MOTH-FLAME OPTIMIZATION FOR OPTIMAL REACTIVE POWER DISPATCH

Khai Phuc Nguyen and Goro Fujita
Power system laboratory, Shibaura Institute of Technology

ABSTRACT

This paper proposed an application of Moth-flame optimization for optimal reactive power dispatch. Moth-flame optimization is a modern nature-inspired optimization technique that illustrates this behavior of moths to search the global solution. this method has been employed for the optimal reactive power dispatch (ORPD). The objective of the ORPD is to identify the reactive power controlled variables to minimize the power loss and enhance the performance of voltage profile. In order to investigate the effect of Moth-flame optimization on solving this problem, the IEEE 30-bus power system has been obtained. Numerical results show that Moth-flame optimization is better than other methods in literature.

KEYWORDS

Optimal reactive power dispatch, Moth-flame optimization, Power loss, Optimal power flow

1. INTRODUCTION

Optimal reactive power dispatch (ORPD) is a special type of the optimal power flow. It only focuses on controlling variables related with reactive power such as: output voltage of generators, load change tap of transformers, reactive power sources, etc. In literature, the objective of this problem is to minimize power loss and enhance performance of voltage profile. Therefore, ORPD tool is very useful and well-known in operating the power system.

Many optimization techniques have been proposed to solve the optimal reactive power dispatch problems. In the past, some classical methods such as linear programming (Aoki et al., 1988), quadratic programming (Quintana & Santos-Nieto, 1989), Lagrange approach (de Sousa et al., 2012) have been applied for this problem. However, the disadvantages of these techniques are difficult to handle large systems, easy convergence to local optima. Some of them only calculate on continuous and differential objective functions. In recent years, despite of the development of computers, stochastic search methods have been widely employed for the ORPD. For example, El Ela et al. applied Differential evolution (DE) for ORPD in the IEEE 30-bus system (El Ela et al., 2011); S. Durairaj et al. proposed a version of Genetic algorithm (GA) for ORPD considering voltage stability enhancement (Durairaj et al., 2006). Their works show that these evolutionary methods have been successful to search the global optima; however, each stochastic search method only effects on some problems. Hence, the development of these methods to find an effective algorithm is continued.

Recent months, Seyedali Mirjalili has developed a powerful nature-inspired optimization named Moth-flame optimization (MFO) (Mirjalili, 2015). This method is based on the strategy of moths to identify their navigation in night. A moth is an insert in nature and usually earns food in night. The moth maintains a fixed angle with the moon light to fly in night. However, if the moth were attracted to artificial light sources, such as circle lights, it would be stuck in a deadly spiral fly path. Moth-flame optimization illustrates the spiral fly path of moths while searching the global optimum. Following works of Seyedali Mirjalili show that MFO is better than six well-known optimization techniques on seven basic tested benchmarks. MFO is also favorable to solve engineering problems, such as designing gear trains in mechanical engineering or three-bar truss in civil engineering. In this paper, we apply MFO for solving the ORPD, one of popular operating problems in power system. Numerical results evaluated on the IEEE 30-bus system show that MFO is better than Differential evolution and Genetic algorithm.

This paper includes five parts. The second part describes the objective function and operational constraints of this problem. The next part describes Moth-flame optimization. Numerical results are shown in the fourth part and the last part is our conclusion and future work.

2. PROBLEM FORMULATION

2.1 Objective function

The main objective of the optimal reactive power dispatch is to minimize the power loss. Thus, the objective function is expressed as following:

$$\min F, F = P_{loss} = \sum_{l=1}^{br} R_l I_l^2$$

$$= \sum_{i=1}^{b} \sum_{\substack{j=1 \\ i \neq j}}^{b} \left[V_i^2 + V_j^2 - 2V_i V_j \cos\left(\delta_i - \delta_j\right) \right] Y_{ii} \cos\varphi_{ij} \quad (1)$$

where br and b are the number of lines and buses, respectively; R_l is the resistance of line l^{th}; I_l is the current through line l^{th}; V_i and δ_i are the magnitude and angle of voltage at the i^{th} bus, respectively; Y_{ij} and φ_{ij} are the magnitude and angle of the line admittance between bus i^{th} and bus j^{th}, respectively.

