A Novel Adaptive Sine Cosine Algorithm for Global Numerical Optimization

Naveen Sihag
Ph.D. Scholar, Department of Computer Engineering,
Rajasthan Technical University Kota, Rajasthan 324002, India

Abstract:-A novel population based optimization algorithm known as Sine Cosine Algorithm (SCA), 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 SCA and exercised on unconstraint test benchmark function andlocalization of partial discharge in transformer like geometry. SCA algorithm has quality feature that it uses simple trigonometric terms like sine and cosine term for every unconstrained and complex constrained optimization problem. Integration of new randomization adaptive technique provides potential that ASCA algorithm to attain global optimal solution and faster convergence with less parameter dependency. Adaptive SCA (ASCA) solutions are evaluated and results shows its competitively better performance over standard SCA optimization algorithms.

Keywords:-Meta-heuristic; Sine Cosine Algorithm; Adaptive technique; Global optimal; Benchmark function; Transformer.

I. INTRODUCTION

A novel population based Sine Cosine algorithm [1] based on simple sine and cosine terms for both exploration and exploitation in optimization problem. In this algorithm random value plays very important role and integrated with adaptive technique that it changes position of current solution towards destination solution according to its fitness function.

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 SCA 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. SCA 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 Sine Cosine 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.

ISSN No:-2456 –2165

II. SINE COSINE ALGORITHM (SCA)

Newly proposed algorithm by SeyedaliMirjalili known as Sine Cosine Algorithm (SCA) simply based on Sine Cosine function used for exploration and exploitation phases in optimization problems.

$$X_i^{t+1} = X_i^t + r_1 \times \sin(r_2) \times \left| r_3 p_i^t - x_i^t \right| \quad (1)$$

$$X_i^{t+1} = X_i^t + r_1 \times \cos(r_2) \times \left| r_3 p_i^t - x_i^t \right| \quad (2)$$

Where:

X_i^t Location of current solution at *t-th* iteration in *i-th* dimension, r_1, r_2, $r_2$random value, $P_i$location of targeted optimal solution. Equation (1) and Equation (2) uses $r_4 \leq 0.5$, $r_4 \geq 0.5$ condition for exploration and exploitation.

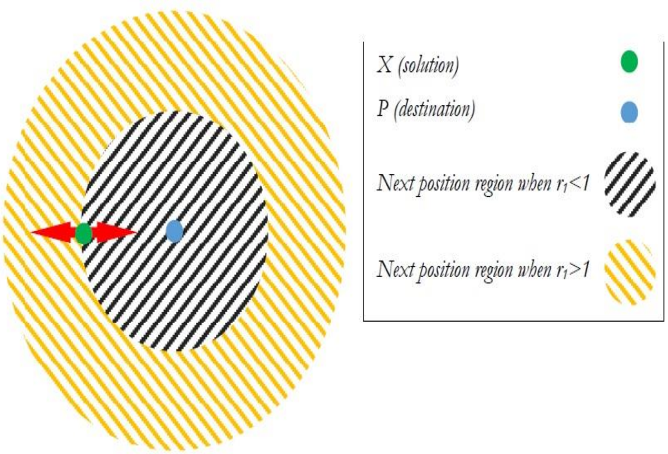


Fig.1:Illustrating Next Step Towards Targeted Optimum Solution

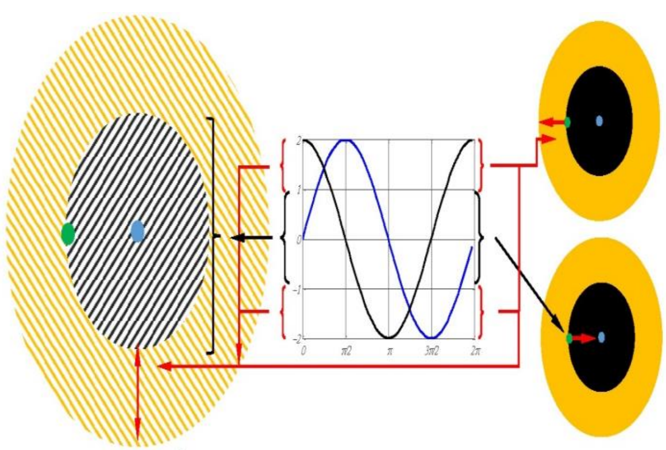


Fig.2:Basic Principle of SCA Algorithm

III. ADAPTIVE SCA 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.

$$X_i^{t+1} = X_i^t + randn * \left(\frac{1}{t}\right)^{\left|((bestf(t) - fi(t))/(bestf(t) - worstf(t)))\right|}$$
(3)

