A Novel Adaptive Ant Lion Optimizer for Global Numerical Optimization

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***Abstract* - A novel bio-inspired optimization algorithm based on the hunting process of Ant Lions in nature is known the Ant Lion optimizer (ALO) Algorithm in contrast to meta-heuristics; 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 ALO and exercised on unconstraint test benchmark function and localization of partial discharge in transformer like geometry. ALO algorithm has quality feature that it uses simple mathematical equation to update position of Ants towards targeted optimal solution over the end of maximum iteration limit. Integration of new randomization adaptive technique provides potential that AALO algorithm to attain global optimal solution and faster convergence with less parameter dependency. Adaptive ALO (AALO) solutions are evaluated and results shows its competitively better performance over standard ALO optimization algorithms.**

Keywords: Meta-heuristic; Ant Lion optimizer; Adaptive technique; Global optimal; Hunting; Sensor Position.

1. INTRODUCTION

The ALO technique reflects the intellectual activities of antlions in hunting ants in environment. The ALO algorithm [1] inspired by hunting process and it is the interface between antlions and ants in the trap. To model such interfaces, ants have to travel over the exploration space, and antlions are permitted to pursuit them and become fitter using traps.

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 ALO 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 in algorithm for solving different constrained or unconstraint optimization problems. ALO 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 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 Ant Lion optimizer 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 5 PD localization by acoustic emission, in section 6 conclusion is drawn. Finally, acknowledgment gives regards detail and at the end, references are written.

2. ANT-LION OPTIMIZER

The ALO technique proposed by Seyedali Mirjalili that reflects the intellectual activities of antlions in hunting ants in environment. To model such interfaces, ants have to travel over the exploration space, and antlions are permitted to pursuit them and become fitter using traps [1].

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2.1. Operators of ALO algorithm

As ants travel randomly in nature when searching for food, a random walk is selected for demonstrating ants' movement and it is given by following equation:

$$X(t)=[0, cumsum(2r(t\_1)-1), cumsum(2r(t\_2)-1), \dots, cumsum(2r(t\_n)-1)] \quad (1)$$

Where, cumsum computes the cumulative sum, n is the maximum no. of iteration, t is the step of random walk (iteration), and $r(t)$ is a stochastic function defined as follows:

$$r(t)=\begin{cases} 1 \rightarrow rand > 0.5 \\ 0 \rightarrow rand \le 0.5 \end{cases}$$

Where, t is the step of random walk and rand represents a random number created by uniform distribution in the interval of [0, 1].
The location of ants are kept and used during optimization in the given matrix:

$$M_{Ant}=\begin{bmatrix} A_{11} & A_{12} & . & . & A_{1d} \\ A_{21} & A_{22} & . & . & A_{2d} \\ . & . & . & . & . \\ . & . & . & . & . \\ A_{n1} & A_{n2} & . & . & A_{nd} \end{bmatrix} \quad (2)$$

Where: M_{Ant} = the matrix for storing the location of every ants, A_{ij} = the value for j^{th} variable (dimension) of i^{th} ant, n = the no. of ants and d = the total no. of variables.
For calculating individual ant, *a* fitness function is used in optimisation and subsequent matrix saves the fitness value of each ants:

$$M_{OA}=\begin{bmatrix} f\left(\left[A_{11}, A_{12}, \dots, A_{1d}\right]\right) \\ f\left(\left[A_{21}, A_{22}, \dots, A_{2d}\right]\right) \\ \vdots \\ \vdots \\ f\left(\left[A_{n1}, A_{n2}, \dots, A_{nd}\right]\right) \end{bmatrix} \quad (3)$$

Where, M_{OA} = the matrix for storing the each ant fitness, A_{ij} = the value of j^{th} variable of i^{th} ant, n = the total no. of ants and f = the objective function.
So we suppose that ants as well as the antlions are hiding somewhere in the search area. So as to store their locations and fitness values, the following matrices are used:

$$M_{Antlion}=\begin{bmatrix} AL_{11} & AL_{12} & . & . & AL_{1d} \\ AL_{21} & AL_{22} & . & . & AL_{2d} \\ . & . & . & . & . \\ . & . & . & . & . \\ AL_{n1} & AL_{n2} & . & . & AL_{nd} \end{bmatrix} \quad (4)$$

Where: $M_{Antlion}$ = the matrix for storing the location of individual antlion, AL_{ij} = the value of j^{th} variable of i^{th} antlion, n = no. of ants and d = the no. of variables.

$$M_{OAL}=\begin{bmatrix} f\left(\left[AL_{11}, AL_{12}, \dots, AL_{1d}\right]\right) \\ f\left(\left[AL_{21}, AL_{22}, \dots, AL_{2d}\right]\right) \\ \vdots \\ \vdots \\ f\left(\left[AL_{n1}, AL_{n2}, \dots, AL_{nd}\right]\right) \end{bmatrix} \quad (5)$$

Where, M_{OAL} = the matrix for storing the fitness of individual antlion, AL_{ij} = the value of j^{th} variable of i^{th} antlion, n = no. of ants and f = the objective function.

