DECLINE OF ACTIVE POWER LOSS BY IMPROVED MOTH-FLAME OPTIMIZATION ALGORITHM

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Abstract: *In this paper, Improved Moth-Flame Optimization (IMFO) algorithm has been proposed for solving Reactive power problem. Navigation method of moths in nature called transverse orientation is the key inspiration of the moth-flame algorithm (MFO). By maintaining a fixed angle with respect to the moon, Moths fly in the night and it's an effective mechanism for moths travelling in a straight line for long distances. Due to very slow convergence and poor precision, an improved version of MFO algorithm based on Levy-flight strategy has been proposed to solve the reactive power problem. The diversity of the population can be increased by Levy-flight to overcome premature convergence in order to reach the global optimal solution. This methodology improves the trade-off between exploration and exploitation ability of moth-flame algorithm (MFO).The proposed Improved Moth-Flame Optimization (IMFO) algorithm has been tested in standard IEEE 30,57,118 bus test systems and simulation results show clearly about the better performance of the proposed algorithm in reducing the real power loss with control variables within the limits.*

1. INTRODUCTION

To till date various methodologies has been applied to solve the Optimal Reactive Power problem. Many types of mathematical methodologies like linear programming, gradient method (Alsac et al., 1973; Lee et al., 1985; Monticelli et al., 1987; Deeb et al., 1990; Hobson, 1980; Lee et al., 1993; Mangoli et al., 1993; Canizares et al., 1996) [1-8] has been utilized to solve the reactive power problem, but those techniques found difficult in handling the constraints in the reactive power problem.. After that various types of evolutionary algorithms (Berizzi et al., 2012; Roy et al., 2012; Hu et al., 2010; Eleftherios et al., 2010) [9-12] has been applied to solve the reactive power problem. But some algorithm good in exploration means, it lacks in exploitation and few algorithm's good in exploitation but lack in exploration. Speed of convergence is poor for some algorithms even though they got good trade-off between exploration and exploitation. In this paper, Improved Moth-Flame Optimization (IMFO) algorithm has been proposed for solving Reactive power problem. Navigation method of moths in nature called transverse orientation is the key inspiration of the moth-flame algorithm (MFO). By maintaining a fixed angle with respect to the moon, Moths fly in the night [13] and it's an effective mechanism for moths travelling in a straight line for long distances. Due to very slow convergence and poor precision, an improved version of MFO algorithm based on Levy-flight strategy has been proposed to solve the reactive power problem. The diversity of the population can be increased by Levy-flight to overcome premature convergence in order to reach the global optimal solution. This methodology improves the trade-off between exploration and exploitation ability of moth-flame algorithm (MFO).The proposed Improved Moth-Flame Optimization (IMFO) algorithm has been tested in standard IEEE 30, 57,118 bus test systems and simulation results show clearly about the better performance of the proposed algorithm in reducing the real power loss with control variables within the limits.

2. OBJECTIVE FUNCTION

2.1. Active power loss

Main objective of the reactive power dispatch problem is to minimize the active power loss and mathematically written by,

$$\mathrm{F} = P_L = \sum_{\mathrm{k}\in\mathrm{Nbr}} \mathrm{g_k}\left(\mathrm{V_i^2} + \mathrm{V_j^2} - 2\mathrm{V_i}\mathrm{V_j}\cos\theta_{\mathrm{ij}}\right) \tag{1}$$

where*:* F - objective function, P_L – power loss, g_k – conductance of branch, V_i and V_j are voltages at buses i, j, Nbr - total number of transmission lines in power systems.

2.2. Voltage profile improvement

Objective function *F* has be rewritten to minimize the voltage deviation in PQ buses as follows,

$$\mathrm{F} = P_L + \omega_\mathrm{v} \times \mathrm{VD} \tag{2}$$

where VD – voltage deviation, ω_v- is a weighting factor of voltage deviation.

