ISSN: 2456-9348
Vol (02) _Issue (02) Impact Factor: 4.520

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International Journal of Engineering Technology Research & Management

# A NOVEL ADAPTIVE MOTH FLAME OPTIMIZATION ALGORITHM FOR GLOBAL NUMERICAL OPTIMIZATION

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**ABSTRACT**
A novel bio-inspired optimization algorithm based on the navigation strategy of Moths in universe called the Moth-Flame optimization (MFO) Algorithm in contrast to meta-heuristic, main feature is randomization having a relevant role in both exploration and exploitation in optimization problem. A novel randomization technique termed adaptive technique is integrated with MFO and exercised on unconstraint test benchmark function andlocalization of partial discharge in transformer like geometry.MFO algorithm has quality feature that it uses logarithmic spiral function so it covers a vast area in exploration phase then addition with powerful randomization adaptive technique potent the AMFO algorithm to attain global optimal solution and faster convergence with less parameter dependency. Adaptive MFO (AMFO) solutions are evaluated and results shows its competitively better performance over standard optimization algorithms.

**Keywords:**
Meta-heuristic; Moth-Flame optimizer; Adaptive technique; Global optimal; Navigation; Partial Discharge.

## INTRODUCTION

A novel nature –inspired, Moth-Flame optimization algorithm [1] based on the navigation mechanism called transverse orientation of Moths in space. Transverse orientation for navigation uses a constant angle by Moths with respect to Moon as Moon is thousands of miles away from Moths so this mechanism guarantees for flying in straight direction. Moths applied this transverse mechanism for artificial lights that is more nearer to Moths in compare to Moon, then Moths are tricked as they do not keep fixed angle with respect to flame or angle is gradually decreasing so fly around flames in a Logarithmic spiral way and finally converges towards the flame. This Logarithmic spiral way represents the exploration area and it guarantees to exploit the optimum solution.

In the meta-heuristic algorithms, randomization play a very important role in both exploration and exploitation where more strengthen randomization techniques are Markov chains, Levy flights and Gaussian or normal distribution and new technique is adaptive technique. So meta-heuristic algorithms on integrated with adaptive technique results in less computational time to reach optimum solution, local minima avoidance and faster convergence.

In past, many optimization algorithms based on gradient search for solving linear and non-linear equation but in gradient search method value of objective function and constraint unstable and multiple peaks if problem having more than one local optimum.

Population based MFO is a meta-heuristic optimization algorithm has an ability to avoid local optima and get global optimal solution that make it appropriate for practical applications without structural modifications for solving different constrained or unconstraint optimization problems. MFO integrated with adaptive technique reduces the computational times for highly complex problems.

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 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] that

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can accelerate its global convergence speed. Evolutionary constraint handling scheme is used in Interior Search Algorithm (ISA) [26] that avoid upper and lower limits of variables.
The remainder of this paper is organized as follows: The next Section describes the Moth-flame optimizer algorithm and its algebraic equations are given in Section 2. Section 3 includes description of Adaptive technique. Section 4 consists of simulation results of unconstrained benchmark test function, convergence curve and tables of results compared with source algorithm. In Section 5PD localization by acoustic emission,in section 6conclusion is drawn. Finally, acknowledgment gives regards detail and at the end, references are written.

## MOTH-FLAME OPTIMIZER

Moth-Flame optimizer is first introduced by SeyedaliMirjalili in 2015 [1]. MFO is a population based algorithm; we represent the set of moths in a matrix:

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

Where *n* represents number of moths and d represents number of variables (dimension).
For all the moths, we also assume that there is an array for storing the corresponding fitness values as follows:

$$OM = \begin{bmatrix} OM_1 \\ OM_2 \\ . \\ . \\ OM_n \end{bmatrix} \tag{2}$$

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 is passed to the fitness function and the output of the fitness function is assigned to the corresponding moth as its fitness function ($OM_1$in the matrix *OM* for instance).
Other key components in the proposed algorithm are flames. We consider a matrix similar to the moth matrix:

$$F = \begin{bmatrix} FL_{1,1} & FL_{1,2} & . & . & FL_{1,d} \\ FL_{2,1} & FL_{2,2} & . & . & FL_{2,d} \\ . & . & . & . & . \\ . & . & . & . & . \\ FL_{n,1} & FL_{n,2} & . & . & FL_{n,d} \end{bmatrix} \tag{3}$$

Where *n* shows number of moths and *d* represents 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:

ISSN: 2456-9348
Vol (02) _Issue (02) Impact Factor: 4.520



$$OF = \begin{bmatrix} OFL_1 \\ OFL_2 \\ . \\ . \\ OFL_n \end{bmatrix} \quad (4)$$

Where $n$ is the number of moths.

Here, it should be noted that moths and flames both are solutions. The difference between them is the way we treat and update them, in iteration. The moths are actual search agents that move around the search space, whereas flames are the best position of moths that obtains 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:

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

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

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

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 tothe termination Criterion satisfaction:

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

In order to mathematical model this behavior, wechange the position of each Moth with respect to 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:

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

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].

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

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 is adaptively decreased over the course of iterations. We use the following formula:

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

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

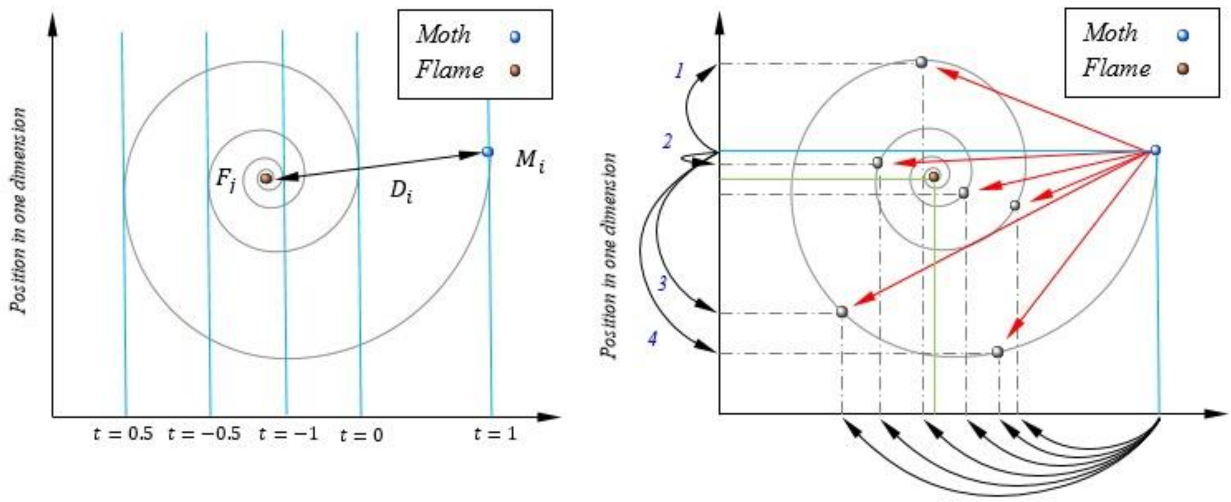


*Fig. 1:A conceptual model of position updating of a moth around a flame*

We utilize Quicksortalgorithm,thesortisof$O(n\log n)$inthebestand$O(n^2)$worstcondition,respectively.Consideringthe $P$function,so,totalcomputationalcomplexityisdefinedasfollows:

$$O(MFO) = O(t(O(\text{Quick sort}) + O(\text{position update})))$$

$$O(MFO) = O(t(n^2 + n*d)) = O(tn^2 + tnd) \quad (13)$$

Where $n$ shows number of moths, $t$ represents maximum number of iterations, and $d$ represents number of variables.

## ADAPTIVE MFO

In the meta-heuristic algorithms, randomization play a very important role in both exploration and exploitation where more randomization techniques are Markov chains, Levy flights and Gaussian or normal distribution and new technique is adaptive technique. 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 initial parameter and step size or position towards optimum solution is adaptively changes according to its functional fitness value o15ver the course of iteration. So mete-heuristic algorithms on integrated with adaptive technique results in less computational time to reach optimum solution, local minima avoidance and faster convergence.

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$$X_i^{t+1} = X_i^t + randn * \left(\frac{1}{t}\right)^{\left|((bestf(t) - fi(t))/(bestf(t) - worstf(t)))\right|} \quad (14)$$

Where $X_i^{t+1}$ new solution of *i*-th dimension in *t*-th iteration $f(t)$ is the fitness value

**Simulation Results for Unconstraint Test Benchmark Function**

***Table 1: Benchmark Test functions***

| No. | Name | Function | Dim | Range | Fmin |
|---|---|---|---|---|---|
| F1 | Sphere | $f(x) = \sum_{i=1}^{n} x_i^2 * R(x)$ | 10 | [-100, 100] | 0 |
| F2 | Schwefel 2.22 | $f(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert * R(x)$ | 10 | [-10, 10] | 0 |
| F3 | Schwefel 1.2 | $f(x) = \sum_{i=1}^{n} \left( \sum_{j-1}^{i} x_j \right)^2 * R(x)$ | 10 | [-100, 100] | 0 |
| F4 | Schwefel 2.21 | $f(x) = \max_i \{ \lvert x_i \rvert, 1 \le i \le n \}$ | 10 | [-100, 100] | 0 |
| F5 | Rosenbrock's Function | $f(x) = \sum_{i=1}^{n-1} \left[ 100\left(x_{i+1} - x_i^2\right)^2 + \left(x_i - 1\right)^2 \right] * R(x)$ | 10 | [-30, 30] | 0 |
| F6 | Step Function | $f(x) = \sum_{i=1}^{n} \left( [x_i + 0.5] \right)^2 * R(x)$ | 10 | [-100, 100] | 0 |
| F7 | Quartic Function | $f(x) = \sum_{i=1}^{n} i x_i^4 + random[0,1) * R(x)$ | 10 | [-1.28, 1.28] | 0 |
| F8 | Schwefel 2.26 | $F(x) = \sum_{i=1}^{n} -x_i sin\left(\sqrt{\lvert x_i \rvert}\right) * R(x)$ | 10 | [-500, 500] | (-418.9829*5) |

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| | | | | | |
|---|---|---|---|---|---|
| F9 | Rastrigin | $F(x)=\sum_{i=1}^{n}\left[x_i^2-10cos(2\pi x_i)+10\right]*R(x)$ | 10 | [-5.12, 5.12] | 0 |
| F10 | Ackley's Function | $F(x)=-20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-exp\left(\frac{1}{n}\sum_{i=1}^{n}cos(2\pi x_i)\right)+20+e*R(x)$ | 10 | [-32, 32] | 0 |
| F11 | Griewank Function | $F(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}cos\left(\frac{x_i}{\sqrt{i}}\right)+1*R(x)$ | 10 | [-600, 600] | 0 |
| F12 | Penalty 1 | $F(x)=\frac{\pi}{n}\left\{\begin{array}{l}10sin(\pi y_1)+\sum_{i=1}^{n-1}(y_i-1)^2\\\left[1+10sin^2(\pi y_{i+1})\right]+(y_n-1)^2\end{array}\right\}$ $y_i=1+\frac{x_i+1}{4}$, $u(x_i,a,k,m)=\begin{cases}k(x_i-a)^m & x_i>a\\0 & -a<x_i<a\\k(-x_i-a)^m & x_i<-a\end{cases}$ | 10 | [-50, 50] | 0 |
| F13 | Penalty 2 | $F(x)=0.1\left\{\begin{array}{l}sin^2(3\pi x_1)+\sum_{i=1}^{n}(x_i-1)^2\\\left[1+sin^2(3\pi x_i+1)\right]\\+(x_n-1)^2\left[1+sin^2(2\pi x_n)\right]\end{array}\right\}+\sum_{i=1}^{n}u(x_i,5,100,4)*R(x)$ | 10 | [-50, 50] | 0 |