2.2 Operational constraints

The optimal solutions have to satisfy all of operational constraints such as the power balance constraint, limitation of bus voltages and transmission lines.

2.2.1 Power balance constraint:

As other problems for operation in a power system, the balance of generating and demand powers must be satisfied at each node. Two below equations describe the balance of active and reactive powers in a power system:

$$P_{G,i} - P_{D,i} = = V_i \sum_{i=1}^{b} \left[V_j \left[G_{ij} \cos\left(\delta_i - \delta_j\right) + B_{ij} \sin\left(\delta_i - \delta_j\right) \right] \right] \quad (2)$$

$$Q_{G,i} - Q_{D,i} = = V_i \sum_{i=1}^{b} \left[V_j \left[G_{ij} \sin\left(\delta_i - \delta_j\right) - B_{ij} \sin\left(\delta_i - \delta_j\right) \right] \right] \quad (3)$$

where $P_{G,i}$ and $Q_{G,i}$ are the active and reactive generating powers at the i^{th} bus, respectively; $P_{D,i}$ and $Q_{D,i}$ are the active and reactive of demand powers at the i^{th} bus, respectively. G_{ij} and B_{ij} represent the real and imaginary components of element Y_{ij} of the admittance matrix, respectively.

2.2.2 Limitation constrains of generators:

Terminal voltage and reactive output power of a generator work in range as follows:

$$V_{Gi,\min} \le V_{Gi} \le V_{Gi,\max} \quad (4)$$

$$Q_{Gi,\min} \le Q_{Gi} \le Q_{Gi,\max} \quad (5)$$

2.2.3 Limitation of shunt-VAR compensators

The reactive power sources are bounded as follows:

$$Q_{Ci,\min} \le Q_{Ci} \le Q_{Ci,\max} \quad (6)$$

2.2.4 Limitation of transformer load changers

Upper and lower limits restrict transformer tap settings as shown below:

$$V_{Ti,\min} \le V_{Ti} \le V_{Ti,\max} \quad (7)$$

2.2.5 Limitation of load bus voltages:

In order to keep the power system operate in stability and commit power quality, voltages at load buses must be maintained around a nominal value.

$$V_{li,\min} \le V_{li} \le V_{li,\max} \quad (8)$$

2.2.6 Limitation of transmission lines:

Because of limited thermal condition, all transmission lines in the power system have to satisfy an upper bound as follow:

$$\left|S_{li}\right| \le S_{li}^{\max} \quad (9)$$

3. MOTH-FLAME OPTIMIZATION

Moths are fancy insects and familiar with butterflies. Moths have a special navigation method at night. They use the moon light to direct their fly by maintaining a constant angle with respect to the moon. Since the moon is far away from the earth, this mechanism help moths fly in a straight path. However, moths are usually confused because of artificial light sources. The human-made circle lights attract moths and let them into a deadly way (Gaston et al., 2013; Frank, 2005). When moths see a circle light, they keep maintaining a fixed angle with the light. Unfortunately, the light compared with the moon is extremely close, thus moths' fly path becomes a spiral path. Fig. 1 shows a conceptual model of this behavior.

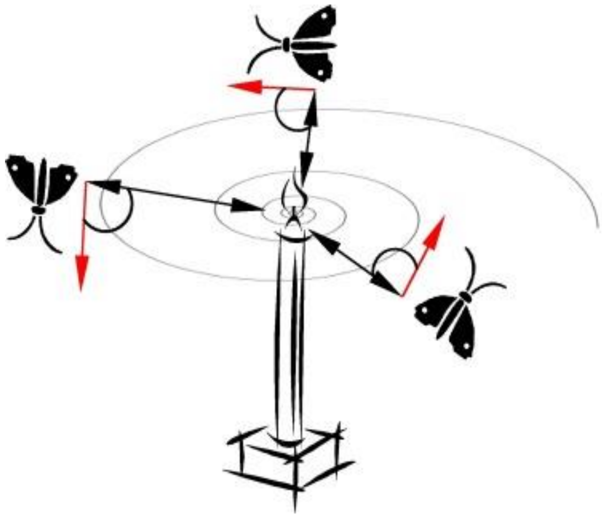

Figure 1: Spiral-flying path around a close light (Mirjalili, 2015)