Where

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

ISSN No:-2456 –2165

IV. SIMULATION RESULTS FOR UNCONSTRAINT TEST BENCHMARK FUNCTION

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	$f(x)=\sum_{i=1}^{n} i x_i^4 + random[0,1) * R(x)$	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)
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	$F(x)=\frac{\pi}{n}\left\{\begin{matrix} 10sin(\pi y_1)+\sum_{i=1}^{n-1}(y_i-1)^2 \\ \left[1+10sin^2(\pi y_{i+1})\right]+(y_n-1)^2 \end{matrix}\right\}$ $y_i=1+\frac{x_i+1}{4}$, $u(x_i,a,k,m)=\begin{cases} k(x_i-a)^m & x_i>a \\ 0 & -a<x_i<a \\ k(-x_i-a)^m & x_i<-a \end{cases}$	10	[-50, 50]	0
F13	Penalty 2	$F(x)=0.1\left\{\begin{matrix} sin^2(3\pi x_1)+\sum_{i=1}^{n}(x_i-1)^2 \\ \left[1+sin^2(3\pi x_i+1)\right] \\ +(x_n-1)^2\left[1+sin^2(2\pi x_n)\right] \end{matrix}\right\}$ $+\sum_{i=1}^{n}u(x_i,5,100,4)*R(x)$	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	Branin Function	$f(x)=\left(x_2-\frac{5.1}{4\pi^2}x_1^2+\frac{5}{\pi}x_1-6\right)^2+$ $10\left(1-\frac{1}{8\pi}\right)\cos x_1+10$	2	[-5,0] [10,15]	0.398
F17	Goldstein and Price Function	$f(x)=\left[\begin{matrix} 1+(x_1+x_2+1)^2 \\ \left(\begin{matrix} 19-14x_1+3x_1^2- \\ 14x_2+6x_1x_2+3x_2^2 \end{matrix}\right) \end{matrix}\right]*$ $\left[\begin{matrix} 30+(2x_1-3x_2)^2 \\ *\left(\begin{matrix} 18-32x_1+12x_1^2+ \\ 48x_2-36x_1x_2+27x_2^2 \end{matrix}\right) \end{matrix}\right]$	2	[-2,2]	3

ISSN No:-2456 –2165

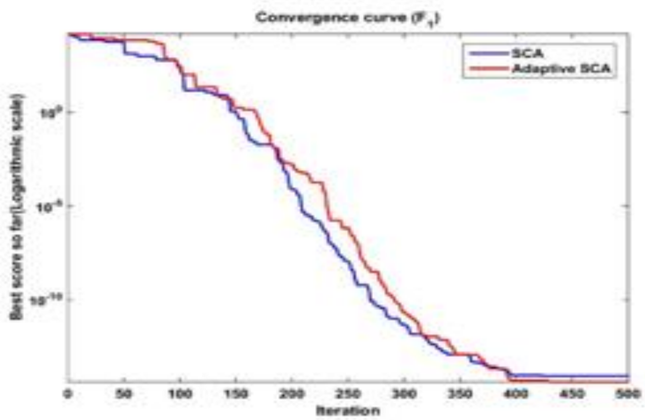
F18	Hartman 1	$f\left(x\right)=-\sum_{i=1}^{4}c_i \exp\left(-\sum_{j=1}^{3}a_{ij}\left(x_j-p_{ij}\right)^2\right)$	3	[0,1]	-3.86
F19	Hartman 2	$f_{20}\left(x\right)=-\sum_{i=1}^{4}c_i \exp\left(-\sum_{j=1}^{6}a_{ij}\left(x_j-p_{ij}\right)^2\right)$	6	[0,1]	-3.32
F20	Shekel 1	$f\left(x\right)=-\sum_{i=1}^{5}\left[\left(X-a_i\right)\left(X-a_i\right)^T+c_i\right]^{-1}$	4	[0,10]	-10.1532
F21	Shekel	$f\left(x\right)=-\sum_{i=1}^{7}\left[\left(X-a_i\right)\left(X-a_i\right)^T+c_i\right]^{-1}$	4	[0,10]	-10.4028
F22	Shekel	$f\left(x\right)=-\sum_{i=1}^{10}\left[\left(X-a_i\right)\left(X-a_i\right)^T+c_i\right]^{-1}$	4	[0,10]	-10.5363
F23	Cube function	$f\left(x\right)=100(x_2-x_1^3)^2+(1-x_1)^2$	30	[-100, 100	0
F24	Matyas function	$f(x)=0.26(x_1^2+x_2^2)-0.48x_1x_2$	30	[-30, 30]	0
F25	Powell function	$f(x)=\sum_{i=1}^{D-2}\left\{\begin{matrix}(x_{i-1}+10x_i)^2+5(x_{i+1}-x_{i+2})^2+\\(x_i-2x_{i+1})^4+10(x_{i-1}-x_{i+2})^4\end{matrix}\right\}$	4	[-30, 30]	0
F26	Beale Function	$f(x)=\left\{\begin{matrix}\left(1.5-x_1+x_1x_2\right)^2+\left(2.25-x_1+x_1x_2^2\right)^2\\+\left(2.625-x_1+x_1x_2^3\right)^2\end{matrix}\right\}$	30	[-100, 100]	0
F27	levy13 function	$f(x)=\left\{\begin{matrix}\sin^2\left(3\pi x_1\right)+\left(x_1-1\right)^2\left(1+\sin^2\left(3\pi x_2\right)\right)\\+\left(x_2-1\right)^2\left(1+\sin^2\left(2\pi x_2\right)\right)\end{matrix}\right\}$	30	[-10, 10]	0