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| | | | | | |
|---|---|---|---|---|---|
| F14 | De Joung (Shekel's Foxholes) | $F(x)=\left(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}\left(x_i-a_{ij}\right)^6}\right)^{-1}$ | 2 | [-65.536, 65.536] | 1 |
| F15 | Kowalik's Function | $f(x)=\sum_{i=1}^{11}a_i-\left[\frac{x_i\left(b_i^2+b_ix_2\right)}{b_i^2+b_ix_3+x_4}\right]^2$ | 4 | [-5,5] | 0.00030 |
| F16 | Cube function | $f(x)=100(x_2-x_1^3)^2+(1-x_1)^2$ | 30 | [-100, 100 | 0 |
| F17 | Matyas function | $f(x)=0.26(x_1^2+x_2^2)-0.48x_1x_2$ | 30 | [-30, 30] | 0 |
| F18 | Powell function | $f(x)=\sum_{i=1}^{D-2}\begin{Bmatrix}(x_{i-1}+10x_i)^2+5(x_{i+1}-x_{i+2})^2+\\(x_i-2x_{i+1})^4+10(x_{i-1}-x_{i+2})^4\end{Bmatrix}$ | 4 | [-30, 30] | 0 |
| F19 | Beale Function | $f(x)=\begin{Bmatrix}\left(1.5-x_1+x_1x_2\right)^2+\left(2.25-x_1+x_1x_2^2\right)^2\\+\left(2.625-x_1+x_1x_2^3\right)^2\end{Bmatrix}$ | 30 | [-100, 100] | 0 |
| F20 | levy13 function | $f(x)=\begin{Bmatrix}\sin^2(3\pi x_1)+(x_1-1)^2\left(1+\sin^2(3\pi x_2)\right)\\+(x_2-1)^2\left(1+\sin^2(2\pi x_2)\right)\end{Bmatrix}$ | 30 | [-10, 10] | 0 |

*Table 2: Internal Parameters*

| Parameter Name | Search Agents no. | Max. Iteration no. | No. of Evolution |
|---|---|---|---|
| F1-F16, F18, F20 | 30 | 500 | 20-30 |
| F17 | 30 | 100 | 20-30 |
| F19 | 30 | 300 | 20-30 |
| Acoustic PD Localization | 40 | 200 | 20 |
| **Note:-** Scale specified on axis, Not specified means axis are linear scale | | | |

ISSN: 2456-9348
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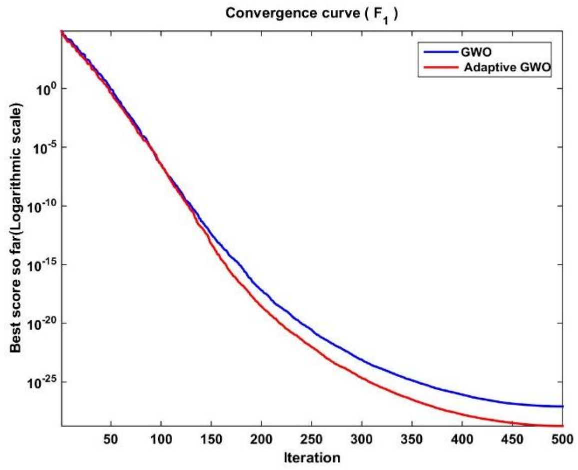
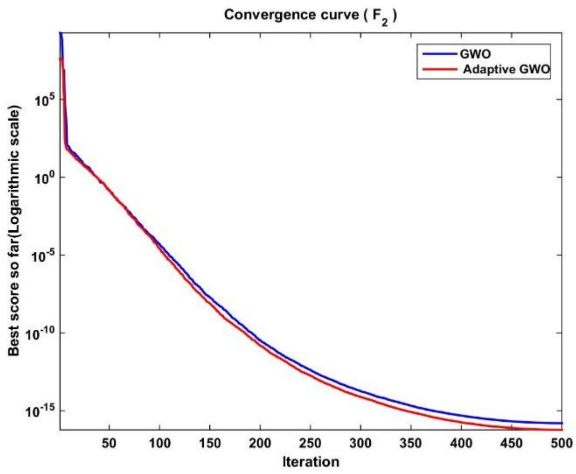
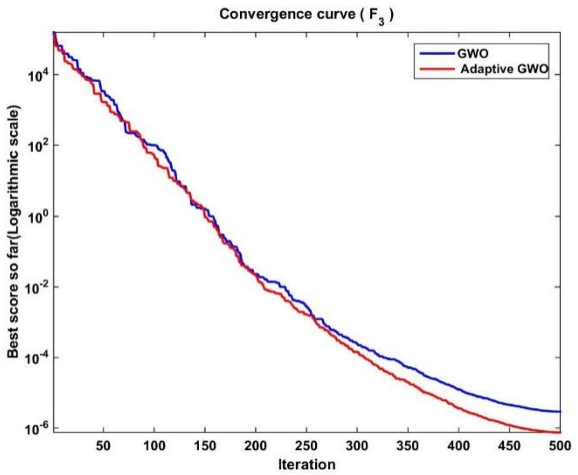
*F*1



