magnitude at load bus V_L and reactive power output at generator bus Q_G . Similarly vector of control variables consist of generator output voltage V_G , reactive power compensation output Qc and regulating transformer T. n_{pv}- stands for no. of generator buses, n_{pq}-stands for no. of load buses, n_c-stands for no. of compensating devices and n_t- stands for no. of regulating transformers.

A. Objective function

The prime intention of ORPD problem is the total real power loss which must curtailed in transmission lines. In practical, the ORPD problem may be formulated emblematic by

$$P_{Loss}(x,u) = \sum_{k=1}^{N_{TL}} G_{TL(i,j)} \left[V_i^2 + V_j^2 - 2V_iV_j \cos\theta_{ij} \right] --- (1)$$

Where P_{Loss} is real power loss; '$_{TL}$' is transmission line enclosed by bus 'i' and 'j'; N_{TL} is the No. of transmission lines; $G_{TL(i,j)}$ is conductance of transmission lines '$_{TL}$' enclosed by bus 'i' and 'j'; V_i is the voltage magnitude at bus 'i'; V_j is the voltage magnitude at bus 'j'; θ_{ij} is voltage angle difference between buses 'i' and 'j'

The point of the Constraints are illustrate by

The curtailment of the prime objective function equation (1) is organized to the number of equality and inequality constraints. These constraints are described like this

B. Equality constraints

The equilibrium constraints on state variables are given by

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij}\cos\theta_{ij} + B_{ij}\sin\theta_{ij}\right) = 0$$

$$\text{for } i = 1, \ldots\ldots, n_{pv} + n_{pq} ----(2)$$

$$Q_{Gi} - Q_{Di} + Q_{Ci} - V_i \sum_{j=1}^{N_B} V_j \left(G_{ij}\sin\theta_{ij} - B_{ij}\cos\theta_{ij}\right) = 0$$

$$\text{for } i = 1, \ldots \ldots, n_{pq} ------(3)$$

where, N_B - denotes the No. of buses, n_{pv} is No. of generator buses, and n_{pq} is No. of load buses, G_{ij}, B_{ij} are the mutual conductance and suceptance enclosed by bus 'i' and 'j'; P_{Gi}, Q_{Gi} are real & reactive power generation at bus 'i'; P_{Di}, Q_{Di} are real & reactive power load at bus 'i'; Q_{ci} is the VAR compensation source at bus 'i';

C. *Inequality constraints*

The inequality constraints on security bounds are access by

$$P_{Gslack}^{min} \le P_{Gslack} \le P_{Gslack}^{max} -----------(4)$$

$$V_i^{min} \le V_i \le V_i^{max} \text{ for } i = 1 \ldots \ldots \ldots . n_{pq} ----- (5)$$

$$Q_{Gi}^{min} \le Q_{Gi} \le Q_{Gi}^{max} \text{ for } i = 1 \ldots \ldots \ldots . n_g ----- (6)$$

$$S_l \le S_l^{max} - \text{for } l = 1 \ldots n_l -----------(7)$$

The inequality constraints on regulating variable bounds are access by

$$V_{Gi}^{min} \le V_{Gi} \le V_{Gi}^{max} \text{ for } i = 1, \ldots.., n_{pv} ----(8)$$

$$T_k^{min} \le T_k \le T_k^{max} \text{ for } i = 1, \ldots n_t ------(9)$$

$$Q_{Ci}^{min} \le Q_{Ci} \le Q_{Ci}^{max} n_c \text{ for } i = 1, \ldots . n_c ----(10)$$

where, 'n_{pv}' is No. of generator buses; 'n_t' is No. of regulating transformers; 'n_c' is No. of compensating devices; 'S_l' - denotes the apparent power flow limit in transmission line 'l';

Hence, the equation (1) is replaced by the following

Formation

$$F(x, u) = P_{Loss} + (P_{Gi,slack} - P_{Gi,slack}^{lim})^2 + \lambda V_i \sum_{i=1}^{N_{LB}} (V_i - V_i^{lim})^2$$

$$+ \lambda Q_{Gi} \sum_{i=1}^{N_{GB}} (Q_{Gi} - Q_{Gi}^{lim})^2 -------- (11)$$

Where λV_i, λQ_{Gi} are the penalty factors in equation (11). The λV_i, λQ_{Gi} values are taken from [35]. They are defined as follows:

$$V_i^{lim} = \begin{cases} V_i^{min} \text{ if } V_i < V_i^{min} \\ V_i^{max} \text{ if } V_i > V_i^{max} \end{cases}$$

$$Q_i^{lim} = \begin{cases} Q_{Gi}^{min} \text{ if } Q_{Gi} < Q_{Gi}^{min} \\ Q_{Gi}^{max} \text{ if } Q_{Gi} > Q_{Gi}^{max} \end{cases}$$

The power system intention function is computed by realizing load flow computation with the set of specified operational constraints stated above.

