# An Enhanced Moth Flame Algorithm for Peak Load Distribution Optimization

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**Abstract.** Peak load distribution optimization (PLD) is a typical multi-constrained nonlinear optimization problem considered an essential vital part of the power system to achieve energy-saving and consumption reduction. This study introduces an enhanced version of the moth flame optimization algorithm (EMFO) for the PLD problem. The actual operation constraints of the power system of the PLD are modeled for the objective function of optimization. In the experimental section, the IEEE-bus benchmark system is used as the case study to test the performance of the proposed scheme. The results show that the proposed scheme can solve the power system PLD problem with feasibility and significant economic benefits.

**Keywords:** Peak load distribution optimization; Regulation load distribution power; Peak shaving cost; Enhanced moth flame algorithm.

## 1 Introduction

Peak load distribution optimization (PLD) is one of the essential load dispatch problems to allocate power generations system optimally [1]. A power generation system includes multiple power generation units to achieve minimum power generation cost under the system constraints [2]. The optimization problem is to find a decision that makes one or more relationship indicators reach the maximum (or minimum) under the restriction of a series of objective or subjective conditions [3]. Increasing the clean energy installed capacity share is an unavoidable prerequisite for the power system's healthy and long-term development [4]. Thermal power, however, continues to account for a significant component of the country's power supply structure due to its long history of evolution [5]. As the penetration rate of clean energy in the grid rises, the area available for thermal power generation will inevitably shrink, and thermal power units will gradually transition to a peak-shaving role [6].

The power generation cost has attracted much attention from scholars as a review of the literature. Current research works primarily focus on calculating the economic benefits of thermal power peak shaving [7]. The goal function of maximizing clean energy consumption, development of peak shaving auxiliary markets, power peaking load distribution, and power peaking load distribution are complex nonlinear problems [8].
The traditional optimization methods, e.g., linear programming, gradian climbed hilling, square optimum, would be faced the computation complex times when dealing with the complicated problem like the nonlinear PLD [9]. The metaheuristic algorithms [10], e.g., genetic algorithms (GA) [11], swarm algorithms (PSO)[12], evolution algorithms (DE), improved bat algorithms (IBA) [3][13] effectively solve the typical PLD problems.
The moth flame optimizer (FMO) [14] is a newly proposed metaheuristic algorithm inspired by the moth behavior in flying spiral trajectory for lighting flame. Still, it has disadvantages, such as optimal local solution, slow convergence rate, etc., making the problem's solution unsatisfactory. Optimizing large-scale power systems such as the PLD is still falling into the local optimum if the algorithm lacks diversity agents.
This study proposes an enhanced version for the moth flame optimization algorithm (EMFO) based on chaotic sequence and quadratic interpolation to improve its diversity agent. It means the algorithm's exploration and development capabilities could be effectively balanced and enhanced—the algorithm's convergence speed. As the analysis statement, a solution to the peak-load cost estimation of power load distribution is modeled to minimize the cost based on a novel EFMO. The suggested resolution is implemented to provide a particular reference for the optimized operation of thermal power under a high-proportion clean energy grid.

## 2 Peak Load Distribution Model

The receiving-end power grid unit acts as a peak-shaving unit, compressing its own power generation space to guarantee clean energy consumption [6]. The peak shaving process compared with the original power generation plan [15]. This part of the on-grid electricity revenue loss is the unit opportunity cost. For peak shaving thermal power unit *i-th*, its opportunity cost calculates as the following formula.

$$R_i = \sum_{t=1}^{T}(P_{i,t}^{sc} - P_{i,t}^{ac}) \times \Delta t \times \rho^{BG} \tag{1}$$

In the formula $R$ is the opportunity cost of thermal power unit $i$; $T$ is the scheduling period; $P_{i,t}^{sc}$ is the planned power generation; $P_{i,t}^{ac}$ is the power generation after peak shaving; $\Delta t$ is the generation time of thermal power during this period; $\rho^{BG}$ is the on-grid price of thermal power. The output reduction of peak-shaving thermal power units has lost part of the on-grid power. Due to the power output status change, the production cost of power generation has also changed correspondingly. The second-order function is modeled as follows.

$$C_{gi} = aP^2 + bP + c \tag{2}$$

Where $C_{gi}$ is the power generation cost of the production power unit $I$; $P$ is the unit's output, and $a$, $b$, and $c$ are the unit coefficients. The change in the production cost of peak-shaving thermal power plants can be expressed as follows..