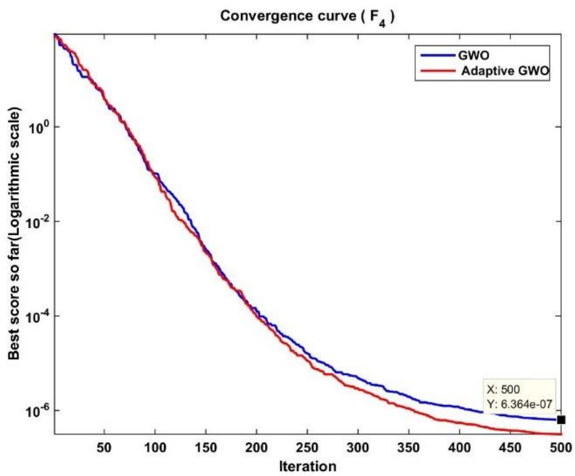

*F*2



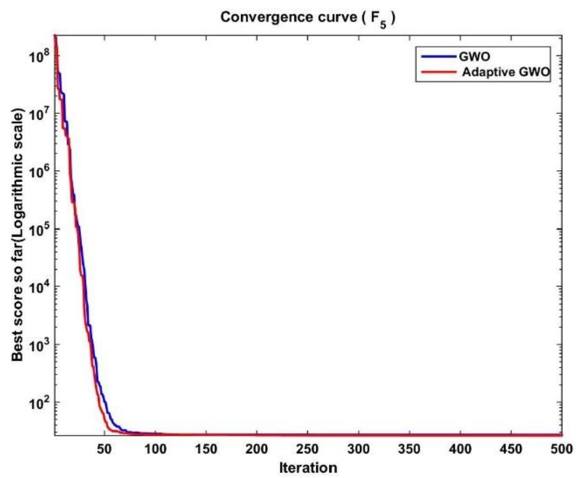

*F*3



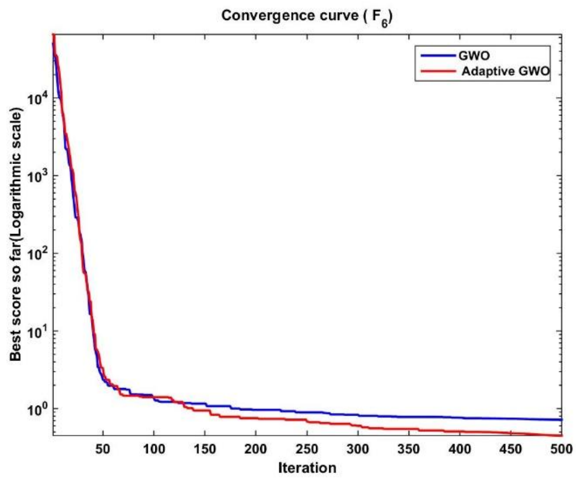

*F*4




*F*5




*F*6



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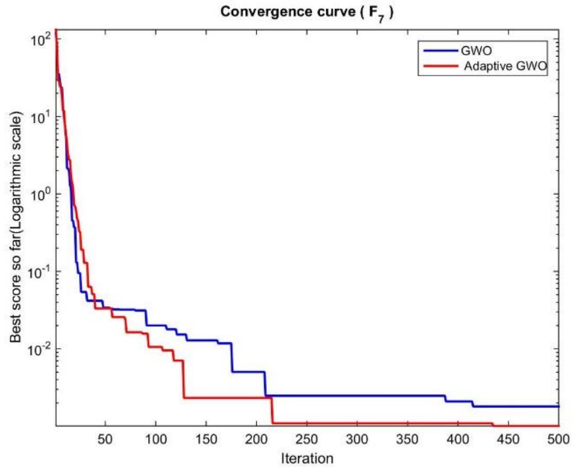
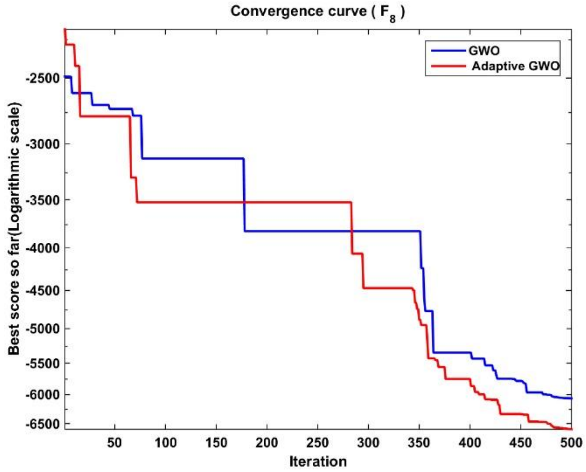
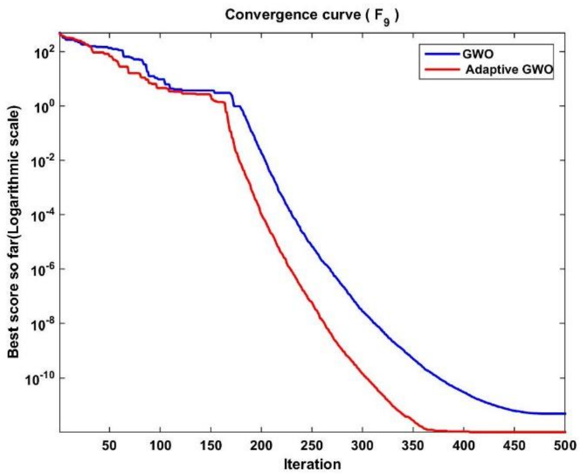
$F_7$



