Optimal Power Flow Solutions for Power System Operations Using Moth-Flame Optimization Algorithm

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Abstract This article proposes a recent novel metaheuristic optimization technique: Moth-Flame Optimizer (MFO) to solve one of the most important problems in the power system namely Optimal power flow (OPF). Three objective functions will be solved simultaneously: minimizing fuel cost, transmission loss, and voltage deviation minimization using a weighted factor. To show the effectiveness of proposed MFO in solving the mentioned problem, the IEEE 30-bus test system will be used. Then the obtained result from the MFO algorithm is compared with other selected well-known algorithms. The comparison proves that MFO gives better results compared to the other compared algorithms. MFO gives a reduction of 14.50% compared to 13.38 and 14.15% for artificial bee colony (ABC) and Improved Grey Wolf Optimizer (IGWO) respectively.

Keywords Optimal power flow · MFO · Economic dispatch · Optimal reactive power

1 Introduction

Optimal power flow (OPF) has attained increasing interest from electrical researchers since it is a key tool that helps utility power system to determine the optimal economic and operational security of the electric grid. The predominant purpose of OPF is to optimize certain objective functions such as: minimizing fuel cost, emission, transmission loss, voltage deviation, etc. while meeting certain

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operation constraints like line capacity, bus voltage, generator capability, and power flow balance. The aforementioned objective functions can be solved as a single or multi-objective problem.

Optimal reactive power dispatch (ORPD) is a part of Optimal power flow (OPF). ORPD has a substantial impact on the security and the economic operation of the electric grid system. ORPD problem contains continuous and discrete variables so it considered a mixed nonlinear problem. The control variables of the ORPD problem are the reactive power outputs of generators and static VAR compensators, bus voltage magnitudes, and angles. Another sub-problem of OPF is Economic dispatch (ED) which one of the complex problems in the power system which aims to find the optimal allocation of generator unit output to meet the load demand at the lowest economic generation cost while satisfying the equality and inequality constraints.

Several optimization techniques have been used to solve the OPF ranging from traditional to metaheuristic optimization algorithms. In recent years, metaheuristic optimization algorithms have been developed for simulating some of the chemical, physical and biological phenomena. Lately, many nature-inspired meta-heuristic algorithms have been applied to solve the OPF problem and its sub-problem ORPD and ED. Artificial Bee Colony (ABC) [1], Opposition-Based Gravitational Search Algorithm (OGSA) [2], Grey Wolf Optimizer (GWO) [3] and Harmony Search Algorithm (HAS) [4] have been to solve ORPD separately. On the other hand, ED has been solved by many meta Meta-heuristic such as Grey Wolf Optimizer (GWO) [5], Moth-Flame Optimization (MFO) algorithm [6], A Particle Swarm Optimization PSO [7], and Genetic Algorithm (GA) [8]. Moreover, A lot of optimization techniques have been implemented to solve the ED problem and ORPD problem simultaneously such as improved grey wolf optimizer IGWO [9], Modified Sine-Cosine algorithm (MSCA) [10], Gravitational Search Algorithm (GSA) [11] and Particle Swarm Optimization (PSO) [12].

According to no free lunch theorem, a single meta-heuristic algorithm is not best for every problem [13], so in this paper, Moth-Flame Optimizer will be considered to solve the optimal power flow (OPF) problem. The performance of the proposed technique is tested on the standard IEEE 30-bus test system where the objective functions are the minimization of generation fuel cost, minimization of power losses and voltage profile improvement.