Basing on the convergence of moths towards the light, Seyedali Mirjalili proposed the Moth-flame optimization. In MFO, each moth represents a solution and variables of the problem are the position of the moth. Flames, which are artificial light sources, store the best positions of the moths. The new position of a moth is updated with respect to a flame via the spiral function as following equation. Fig. 2 illustrates the positions of the flame, the moth and the logarithmic spiral function.

$$M_i = S(M_i, F_j) = D_i \cdot e^{bt} \cdot \cos(2\pi t) + F_j \quad (10)$$

where:

- M_i indicates the position of the i^{th} moth.
- F_j indicates the position of the j^{th} flame.

- b is a constant for defining the shape of logarithmic spiral.
- t is a random number in the range [-1;1].
- D_i indicates the distance between the M_i moth and F_j flame. D_i is calculated as follows:

$$D_i = \left| F_j - M_i \right| \qquad (11)$$

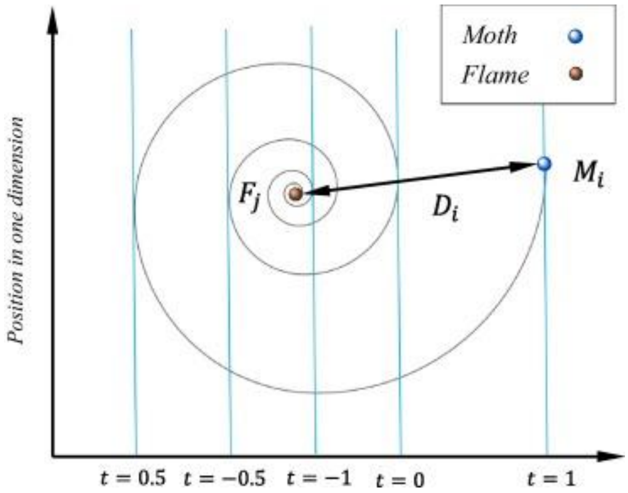

Figure 2: Logarithmic spiral, space around a flame, and the position with respect to t (Mirjalili, 2015)

In order to enhance performance of moths on searching the global optimum, the author proposed a limited number of flames that moths are attracted to. This number is decreased over the course of iterations to cause moths to focus on global solution at the end of the process. The following formula defines this number:

$$flame\_no = round\left(N - it \cdot \frac{N-1}{T} \right) \qquad (12)$$

where it is the current number of iteration, N is the maximum number of flames and T is the maximum number of iterations.

4. SIMULATION RESULTS:

Proposed Moth-flame optimization has been applied to solve the optimal reactive power dispatch problem in the IEEE 30-bus power system. The obtained numerical results are compared with Differential evolution algorithm (El Ela et al., 2011) and Genetic algorithm (Durairaj et al., 2006). This application has been coded in Matlab 2015a and run in a personal computer with a 2.13GHz Core i3 processor M330 and 4GB RAM. The benchmark has been run 30 independent trials. In order to calculate power flow, we have employed the Newton-Raphson method by the Matpower toolbox (Zimmerman et al., 2011).

This case study is the standard IEEE 30-bus system. The tested system consists of 6 generators, 41 branches and 24 load buses. There are nine installed reactive sources at the 10^{th}, 12^{th}, 15^{th}, 17^{th}, 20^{th}, 21^{th}, 23^{th}, 24^{th} and 29^{th} buses. Four branches are transformers with tap changers in lines (6, 9), (6, 10), (4, 12) and (27, 28). The reactive power generation limits are taken from (Mahadevan & Kannan, 2010) and the maximum apparent power flows of transmission lines are given in (Ayan & Kl, 2012). The limitations of transformer lap changers, generator voltage and voltages at load buses are as follows:

$$\begin{aligned} 0.95 &\le V_{Gi} \le 1.1 \\ 0.90 &\le V_{Ti} \le 1.1 \\ 0.95 &\le V_{li} \le 1.1 \end{aligned} \qquad (13)$$