DESCRIPTION OF MOTH-FLAME ALGORITHM

The Moth-Flame optimization algorithm was refined by Seyedali Mirijali in 2015 [29] (http://www.alimirjalili.com/MFO.html.). The Moths are sumptuous insects that belong to butterfly families. There are 1, 60,000 different groups of insects in nature. They have two phases in their natural life. One phase is larvae and the other is adult phase. The larvae are transformed in to moth in swaddle.

In real life, the moths fly only at night. The moths find the moon light and begin to move. In view of this process, a moth will continue to fly by setting some angle in the direction of moon. This effective system creates linear path for moth to move long distance at night. Figure -1 shows an imaginary model of the moth's travel orientation. If the distance between moon and moth is vast, the above system guarantees the chance of the moth to move in linear path.

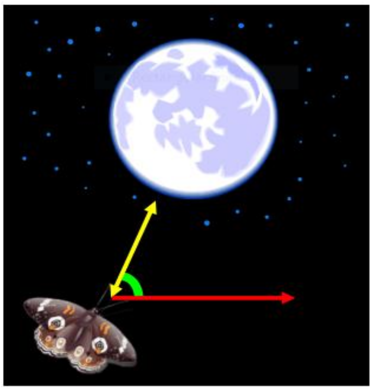

Figure 1: Transverse orientation [29]

Though the strength of travel orientation, we generally note that moths move spirally, encompassing the light. When moths observe an artificial light created by humans, they will move in linear path towards the light by setting some angle in the direction of light. Since such a flame or light is too close, the moths will flow in spiral path by maintaining the same angle to the flame or light source. Figure-2 shows the imaginary model of circular flying path encompassing close flame or light source. We may realize from figure -2, the moth finally converges close to the flame or light source. This is formulated mathematically to arrive at an optimizer termed, Moth-Flame Optimization algorithm.

(A). MATHEMATICAL MODELLING FOR MFO ALGORITHM

In the intended Moth-Flame algorithm, it is assumed that the moths are the candidate for solution & the dispute variables are assumed for moth's position in the searching area. So, the moths will flow in 1-D,2-D,3-D or the moth's vector position will change in dimensional searching area. The MFO algorithm is considered like population based and in matrix form the moths set are revealed like in equation (12),

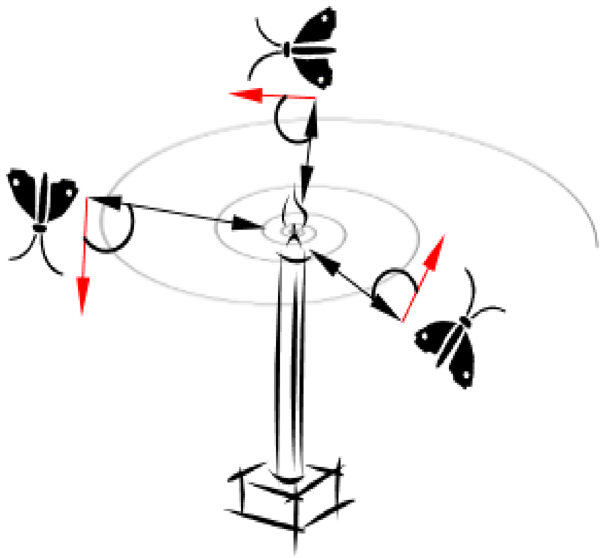

Figure 2: Spiral flying path around close light sources.[29]

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & \cdots & m_{1,d} \\ m_{2,1} & m_{2,2} & \cdots & \cdots & m_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ m_{n,1} & m_{n,2} & \cdots & \cdots & m_{n,d} \end{bmatrix} \quad ---- (12)$$

Where 'n' denotes the No. of moths &'d' denotes the No. of variables (dimensions)

Also, we assume that for the set of moths, there is lineup for saving the interrelated fitness values like in equation (13)

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ \vdots \\ OM_n \end{bmatrix} \quad ---- (13)$$

Where 'n' is the set of moths.

The flames are assumed to be the other key components in this algorithm and this matrix is like moth matrix in equation (14)

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \cdots & \cdots & F_{1,d} \\ F_{2,1} & F_{2,2} & \cdots & \cdots & F_{2,d} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ F_{n,1} & m_{n,2} & \cdots & \cdots & F_{n,d} \end{bmatrix} \quad ---- (14)$$

Where 'n' denotes the No. of moths and 'd' denotes the No. of variables (dimension). From equation (14) ,The M & F lineup are equal dimensions. The flames also assumed like moths, there is lineup for saving the interrelated fitness values like in equation (15)

$$OF = \begin{bmatrix} OF_1 \\ OF_2 \\ \vdots \\ OF_n \end{bmatrix} \quad ---- (15)$$

Where 'n' denotes the No. of moths. From equation (12) to (15) realize that the moths & flames are the solutions. The dissension between moth and flames are updated by every iteration. The real search agents are the moths and they will flow encompassing the search area by considering lights in the finest spot to the moths that have realized so far. Consquently, every moth inspects the light and updates its aim, determining a greater position, With this system, a moth always finds the best solution.