Table 1: Benchmark Test Functions

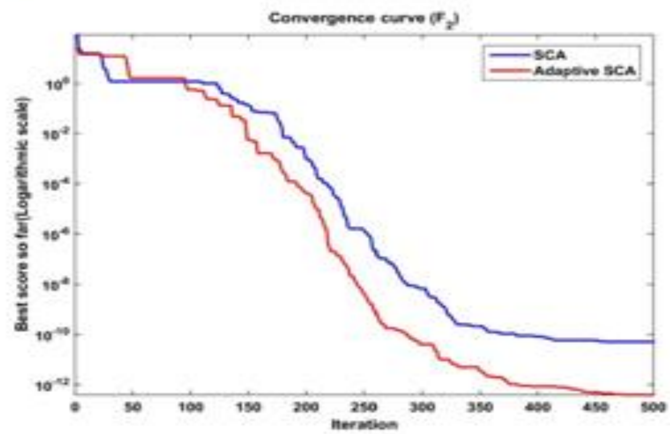
Parameter Name	**Search Agents no.**	**Max. Iteration no.**	**No. of Evolution**
F1-F27	30	500	20-30
Acoustic PD Localization	40	200	30
Note:- Scale specified on axis, Not specified means axis are linear scale			

Table 2: Internal Parameters

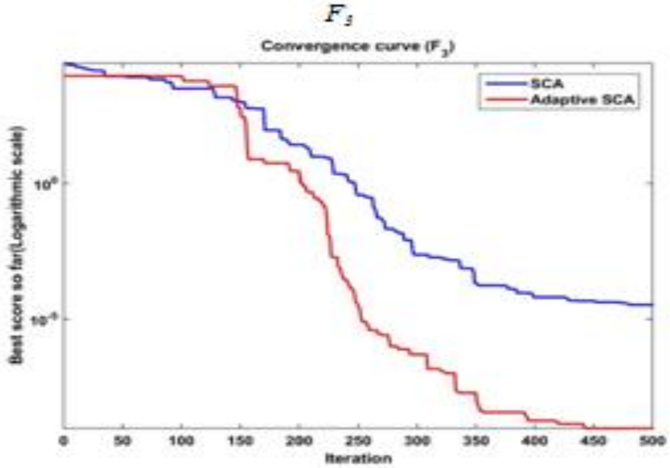
F_1