Table 1: Numerical results of compared methods for IEEE 30-bus tested system

	MFO	DE (El Ela et al., 2011)	GA (Durairaj et al., 2006)
Best [MW]	4.5125	4.5550	4.6501
Mean [MW]	4.5219	-	-
Worst [MW]	4.5331	-	-
Standard deviation	0.0083	-	-

Table 2: Optimal solution proposed by MFO

Control variables	MFO	Control variables	MFO
V_{G1} (p.u.)	1.1	Q_{C20} (MVar)	4.0951
V_{G2} (p.u.)	1.0943	Q_{C21} (MVar)	5.0
V_{G5} (p.u.)	1.0747	Q_{C23} (MVar)	2.5329
V_{G8} (p.u.)	1.0766	Q_{C24} (MVar)	5.0
V_{G11} (p.u.)	1.1	Q_{C29} (MVar)	2.2105
V_{G13} (p.u.)	1.1	T_{6-9} (p.u.)	1.0403
Q_{C10} (MVar)	5.0	T_{6-10} (p.u.)	0.9
Q_{C12} (MVar)	5.0	T_{4-12} (p.u.)	0.9758
Q_{C15} (MVar)	4.9790	T_{28-27} (p.u.)	0.9636
Q_{C17} (MVar)	5.0		
Power loss (MW)		4.5125	

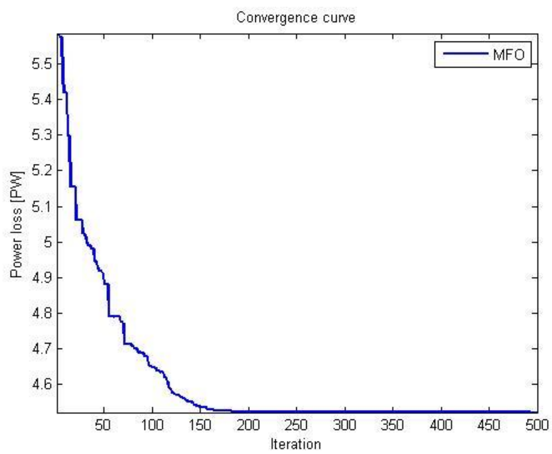

Figure 3: Convergence characteristic of MFO in the IEEE 30-bus system

According to numerical results in Tab. 1, the proposed MFO gives better solution than Differential evolution and Genetic algorithm. Tab. II shows the optimal solution proposed by MFO. Within this solution, most of capacitors have injected maximum reactive power into the system. In addition, Fig. 3 illustrates the convergence curve of MFO. The proposed method fast converges at the beginning of the search process and finds the optimal solution.

5. CONCLUSION

The proposed Moth-flame optimization has been successful in solving the optimal reactive power dispatch. This method simulates the spiral-flying path of a moth in nature when it is attracted to an artificial light. Each moth represent a solution and flames store the best solutions. The new position of a moth is updated via the spiral function with respect to flames. MFO is really a powerful and robust algorithm. For the IEEE 30-bus system, its proposed solution is better than these of Differential evolution and Genetic algorithm. Thus, MFO is favorable to apply for a larger system.

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Khai Phuc Nguyen received his B.Eng. and M.Eng. degrees in electrical engineering from Ho Chi Minh City University of Technology, Vietnam, in 2010 and 2012, respectively. He is a Ph.D. student at Shibaura Institute of Technology, Tokyo, Japan. His research interests Artificial Intelligence (AI) in power system optimization, power system operation and control, power system analysis and automation in power system.

Goro Fujita received the B.Eng., M.Eng. and Ph.D. degrees in electrical engineering from Hosei University, Tokyo, Japan in 1992, 1994 and 1997 respectively. He is a Professor at Shibaura Institute of Technology, Tokyo, Japan. His interest is in power system control including dispersed power systems. He is a Professional Engineer in Japan and First Class Licensed Engineer of Electric Facility.

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