The MFO algorithm has three-columns that proximate the global solutions of the optimization problems and is specified as follows

MFO = (I, P, T)---(16)

'I' denotes the function that develops a desultory population of moths & interrelated trim values. The systematic imitation of this activity is as follows:

I:θ → { M,OM }--(17)

The 'P' denotes the prime function, the moths flow around the searching area. This function acquired the matrix of M and recurrence is updated finally.

P: M → M---(18)

If the ending measure is satisfied, the 'T' activity returns true and false if the ending measure is not fulfilled.

$$T:M \rightarrow \{ \text{true, false} \} \quad (19)$$

In favor of mathematical imitation for this nature, every moth's position is updated in the direction of flame or light realizing the following equation

$$M_i = S (M_i, F_j) \quad (20)$$

Where 'M_i' denotes the i^{th} moth, F_j denotes the j^{th} flame & 'S' denotes the spiral function.

In view of the moth's updating position in this system, logarithmic spiral is selected based on the subsequent conditions:

(i). Spiral's origin dot should come from the moth.

(ii) Spiral's end point should be the flame's position

(iii) The variation of limits for spiral should be within the

Searching area.

Considering the above points, The MFO algorithm's logarithmic spiral is given below:

$$S(M_i, F_j) = D_i \cdot e^{bt} . \cos (2\pi t) + F_j \quad (21)$$

where 'D_i' denotes the gap between i^{th} moth to j^{th} flame, 'b' denotes the constant for logarithmic spiral format and 't' denotes a desultory No. in [-1, 1].

D_i is computed as follows;

$$D_i = | F_j - M_i | \quad (22)$$

where M_i denotes the i^{th} moth, F_j denotes the j^{th} flame & D_i denotes the gap between i^{th} moth to j^{th} flame.

Figure -3 shows logarithmic spiral, space encompassing the flame & considering the different 't' position on the curvature.

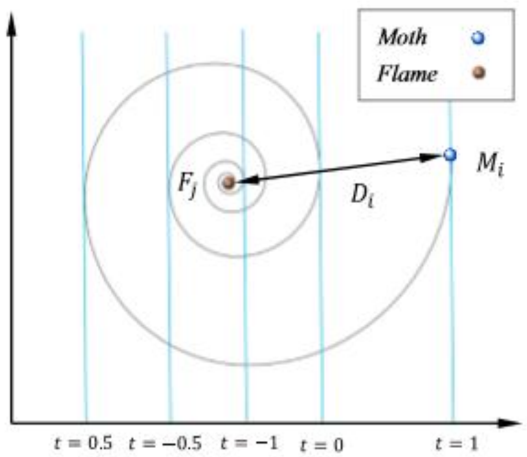

Figure 3: Logarithmic spiral, space encompassing the flame & considering the different 't' position on the curvature [29]

Figure-4 shows an imaginary model of the moth's updating position encompassing a flame. The following points are concluded from this model.

(i) The moth can converge at each and every point in closeness of light by altering t.

(ii) The lesser the t, the nearer the length for the flame

(iii) The frequent updating position for moth on two sides is improved when the moth realizes its proximity to the light.

Another task considered here is the moth's updating position in place of 'n' i.e. various points in the rummage area may reduce exploitation of the finest assuring solutions. To realize this matter, an adaptive system is suggested for the sum of flames. From Figure-5, we can observe how the sum of flames is reduced adaptively during iteration process.

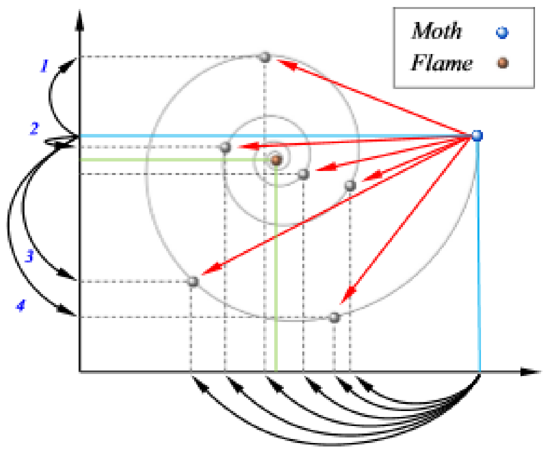

Figure 4: Some of the possible positions that can be reached by a moth w.r.t. a flame using the logarithmic spiral [29]

$$flame\ no = round\left(N - l * \frac{N-1}{T}\right) \quad (23)$$

The above specified equation is realized in view of this regard.