$$\Delta C_{i,t} = C_{gi} \times P_{i,t}^{sc} - C_{gi} \times P_{i,t}^{ac} \quad (3)$$

In formula, $\Delta C_{i,t}$ is the change in power generation cost during $t$. When it is a positive number, it indicates that the cost of power generation has decreased, otherwise, it suggests that the cost of power generation has increased; $C_{gi} \times P_{i,t}^{sc}$ is the planned power generation cost, and $C_{gi} \times P_{i,t}^{ac}$ is the actual power generation cost. Based on the above processing, the total cost of peak shaving of thermal power units is shown in the following formula.

$$R_{ac,i} = R_i - \sum_{t=1}^{T} \Delta C_{i,t} \quad (4)$$

In the formula, $R_{ac,i}$ is the total cost of peak shaving of the thermal power unit. A model of minimizing peaking cost as the objective function of the power peaking load distribution will be presented in Section 4.

# 3 Enhanced Moth Flame Optimization

The moth flame optimization algorithm (MFO) [14] is a new metaheuristic algorithm that has advantages as understand and implement quickly and few parameters. Still, it has disadvantages, e.g., fulling local optimum and slow convergence when dealing with a complex problem. The enhanced moth flame optimization (EMFO) algorithm is proposed in this section using chaotic initialization and Gaussian mutation to improve the algorithm's ability to jump out of the local optimum. The brief presentation is listed as follows. First, the moth population is initialized using cubic chaotic mapping to make the moths more evenly distributed in the search space. Second, Gaussian mutation is used to perturb a small number of poor individuals population. Third, the Archimedes curve is used to broaden the search range and improve the ability to explore the previously unexplored territory.

## 3.1 Moth Flame Optimization

Let $Mo$ be a matrix of the spatial position of the moth in the MFO algorithm [14] with n is a moth population size and d is a dimension of the space search problem. The position matrix in space is similar to the space matrix of moths, represented as follows.

$$Mo(n,d) = \begin{bmatrix} m_{o11} & m_{o12} & \cdots & m_{o1d} \\ m_{o21} & m_{o22} & \cdots & m_{o2d} \\ \vdots & \vdots & \vdots & \vdots \\ m_{on1} & m_{on2} & \cdots & m_{ond} \end{bmatrix} \quad (5)$$

Let $OMo$ be the objective function value as of other moths' individual space stored by the matrix *Mo* as follows.

$$OMo = [om_{o1}, om_{o2}, \dots, om_{on}]^T \quad (6)$$

Let *Fr* be the flame core of the algorithm with their objective function values as follows.

$$Fr(n,d) = \begin{bmatrix} f_{r11} & f_{r12} & \cdots & f_{r1d} \\ f_{r21} & f_{r22} & \cdots & f_{r2d} \\ \vdots & \vdots & \vdots & \vdots \\ f_{rn1} & f_{rn2} & \cdots & f_{rnd} \end{bmatrix} \quad (7)$$

The objective function value is calculated for the flame's position as follows.

$$OFr = [of_{r1} \quad of_{r2} \quad \dots \quad of_{rn}]^T \tag{8}$$

The flame reduction principle process is implemented as given in the following formula.

$$flame_r = Round(N - t \times \frac{N-1}{T}) \tag{9}$$

Where $i$ and $T$ are the current number of iterations and the maximum number of iterations, respectively; $N$ is the maximum number of flames.

$$D_i = |Fr_j - Mo_i| \tag{10}$$

where $D_i$ is the distance of the flame to moth that are flying moth move towards the flame position. The movement path is given as a logarithmic spiral curve, and the curve is taken as the primary update mechanism of the moth. The logarithmic spiral curve of the algorithm is defined as follows.

$$S(Mo_i, Fr_j) = D_i e^{bt} \cos(2\pi t) + Fr_j \tag{11}$$

Where $S(Mo_i, Fo_j)$ is the updated position of the moth; *D* is the distance between the *i-th* moth and the *j-th* flame; is a constant related to the shape of the spiral; *b* is a random number, the value interval is *[-1,1]*; $e^{bt} \cdot \cos(2\pi t)$ is the right a number spiral curve expression.

