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Adaptive Mfo Algorithm for Partial Discharge Localization Using Acoustic Emission Technique

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Abstract: - The Moth-Flame Optimization (MFO) Algorithm, a ground-breaking bio-inspired optimization approach, draws inspiration from the navigation behavior of moths in the universe. Diverging from traditional meta-heuristics, its distinctive characteristic lies in the pivotal role of randomization, which plays a significant role in both exploring and exploiting optimization problems.

This innovative algorithm incorporates an adaptive randomization technique, seamlessly integrated with MFO. The algorithm is put through rigorous testing using unconstrained benchmark functions and the localization of partial discharge in transformer geometry. Leveraging the logarithmic spiral function distinguishes MFO, enabling it to cover expansive areas during the exploration phase. When coupled with the potent adaptive randomization technique, the resulting Adaptive MFO (AMFO) algorithm excels in achieving global optimal solutions with faster convergence and reduced parameter dependency. Evaluation of AMFO solutions demonstrates its competitive performance superiority over conventional optimization algorithms.

Keywords: Meta-heuristic, Moth-Flame optimizer, Adaptive technique, Acoustic emission, Partial discharge, Transformer.

I. INTRODUCTION

An innovative algorithm, known as the Moth-Flame optimization algorithm [1], draws inspiration from nature and is based on the transverse orientation navigation mechanism observed in moths. Moths employ a constant angle in relation to the Moon, which is situated thousands of miles away, ensuring straight flight. Adapting this transverse mechanism to artificial lights closer to the moths than the Moon, they are deceived by a dynamic angle concerning the flame. This angle gradually decreases, leading moths to navigate around flames in a logarithmic spiral pattern, ultimately converging towards the flame. The logarithmic spiral serves as the exploration area, ensuring both exploration and exploitation of the optimal solution.

Randomization is a crucial factor in meta-heuristic algorithms, significantly influencing both exploration and exploitation. Enhanced randomization techniques, such as Markov chains, Levy flights, and Gaussian or normal distribution, play a vital role in these processes. Additionally, the incorporation of adaptive techniques in meta-heuristic algorithms leads to reduced computational time for achieving optimal solutions, avoidance of local minima, and faster convergence.

Historically, numerous optimization algorithms relied on gradient search to address both linear and non-linear equations. However, in the gradient search method, the stability of the objective function and constraints becomes precarious, especially in scenarios with multiple local optima, leading to the presence of unstable values and multiple peaks.

The meta-heuristic optimization algorithm known as Population-based MFO demonstrates the ability to steer clear of local optima, enabling the attainment of globally optimal solutions. This characteristic renders it well-suited for practical applications without requiring structural modifications to address diverse constrained or unconstrained optimization problems. The integration of MFO with adaptive techniques serves to decrease computational times, particularly for highly intricate problems.

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Paper under literature review are: Adaptive Cuckoo Search Algorithm (ACSA) [2] [3], QGA [4], Acoustic Partial discharge (PD) [5] [6], HGAPSO [7], PSACO [8], HSABA [9], PBILKH [10], KH-QPSO [11], IFA-HS [12], HS/FA [13], CKH [14], HS/BA [15], HPSACO [16], CSKH [17], HS-CSS [18], PSOHS [19], DEKH [20], HS/CS [21], HSBBO [22], CSS-PSO [23] etc.

Recently trend of optimization is to improve the performance of meta-heuristic algorithms [24] by integrating with chaos theory, Levy flights strategy, Adaptive randomization technique, Evolutionary boundary handling scheme, and genetic operators like as crossover and mutation. Popular genetic operators used in KH [25] which can accelerate its global convergence speed. Evolutionary constraint handling scheme used in Interior Search Algorithm (ISA) [26] that avoid upper and lower limits of variables.

II. MOTH-FLAME OPTIMIZER

Use this document as a template by simply typing your text into it. Moth-Flame optimizer is first introduced by Seyedali Mirjalili in 2015 [1]. MFO is a population-based algorithm; we represent the set of moths in a matrix:

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

Where, n represents a number of moths and d represents the number of variables (dimension).

For all the moths, we also assume that there is an array for storing the corresponding fitness values as follows:

$$OM = \begin{bmatrix} OM1 \\ OM2 \\ . \\ . \\ OMn \end{bmatrix} \quad (2)$$

Where, n is the number of moths.

Note that the fitness value is the return value of the fitness (objective) function for each moth. The position vector (first row in the matrix M for instance) of each moth passed to the fitness function and the output of the fitness function assigned to the corresponding moth as its fitness function (OM1 in the matrix OM for instance).