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2.2. Random Walk of Ants

Each of the behaviors is mathematically modeled as:

The Random walks of ants is calculated as follows equation (6)

$$x_i^t = \frac{(x_i^t - x_i)*(d_i - c_i^t)}{(d_i^t - a_i)} + c_i \quad (6)$$

Where, a_i = the minimal of random walk of i^{th} variable, b_i = the Maximum of random walk in i^{th} variable.

2.3. Trapping in Antlions pits

The Trapping in ant lion's pits is calculated as follows equation (7) and equation (8)

$$c_i^t = Antlion_j^t + c^t \quad (7)$$

$$d_i^t = Antlion_j^t + d^t \quad (8)$$

2.4. Sliding Ants towards Antlion

The Sliding ants towards ant lion calculated as follows equation (9) and equation (10)

$$c^t = \frac{c^t}{I} \quad (9)$$

$$d^t = \frac{d^t}{I} \quad (10)$$

Where, I = ratio, c^t = the minimal of total variables at t^{th} iteration, and d^t = the vector containing the maximum of total variables at t^{th} iteration.

2.5. Catching prey and re-building the pit

Catching prey and re-building the pits calculated as follows equation (11)

$$Antlion_j^t = Ant_i^t if [f(Ant_i^t)] > f(Antlion_j^t) \quad (11)$$

Where, t = the current iteration, $Antlion_j^t$= the location of chosen j^{th} antlion at t^{th} iteration, and Ant_i^t= the location of i^{th} ant at t^{th} iteration.

2.6. Elitism

Elitism of ant lion calculated using roulette wheel as follows equation (12)

$$Ant_i^t = \frac{R_A^t + R_E^t}{2} \quad (12)$$

Where, R_A^t = the random walk nearby the antlion chosen by means of the roulette wheel at t^{th} iteration, R_E^t = the random walk nearby the elite at t^{th} iteration, Ant_i^t = the location of i^{th} ant at t^{th} iteration.

3. ADAPTIVE ALO ALGORITHM

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.

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

Where

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

4. SIMULATION RESULTS FOR UNCONSTRAINT TEST BENCHMARK FUNCTION

Table 1: Benchmark Test functions

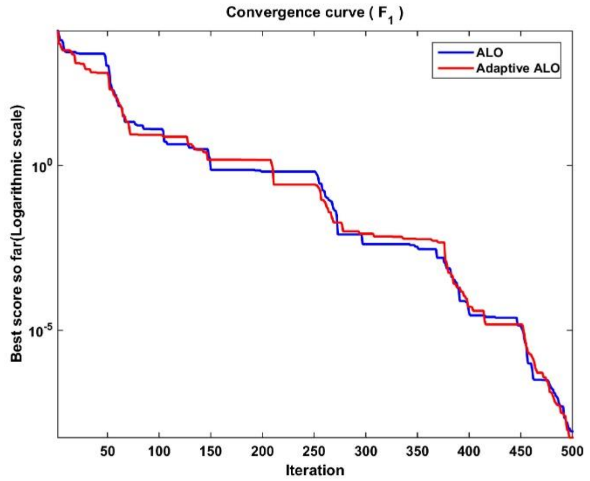
No.	Name	Function	Dim	Range	Fmin
F1	Sphere	$f(x)=\sum_{i=1}^{n} x_i^2 * R(x)$	10	[-100, 100]	0
F2	Schwefel 2.22	$f(x)=\sum_{i=1}^{n}\lvert x_i\rvert+\prod_{i=1}^{n}\lvert x_i\rvert * R(x)$	10	[-10, 10]	0
F3	Schwefel 1.2	$f(x)=\sum_{i=1}^{n}\left(\sum_{j-1}^{i} x_j\right)^2 * R(x)$	10	[-100, 100]	0
F4	Schwefel 2.21	$f(x)=\max_i\left\{\lvert x_i\rvert, 1\le i\le n\right\}$	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	$f(x)=\sum_{i=1}^{n}\left(\left[x_i+0.5\right]\right)^2 * R(x)$	10	[-100, 100]	0
F7	Quartic Function	$f(x)=\sum_{i=1}^{n} ix_i^4+random[0,1) * R(x)$	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)
F9	Rastrigin	$F(x)=\sum_{i=1}^{n}\left[x_i^2-10cos\left(2\pi x_i\right)+10\right] * R(x)$	10	[-5.12, 5.12]	0
F10	Ackley's Function	$F(x)=-20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n} x_i^2}\right)-$ $exp\left(\frac{1}{n}\sum_{i=1}^{n} cos\left(2\pi x_i\right)\right)+20+e * R(x)$	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	$F(x)=\frac{\pi}{n}\left\{\begin{matrix}10sin\left(\pi y_1\right)+\sum_{i=1}^{n-1}\left(y_i-1\right)^2 \\ \left[1+10sin^2\left(\pi y_{i+1}\right)\right]+\left(y_n-1\right)^2\end{matrix}\right\}$ $y_i=1+\frac{x_i+1}{4},$ $u(x_i,a,k,m)=\begin{cases}k\left(x_i-a\right)^m & x_i>a \\ 0 & -a<x_i<a \\ k\left(-x_i-a\right)^m & x_i<-a\end{cases}$	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
F14	De Joung (Shekel's Foxholes)	$F(x)=\left(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}(x_i-a_{ij})^6}\right)^{-1}$	2	[-65.536, 65.536]	1
F15	Kowalik's Function	$f(x)=\sum_{i=1}^{11}a_i-\left[\frac{x_i(b_i^2+b_ix_2)}{b_i^2+b_ix_3+x_4}\right]^2$	4	[-5,5]	0.00030
F16	Shekel	$f(x)=-\sum_{i=1}^{10}\left[(X-a_i)(X-a_i)^T+c_i\right]^{-1}$	4	[0,10]	-10.5363
F17	Cube function	$f(x)=100(x_2-x_1^3)^2+(1-x_1)^2$	30	[-100, 100	0
F18	Matyas function	$f(x)=0.26(x_1^2+x_2^2)-0.48x_1x_2$	30	[-30, 30]	0
F19	Powell function	$f(x)=\sum_{i=1}^{D-2}\left\{\begin{array}{l}(x_{i-1}+10x_i)^2+5(x_{i+1}-x_{i+2})^2+ \\ (x_i-2x_{i+1})^4+10(x_{i-1}-x_{i+2})^4\end{array}\right\}$	4	[-30, 30]	0
F20	Beale Function	$f(x)=\left\{\begin{array}{l}\left(1.5-x_1+x_1x_2\right)^2+\left(2.25-x_1+x_1x_2^2\right)^2 \\ +\left(2.625-x_1+x_1x_2^3\right)^2\end{array}\right\}$	30	[-100, 100]	0
F21	levy13 function	$f(x)=\left\{\begin{array}{l}\sin^2(3\pi x_1)+(x_1-1)^2\left(1+\sin^2(3\pi x_2)\right) \\ +(x_2-1)^2\left(1+\sin^2(2\pi x_2)\right)\end{array}\right\}$	30	[-10, 10]	0