### 3.2 An Enhancement of FMO

Gaussian mutation mechanism is used to determine the flame space position, leading to the effective utilization of the current global optimal moth. With the updated formulas of the solution in the algorithm, the space vector position of each moth is directly related to the position of the closest flame space. The selected individual's worst fitness value is applied to mutate to the moth population scale; it represents the variance convenient for controlling and narrowing the update range and appropriately increasing the population diversity of the algorithm. The improved moth generation formula is described as follows.

$$\gamma_i = 4\gamma_{i-1}n^3 - 3\gamma_{i-1}n \tag{12}$$

where $\gamma_i$ is a random generator as cubic chaotic; $-1 \leq \gamma \leq 1, \quad n = 0,1, \dots, N$. The initializing the moth population using a cubic chaotic map is the map to the solution space as the following formula.

$$x_{id} = L_d + (1 + \gamma_{id}) \times \frac{U_d - L_d}{2} \tag{13}$$

where $U$ and $L$ are the upper and lower bound of the search space; d is the dimensional coordinate of the generated i-th moth.

$$M_{new}^t = M_j^{*t} + Gaussian(\mu, \sigma^2) \tag{14}$$

where $Gaussion(\mu, \sigma^2)$ is generation of the population; $n$ is the moth population size; $\sigma$ is the proportion of variation; $\mu$ is the mean value; According to experience of the variance, the value of $\sigma$ is set to 1/6 in the algorithm.

## 4 The EFMO for Load Distribution Optimization

The optimization problem of the PLD is modeled as its objective function with the total amount of incoming electricity from the receiving end power system grid. It is determined by the total amount of incoming electricity or additional local clean energy issuance at each period. The peak load share based on the peaking cost of each power unit is bear over time, minimizing the thermal power peaking load distribution [15].

$$obj = \min(\sum_{i=1}^{N} R_{ac,i}) \tag{15}$$

where $obj$ is the objective function; $N$ is the total number of peak-shaving thermal power units, and other parameters are the same as above. Subjective to the objective function is dealing with its constraints.

Power balance constraint is given as follows.

$$\sum_{i=1}^{N} \Delta P_{i,t} = \Delta P_t \quad (t = 1,2,\dots,T) \tag{16}$$

In the formula: $\Delta P_{i,t}$ is the peak-shaving load allocated to the $i$-th thermal power unit at time t; $\Delta P_t$ is the total peak-shaving demand of the power grid at time $t$.

The active output of the power units constraint is expressed as follows.

$$P_{i,min} \le P_{i,t} \le P_{i,max} \tag{17}$$

where $P_{i,min}$ and $P_{i,max}$ are the minimum and maximum technical output of the thermal power unit, respectively. Generating units climbing ability constraints are presented as follows.

$$\begin{cases} P_{i,t} - P_{i,t-1} \le A_{u,i} \\ P_{i,t-1} - P_{i,t} \le A_{d,i} \end{cases} \quad (i = 1,2,\dots,N) \tag{18}$$

where $A_{u,i}$ and $A_{d,i}$ are the maximum climbing ability and the maximum downward climbing ability of the thermal power unit, respectively.

The minimum startup and shutdown constraints of the unit is expressed as below.

$$\begin{cases} (Y_{i,t-1}^{on} - U_{i,min}^{on})(s_{i,t-1} - s_{i,t}) \ge 0 \\ (Y_{i,t-1}^{off} - U_{i,min}^{off})(s_{i,t} - s_{i,t-1}) \ge 0 \end{cases} \tag{19}$$

where $Y_{i,t-1}^{on}$ and $Y_{i,t-1}^{off}$ are respectively when the thermal power unit $i$ actually starts and stops time; $U_{i,min}^{on}$ and $U_{i,min}^{off}$ are the minimum start and stop time of thermal power unit $i$; $s_{i,t}$ are the state variables of thermal power unit, 1 means running, 0 means stop. Algorithm 1 shows a pseudo-code of the EFMO for the PLD as the steps of the process optimization.