The Voltage deviation is given by:

$$\mathrm{VD} = \sum_{i=1}^{Npq} |V_i - 1| \tag{3}$$

where Npq - number of load buses.

2.3. Equality Constraint

The power balance equation with respect to the equality constraint of the problem is written as follows:

$$P_G = P_D + P_L \tag{4}$$

where P_G- total power generation, P_D - total power demand.

2.4. Inequality Constraints

The inequality constraint with upper and lower bounds on the active power of slack bus (P_g), and reactive power of generators (Q_g) are written as follows:

$$P_{gslack}^{min} \leq P_{gslack} \leq P_{gslack}^{max} \tag{5}$$

$$Q_{gi}^{min} \leq Q_{gi} \leq Q_{gi}^{max}, i \in N_g \tag{6}$$

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

$$V_i^{min} \leq V_i \leq V_i^{max}, i \in N \tag{7}$$

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

$$T_i^{min} \leq T_i \leq T_i^{max}, i \in N_T \tag{8}$$

Upper and lower bounds on the compensators (Q_c) is given by:

$$Q_c^{min} \leq Q_c \leq Q_C^{max}, i \in N_C \tag{9}$$

where N is the total number of buses, N_g is the total number of generators, N_T is the total number of Transformers, N_c is the total number of shunt reactive compensators.

3. MOTH-FLAME OPTIMIZATION (MFO) ALGORITHM

Moth-flame optimization algorithm is based on the simulation of the behaviour of moths which has special navigation methods in night. Navigation method of moths in nature called transverse orientation is the key inspiration of the moth-flame algorithm (MFO).

By maintaining a fixed angle with respect to the moon, Moths fly in the night and it's an effective mechanism for moths travelling in a straight line for long distances. Set of moths is represented in a matrix N in the MFO algorithm. There is an array ON for all the moths, to store the corresponding fitness values. Flames are other one of key components in the moth-flame algorithm.

It is also assumed that there is an array OL for the flames, a matrix S similar to the moth matrix is considered to store the corresponding fitness values.

Three-tuple in MFO algorithm defined as follows:

$$MFO = (Q, G, H) \tag{10}$$

An arbitrary population of moths is created by the function Q. Q function mathematical model is given is as follows:

$$Q: \emptyset \rightarrow \{N, ON\} \tag{11}$$

Moths move around the exploration space on basis of G function. G function received the matrix of N and returns its modernized one ultimately:

$$G: N \rightarrow N \tag{12}$$

When the termination criterion is satisfied H function returns true and it will be false when termination criterion is not satisfied:

$$H: N \rightarrow \{True, False\} \tag{13}$$

MFO algorithm is defined as follows, with Q, G, and H, as the general framework:

N = ( );
When (N) is equal to false condition, then: N = (N)
End.

P Function is iteratively run after the initialization, until the H function returns true.

When simulating the behaviour of moths mathematically, with respect to a flame the position of each moth is updated using the following equation:

$$N_i = SL(N_i, Fl_j) \tag{14}$$

The ith moth indicated by N_i, jth flame indicated by Fl_j, and SL imply the spiral function.

Spirals are utilized by following conditions: (a) initial point of the Spiral's should start from the moth; (b) final point of the Spiral's should be the position of the flame; (c) in the search space fluctuation range of spiral should not exceed the space limit.

Considering these points, a logarithmic spiral is defined for the MFO algorithm as follows:

$$SL(N_i, Fl_j) = DT_i \cdot e^{bt} \cdot cos(2\pi f t) + Flj \tag{15}$$

Distance of the ith moth for the jth flame is indicated by DT_i, for defining the shape of the logarithmic spiral b is a constant, and t is an arbitrary number in the range [−1, 1].

Calculation of DT is as follows:

$$DT_i = |Fl_j - N_i| \tag{16}$$

where N_i indicate the ith moth, Fl_j indicates the jth flame, and DT_i indicates the distance of the ith moth for the jth flame. Spiral flying path of moths described by Equation (16). The next position of a moth is defined with respect to a flame by equation (16).