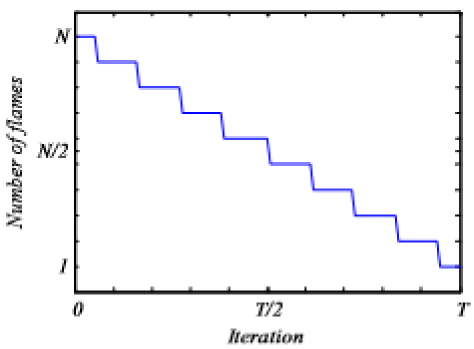

Figure-5 Number of flame is reduced adpatively during iteration process[29]

Where ‘l’ denotes the Iteration number in current position, ‘N’ denotes maximal sum of flames and ‘T’ denotes the maximal iteration number.

(b). COMPUTATION OF COMPLEXITY FOR MFO ALGORITHM

The computation complexity is a metric key for an algorith to realize its running time. It depends on the number of maxium iterations, sum of variables, sum of moths and an assorted system of flames in every iteration. By reason of quicksort algorithm is realized , the sort’s computation complexity of O(nlogn) & $O(n^2)$ in the finest and least case respectively. In view of the ‘P’ function, the total calculation of complexity is assigned as follows:

$$O(MFO) = O(T(O(\text{Quick sort}) + O(\text{position update}))) \text{—} (24)$$

$$O(MFO) = O(t(n^2+n \times d)) = O(tn^2 + tnd) \text{ ---------------------} (25)$$

Where ‘n’ denotes the set of moths, ‘t’ denotes the maximum value of iterations and ‘d’ denotes the set of variables.

From the above theoretical and mathematical access, we can observe that the MFO algorithm capable to develop the initial desultory solutions possibly and convergence very quickly to a finer position in the searching area.

THE PROPOSED MFO ALGORITHM TO REALIZE ORPD PROBLEM

Step:1. Select the power system data and identify the algorithm for objective functioning of the ORPD problem. The system should specify the number of control variables within the boundary limits. The power system line data, bus data and boundary limits are taken from [17,25 & 30].

Step:2. Set up the number of moths & the flame by applying the equation (23) and fix the maximum number of iteration.

Step 3: Take the function specifics & function valuation. (Dimensions of variables and boundary limits)

Step:4. The moths’ position is assumed as a control variable in ORPD problems. These control variables are generator output voltage, regulating transformers and reactive power compensating devices that are setup randomly in boundary limits.

Step:5 Map the control variables from every set of moth into testing data (line data & bus data for ORPD) problem.

Step:6 Evaluate the objective function from load flow by newton-raphson method for each moth [OM = Fitness function (M)] by equation (11).

Step:7. Store the finest solution in F (using equation (14)) store & position

Step:8. Update the positions by applying equation (22) for every set of moth.

Step: 9: Check if the variables are away from boundary limits

Step: 10.If Yes, Tag the variables at the boundary limits.

Step:11. If No, check the if the termination criterion is reached.

Step:12. If termination criterion is reached, print the best solution calculated by algorithm and then stop it.

Step:13. If the ending criterion is not reached, go to step 5 and repeat the process till the best solution.