2 Problem Formulation

Since the OPF problem is a nonlinear complex optimization problem that minimizes certain objective functions while subjected to equality and inequity constraints. It can be express as follow:

$$\mathrm{Min\,f}\ (\mathrm{y,x}) \tag{1}$$

while subject to

$$\mathrm{h}\ (\mathrm{x}) = 0 \tag{2}$$

$$\mathrm{g}\ (\mathrm{x}) \leq 0 \tag{3}$$

In this paper, economic dispatch, Optimal reactive power dispatch, and voltage profile improvement will be taking into consideration as objectives functions as follow:

2.1 Economic Dispatch

The main objective function of economic dispatch is to reduce the generation cost which can be formulated as a quadratic equation [14].

$$F_1 = min\,(\sum_{i=1}^{N} F_i(P_i)) = \sum_{i=1}^{N} \left(a_i + b_i P_i + c_i P_i^2\right) \tag{4}$$

where F_1 Is the total fuel cost, N is the total number of generating units, F_i Is the fuel cost of generator *i*, P_i Is the power generated by generator *i* and a_i, b_i And c_i Are the cost coefficients of generator *i*.

2.2 Optimal Reactive Power Dispatch Problem

The objective function of ORPD is to minimize the real transmission system power losses while satisfying the equality and inequality constraint. It is formulated as follow [15]:

$$F_2 = min(P_{Loss}) = min \sum_{i=1}^{N} P_L = \sum_{i=1}^{N} G_{ij}\left(V_i^2 + V_j^2 - 2V_iV_j\,cos\delta_{ij}\right) \tag{5}$$

where P_{Loss} Is the real power losses in the transmission system and N is the number of lines. Also, G_{ij} Is the line conductance between the *i*-th and *j*-th buses. While $V_i\,and\,V_j$ Are the voltage at the *i*-th and *j*-th buses respectively and δ_{ij} Is the voltage phase angles of the *i*-th and *j*-th buses.

2.3 Voltage Profile Enhancement

The objective function of Voltage profile enhancement is to minimize the voltage deviation [3]:

$$F_3 = min\,(VD) = min\sum_{i=1}^{N_d}|V_i - 1| \tag{6}$$

where V_i Is the voltage at i load bus and N_d Is the number of load buses.

2.4 The Weighted Objective Functions

The proposed optimization objective function can be formulated by combing the three aforementioned objective functions into a signal objective function as fellow [9]:

$$F = F_1 + w_1\,F_2 + w_2\,F_3 \quad \$/\mathrm{h} \tag{7}$$

where w_1 and w_2 are the weighting factors which can be selected by the user [9].

2.5 Equality Constraints

The load power flow balance equation is equality constraints which states that total load demand plus the total power losses should be equaled to the total power generation. The equality constraint equation can be described as following [9]:

$$P_{Gi} = P_{Di} + V_i\sum_{j\in N_i} V_j\left(G_{ij}\,Cos\,\theta_{ij} + B_{ij}\,Sin\,\theta_{ij}\right) \tag{8}$$

$$Q_{Gi} = Q_{Di} + V_i\sum_{j\in N_i} V_j\left(B_{ij}\,Cos\,\theta_{ij} - G_{ij}\,Sin\,\theta_{ij}\right) \tag{9}$$

2.6 Inequality Constraints

Generator Limit

The voltage, real power and reactive power of the generator must be constrained within their minimum and maximum value limit [9]:

$$V_{Gi}^{min} \leq V_{Gi} \leq V_{Gi}^{max} \qquad i = 1, 2, \ldots, N \tag{10}$$

$$P_{Gi}^{min} \leq P_{Gi} \leq P_{Gi}^{max} \qquad i = 1, 2, \ldots, N \tag{11}$$

$$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max} \qquad i = 1, 2, \ldots, N \tag{12}$$

Transformer Tap Setting

The tap ratio of the transformer must be constrained within their minimum and maximum value limit [9]:

$$T_{i}^{min} \leq T_{i} \leq T_{i}^{max} \qquad i = 1, 2, \ldots, N_T \tag{13}$$

Reactive Compensators

The shunt VAR compensator must be constrained within their minimum and maximum value limit [9]:

$$Q_{Ci}^{min} \leq Q_{Ci} \leq Q_{Ci}^{max} \qquad i = 1, 2, \ldots\ldots, N_C \tag{14}$$