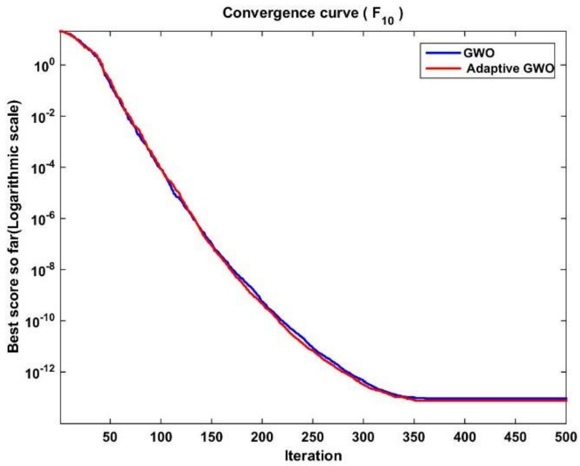

$F_8$



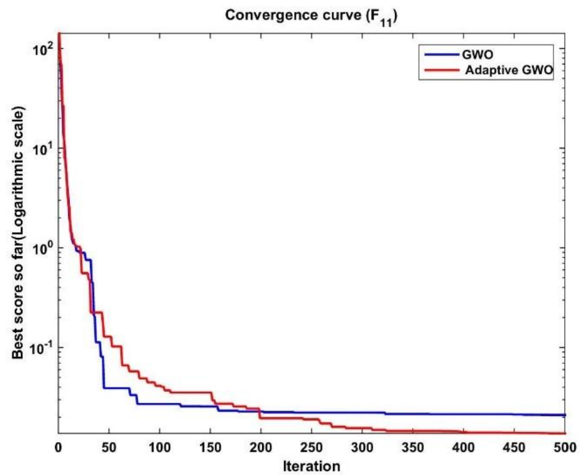

$F_9$



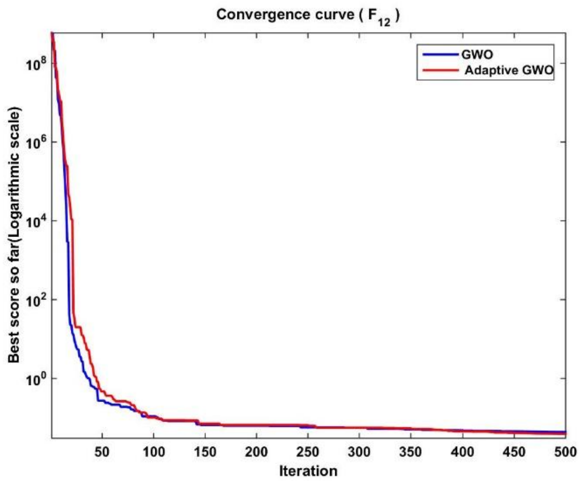

$F_{10}$




$F_{11}$




$F_{12}$



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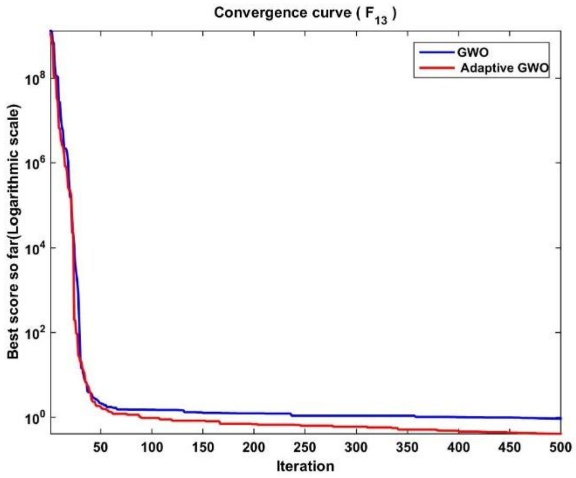
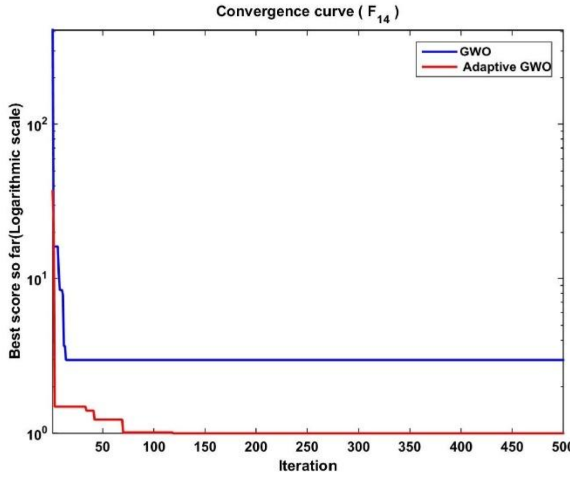
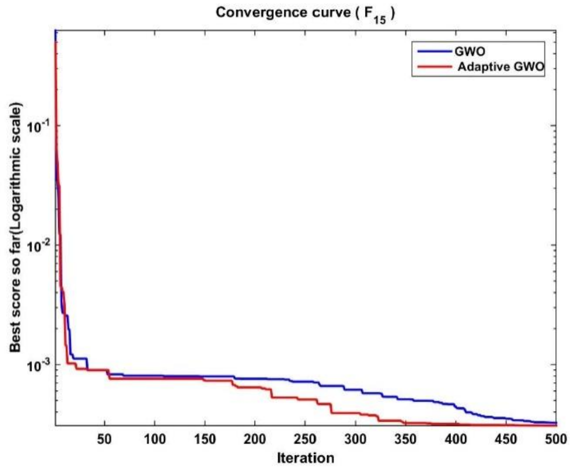
$F_{13}$



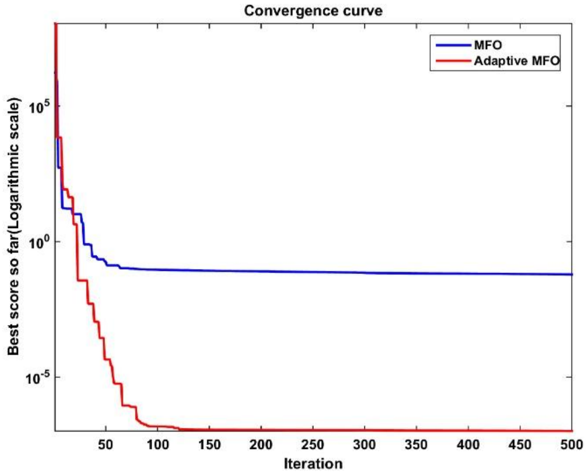

$F_{14}$



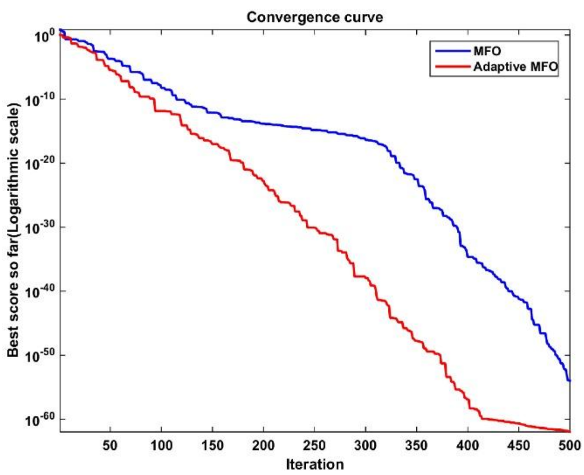

$F_{15}$



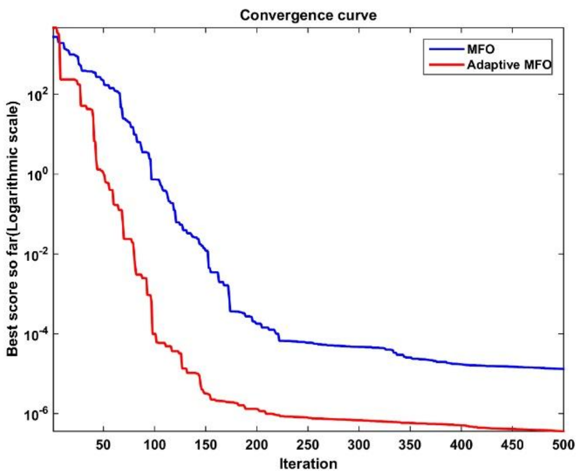

$F_{16}$




$F_{17}$




$F_{18}$



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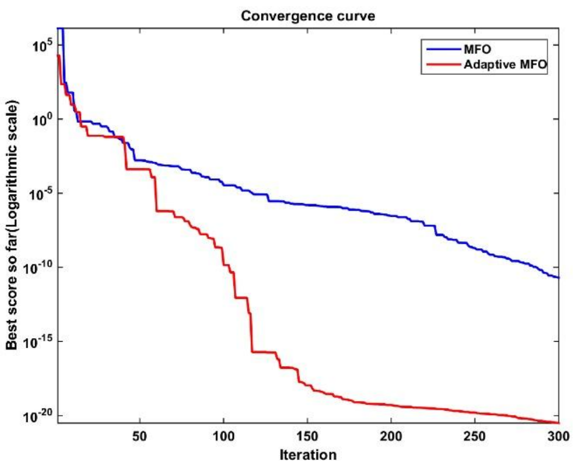
$F_{19}$