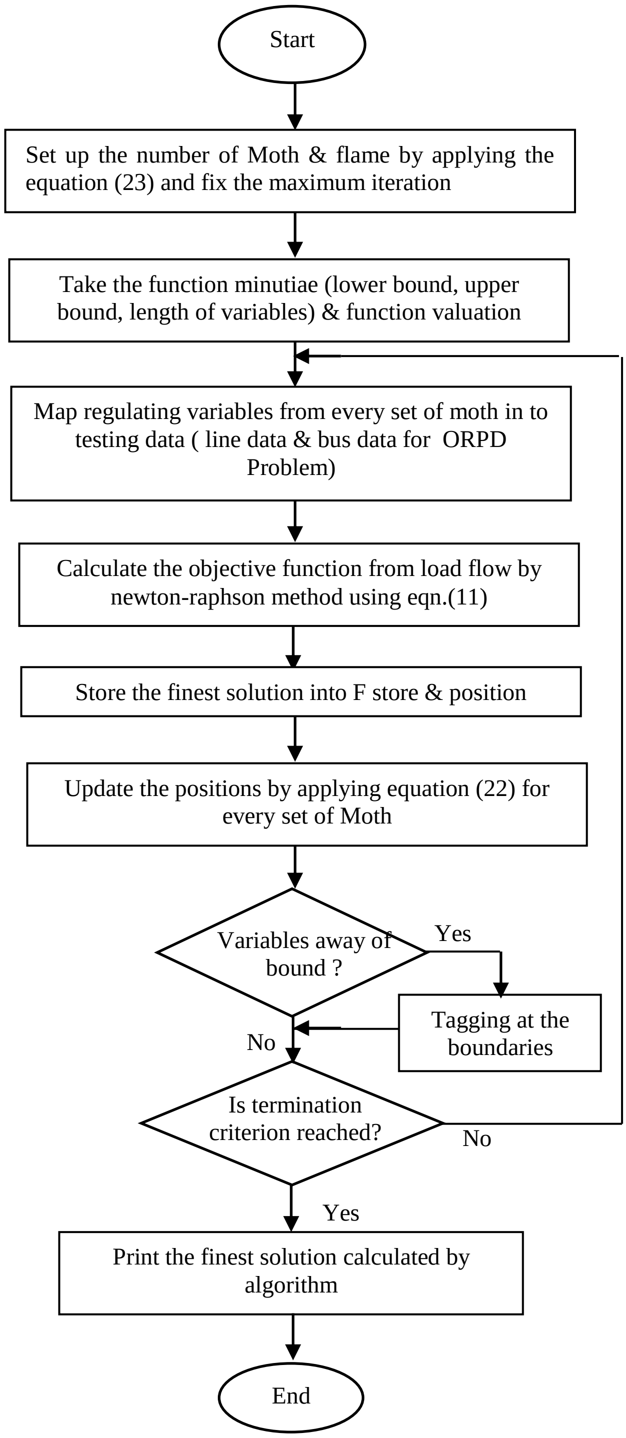

Figure - 6 Flow chart for MFO algorithm

NUMERICAL RESULTS AND DISCUSSIONS

In this section, the Moth-Flame optimization algorithm approach is realized for standard IEEE-30 and 57 bus systems whose demands and initial active power generations are similar as in the base case [17 &25]. The procedural steps are followed based on flow chart shown in figure - 6. The following regulating variable parameters are considered in ORPD problems.

(i) The generator output voltage – continuous variable

(ii) Regulating transformer –Discrete variable

(iii) VAR compensating devices – Discrete variable

The ORPD problem was realized with 100 MVA base for all the test cases. The Newton-Raphson load flow approach is realized for controlling the equality and inequality constraint violation. The results obtained by simulation of the MFO algorithm were done in MATLAB 2016 on a Intel(R), core(TM) i5-6200 U CPU @2.40 GHz, 8.0 GB RAM processor. The real power loss base case and optimal variables of boundary margins are given in table 1 & 2.

Table-1: Test system details

Control variables	IEEE-30 bus	IEEE-57 bus
No.of control variables	12	25
No.of regulating Tranformers(T)	4	15
No.of generator buses (V_G)	6	7
No.of reactive power sources(Q_C)	2	3
P_{Loss} Base case (MW)	17.5569	28.4620

Table -2 Settings of boundary values

Variable	Minimum	Maximum	Step
T	0.9	1.1	0.02
V_G	0.9	1.1	-
Q_{C10}	0	0.2	0.05
Q_{C24}	0	0.04	0.01

Table-3: Boundary values of bus voltage & tap settings

V_G^{min}	V_G^{max}	V_{Gpq}^{min}	V_{Gpq}^{max}	T_K^{min}	T_K^{max}
0.94	1.06	0.94	1.06	0.9	1.1

Table-4 Boundary values of reactive power sources

Bus	18	25	53
Q_C^{min}	0.0	0.0	0.0
Q_C^{max}	0.10	0.053	0.063

CASE -1 IEEE-30 BUS SYSTEM

The standard IEEE-30 bus system consists of 41- branches, six generators at 1,2,5,8,11,& 13 and 4 branches of regulating transformers. The switchable reactive power devices are linked on buses 10 & 24. The search area for this case, 12 control variables are taken.

In this case, the system parameters are chosen from table-2.and the population was set to 50 and iteration was fixed to 100. In order to obtain the optimal setting values, the simulation programme was run 50 times by MFO algorithm. From these assessments of algorithm outcome values, the best value of real power loss and its corresponding optimal variables were chosen. The real power loss & the statistical results of 30 – bus system were compared with well-known algorithm of same data as given in table -5 to table -7. From this result, we realize that the real power loss curtailment was upgraded from IP[17] 7.63%, PSO[17] 8.13%, DEA strategy-1[17] 8.65% and 10.48% from Moth-Flame optimization algorithm. Also, from Table 6 & 7, we can observe the statistical results which show better values.

The convergence characteristics of 30-bus system MFA & DEA [17] is shown in figure -7 and figure -8 respectively

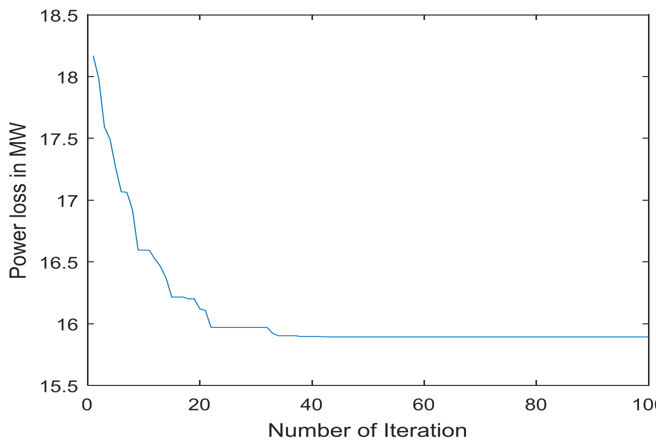

Figure -7 Convergence characteristics of 30-bus system

The Moth-flame algorithm converged from 10-20 iterations smoothly and compass the best power loss values by comparing the figure -8.