Table 2: Internal Parameters

Parameter Name	Search Agents no.	Max. Iteration no.	No. of Evolution
F1-F21	30	500	20-30
Acoustic PD Localization	40	200	20
Note:- Scale specified on axis, Not specified means axis are linear scale			

F_1



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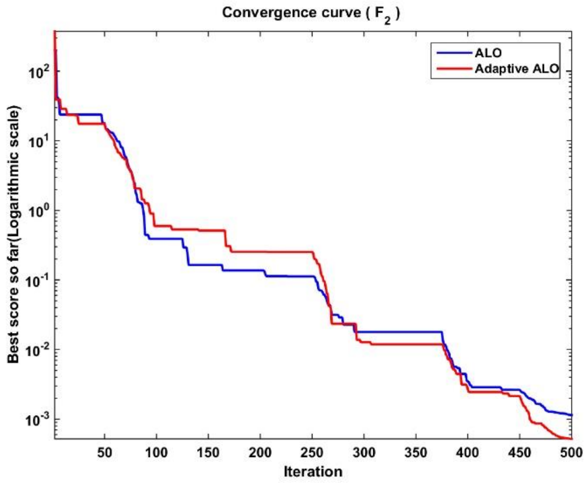

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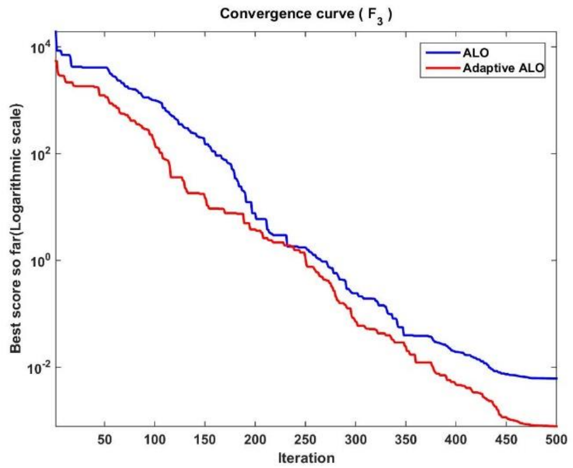