Other key components of the proposed algorithm are flames. We consider a matrix similar to the moth matrix:

$$F = \begin{bmatrix} FL1,1 & FL1,2 & . & . & FL1,d \\ FL2,1 & FL2,2 & . & . & FL2,d \\ . & . & . & . & . \\ . & . & . & . & . \\ FLn,1 & FLn,2 & . & . & FLn,d \end{bmatrix} \quad (3)$$

Where, n shows a number of moths and d represents the number of variables (dimension).

We know that the dimension of M and F arrays are equal. For the flames, we also assume that there is an array for storing the corresponding fitness values:

$$OF = \begin{bmatrix} OFL1 \\ OFL2 \\ . \\ . \\ OFLn \end{bmatrix} \quad (4)$$

Where, n is the number of moths.

Here, it should note that moths and flames both are solutions. The difference between them is the way we treat and update them, in the iteration. The moths are actual search agents that move around the search space, whereas flames are the best position of moths that obtain so far. Therefore, each moth searches around a flame and updates it in case of finding a better solution. With this mechanism, a moth never loses its best solution.

The MFO algorithm is three-rows that approximate the global solution of the problems defined like as follows:

$$\mathrm{MFO} = (I, \mathrm{P}, \mathrm{T}) \quad (5)$$

I is the function that yields an uncertain population of moths and corresponding fitness values. The methodical model of this function is as follows:

$$I: \emptyset \rightarrow \{M, OM\} \quad (6)$$

The P function, which is the main function, expresses the moths around the search space. This function receives the matrix of M and takes back its updated one at every time with each iteration.

$$P: M \rightarrow M \quad (7)$$

The T returns true and false according to the termination Criterion satisfaction:

$$T: M \rightarrow \{true, false\} \quad (8)$$

To mathematical model this behavior, we change the position of each Moth concerning a flame using the following equation:

$$M_i = S(M_i, F_j) \quad (9)$$

Where M_i indicate, the i^{th} moth, F_j indicates the j^{th} flame and S is the spiral function.

Considering these points, we define a log (logarithmic scale) spiral for the MFO algorithm as follows:

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

Where: $D_i$expresses the distance of the moth for the j^{th} flame, b is a constant for expressing the shape of the log (logarithmic) spiral, and t is a random value in [-1, 1].

$$Di = |Fj - Mi| \quad (11)$$

Where: M_i indicate the i^{th} moth, F_j indicates the j^{th} flame, and where D_i expresses the path length of the i^{th} moth for the j^{th} flame.

The number of flames adaptively decreased over the course of iterations. We use the following formula:

$$flame\ no = round\left(N - l \cdot \frac{N-1}{T}\right) \quad (12)$$

Where l is the current number of iterations, N is the maximum number of flames, and T indicates the maximum number of iterations.

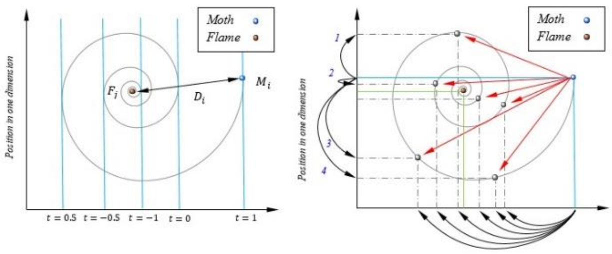

Fig. 1. Conceptual model of position updating of a moth around a flame [1]

We utilize Quicksort algorithm; the sort is of $O(n \log n)$ in the best and $O(n^2)$ worst condition, respectively. Considering the P function, so, total computational complexity is defined as follows:

$$O(MFO) = O\Big(t\,\big(O(Quick\ sort) + O(position\ update)\big)\Big)$$

$$O(MFO) = O(t(n^2 + n \cdot d)) = O(t \cdot n^2 + t \cdot n \cdot d)$$

Where *n* shows a number of moths, *t* represents the maximum number of iterations, and *d* represents the number of variables.