In the spiral equation the t parameter defines how much the next position of the moth should be close to the flame ($t = -1$ is the closest position to the flame, while t=1 shows the farthest). Position updating in equation (15) requires the moths to move towards a flame, & it lead to be trapped in local optima quickly.

Each moth is obliged to update its position using only one of the flames by equation (15) to prevent trap in local optima. In the search space the position updating of moths with respect to n different locations may degrade the exploitation to reach best promising solutions. An adaptive mechanism is provided to the number of flame to resolve degrade problem & it done by following equation,

$$Flame\ number = round\ \left(K - l * \frac{K - cn}{IN}\right) \tag{17}$$

The current number of iteration is given by cn, maximum number of flames indicated by K, and the maximum number of iterations by IN. Exploration and exploitation of the search space is perfectly balanced by gradual decrement in number of flames.

Position of moths has been initialized
While (Iteration <= Max iteration);
By equation (17) update the flame number
ON = Fitness Function (N);
If iteration = = 1
Fl = sort (N); OFl = sort(ON);
Else
Fl = sort (N_{t-1}, N_t); OFl = sort(N_{t-1}, N_t);
End
For i=1:n ; For j=1:d
Modernize r and t
By equation (16) calculate DT using with respect to the corresponding moth
By equations (14) and (15) renew (i, j) with respect to the corresponding moth
End End.

4. LEVY-FLIGHT

Animals look for food in arbitrary manner, as moving place to place. The choice of the direction relies only on a mathematical model [15], which is called Levy- flight & it have been applied to optimization problems which show its promising capability [14,15].Mathematically exclamation, an easy version of Levy distribution can be defined as [14],

$$L(s,\gamma,\mu) = \begin{cases} \sqrt{\frac{\gamma}{2\pi}} & exp\left[-\frac{\gamma}{2(s-\mu)}\right]\frac{1}{(s-\mu)^{3/2}} \quad if\ 0 < \mu < s < \infty \\ 0 \quad if\ s \leq 0 \end{cases} \tag{18}$$

where $\gamma > 0$ parameter is scale (controls the scale of distribution) parameter, μ parameter is location or shift parameter. In general, Levy distribution should be defined in terms of Fourier transform as follows [14],

$$F(k) = exp\left[-\alpha|k|^{\beta}\right], 0 < \beta \leq 2 \tag{19}$$

where α is a parameter within [-1,1] interval and known as scale factor. By Levy flight, new-fangled state of the particle is designed as [15],

$$X^{t+1} = X^t + \alpha \oplus Levy\ (\beta) \tag{20}$$

α is the step size which must be related to the scales of the problem of interest.

In the proposed method α is arbitrary number for all dimensions of particles [14].

$$X^{t+1} = X^t + random\left(size(D)\right) \oplus Levy(\beta) \tag{21}$$

The product $\oplus$ means entry-wise multiplications. A non-trivial scheme of generating step size s samples are summarized as follows [14],

$$X^{t+1} = X^t + random\left(size(D)\right) \oplus Levy(\beta) \sim 0.01 \frac{u}{|v|^{1/\beta}} \left(x_j^t - gb\right) \tag{22}$$

where *u* and *v* are drawn from the normal distributions. That is [15],

$$u \sim N(0, \sigma_u^2) \quad v \sim N(0, \sigma_v^2) \tag{23}$$

with

$$\sigma_u = \left\{\frac{\Gamma(1+\beta) sin(\pi\beta/2)}{\Gamma[(1+\beta)/2]\beta 2^{(\beta-1)/2}}\right\}^{1/\beta}, \sigma_v = 1 \tag{24}$$

Here Γ is standard Gamma function. While performing distribution by Levy flights [14] is the value taken by the β parameter and it substantially affects distribution.