*Algorithm 1.* EFMO's pseudo-code for the PLD

1: Initialization parameters: population size *N*, dimension *D*, maximum number of iterations *MaxT*;
2: Mapping modeling optimization space to moth solutions; Randomly initialize the moth position $Mo$ in the search space;
3: **while** (l <= *MaxT*)
4: Calculate the objective function value *OMo* of each moth, Eqs.(5),(6);
5: Calculate the number of flames, Eqs(7),(8)

6: If the current iteration number $l = 1$, update the flame population according to $OFr = sort\ (OMo)$, $Fr = sort\ (Mo)$;
7: Otherwise, update the flame population according to $OFr = sort\ (OMol - 1, OMl)$, $Fr = sort(Ml - 1, Ml)$;
8: Record the first flame as the best individual;
9: **for** $i = 1$ to $N$ do
10: Update the position of the moth;
11: Determine whether the individual position of the moth exceeds the upper and lower limits of the search space;
12: If it exceeds the boundary, re-initialize the position in the search space;
13: **end for**
14: **end while**
15: Output the optimal solution.

Fig. 1 displays the solution process as a flowchart of the gusseted EFMO for the OLD problem.

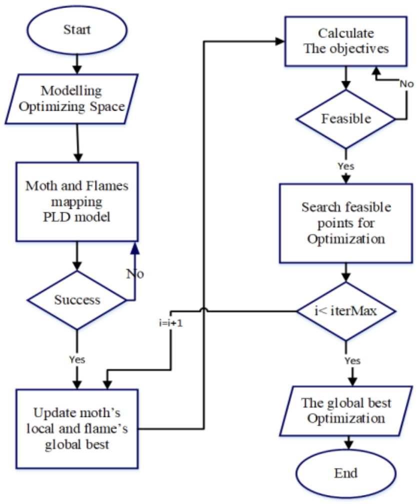


**Fig. 1.** A flowchart of the gusseted EFMO for the PLD problem

**Table 1.** Power generation cost coefficient parameters of the thermal power unit for peak load regulation

| Plants installed capacity/MW | Power generation cost factors | | |
|---|---|---|---|
| | $a$ | $b$ | $c$ |
| 135 | 0.024 1 | 236.3 | 17 066 |
| 150 | 0.024 0 | 236.02 | 18 082 |
| 300 | 0.022 4 | 233 | 27 405 |
| 350 | 0.022 0 | 232.3 | 31 621 |

| | | | |
|---|---|---|---|
| 360 | 0.021 9 | 232.11 | 32 298 |
| 467 | 0.020 8 | 230.12 | 39 541 |
| 600 | 0.019 1 | 228 | 50 000 |
| 660 | 0.018 9 | 226.53 | 52 606 |
| 1000 | 0.015 0 | 220 | 75 000 |

## 5 Experimental Results

The selection standard is adopted the load power in typical calculation daily. All power plants in the power grid are turned on, and the load rate is relatively high: Table 1 displays the power generation cost and coefficient parameters of a power grid system. The amount of renewable energy generation that the power grid can absorb is directly proportional to the power system's peak shaving capacity.
The peak-shaving demand curve is set to ensure the electricity grid's safe and steady operation. An IEEE benchmark power grid system [16] with fifteen plants is used to test the performance of the EFMO in order to verify its dependability and effectiveness. The unit test system also considers slow-changing rate, ascending, and output upper and lower limitations, and total load demand. The suggested EFMO's results are compared to the MFO [14], PSO[12], and IBA[3]. The number of search agents is uniformly set to 30 in all algorithms during the simulation, and the maximum number of iterations is 1000.

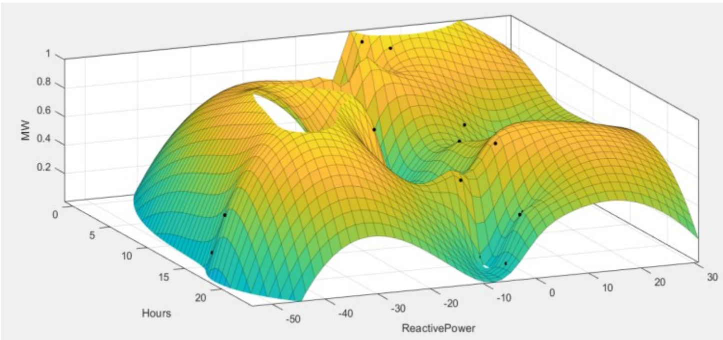


**Fig. 2.** A obtained peak-shaving load distribution curve from the EFMO

Figure 2a illustrates the visual graph of the introduced scheme for the peak-shaving load distribution of a power grid system.