3 Moth-Flame Optimizer (MFO)

Moth-flame optimizer is a new stochastic nature-inspired algorithm proposed by Mirjalili in 2015 [16]. Moths are insects related to butterflies and they go through two-stage in their lifetime which is larvae moth and adult moth. The special navigation technique used by moths to travel at night called transverse orientation. The idea of transverse orientation is by maintaining a fixed angle of natural light such as the moon, moths can ensure to travel in a straight line. Since the moon is too far, it stays stationary and provides a fixed reference point for moths to navigate in a straight line. However, the advent of lamps, moths get confused and take the lamplight as an artificial moon and tries to keep a constant distance from it and end up circling the artificial light since light is too close.

3.1 MFO Mathematical Formulation

The number of moths can be represented as matrix [16]:

$$M = \begin{bmatrix} m_{1,1} & m_{1,2} & \cdots & m_{1,d} \\ m_{2,1} & m_{2,2} & \ldots & m_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ m_{n,1} & m_{1,1} & \ldots & m_{n,d} \end{bmatrix} \tag{15}$$

Where n is moths' number which represents the candidate solutions and d is the number variables.

To store the corresponding fitness value of each moth into an array as following [16]:

$$OM = \begin{bmatrix} OM_1 \\ \vdots \\ \vdots \\ OM_n \end{bmatrix} \tag{16}$$

A matrix like Moths matrix is designed for flames [16]:

$$F = \begin{bmatrix} F_{1,1} & F_{1,2} & \cdots & F_{1,d} \\ F_{2,1} & F_{2,2} & \ldots & F_{2,d} \\ \vdots & \vdots & \vdots & \vdots \\ F_{n,1} & F_{1,1} & \ldots & F_{n,d} \end{bmatrix} \tag{17}$$

Where n is moths' number which represents the candidate solutions and d is the number variables.

To store the corresponding fitness value of each flame into an array as following [16]:

$$OF = \begin{bmatrix} OF_1 \\ \vdots \\ \vdots \\ OF_n \end{bmatrix} \tag{18}$$

It is important to note that flames and moths are both candidate solutions. However, they differ only by the approach to update. Hence, the actual search agents that go around the search space are the moths whereby the best locations of moth gained so far are the flames. When searching the search space, each moth drops flame as a pinpoint, so it can search around the flame and updated it in case of finding a better solution. By applying this, the moth will never lose its best result obtained so far. The way moth updates their location depending on flames can be modeled as fellow [16]:

$$M_i = S\left(M_i, F_j\right) \tag{19}$$

where M_i, F_j indicate the *i*-th moth and *j*-th flame respectively while S represents the spiral function. The logarithmic spiral function that used to as the update mechanism is modeled as fellow [16]:

$$S\left(M_i, F_j\right) = D_i \cdot e^{bt} \cdot Cos(2\pi t) + F_j \tag{20}$$

where D_i Indicates the distance of the i-th moth for the j-th flame, b is a constant which defines the shape of the logarithmic spiral, and t is a random value within the range of $[-1, 1]$. D_i Is calculated as following [16]:

$$D_i = \left|F_j - M_i\right| \tag{21}$$

where M_i Indicate the i-th moth, F_j Indicates the j-th flame.

To guarantee the processes of exploration and exploitation of the search area, moths move around the flames and are not essential to fly within the area between the flames and moths which modeled by the spiral Eq. (20). When the subsequent position situated outside the space between the flame and the moth, exploration occurs. However, when the next position located within the area between the flame and the moth, exploitation occurs. To reach a global optimum and not to be stuck in local optima, every moth must update its location according to corresponding flames in Eq. (20) Fig. 1.