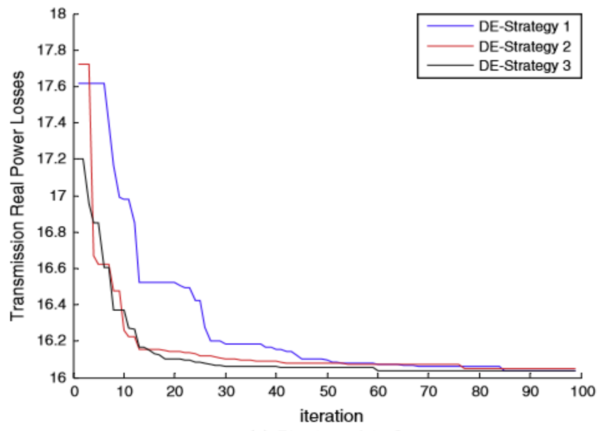

Figure -8 Convergence characteristics of 30-bus system [32]

Table -5: Optimal settings of regulating variables for the IEEE 30-bus

Variables	IP[17]	PSO[17]	DEA[17] Strategy1	MFA
V_{G1}	1.0999	1.1000	1.1000	1.1000
V_{G2}	1.0741	1.0742	1.0822	1.0932
V_{G5}	1.0398	1.0418	1.0503	1.0531
V_{G8}	1.0469	1.0483	1.0574	1.0594
V_{G11}	1.0853	1.1000	1.0996	1.1000
V_{G13}	1.0796	1.0999	1.0999	1.1000
T_{6-9}	1.0114	1.0258	1.0817	1.0189
T_{6-10}	0.9834	0.9383	0.9142	0.9001
T_{4-12}	1.0116	0.9787	1.0069	1.0199
T_{28-27}	0.9729	0.9491	0.9628	0.9677
Q_{10}	0.1302	0.1994	0.2000	0.2000
Q_{24}	0.0292	0.0398	0.0399	0.0400
P_{Loss}	16.2180	16.1296	16.0386	15.8921

Table 6: Statistical results of IEEE-30 bus system

Methods	Worst P_{Loss} MW	Aveg. P_{Loss} MW	Best P_{Loss} MW	Std.dev P_{Loss} MW	cpu time (sec)
IP	16.2180	-	-	-	0.75
PSO	16.1296	17.5040	17.8190	0.00034	8.45
DEA Strategy1	16.0386	17.1563	18.6538	0.00025	8.7229
MFA	15.8921	15.9126	16.0591	0.00049	8.2967

Table -7 : Minimum loss realized by different methods of IEEE-30 bus

Test system	worst	best	Average
EP[12]	16.6759	17.8189	17.2504
DE[12]	16.4898	16.5194	16.4939
CSSP[11]	16.3861	16.4807	16.4148
ABC[22]	16.2325	17.6930	16.5908
DE[22]	16.2184	16.6272	16.3176
DE-ABC[22]	16.2163	16.2164	16.2163
IP[17]	16.218	-	-
PSO[17]	16.1296	16.8190	16.5040
DEA[17] (Strategy 1)	16.0386	18.6538	17.1563
MFA	15.8921	16.0591	15.9126

CASE -2 IEEE-57 BUS SYSTEM

In this section, the IEEE-57 bus system has been realized for obtaining the optimal settings of control variables. Seven generators are placed at 1,2,3,6,8,9,&12 and 80 branches of which 15 branches were under regulating transformers. The adjustable reactive power devices are mediated at buses 18, 25 & 53. The boundary limits of control variables (table 3 to table- 4), bus data and line data were taken from [25&30]. In total, 25 optimal variables were considered from 57-bus system. This problem was approached by single–objective optimization where the real power loss was curtailed in transmission lines. The algorithm results were analyzed and compared with other algorithm results are given in table -8.

Figure-9 shows the convergence characteristics of Moth-Flame algorithm for the best power loss result. The least possible power loss realized from MFO algorithm is 0.224223 p.u. The MFO algorithm result improved to 1.26 % compared to the previous achieved least possible solution of 0.2278 p.u. The computation time was also less compared to other algorithms. These are tabulated in table no-8 except for PSO-07[32].