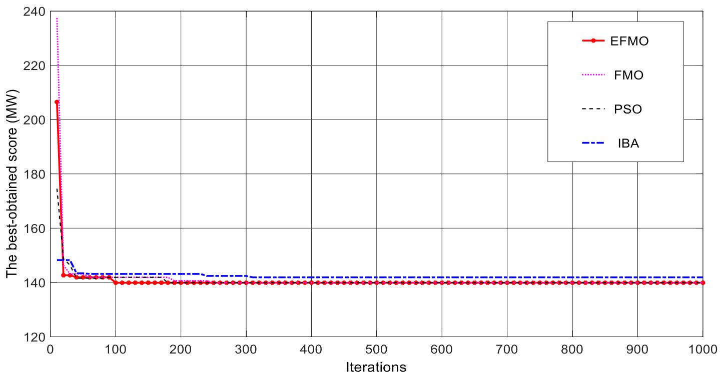


**Fig. 3.** Comparison of the suggested scheme with the other algorithms,e.g., the FMO[14], PSO[12], and IBA[3] algorithms for the LPD problem in terms of convergence curve

Fig. 3 shows the comparison of the suggested method with the other algorithms,e.g., the FMO[14], PSO[12], and IBA[3] algorithms for the LPD problem. It can be seen that the EFMO produces the convergence fastest and increases the quality of performance for the optimization problem.

**Table 2.** Comparison of obtained results of the suggested EFMO with the FMO, PSO, and IBA algorithms for the grid system of fifteen plant units.

| Plant Units | **EFMO** | FMO | PSO | IBA |
|---|---|---|---|---|
| $P_1$ | 297.42 | 268.17 | 312.07 | 250.63 |
| $P_2$ | 289.78 | 318.50 | 288.14 | 263.40 |
| $P_3$ | 77.27 | 91.00 | 89.61 | 81.34 |
| $P_4$ | 91.00 | 14.00 | 85.32 | 48.37 |
| $P_5$ | 254.81 | 181.32 | 174.03 | 307.02 |
| $P_6$ | 234.81 | 322.00 | 214.02 | 234.94 |
| $P_7$ | 236.67 | 325.50 | 141.63 | 263.88 |
| $P_8$ | 119.70 | 42.00 | 154.56 | 100.87 |
| $P_9$ | 86.01 | 103.61 | 106.72 | 51.64 |
| $P_{10}$ | 62.89 | 30.08 | 108.21 | 99.42 |
| $P_{11}$ | 37.58 | 51.77 | 50.72 | 42.99 |
| $P_{12}$ | 18.33 | 31.76 | 36.51 | 32.59 |
| $P_{13}$ | 21.98 | 17.50 | 51.99 | 45.90 |
| $P_{14}$ | 20.45 | 25.90 | 28.74 | 25.45 |
| $P_{15}$ | 20.78 | 37.09 | 31.16 | 20.76 |
| Total power output (MW.) | **1869.48** | 1860.20 | 1873.44 | 1869.19 |
| Total generation cost ($/h.) | **23500.37** | 23645.18 | 23712.08 | 23697.81 |

| | | | | |
|---|---|---|---|---|
| Power loss (MW.) | **27.10** | 27.60 | 32.46 | 28.21 |
| Deviation | 0.02 | 0.03 | 0.02 | 0.02 |
| Total CPU times (sec.) | 0.33 | **0.32** | 0.85 | 1.14 |

Table 2 depicts a comparison of obtained results of the suggested FMO with the FMO, PSO, and IBA algorithms for the grid system of fifteen plant units. The compared results show that the total cost of system peak shaving of the EFMO is better than the FMO, PSO, and IBA. It means that the proposed EFMO has a more vital ability to avoid local optimal solutions. The EFMO can provide a specific reference for optimizing the power operation under the background of high clean energy penetration and calculating the power peak-shaving compensation costs.

## 6 Conclusion

This paper proposed an enhanced moth flame optimization algorithm (EMFO) to avoid the original one's falling local optimum for the peak load distribution (PLD) problem. Based on the peak load cost theory, the objective function is constructed for the power peak load distribution model. The actual operation constraints of the PLD power system are dealing with using the penalty function in optimization. In the experimental section, the case study of the selected IEEE-bus benchmark system is used to test the performance of the proposed EFMO system. The suggested scheme results are compared with the previous schemes in the literature show that the proposed EFMO can solve the power system PLD problem with significant economic benefits. In future work, we will extend implementation with a complicated benchmark CEC 2019 function test suite to prove the proposed EFS performance and compare the results with various swarm algorithms.

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