$$flame\,no = round\left(N - l * \frac{N-1}{T}\right) \tag{22}$$

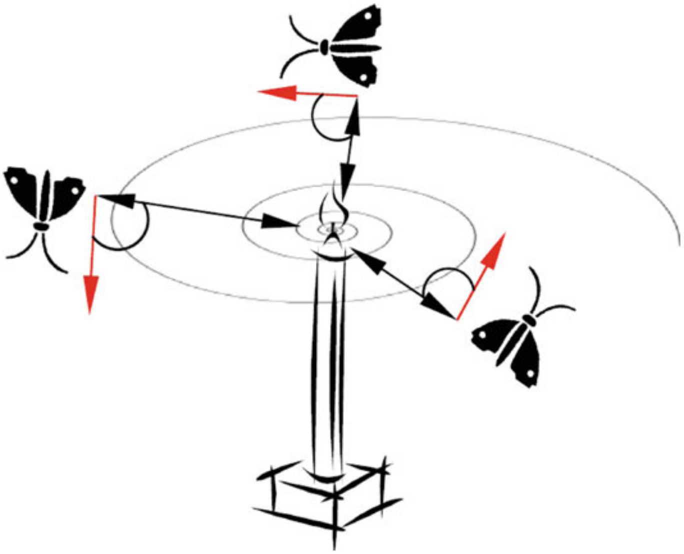
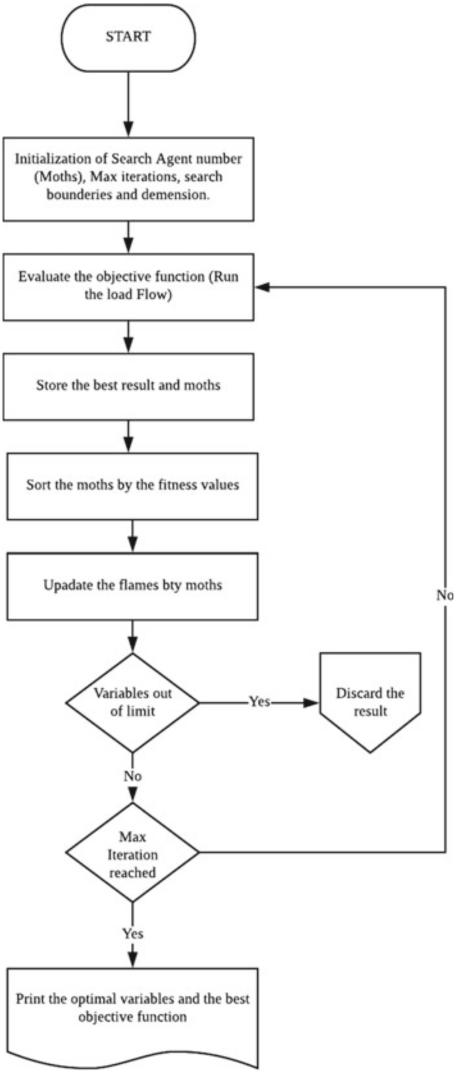


Fig. 1 The spiral flying path of Moth around light source [16]

3.2 Implementing MFO in Solving ORPD and ED Problems

The utilization of the MFO algorithm in solving the optimal ORPD problem and ED problem is via obtaining the optimal control variables to minimize the objective functions while fulfilling the equality and inequality constraints. The implementing MFO In Solving ORPD and ED problems are shown in the flow chart below Fig. 2:

Fig. 2 MFO flow chart for solving the objective function



4 Results and Discussion

To find the best optimal setting of the control variables for the OPF problem, the proposed MFO method is tested on the standard IEEE 30-bus test system.

All simulations were carried out in a MATLAB R2017a and MATOWER 6.0 software package on a personal computer with an i5 processor, 1.6 GHz, 64 bits and 8 GB RAM. In this paper, 30 search agents were selected, and the maximum iteration was 300. Moreover, the weighting factors w_1 and w_2 are selected as 1950 and 200 respectively.