5. PROPOSED IMPROVED MOTH- FLAME (IMFO) OPTIMIZATION ALGORITHM

Proposed IMFO algorithm‘s global search ability is strengthened using arbitrary walk with help of Levy-flight to eliminate the weakness of MFO algorithm [13] Improved Moth-flame algorithm (IMFO) for solving Reactive power problem given below.

Position of moths has been initialized
While (Iteration <= Max iteration) ; By equation (17) update the flame number
ON = Fitness Function (N);
If iteration = = 1
Fl = sort (N); OFl = sort(ON);
Else
Fl = sort ($N_t - 1$, N_t); OFl = sort(N_{t-1}, N_t);
End
For i=1:n ; For j=1:d

Modernize r and t
By equation (16) calculate DT using with respect to the corresponding moth
By equations (14) and (15) renew (i, j) with respect to the corresponding moth
End
For each search agent renew the position of the existing search agent by using Levy-flight
End
When Iteration = Iteration + 1;
End

6. SIMULATION RESULTS

In standard IEEE 30-bus, 41 branch system validity of proposed Improved Moth-Flame Optimization (IMFO) algorithm has been verified and the system has 6 generator-bus voltage magnitudes, 4 transformer-tap settings, and 2 bus shunt reactive compensators. 2, 5, 8, 11 and 13 are considered as PV generator buses, Bus 1 is taken as slack bus and others are PQ load buses. Primary variables limits are given in *Table 1*.

Table 1. Primary Variable Limits (Pu)

List of Variables	Minimum	Maximum	group
Generator Bus	0.95	1.1	Continuous
Load Bus	0.95	1.05	Continuous
Transformer-Tap	0.9	1.1	Discrete
Shunt Reactive Compensator	-0.11	0.31	Discrete

In *Table 2* the power limits of generators buses are listed.

Table 2. Generators Power Limits

Bus	Pg	Pgminimum	Pgmaximum	Qgminimum	Qmaximum
1	96.00	49	200	0	10
2	79.00	18	79	-40	50
5	49.00	14	49	-40	40
8	21.00	11	31	-10	40
11	21.00	11	28	-6	24
13	21.00	11	39	-6	24

Table 3 shows the proposed Improved Moth-Flame Optimization (IMFO) algorithm successfully kept the control variables within limits.

Table 4 narrates about the performance of the proposed Improved Moth-Flame Optimization (IMFO) algorithm.

Fig 1 shows about the voltage deviations during the iterations and Table 5 list out the overall comparison of the results of optimal solution obtained by various methods.

Table 3. After optimization values of control variables

List of Control Variables	*IMFO*
V1	*1.0512*
V2	*1.0434*
V5	*1.0297*
V8	*1.0382*
V11	*1.0735*
V13	*1.0529*
T4,12	*0.00*
T6,9	*0.01*
T6,10	*0.90*
T28,27	*0.91*
Q10	*0.10*
Q24	*0.10*
Real power loss	*4.2898*
Voltage deviation	*0.9090*