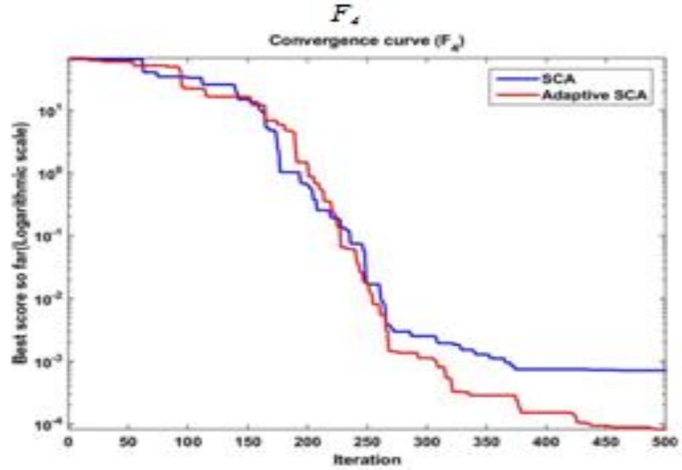
F_2



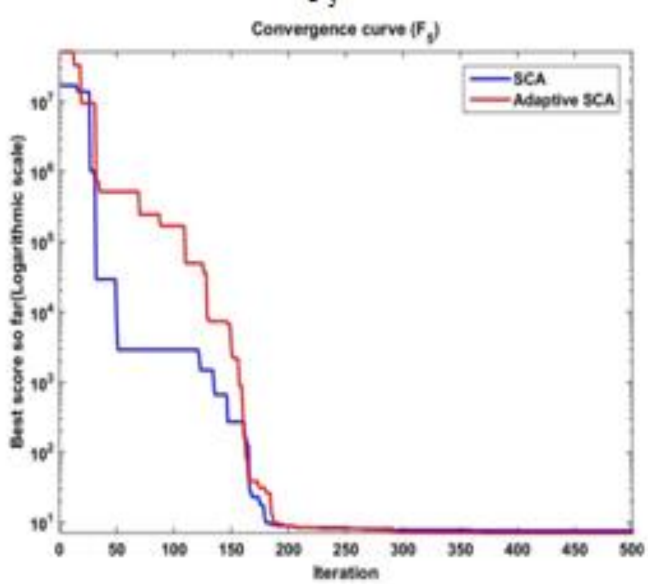
F_3



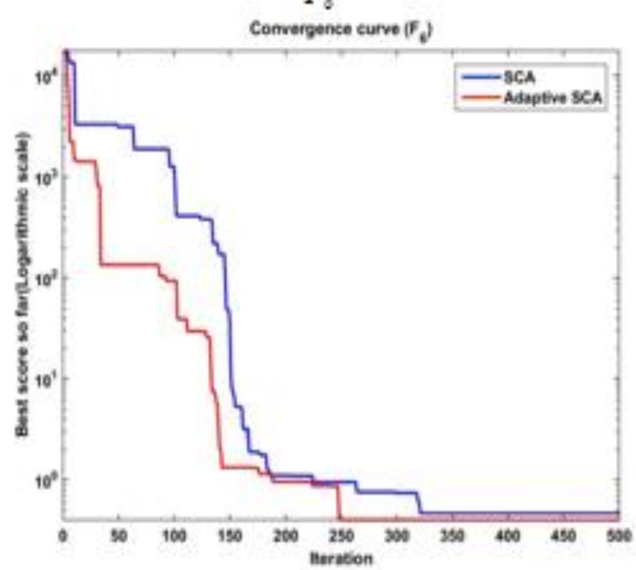
F_4



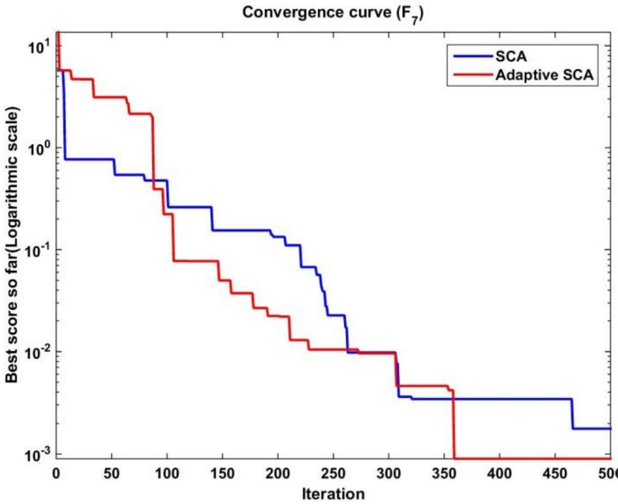
F_5



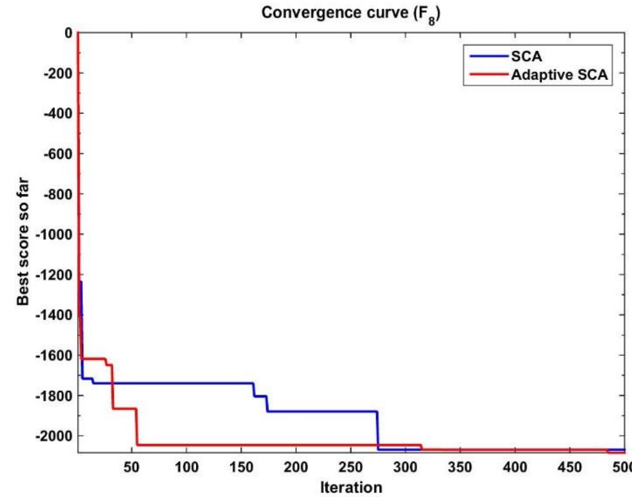
F_6



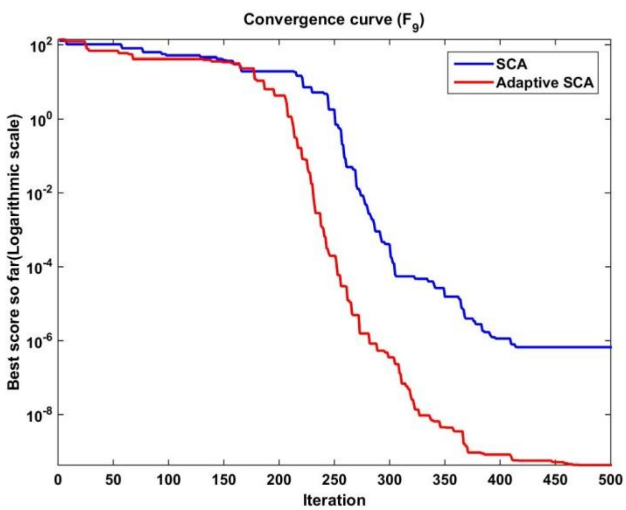
F_7



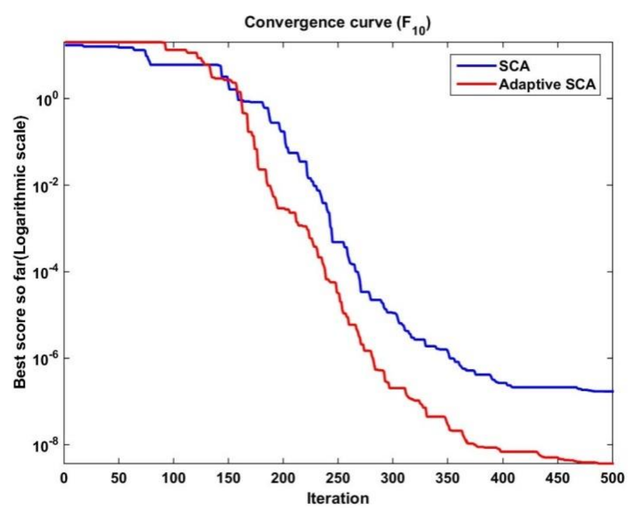
F_8



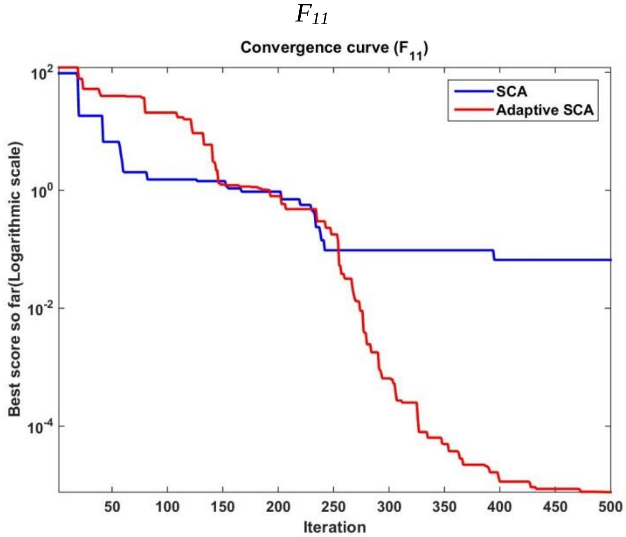