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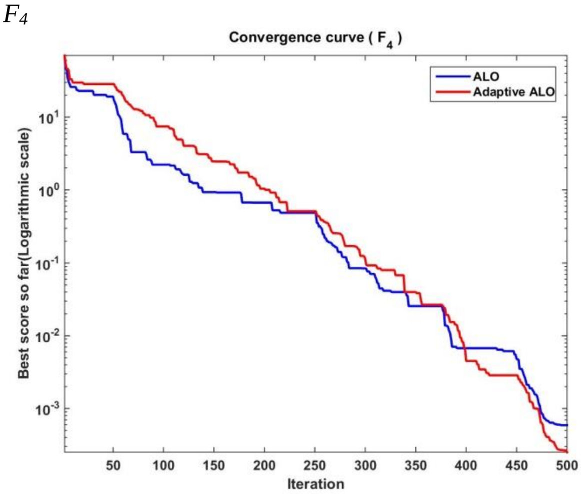

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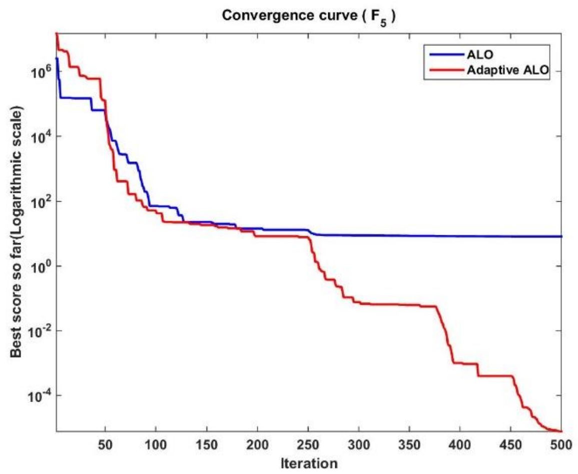

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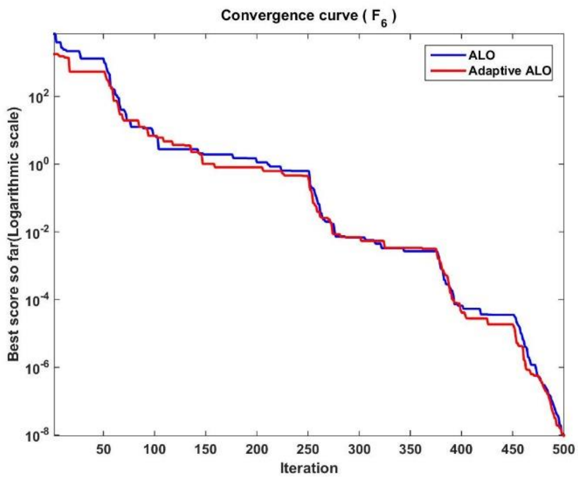
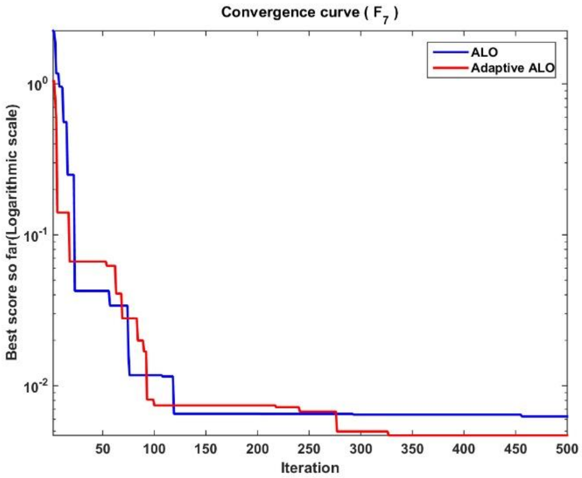
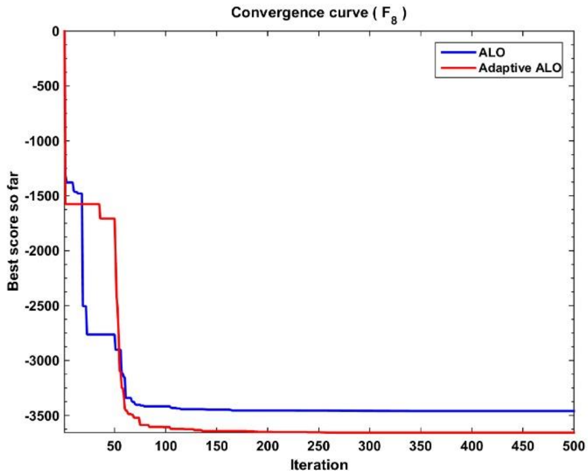