Table 4. Performance of IMFO algorithm

Iterations	*25*
Time taken (secs)	*7.89*
Real power loss	*4.2898*

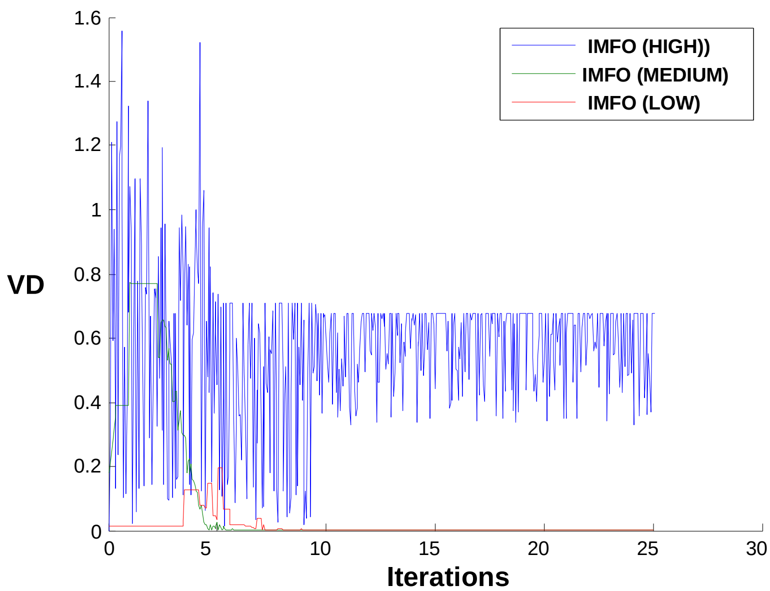

Fig. 1. Voltage deviation (VD) characteristics

Table 5. Comparison of results

List of Techniques	*Real power loss (MW)*
SGA(Wu et al., 1998) [16]	*4.98*
PSO(Zhao et al., 2005) [17]	*4.9262*
LP(Mahadevan et al., 2010) [18]	*5.988*
EP(Mahadevan et al., 2010) [18]	*4.963*
CGA(Mahadevan et al., 2010) [18]	*4.980*
AGA(Mahadevan et al., 2010) [18]	*4.926*
CLPSO(Mahadevan et al., 2010) [18]	*4.7208*
HSA (Khazali et al., 2011) [19]	*4.7624*
BB-BC (Sakthivel et al., 2013) [20]	*4.690*
MCS(Tejaswini sharma et al.,2016) [21]	*4.87231*
Proposed IMFO	*4.2898*

At that Improved Moth-Flame Optimization (IMFO) algorithm has been tested in standard IEEE-57 bus power system. The reactive power compensation buses are 18, 25 and 53. Bus 2, 3, 6, 8, 9 and 12 are PV buses and bus 1 is selected as slack-bus. The system variable limits are given in *Table 6*.

The preliminary conditions for the IEEE-57 bus power system are given as follows:
Pload = 12.129 p.u. Qload = 3.069 p.u.

The total initial generations and power losses are obtained as follows:
$\sum P_G$ = 12.471 p.u. $\sum Q_G$ = 3.3160 p.u.
Ploss = 0.25875 p.u. Qloss = -1.2074 p.u.

Table 6. Variable Limits

Reactive Power Generation Limits							
Bus no	*1*	*2*	*3*	*6*	*8*	*9*	*12*
Qgmin	*-1.4*	*-.015*	*-.02*	*-0.04*	*-1.3*	*-0.03*	*-0.4*
Qgmax	*1*	*0.3*	*0.4*	*0.21*	*1*	*0.04*	*1.50*
Voltage And Tap Setting Limits							
vgmin	*Vgmax*	*vpqmin*	*Vpqmax*	*tkmin*	*tkmax*		
0.9	*1.0*	*0.91*	*1.05*	*0.9*	*1.0*		
Shunt Capacitor Limits							
Bus no	*18*	*25*	*53*				
Qcmin	*0*	*0*	*0*				
Qcmax	*10*	*5.2*	*6.1*				

Table 7 shows the various system control variables i.e. generator bus voltages, shunt capacitances and transformer tap settings obtained after optimization which are within the acceptable limits. In Table 8, shows the comparison of optimum results obtained from proposed methods with other optimization techniques. These results indicate the robustness of proposed approaches for providing better optimal solution in case of IEEE-57 bus system.