F_9



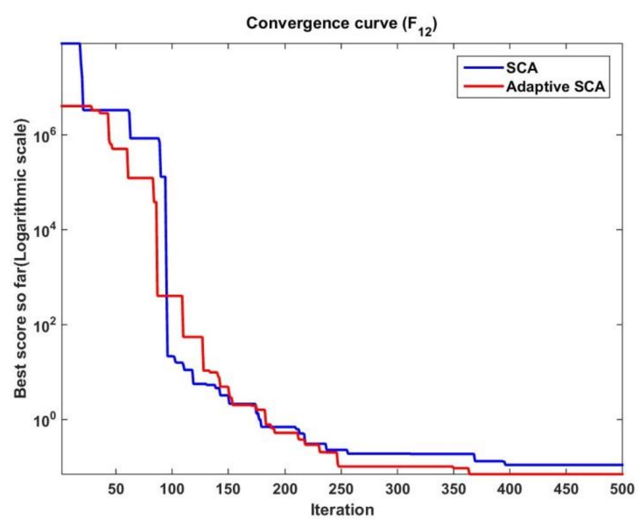
F_{10}



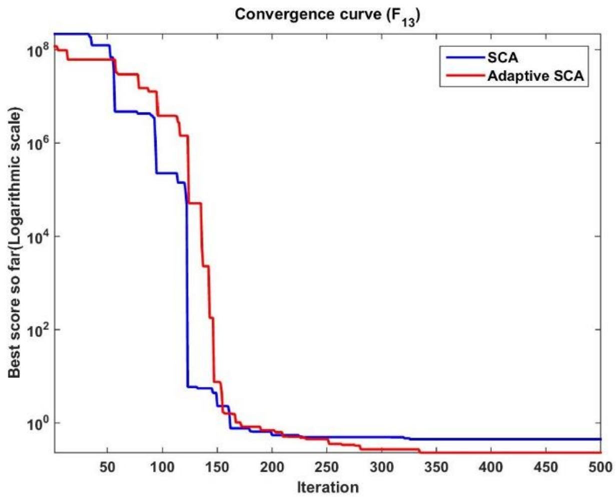
F_{11}



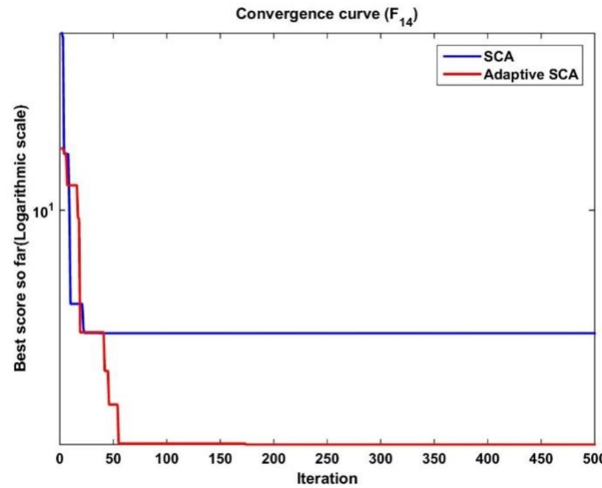
F_{12}



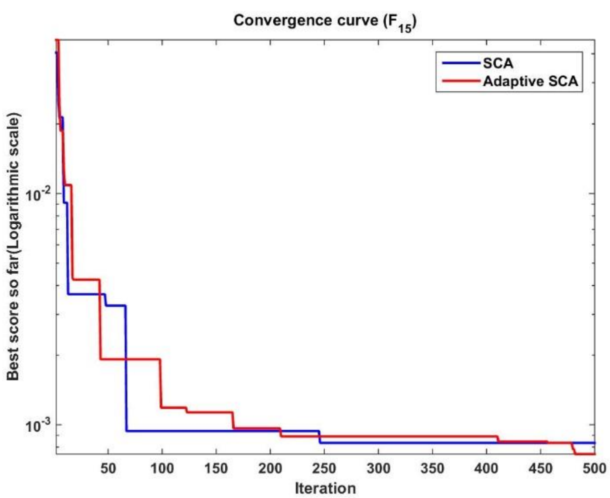
F_{13}



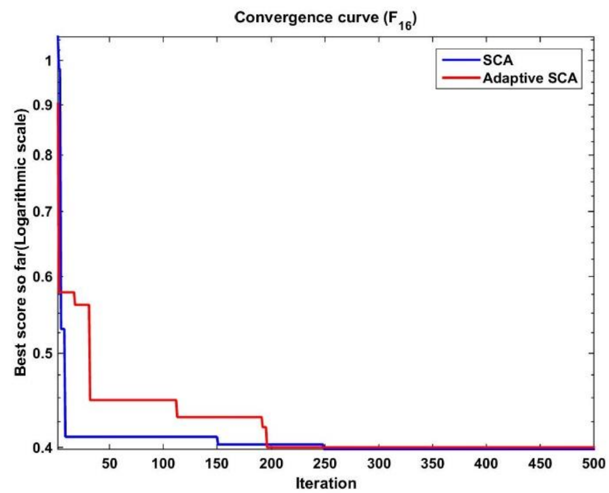
F_{14}



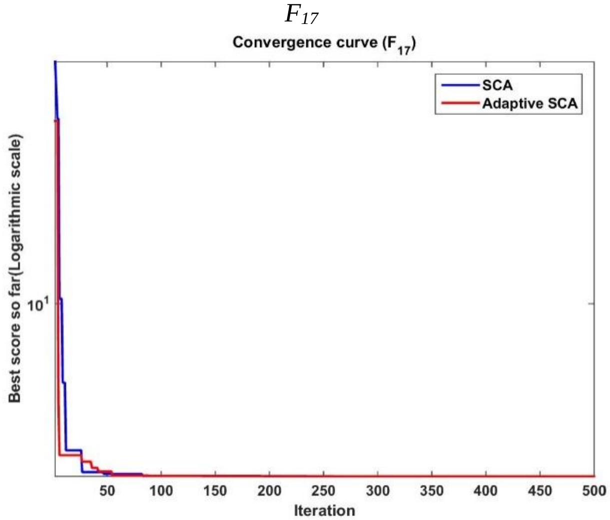
F_{15}



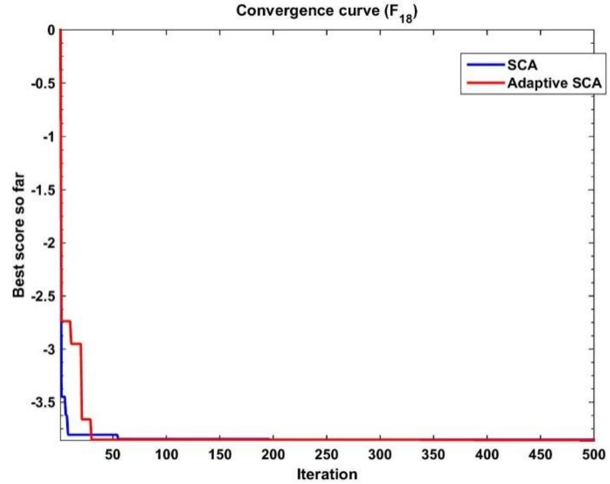