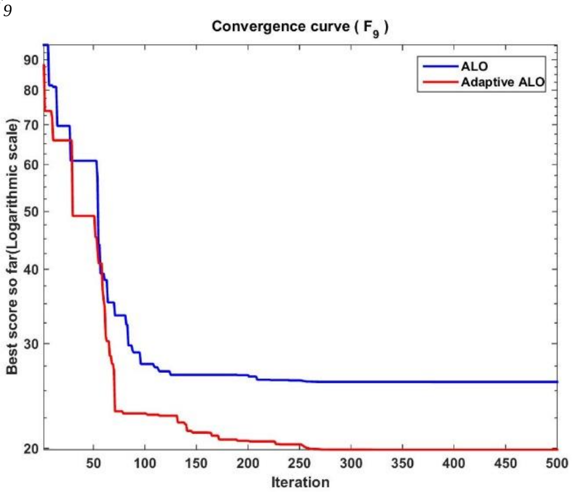
F₇





F_8

F_9



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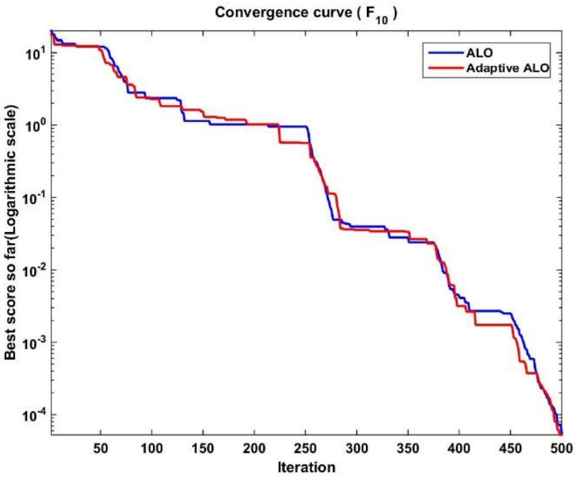

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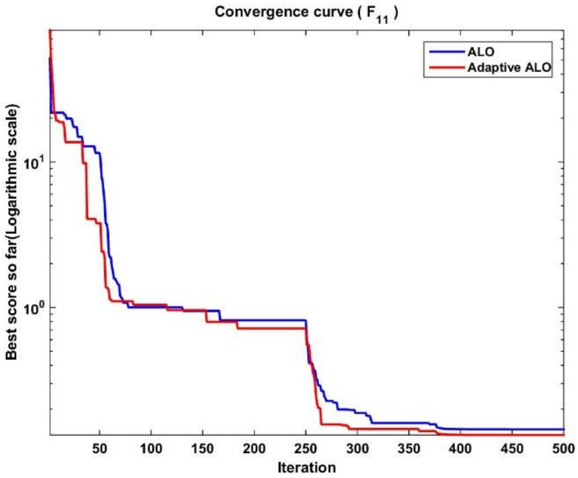

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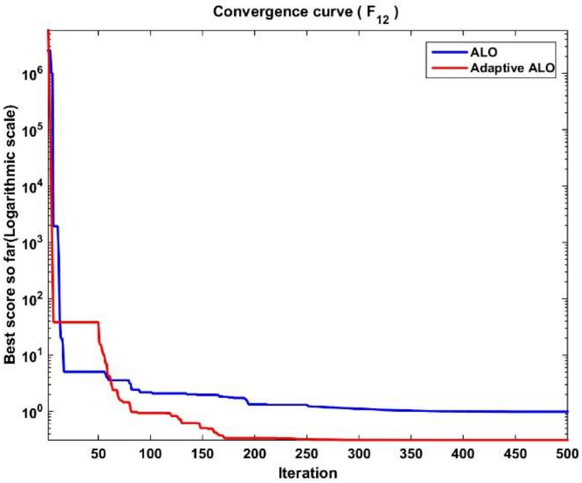

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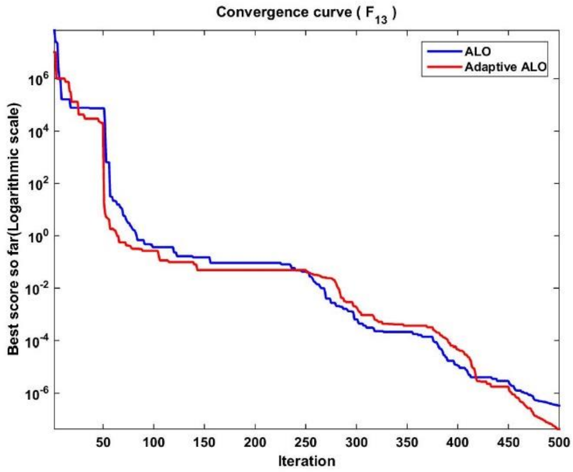

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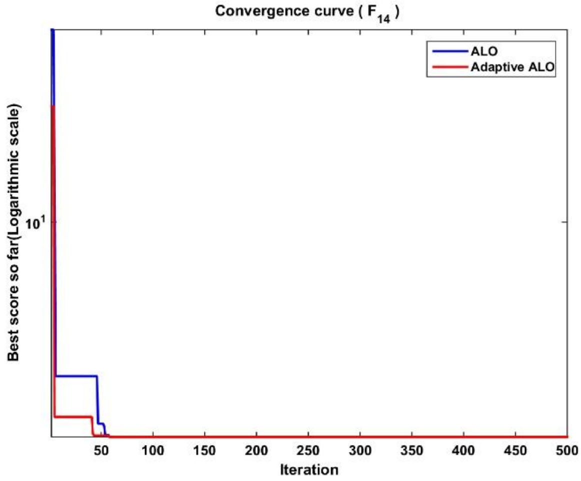