Table 7. Control variables obtained after optimization

Control Variables	IMFO
V1	1.10
V2	1.039
V3	1.038
V6	1.027
V8	1.029
V9	1.006
V12	1.011
Qc18	0.0664
Qc25	0.200
Qc53	0.0476
T4-18	1.004
T21-20	1.043
T24-25	0.861
T24-26	0.876
T7-29	1.057
T34-32	0.879
T11-41	1.011
T15-45	1.030
T14-46	0.910
T10-51	1.020
T13-49	1.060
T11-43	0.910
T40-56	0.900
T39-57	0.950
T9-55	0.950

Table 8. Comparison results

S.No.	Optimization Algorithm	Finest Solution	Poorest Solution	Normal solution
1	NLP [22]	0.25902	0.30854	0.27858
2	CGA [22]	0.25244	0.27507	0.26293

3	*AGA [22]*	*0.24564*	*0.26671*	*0.25127*
4	*PSO-w [22]*	*0.24270*	*0.26152*	*0.24725*
5	*PSO-cf [22]*	*0.24280*	*0.26032*	*0.24698*
6	*CLPSO [22]*	*0.24515*	*0.24780*	*0.24673*
7	*SPSO-07 [22]*	*0.24430*	*0.25457*	*0.24752*
8	*L-DE [22]*	*0.27812*	*0.41909*	*0.33177*
9	*L-SACP-DE [22]*	*0.27915*	*0.36978*	*0.31032*
10	*L-SaDE [22]*	*0.24267*	*0.24391*	*0.24311*
11	*SOA [22]*	*0.24265*	*0.24280*	*0.24270*
12	*LM [23]*	*0.2484*	*0.2922*	*0.2641*
13	*MBEP1 [23]*	*0.2474*	*0.2848*	*0.2643*
14	*MBEP2 [23]*	*0.2482*	*0.283*	*0.2592*
15	*BES100 [23]*	*0.2438*	*0.263*	*0.2541*
16	*BES200 [23]*	*0.3417*	*0.2486*	*0.2443*
17	*Proposed IMFO*	*0.22092*	*0.23016*	*0.22268*

Then Improved Moth-Flame Optimization (IMFO) algorithm has been tested in standard IEEE 118-bus test system [24].The system has 54 generator buses, 64 load buses, 186 branches and 9 of them are with the tap setting transformers. The limits of voltage on generator buses are 0.95 -1.1 per-unit., and on load buses are 0.95 -1.05 per-unit. The limit of transformer rate is 0.9 -1.1, with the changes step of 0.025. The limitations of reactive power source are listed in *Table 9*, with the change in step of 0.01.

Table 9. Limitation of reactive power sources

BUS	*5*	*34*	*37*	*44*	*45*	*46*	*48*
QCMAX	*0*	*14*	*0*	*10*	*10*	*10*	*15*
QCMIN	*-40*	*0*	*-25*	*0*	*0*	*0*	*0*
BUS	*74*	*79*	*82*	*83*	*105*	*107*	*110*
QCMAX	*12*	*20*	*20*	*10*	*20*	*6*	*6*
QCMIN	*0*	*0*	*0*	*0*	*0*	*0*	*0*

The statistical comparison results of 50 trial runs have been list in *Table 10* and the results clearly show the better performance of proposed Improved Moth-Flame Optimization (IMFO) algorithm in reducing the real power loss.

Table 10. Comparison results

Active power loss (MW)	*BBO [25]*	*ILSBBO/ strategy1 [25]*	*ILSBBO/ strategy 2 [25]*	*Proposed IMFO*

Min	*128.77*	*126.98*	*124.78*	*117.64*
Max	*132.64*	*137.34*	*132.39*	*121.72*
Average	*130.21*	*130.37*	*129.22*	*118.32*

7. CONCLUSION

In this paper, Improved moth-flame optimization (IMFO) algorithm been successfully implemented to solve Optimal Reactive Power Dispatch problem. An improved version of MFO algorithm based on Levy-flight strategy has been solved the reactive power problem. The diversity of the population can be increased by Levy-flight to overcome premature convergence in order to reach the global optimal solution. This methodology improved the trade-off between exploration and exploitation ability of moth-flame algorithm (MFO).The proposed IMFO algorithm has been tested in the standard IEEE 30, 57,118 bus systems. Simulation results show that IMFO provided better optimal solution in decreasing the real power loss. The control variables obtained after the optimization by IMFO are well within the limits.

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