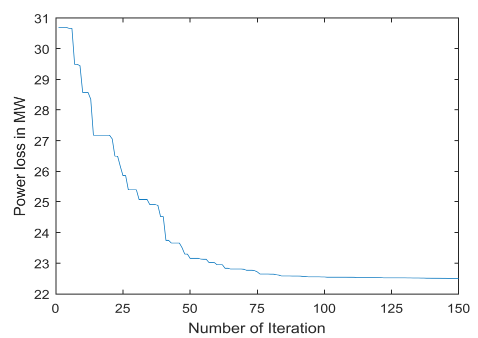

Table-8. [C.V.S. – Control variable settings]

C.V.S	MFOA	CPVEIHBMO	HBMO[34]	GSA[25]	NLP[33]	CGA[33]	AGA[33]	PSO-w[33]	PSO-cf[33]
V_{G1}	1.0999	1.076	1.0980	1.0600	1.0600	0.9686	1.0276	1.0600	1.0600
V_{G2}	1.0877	1.054	1.0910	1.0600	1.0600	1.0493	1.0117	1.0578	1.0586
V_{G3}	1.0711	1.035	1.0750	1.0600	1.0538	1.0567	1.0335	1.04378	1.0464
V_{G6}	1.0642	1.013	1.0600	1.0081	1.0600	0.9877	1.0010	1.0356	1.0415
V_{G8}	1.0800	1.044	1.0570	1.0549	1.0600	1.0223	1.0517	1.0546	1.0600
V_{G9}	1.0773	1.093	1.0040	1.0098	1.0600	0.9918	1.0518	1.0369	1.0423
V_{G12}	1.0670	0.989	0.9983	1.0185	1.0600	1.0044	1.0570	1.0334	1.0371
T_{4-18}	0.9500	1.029	1.1000	1.1000	0.9100	0.9200	1.0300	0.9000	0.9800
T_{4-18}	0.9200	1.034	1.0860	1.0826	1.0600	0.9200	1.0200	1.0200	0.9800
T_{21-20}	1.0600	0.989	1.0835	0.9219	0.9300	0.9700	1.0600	1.0100	1.0100
T_{24-26}	1.0100	1.016	1.0670	1.0617	1.0800	0.9000	0.9900	1.0100	1.0100
T_{7-29}	0.9100	0.994	0.9910	0.9962	1.0000	0.9100	1.1000	0.9700	0.9800
T_{34-32}	0.9990	1.100	1.0893	1.1000	1.0900	1.1000	0.9800	0.9700	0.9700
T_{11-41}	0.9000	1.072	1.0762	1.0746	0.9200	0.9400	1.0100	0.9000	0.9000
T_{15-45}	0.9000	1.000	0.9883	0.9543	0.9100	0.9500	1.0800	0.9700	0.9700
T_{14-46}	0.9000	0.987	0.9340	0.9377	0.9800	1.0300	0.9400	0.9500	0.9600
T_{10-51}	0.9100	0.933	1.003	1.0617	0.9800	1.0900	0.9500	0.9600	0.9700
T_{13-49}	0.9000	1.029	1.844	1.0525	0.9800	0.9000	1.0500	0.9200	0.9300
T_{11-43}	0.9000	1.0923	1.0657	1.1000	0.9800	0.9000	0.9500	0.9600	0.9700
T_{40-56}	0.9990	0.996	0.9942	0.9799	0.9800	1.0000	1.0100	1.0000	0.9900
T_{39-57}	0.9900	1.0645	1.0356	1.0246	1.0800	0.9600	0.9400	0.9600	0.9600
T_{9-55}	0.9100	0.9847	1.0040	1.0373	1.0300	1.0000	1.0000	0.9700	0.9800
Q_{C18}	0.0980	0.0653	0.689	0.0782	0.08352	0.084	0.0168	0.05136	0.09984
Q_{C25}	0.0580	0.0084	0.0076	0.0058	0.00864	0.00816	0.01536	0.05904	0.05904
Q_{C53}	0.0600	0.0763	0.0546	0.0468	0.01104	0.05376	0.03888	0.06288	0.06288
P_{Loss}(p.u)	0.22422	0.2278	0.2324	0.23461	0.2590231	0.252441	0.24564	0.2427052	0.2428022
CPU time(s)	250.845	298.53	305.76	321.48	-	353.08	367.31	406.42	404.63