4.1 IEEE 30-Bus Systems

The bus and line data of the IEEE 30-bus test system is found in [18]. This test system is composed of six generators located at buses 1, 2, 5, 8, 11 and 13, and four transformers located at lines 6–9, 4–12, 9–12, and 27–28. The total load power demand is $283.40 + j126.20$ MVA. Moreover, the total real power losses and the total reactive power losses are 5.6035 MW and 29.9294 MVAr respectively. Figure 3 shows the single line diagram of the IEEE-30 bus system while Table 1 shows the setting of control variables for IEEE 30-bus.

For the purpose of evaluating the performance of the proposed MFO, its optimal results will be compared with the simulation results of other popular optimization

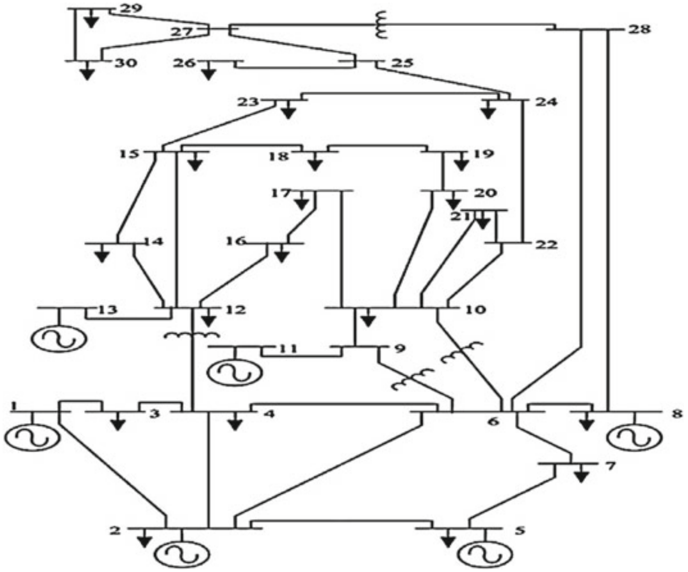


Fig. 3 Single line diagram of the IEEE-30 bus system [18]

Table 1 Upper and lower limit of control variables for the IEEE 30-bus system

Control variable	Upper bound	Lower bound
P_{G1} MW	50	200
P_{G2} MW	20	80
P_{G5} MW	15	50
P_{G8} MW	10	35
P_{G11} MW	10	30
P_{G13} MW	12	40
Generator Voltages $p.u$	0.95	1.1
Transformer Tap Setting $p.u$	0.9	1.1
Reactive Compensator Sizing $MVAr$	−10	10
$Load\ voltage(p.u)$	0.95	1.05

approaches which are ABC [9], IGWO [9]. For fair compression between the MFO and the chosen methods, the optimization results of these methods reported in their respective reference will be inserted into MTAPOWER load flow to evaluate the proposed objective function.

4.2 The Weighted-Objective Function

The three objective functions namely minimizing transmission power losses, minimizing generation cost and voltage profile improvement are compound into one single objective function using the weighting factor which is called the weighted objective function.

Table 2 shows the obtained results of MFO versus the reported optimization method namely artificial bee colony (ABC) and Improved Grey Wolf Optimizer (IGWO). It can be clearly observed that MFO outperforms the other two methods with 967.59 \$/h with a percentage of 14.50% compared to 980.1586 \$/h (13.38%) and 971.4114 \$/h (13.38%) for artificial bee colony (ABC) and Improved Grey Wolf Optimizer (IGWO) respectively. The convergence of MFO is shown in Fig. 4.