$F_{20}$

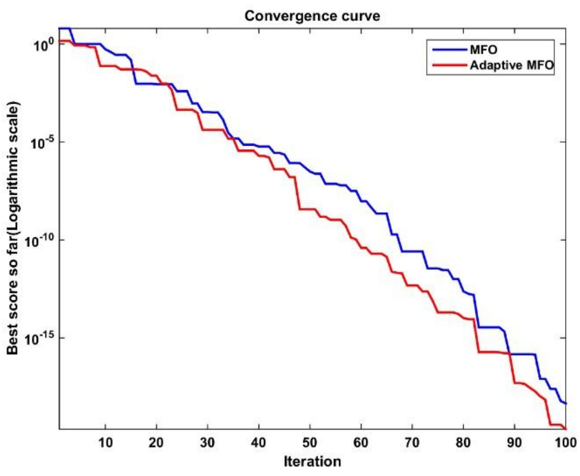



***Fig. 2: Convergence Curve of Benchmark Test Function***

***Table 3: Result for benchmark functions***

| **Function.** | **Moth-Flame optimizer (MFO)** | | | **Adaptive Moth-Flame Optimizer (AMFO)** | | |
|---|---|---|---|---|---|---|
| | **Ave** | **Best** | **S.D.** | **Ave** | **Best** | **S.D.** |
| F1 | 5.043E-14 | 4.9088E-14 | 1.897E-15 | 4.9015E-13 | **1.8855E-14** | 1.8975E-15 |
| F2 | 5 | 5.8126E-09 | 7.0711 | 3.8783E-09 | **1.9674E-09** | 7.0711 |
| F3 | 0.12535 | 0.016445 | 0.15401 | 0.021517 | **0.002442** | 0.15401 |
| F4 | 0.53694 | 0.056767 | 0.67906 | 0.068018 | **0.047005** | 0.67906 |
| F5 | 80.5512 | 7.4857 | 103.3302 | 11.8256 | **1.4594** | 103.3302 |
| F6 | 4.0197E-13 | 1.6146E-13 | 3.4013E-13 | 4.4177E-14 | **6.0356E-15** | 3.4013E-13 |
| F7 | 0.016558 | 0.0063498 | 0.014437 | 0.013578 | **0.0034856** | 0.014437 |
| F8 | -3210.4316 | -3479.1989 | 380.0943 | -3833.7553 | **-3952.9522** | 380.0943 |
| F9 | 22.3865 | 14.9244 | 10.5531 | 13.9294 | **11.9395** | 10.5531 |
| F10 | 0.82311 | 3.5568E-07 | 1.1641 | 1.4354E-07 | **9.3408E-08** | 1.1641 |
| F11 | 0.15008 | 0.14755 | 0.0035761 | 0.16858 | **0.12538** | 0.0035761 |
| F12 | 1.3484E-13 | 8.2781E-14 | 7.3624E-14 | 0.1555 | **3.7085E-14** | 7.3624E-14 |
| F13 | 0.0054937 | 1.5795E-13 | 0.0077692 | 3.3181E-14 | **3.0611E-14** | 0.0077692 |
| F14 | 0.00077827 | 0.0007738 | 6.3267E-06 | 0.00071284 | **0.00067665** | 6.3267E-06 |
| F15 | -2.6567 | -2.6829 | 0.037044 | -6.418 | **-10.1532** | 0.037044 |

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|---|---|---|---|---|---|---|
| F16 | 1.6086 | 0.061081 | 2.1886 | 0.00039161 | **1.034E-07** | 2.1886 |
| F17 | 5.8946E-52 | 1.0619E-54 | 8.3211E-52 | 1.2535E-25 | **1.06628E-62** | 1.7727E-25 |
| F18 | 1.5717E-05 | 1.3193E-05 | 3.5703E-06 | 1.4327E-05 | **3.6142E-07** | 3.5703E-06 |
| F19 | 1.482E-07 | 1.9613E-11 | 2.0956E-07 | 4.9189E-12 | **3.1077E-21** | 2.0956E-16 |
| F20 | 1.4253E-18 | 4.5623E-19 | 1.3705E-18 | 5.4212E-19 | **2.2389E-20** | 7.3501E-19 |

**ACOUSTIC PD LOCALIZATION SENSOR POSITION**

Dielectric breakdown in transformers is most frequently initiated by partial discharges. The consequences of these types of occurrences can be hazardous if not detected in a timely fashion. Regular PD analysis gives an accurate indication of the status of the deterioration process. So it is possible to foretell developing fault condition by online monitoring and precautionary tests. It is very much essential to have information of PD level and location to plan maintenance of electrical equipment.A famous method of understanding the health of the transformer is by studying the partial discharge signals. Monitoring of transformer can be either online or offline. The primary established techniques for electrical PD detection by measuring current or Radio Frequency (RF) pulses. Suppression of interference is one of the main challenges in detecting PDs, either while the transformer is off-line or on-line in a noisy environment. The off-line PD detection methods only provide snapshots in time of part of the transformer's condition. On the other hand, no standards have yet been developed for on-line electrical monitoring of PDs.

It is well known that the occurrence of discharge results in discharge current or voltage pulse, electromagnetic impulse radiation, ultrasonic impulse radiation and visible or ultraviolet light emission. Accordingly, there are several detection methods that have been developed to measure those phenomena respectively. Acoustic detection is one of them which is very famous nowadays.

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. 3. Each sensor will capture acoustic signals at different time as shown in Fig. 4. Time Difference of Arrival (TDOA) algorithm has been implemented to find location of partial discharge source.