C.V.S	CLPSO[33]	SPSO-07[33]	L-DE[33]	L-SACP-DE[33]	L-SaDE[33]	SOS[33]	BBO[10]	BBOT[10]
V_{G1}	1.0541	1.0596	1.0397	0.9884	1.0600	1.0600	1.0600	1.0600
V_{G2}	1.0529	1.0580	1.0463	1.0543	1.0574	1.0580	1.0504	1.0580
V_{G3}	1.0377	1.0488	1.0511	1.0278	1.0438	1.0437	1.0440	1.0442
V_{G6}	1.0313	1.0362	1.0236	0.9672	1.0364	1.0352	1.0376	1.0364
V_{G8}	1.0496	1.0600	1.0538	1.0552	1.0537	1.0548	1.0550	1.0567
V_{G9}	1.0302	1.0433	0.94518	1.0245	1.0366	1.0369	1.0229	1.0377
V_{G12}	1.0342	1.0356	0.99078	1.0098	1.0323	1.0336	1.0323	1.0351
T_{4-18}	0.9900	0.9500	1.0200	1.0500	0.9400	1.0000	0.96693	0.99165
T_{4-18}	0.9800	0.9900	0.9100	1.0500	1.0000	0.9600	0.99022	0.96447

T_{21-20}	0.9900	0.9900	0.9700	0.9500	1.0100	1.0100	1.0120	1.0122
T_{24-26}	1.0100	1.0200	0.9100	0.9800	1.0100	1.0100	1.0087	1.0110
T_{7-29}	0.9900	0.9700	0.9600	0.9700	0.9700	0.9700	0.97074	0.97127
T_{34-32}	0.9300	0.9600	0.9900	1.0900	0.9700	0.9700	0.96869	0.97227
T_{11-41}	0.9100	0.9200	0.9800	0.9200	0.9000	0.9000	0.90082	0.90095
T_{15-45}	0.9700	0.9600	0.9600	0.9100	0.9700	0.9700	0.96602	0.97063
T_{14-46}	0.9500	0.9500	1.0500	1.0800	0.9600	0.9500	0.95079	0.95133
T_{10-51}	0.9800	0.9700	1.0700	0.9900	0.9600	0.9600	0.96414	0.96252
T_{13-49}	0.9500	0.9200	0.9900	0.9100	0.9200	0.9200	0.92462	0.92227
T_{11-43}	0.9500	1.0000	1.0600	0.9400	0.9600	0.9600	0.95022	0.95988
T_{40-56}	1.0000	1.0000	0.9900	0.9900	1.0000	1.0000	0.99666	1.0018
T_{39-57}	0.9600	0.9500	0.9700	0.9600	0.9600	0.9600	0.96289	0.96567
T_{9-55}	0.9700	0.9800	1.0700	1.1000	0.9700	0.9700	0.96001	0.97199
Q_{C18}	0.09888	0.03936	0.0	0.0	0.08112	0.09984	0.09782	0.09640
Q_{C25}	0.05424	0.05664	0.0	0.0	0.05808	0.05904	0.058991	0.05897
Q_{C53}	0.06288	0.03552	0.0	0.0	0.06192	0.06288	0.6289	0.062948
P_{Loss}(p.u)	0.2451520	0.2443043	0.2781264	0.2791553	0.2426739	0.242654	0.24544	0.242616
CPU time(s)	423.30	121.98	426.97	427.23	408.97	383.23	-	-

MFOA- Proposed method

CONCLUSION

This paper describes a newly matured meta-heuristics Moth-Flame optimization algorithm that has been effectually employed to realize ORPD problem. This optimization technique was performed by altering the reactive power constraint parameters such as generator output voltages, regulating transformers and reactive power sources in 30 bus and 57 bus data. The active power loss realized by this new meta heuristic Moth-flame algorithm was studied and it showed better results compared to other techniques (the same data) in table – 6 & 9. This algorithm revealed the number of iterations, convergence characteristics, data processing optimization strategy and engaged an efficient method for handling constraints. The proposed Moth-flame algorithm is strongly endorsed for forthcoming researchers in various fields for solving complex engineering optimization problems.

Nomenclature

C.V.S. – control variable settings

ORPD - optimal reactive power dispatch

EP - evolutionary programme

SARGA - self-adaptive real coded genetic algorithm

DEA - Differential evolutionary algorithm

IP – Interior point method

PSO- Particle swarm optimization

P_{Loss} – Total power loss in transmission lines

TL –Transmission line between bus 'i' and 'j'

G_{TL}-conductance of transmission line 'k' between bus 'i' & 'j'

T_k- Regulating transformer 'k'

Vi –voltage magnitude at bus 'i'

Vj –voltage magnitude at bus 'j'

θ_{ij} is voltage angle difference between buses 'i' and 'j'

N_{TL} – Total number of transmission lines

n_b – Total number of buses in system network

n_{pv} - number of generator buses

n_{pq} - is number of load buses

G_{ij} - mutual conductance between bus 'i' and 'j'.

B_{ij} - suceptance between bus 'i' and 'j'

P_{Gi}, Q_{Gi} - are real and reactive power generation at bus 'i'

P_{Di}, Q_{Di} - are real and reactive power demand at bus 'i'

Q_{Ci} - is the reactive power compensation source at bus 'i';

n_t - is number of regulating transformers;

n_c - number of compensator device

S_l - is the apparent power flow in transmission line 'l';

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