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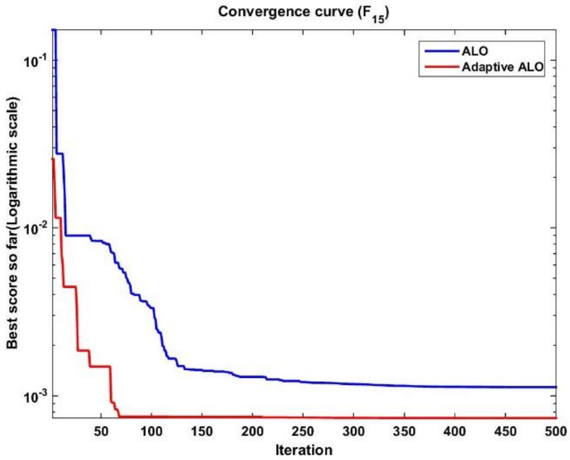

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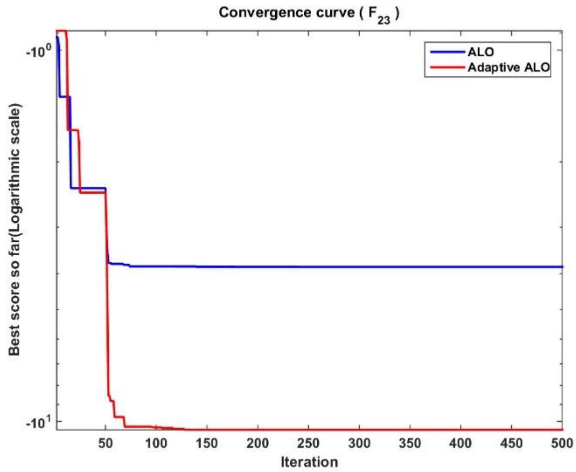

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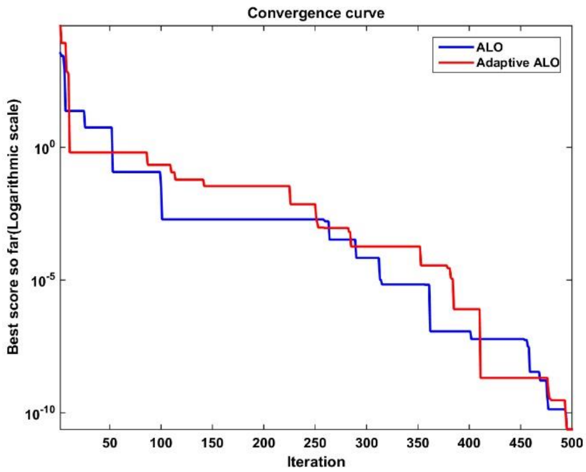

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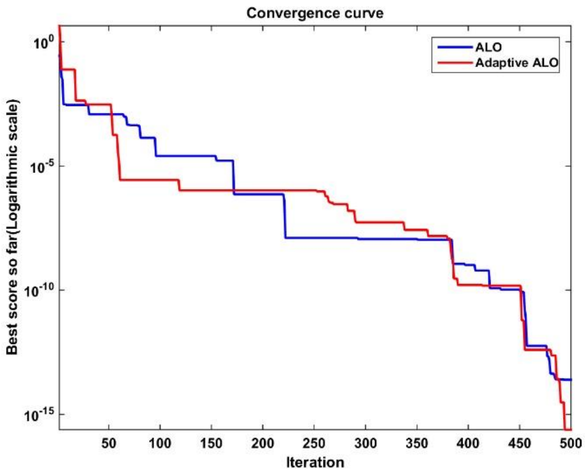

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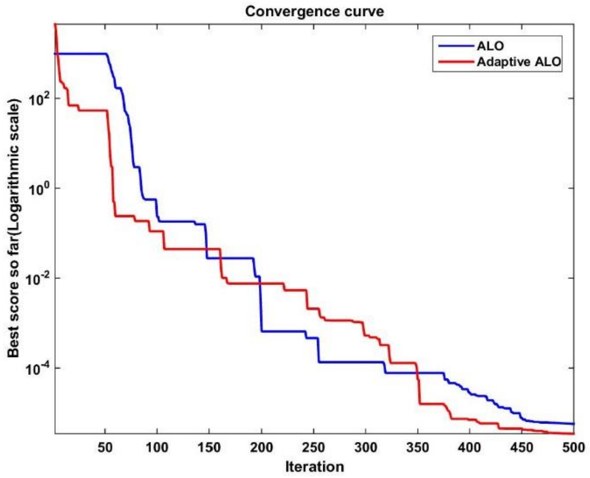
F19