F_{16}



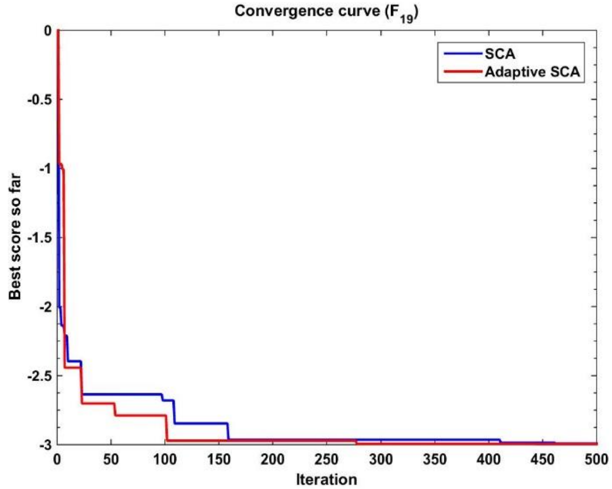
F_{17}



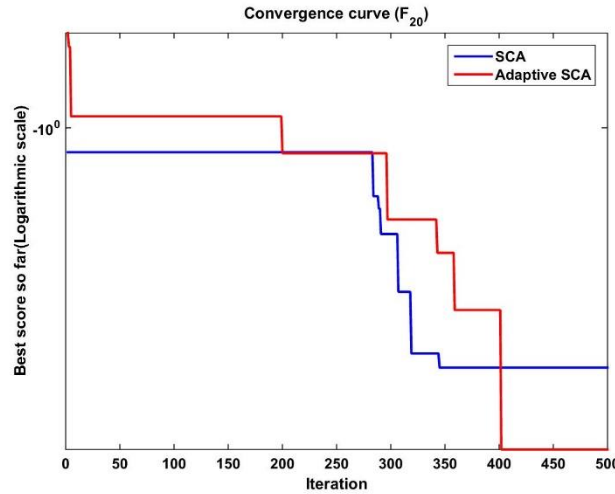
F_{18}



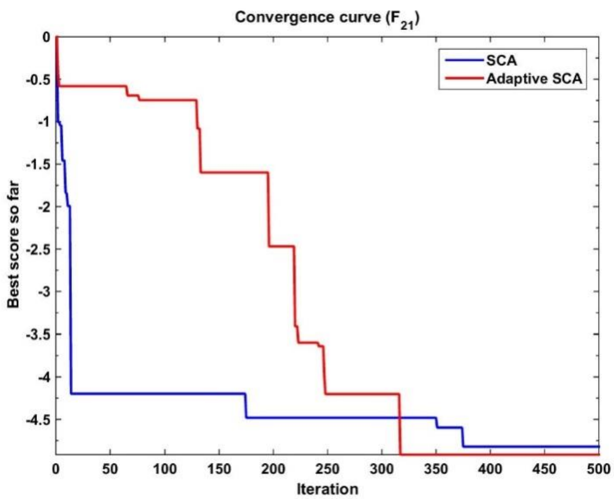
F_{19}



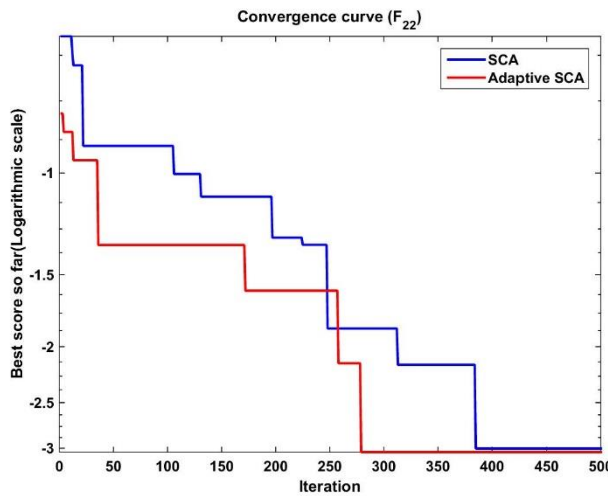
F_{20}



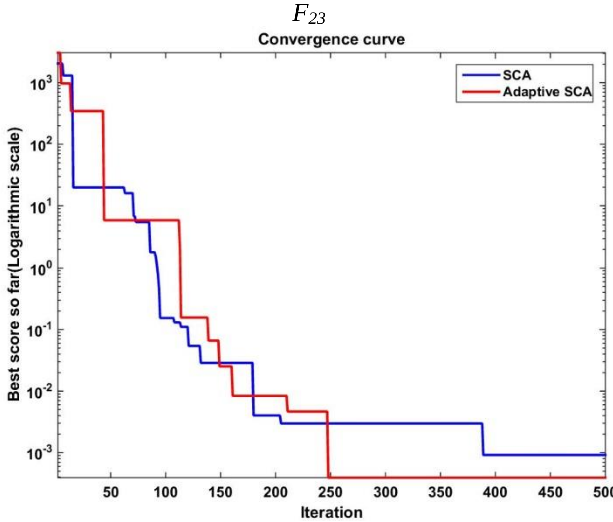
F_{21}



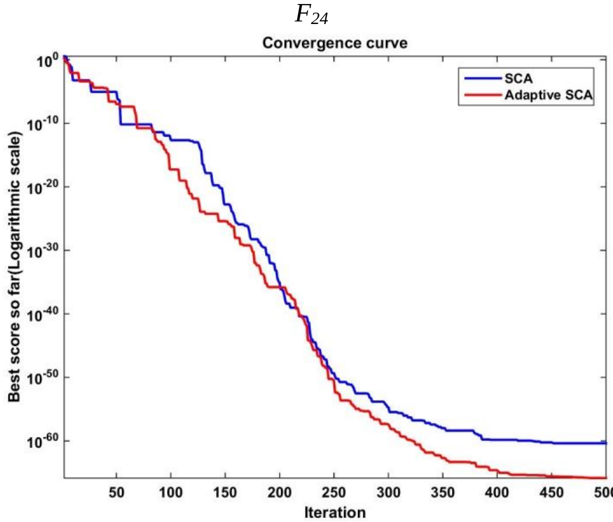
F_{22}



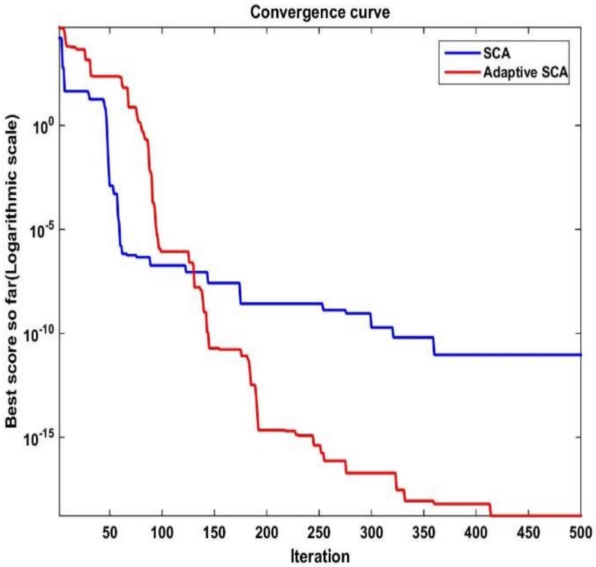
F_{23}