III. ADAPTIVE MFO

Before In the meta-heuristic algorithms, randomization plays a very important role in both exploration and exploitation where more randomization techniques are Markov chains, Levy flights, and Gaussian or normal distribution and a new technique is an adaptive technique. The adaptive technique used by Pauline Ong in Cuckoo Search Algorithm (CSA) [2] and shows improvement in results of CSA algorithms. The Adaptive technique [3] includes best features like it consists of less parameter dependency, not required to define the initial parameter and step size or position towards an optimum solution is adaptively changes according to its functional fitness value over the course of the iteration. So meta-heuristic algorithms on integrated with adaptive technique result in less computational time to reach an optimum solution, local minima avoidance, and faster convergence.

$$X_i^{t+1} = \left(\frac{1}{t}\right)^{\left|\frac{((bestf(t) - fi(t))}{(bestf(t) - worstf(t)))}\right|} \quad (13)$$

Where X_i^{t+1}Step size of an ith dimension in the tth iteration $f(t)$ is the fitness value.

Parameter Name	**Search Agents no.**	**Max. Iteration no.**	**No. of Evolution**
Acoustic PD Localization	40	500	20

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IV. ACOUSTIC PD LOCALIZATION SENSOR POSITION

Partial discharges most commonly initiate dielectric breakdown in transformers. Detecting these events in a timely manner is crucial, as their consequences can be hazardous. Regular analysis of partial discharges provides an accurate assessment of the deterioration process, allowing for the prediction of potential fault conditions through online monitoring and precautionary tests. It is essential to possess information about the level and location of partial discharges to plan maintenance for transformer. A widely recognized approach to evaluating the transformer's health involves studying the signals generated by partial discharges. Transformer monitoring can occur either online or offline. Established techniques for electrical partial discharge detection involve measuring current or Radio Frequency (RF) pulses. Overcoming interference poses a significant challenge in detecting partial discharges, whether the transformer is offline or online in a noisy environment. Offline partial discharge detection methods only offer snapshots in time, providing a limited view of the transformer's condition. Meanwhile, no standards have been developed yet for online electrical monitoring of partial discharges.

The presence of discharge is widely recognized for generating discharge current or voltage pulses, electromagnetic impulse radiation, ultrasonic impulse radiation, and visible or ultraviolet light emission. Consequently, various detection methods have been devised to individually measure these phenomena. Among them, acoustic detection has gained significant prominence in contemporary applications

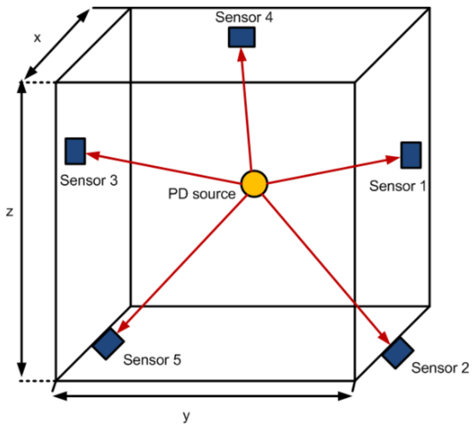

Fig. 2 Visualization of PD Source and Sensor Arrangement

Define PD generates acoustic waves in range of 20 kHz to 1 MHz External system and internal system are two categories of acoustic detection techniques based on sensor location in transformer. External system is widely accepted as sensors are mounted outside of the transformer. An obvious advantage of the acoustic method is that it can locate the site of a PD by algorithms. Electromagnetic interference may cause corruption of signals captured by piezoelectric sensors.

A main objective is to determine the position of the PD source based on signals captured by sensor array inside the transformer tank as shown in Fig. 2. Each sensor will capture acoustic signals at different time as shown in Fig. 3. Time Difference of Arrival (TDOA) algorithm has been implemented to find location of partial discharge source.

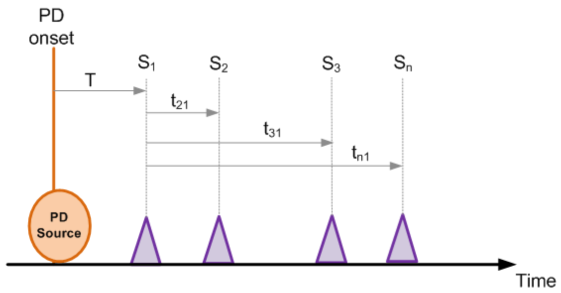

Fig. 3 Schematic of acoustic time differences in reference to electrical PD signal

PDE equation in homogeneous medium for propagation of acoustic wave:

$$\frac{\partial^2 P}{\partial t^2} = v^2 \nabla^2 P = v^2 \left(\frac{\partial^2 P}{\partial x^2} + \frac{\partial^2 P}{\partial y^2} + \frac{\partial^2 P}{\partial z^2}\right) \qquad (14)$$

Where: $P(x, y, z, t)$ pressure wave field; function of space and time; x, y, z Cartesian co-ordinates (mm) and v is acoustic wave velocity (m/s).