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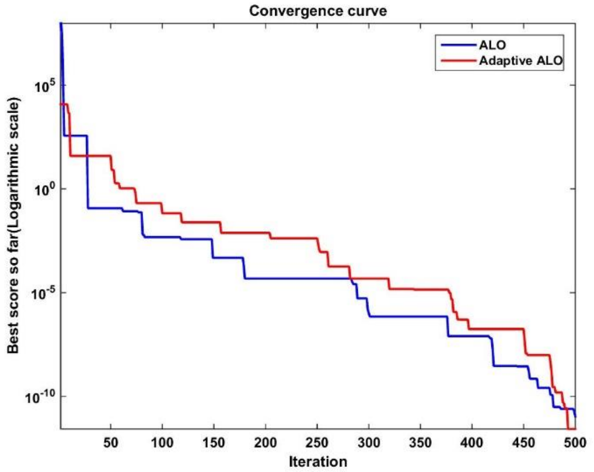

F21

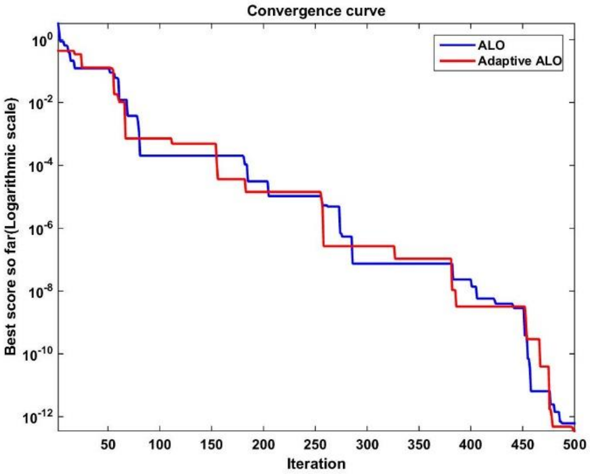

Fig. 1: Convergence Curve of Benchmark Test Function

Table 3: Result for benchmark functions

Fun.	Ant-Lion optimizer (ALO)			Adaptive Ant-Lion Optimizer (AALO)		
	Ave	Best	S.D.	Ave	Best	S.D.
F1	1.1018E-08	8.5917E-09	3.4308E-09	6.9926E-09	5.5958E-09	3.4308E-09
F2	1.35	0.0011442	1.9076	0.2666	0.00052061	1.9076
F3	0.05592	0.0061171	0.070433	0.012982	0.00077882	0.070433
F4	0.0028435	0.00058981	0.0031871	0.0011557	0.00025095	0.0031871
F5	8.8444	8.2563	0.83172	1.5002	7.6731E-06	0.83172
F6	2.1803E-08	1.0074E-08	1.6588E-08	1.0207E-08	9.4448E-09	1.6588E-08
F7	0.014989	0.0062663	0.012335	0.027139	0.0046907	0.012335
F8	-2692.5959	-3459.3448	1084.3467	-2850.0459	-3656.8455	1084.3467
F9	26.3663	25.8689	0.70354	22.884	19.8992	0.70354
F10	0.5776	5.544E-05	0.81677	5.4147E-05	5.2544E-05	0.81677
F11	0.1576	0.14525	0.017463	0.2165	0.1328	0.017463
F12	1.5235	0.98867	0.75642	0.31478	0.31101	0.75642
F13	3.9475E-07	3.3722E-07	8.1357E-08	2.0961E-07	4.28E-08	8.1357E-08
F14	3.9604	1.992	2.7837	2.4871	1.992	2.7837
F15	0.010793	0.0011281	0.013668	0.00074227	0.00073769	6.4749E-06
F23	-3.8354	-3.8354	5.8935E-12	-6.6715	-10.5364	5.4658
F28	3.5236	2.4015E-11	4.9831	5.8609E-11	2.3499E-11	4.9652E-11
F31	6.0627E-14	2.4656E-14	5.0871E-14	9.7097E-15	2.403E-16	1.3392E-14
F34	9.6533E-06	5.7193E-06	5.636E-06	1.0075E-05	3.4594E-06	9.3556E-06

5. 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:

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

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*).