Table 2 The obtained results of MFO for the weighted objective function

Control variables	Initial	ABC [9]	IGWO [9]	MFO
Generator output unit *MW*				
P_{G1} *MW*	99.00	119.338	123.3468	199.9683
P_{G2} *MW*	80.00	54.8327	50.8357	50.84092
P_{G5} *MW*	50.00	29.2442	30.3516	31.36332
P_{G8} *MW*	20.00	35	35	35
P_{G11} *MW*	20.00	30	28.3808	26.79478
P_{G13} *MW*	20.00	21.041	21.5518	20.56381
Generator voltage *p.u*				
V_{G1}	1.060	1.0268	1.0295	1.030482
V_{G2}	1.045	1.0156	1.0171	1.016681
V_{G5}	1.010	0.994	0.9974	0.999912
V_{G8}	1.010	0.9981	1.0006	0.999795
V_{G11}	1.082	1.0459	1.0015	1.029194
V_{G13}	1.071	1.0331	1.0528	1.001948
Transformer tap ratio *p.u*				
T_{4-12}	1.0780	0.98	1.0107	1.040193
T_{6-9}	1.0690	0.9381	0.975	1.002741
T_{6-10}	1.0320	1.0125	1.0556	0.953949
T_{28-27}	1.0680	0.9672	0.978	0.979411
Capacitor bank *MVAr*				
Q_{c10}	0.0	1.4017	2.1785	10
Q_{c12}	0.0	−6.1533	−10	−1.16987
Q_{c15}	0.0	3.5496	10	2.7043
Q_{c17}	0.0	0.5092	3.4209	1.314517
Q_{c20}	0.0	4.8013	7.7976	8.443245
Q_{c21}	0.0	−3.0998	10	10
Q_{c23}	0.0	8.7841	2.256	3.742131
Q_{c24}	0.0	8.4659	9.8128	10
Q_{c29}	0.0	2.4237	3.5445	3.803413
Fuel cost ($\$/h$)	901.3495	833.9610	831.38	830.1046
Power loss, *MW*	5.6035	6.0396	6.06672	6.1289
Voltage deviation, *p.u.*	0.6051	0.1421	0.10867	0.0899
Objective function $/h	**1131.6336**	**980.1586**	**971.4114**	**967.59**

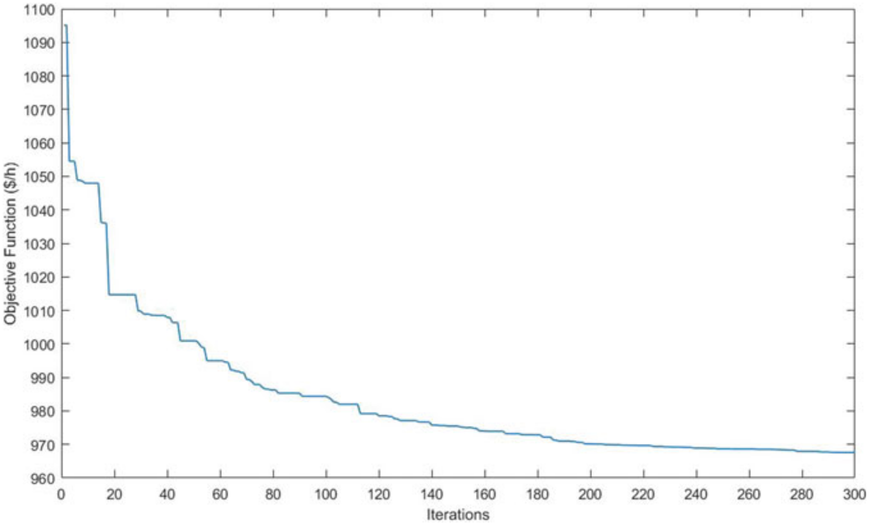


Fig. 4 Convergence performance of MFO for Case 1 (IEEE 30-bus)

5 Conclusion

In this paper, the application of MFO into solving OPF has been carried out. The three objective functions namely minimizing fuel cost, transmission loss, and voltage deviation minimization were compound into one weighted objective function. The performance of MFO has been tested in the standard IEEE 30-bus test system. Therefore, From the obtained result, MFO shows a competitive result in the OPF problem compared to the other optimization techniques in the literature. The application of MFO into a multi-objective function is highly recommended.

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