Table. 1. Transformer Dimension and Coordination Position of Sensor

Element	X-axis (mm)	Y-axis (mm)	Z-axis (mm)
Transformer Dimension	5000	3000	4000
Actual PD source	4500	2600	3700
Sensor (S_1)	2500	0	2000
Sensor (S_2)	2500	1500	4000
Sensor (S_3)	5000	1500	2000
Sensor (S_4)	2500	3000	2000
Sensor (S_5)	0	1500	2000
t_1 =2600 micro-seconds (Reference)			

$\tau_{i1}(\mu s) = [1600, 1500, 1900, 3524.69] - t_1,\ i = 2, 3, 4, 5$ and sensor 1 is assumed as reference sensor [6].

Problem Formulation:

$$\tau_{21} = -1000 \times 10^{-03}, \tau_{31} = -1100 \times 10^{-03},$$
$$\tau_{41} = -700 \times 10^{-03}, \tau_{51} = -924.69 \times 10^{-03},$$
$$P = [(x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2]^{0.5}$$
$$a = [(x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2]^{0.5} - P - v_e\tau_{21};$$
$$b = [(x - x_3)^2 + (y - y_3)^2 + (z - z_3)^2]^{0.5} - P - v_e\tau_{31};$$
$$c = [(x - x_4)^2 + (y - y_4)^2 + (z - z_4)^2]^{0.5} - P - v_e\tau_{41};$$
$$d = [(x - x_5)^2 + (y - y_5)^2 + (z - z_5)^2]^{0.5} - P - v_e\tau_{51};$$
$$Min\,\{D_f(x, y, z, v_e)\} = a^2 + b^2 + c^2 + d^2;$$

Subjected to

$$\left.\begin{array}{l} 0 \le x \le x_{max} \\ 0 \le y \le y_{max} \\ 0 \le z \le z_{max} \\ 1200 \le v_e \le 1500, \quad (m/s)\} \end{array}\right\}$$

Where: $x_{max}, y_{max}, z_{max}$ and v_e are transformer tank dimension and equality sound velocity.

Calculated *PD* source is $P_c(x_c, y_c, z_c)$ comprehensive distance error of it with actual *PD* source $P(x, y, z)$ is $\Delta R = [(x - x_c)^2 + (y - y_c)^2 + (z - z_c)^2]^{0.5}$

Error of each co-ordinate is formulated:

$$\epsilon_r = \left|\frac{L_{act} - L_{cal}}{L_{act}}\right| \times 100\% \qquad (15)$$

Maximum deviation D_{max}

$$D_{max}\begin{Bmatrix}|x_{act}-x_{cal}|\\|y_{act}-y_{cal}|\\|z_{act}-z_{cal}|\end{Bmatrix}_{max} \tag{16}$$

Where; $L_{act}, x_{act}, y_{act}, z_{act}$ and $L_{cal}, x_{cal}, y_{cal}, z_{cal}$ actual and calculated co-ordinates respectively.

Table. 2. Comparison of the result of PD localization

Coordinate (mm)	Actual PD source	MFO	AMFO	GA [4]
x	4500	4381.7521	4381.7725	4223.76
y	2600	2469.6056	2469.6147	2391.71
z	3700	3647.496	3647.5201	3503.04

Table. 3. Error Analysis

Error	MFO	AMFO	GA
Error of x%	2.627	2.627	6.14
Error of y%	5.015	5.014	8.01
Error of z%	1.419	1.418	5.32
D_{max} /mm	130.3944	130.3853	276.24
Comprehensive Error(ΔR/mm)	183.6897	183.6633	398.10

V. Conclusion

After The Moth-Flame Optimizer demonstrates the capability to identify optimal solutions while handling constraints, encompassing both equality and inequality constraints. The optimization process ensures that constraint limits are not violated during the search for the optimal solution. Randomization plays a crucial role in both exploration and exploitation phases. Utilizing adaptive techniques accelerates convergence, introduces randomness, and enhances stochastic behavior to improve solutions. The adaptive technique is employed for random walks in the search space when neighboring solutions are unavailable, guiding the search towards the optimal solution.

The feasibility of the Acoustic PD source localization method based on the AMFO algorithm is affirmed. PD localization using AMFO yields superior results compared to the MFO algorithm and is more accurate than Genetic Algorithms (GA). Extending its applicability beyond constrained problems, the AMFO algorithm proves to be effective in addressing challenging problems with unknown search spaces, as evidenced by its success in various unconstrained problems.

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