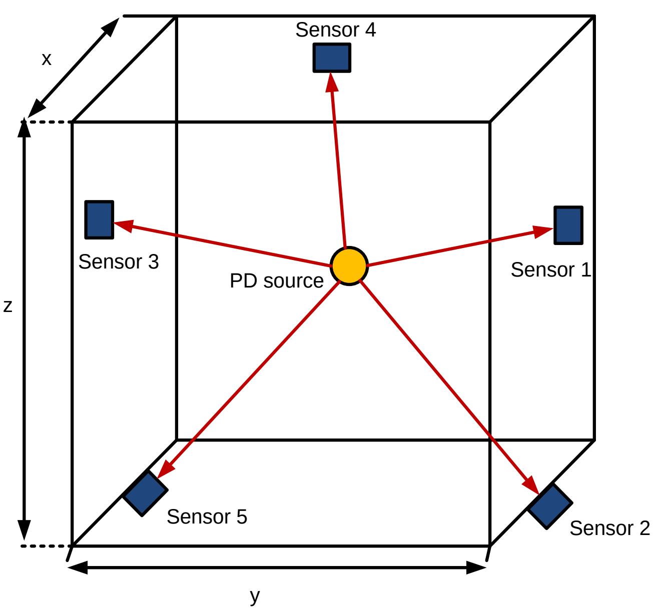

Fig. 2: Visualization of PD source and sensor arrangement

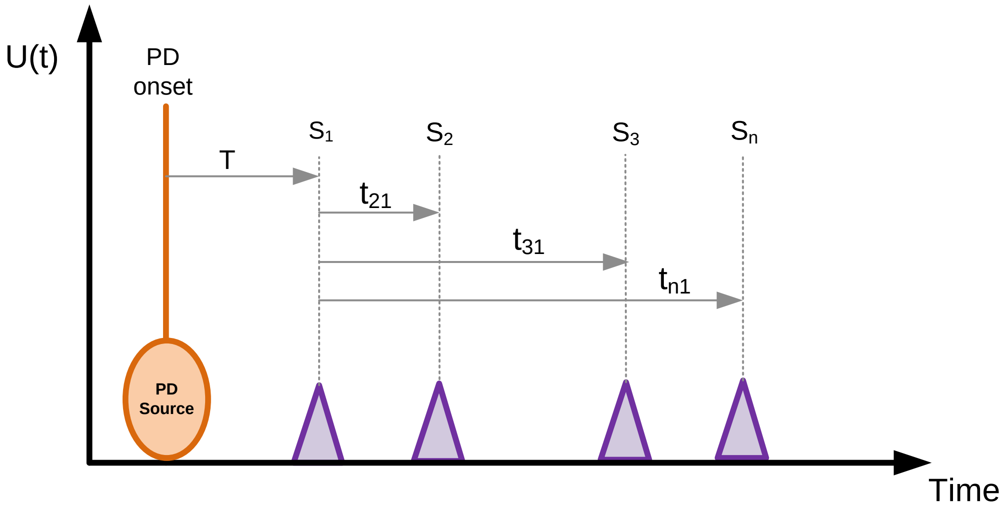

Fig. 3: Schematic of acoustic time differences in reference to electrical PD signal

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:

$$\tau_{21} = -1000\times10^{-03}, \tau_{31} = -1100\times10^{-03}, \\ \tau_{41} = -700\times10^{-03}, \tau_{51} = -924.69\times10^{-03}, \tag{15}$$

$$P = \left[(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2\right]^{0.5} \tag{16}$$

$$a = \left[(x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2\right]^{0.5} - P - \upsilon_e\tau_{21}; \tag{17}$$

$$b = \left[(x-x_3)^2 + (y-y_3)^2 + (z-z_3)^2\right]^{0.5} - P - \upsilon_e\tau_{31}; \tag{18}$$

$$c = \left[(x-x_4)^2 + (y-y_4)^2 + (z-z_4)^2\right]^{0.5} - P - \upsilon_e\tau_{41}; \tag{19}$$

$$d = \left[(x-x_5)^2 + (y-y_5)^2 + (z-z_5)^2\right]^{0.5} - P - \upsilon_e\tau_{51}; \tag{20}$$

$$Min \quad \{D_f(x,y,z,\upsilon_e)\} = a^2 + b^2 + c^2 + d^2; \tag{21}$$

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$$\left.\begin{array}{l} 0 \le x \le x_{\max} \\ 0 \le y \le y_{\max} \\ 0 \le z \le z_{\max} \\ 1200 \le \upsilon_e \le 1500, \quad (m/s \end{array}\right\} \tag{22}$$

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

$$\Delta R = \left[(x - x_c)^2 + (y - y_c)^2 + (z - z_c)^2 \right]^{0.5} \tag{23}$$

Error of each co-ordinate is formulated:

$$\in_r = \left| \frac{L_{act} - L_{cal}}{L_{act}} \right| \times 100\% \tag{24}$$

Maximum deviation D_{max}

$$D_{\max} = \max \left\{ \begin{array}{l} |x_{act} - x_{cal}| \\ |y_{act} - y_{cal}| \\ |z_{act} - z_{cal}| \end{array} \right\} \tag{25}$$

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	ALO	AALO	GA
X	4500	4381.7459	4381.7465	4223.76
Y	2600	2469.6026	2469.603	2391.71
z	3700	3647.4901	3647.4905	3503.04

Table 6: Error analysis

Error	ALO	AALO	GA
Error of x%	2.627	2.627	6.14
Error of y%	5.015	5.322	8.01
Error of z%	1.419	1.419	5.32
D_{max}/mm	130.3974	130.397	276.24
Comprehensive Error(del R/mm)	183.6975	183.6968	398.10

CONCLUSION

Ant Lion 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 AALO algorithm is feasible. PD localization by AALO gives better result than ALO algorithm and also accurate in compare to GA. The ALO result of various unconstrained problems proves that it is also an effective method in solving challenging problems with unknown search space.

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