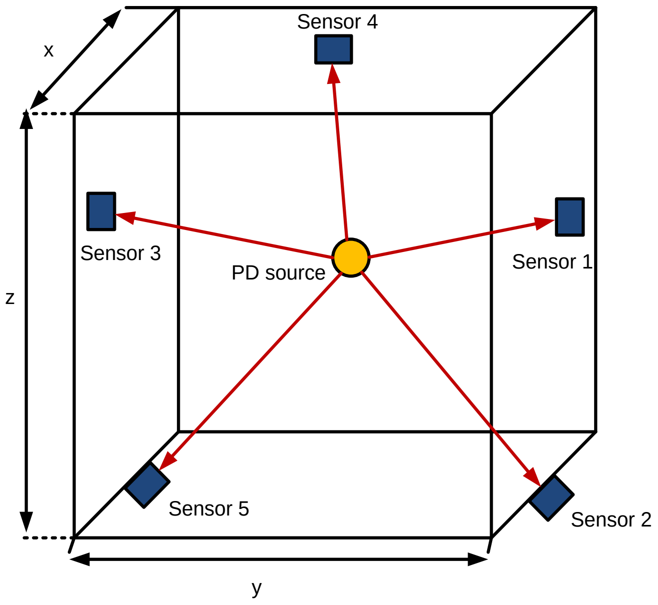
PDE equation in homogeneous medium for propagation of acoustic wave:

$$\frac{\partial^2 P}{\partial t^2} = v^2 \nabla^2 P = v^2 \left( \frac{\partial^2 P}{\partial x^2} + \frac{\partial^2 P}{\partial y^2} + \frac{\partial^2 P}{\partial z^2} \right) \qquad (15)$$

Vol (02) _Issue (02)
ISSN: 2456-9348
Impact Factor: 4.520



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*).

***Fig. 3: Visualization of PD source and sensor arrangement***

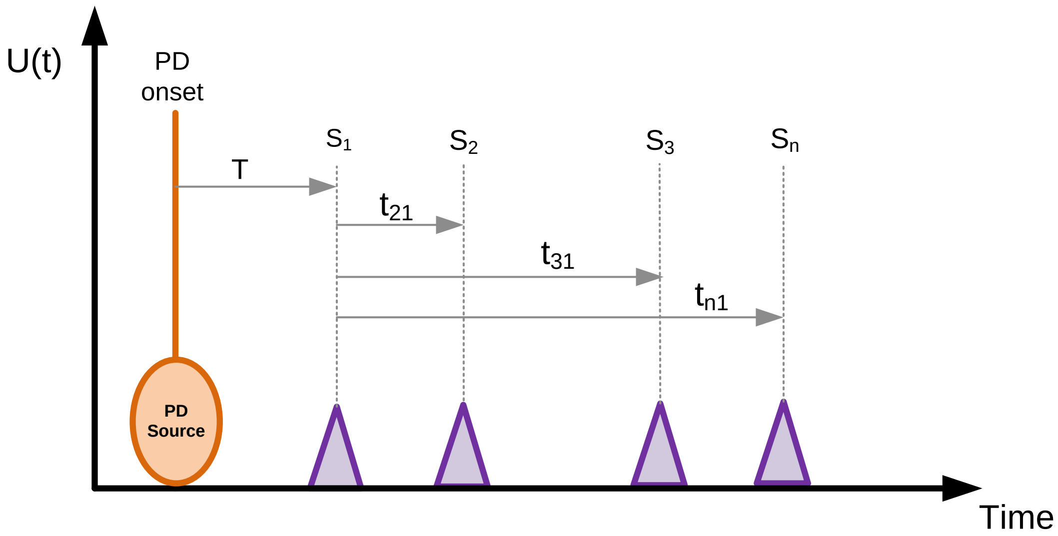



***Fig. 4: Schematic of acoustic time differences in reference to electrical PD signal***

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*Table 4: Transformer dimension and Co-ordination 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 paper [6].

**Problem Formulation:**

$$\tau_{21} = -1000\times10^{-03}, \tau_{31} = -1100\times10^{-03}, \quad \tau_{41} = -700\times10^{-03}, \tau_{51} = -924.69\times10^{-03}, \quad (16)$$

$$P = \left[(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2\right]^{0.5} \quad (17)$$

$$a = \left[(x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2\right]^{0.5} - P - \upsilon_e \tau_{21}; \quad (18)$$

$$b = \left[(x-x_3)^2 + (y-y_3)^2 + (z-z_3)^2\right]^{0.5} - P - \upsilon_e \tau_{31}; \quad (19)$$

$$c = \left[(x-x_4)^2 + (y-y_4)^2 + (z-z_4)^2\right]^{0.5} - P - \upsilon_e \tau_{41}; \quad (20)$$

$$d = \left[(x-x_5)^2 + (y-y_5)^2 + (z-z_5)^2\right]^{0.5} - P - \upsilon_e \tau_{51}; \quad (21)$$

$$Min \quad \{D_f(x,y,z,\upsilon_e)\} = a^2 + b^2 + c^2 + d^2; \quad (22)$$

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$$\left.\begin{array}{l} 0 \le x \le x_{\max} \\ 0 \le y \le y_{\max} \\ 0 \le z \le z_{\max} \\ 1200 \le \upsilon_e \le 1500, \quad (m/s) \end{array}\right\} \tag{23}$$

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

$$\Delta R = \left[ (x - x_c)^2 + (y - y_c)^2 + (z - z_c)^2 \right]^{0.5} \tag{24}$$

**Error of each co-ordinate is formulated:**

$$\in_r = \left| \frac{L_{act} - L_{cal}}{L_{act}} \right| \times 100\% \tag{25}$$

**Maximum deviation $D_{max}$**

$$D_{\max} = \max \left\{ \begin{array}{l} |x_{act} - x_{cal}| \\ |y_{act} - y_{cal}| \\ |z_{act} - z_{cal}| \end{array} \right\} \tag{26}$$

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 5: Comparison of the results 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 |

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*Table 6: 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 |

## CONCLUSION

Moth-Flame Optimizer have an ability to find out optimum solution with constrained handling which includes both equality and inequality constraints. While obtaining optimum solution constraint limits should not be violated. Randomization plays an important role in both exploration and exploitation. Adaptive technique causes faster convergence, randomness, and stochastic behavior for improving solutions. Adaptive technique also used for random walk in search space when no neighboring solution exits to converse towards optimal solution. Acoustic PD source localization method based on AMFO algorithm is feasible. PD localization by AMFO gives better result than MFO algorithm and alsoaccurate in compare to GA.The AMFO result of various unconstrained problems proves that it is also an effective method in solving challenging problems with unknown search space.

## ACKNOWLEDGEMENT

The authors would like to thank Prof.SeyedaliMirjalili, Griffith University for his valuable comments and support. http://www.alimirjalili.com/MFO.html

## REFERENCES

[1] SeyedaliMirjalili,"Moth-flame optimization algorithm: A novel nature-inspired heuristic paradigm," Knowledge-Based System, vol. 89, pages 228-249, 2015.
[2] P. Ong, “Adaptive Cuckoo search algorithm for unconstrained optimization,” The Scientific World Journal, Hindawi Publication, vol. 2014, pp.1-8, 2014.
[3] Manoj Kumar Naik, Rutupaparna Panda, “A novel adaptive cuckoo search algorithm for intrinsic discriminant analysis based face recognition”, in Elsevier journal, “Applied Soft Computing” http://dx.doi.org/10.1016/j.asoc.2015.10.039.
[4] Hua-Long Liu, “Acoustic partial discharge localization methodology in power transformers employing the quantum genetic algorithm” in Elsevier journal, “Applied Acoustics” http://dx.doi.org/10.1016/j.apacoust.2015.08.011.
[5] Liu HL, Liu HD. Partial discharge localization in power transformers based on the sequential quadratic programming-genetic algorithm adopting acoustic emission techniques. EurPhys J ApplPhys 2014;68(01):10801.
[6] Yang Y, Wang BB. Application of unconstrained optimization in ultrasonic locating of transformer partial discharge. Mod Electron Techn 2007; 2007 (3):100–4.
[7] A. Kaveh, S. Malakouti Rad “Hybrid Genetic Algorithm and Particle Swarm Optimization for the Force Method-Based Simultaneous Analysis and Design” Iranian Journal of Science & Technology, Transaction B: Engineering, Vol. 34, No. B1, PP 15-34.
[8] A. Kaveh and S. Talatahari, A Hybrid Particle Swarm and Ant Colony Optimization for Design of Truss Structures, Asian Journal of Civil Engineering (Building And Housing) Vol. 9, No. 4 (2008) Pages 329-348.

[9] IztokFister Jr., Simon Fong, Janez Brest, and IztokFister, A Novel Hybrid Self-Adaptive Bat Algorithm, Hindawi Publishing Corporation the Scientific World Journal Volume 2014, Article ID 709738, 12 pages http://dx.doi.org/10.1155/2014/709738.

[10] Gai-Ge Wang, Amir H. Gandomi, Amir H. Alavi, Suash Deb, A hybrid PBIL-based Krill Herd Algorithm, December 2015.

[11] Gai-Ge Wang, Amir H. Gandomi, Amir H. Alavi, Suash Deb, A hybrid method based on krill herd and quantum-behaved particle swarm optimization, Neural Computing and Applications, 2015, doi: 10.1007/s00521-015-1914-z.

[12] A. Tahershamsi, A. Kaveh, R. Sheikholeslami and S. Kazemzadeh Azad, An improved _rey algorithm with harmony search scheme for optimization of water distribution systems, ScientiaIranica A (2014) 21(5), 1591{1607.

[13] LihongGuo, Gai-Ge Wang, Heqi Wang, and Dinan Wang, An Effective Hybrid Firefly Algorithm with Harmony Search for Global Numerical Optimization, Hindawi Publishing Corporation The ScientificWorld Journal Volume 2013, Article ID 125625, 9 pages doi.org/10.1155/2013/125625.

[14] Gai-Ge Wang, LihongGuo, Amir HosseinGandomi, Guo-Sheng Hao, Heqi Wang. Chaotic krill herd algorithm. Information Sciences, Vol. 274, pp. 17-34, 2014.

[15] GaigeWang and LihongGuo, A Novel Hybrid Bat Algorithm with Harmony Search for Global Numerical Optimization, Hindawi Publishing Corporation Journal of Applied Mathematics Volume 2013, Article ID 696491, 21 pages http://dx.doi.org/10.1155/2013/696491.

[16] A. Kaveh and S. Talatahari “Hybrid Algorithm of Harmony Search, Particle Swarm and Ant Colony for Structural Design Optimization” Z.W. Geem (Ed.): Harmony Search Algo. For Structural Design Optimization, SCI 239, pp. 159–198.

[17] Gai-Ge Wang, Amir H. Gandomi, Xin-She Yang, Amir H. Alavi, A new hybrid method based on krill herd and cuckoo search for global optimization tasks. Int J of Bio-Inspired Computation, 2012, in press.

[18] Ali Kaveh / OmidKhademHosseini, A hybrid HS-CSS algorithm for simultaneous analysis, design and optimization of trusses via force method, Civil Engineering 56/2 (2012) 197–212 doi: 10.3311/pp.ci.2012-2.06 web: http://www.pp.bme.hu/ ci PeriodicaPolytechnica 2012.

[19] A. Kaveh, and A. Nasrollahi ,Engineering Design Optimization Using A Hybrid PSO And HS Algorithm, Asian Journal Of Civil Engineering (Bhrc) Vol. 14, No. 2 (2013) Pages 201-223.

[20] Gai-Ge Wang, Amir Hossein Gandomi, Amir Hossein Alavi, Guo-Sheng Hao. Hybrid krill herd algorithm with differential evolution for global numerical optimization. Neural Computing & Applications, Vol. 25, No. 2, pp. 297-308, 2014.

[21] Gai-Ge Wang, Amir Hossein Gandomi, Xiangjun Zhao, HaiCheng Eric Chu. Hybridizing harmony search algorithm with cuckoo search for global numerical optimization. Soft Computing, 2014. doi: 10.1007/s00500-014-1502-7.

[22] Gaige Wang, LihongGuo, Hong Duan, Heqi Wang, Luo Liu, and Mingzhen Shao, Hybridizing Harmony Search with Biogeography Based Optimization for Global Numerical Optimization, Journal of Computational and Theoretical Nanoscience Vol. 10, 2312–2322, 2013.

[23] S. Talatahari, R. Sheikholeslami, B. FarahmandAzar, and H. Daneshpajouh, Optimal Parameter Estimation for Muskingum Model Using a CSS-PSO Method, Hindawi Publishing Corporation Advances in Mechanical Engineering Volume 2013, Article ID 480954, 6 pages doi.org/10.1155/2013/480954.

[24] A.H. Gandomi, X.S. Yang, S. Talatahari, A.H. Alavi, Metaheuristic Applications in Structures and Infrastructures, Elsevier, 2013.

[25] A.H. Gandomi, A.H. Alavi, Krill Herd: a new bio-inspired optimization algorithm, Common Nonlinear Sci. Numer. Simul. 17 (12) (2012) 4831–4845.

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[26] Gandomi A.H. "Interior Search Algorithm (ISA): A Novel Approach for Global Optimization." ISA Transactions, Elsevier, 53(4), 1168–1183, 2014.