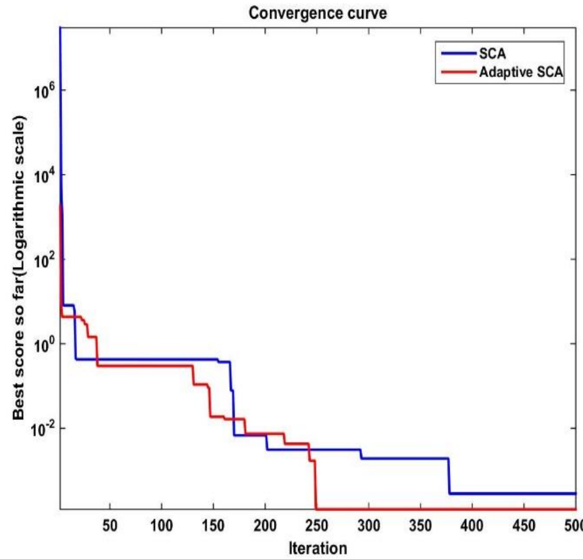
F_{24}



F_{25}



F_{26}



F_{27}

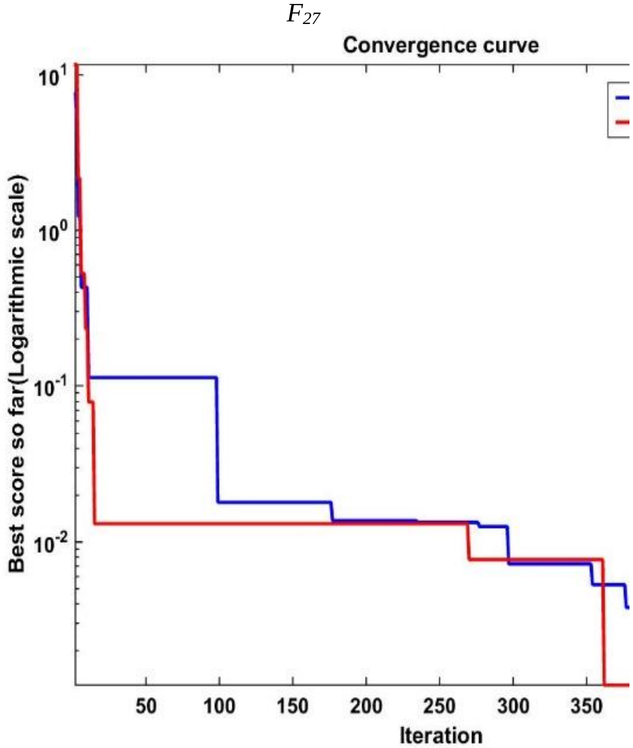


Fig. 3: Convergence Curve of Benchmark Test Function

Function	Sine Cosine Algorithm (SCA)			Adaptive Sine Cosine (ASCA)		
	Ave	Best	S.D.	Ave	Best	S.D.
F1	3.8997e-12	8.3555e-15	5.5031e-12	1.7034e-12	**4.0258e-15**	2.4033e-12
F2	5.1665e-10	5.1897e-11	6.5725e-10	5.3969e-09	**3.9446e-13**	7.6318e-09
F3	0.00013506	3.3344e-05	0.00014385	0.0058211	**8.9735e-10**	0.0082323
F4	0.000742	0.00071183	4.406e-05	0.0005013	**8.1901e-05**	0.00059317
F5	7.7006	7.6561	0.063	7.229	**7.0821**	0.20769
F6	0.4714	0.46241	0.012717	0.42624	**0.39943**	0.037903
F7	0.003145	0.0017773	0.001934	0.0012295	**0.0009001**	0.00046579
F8	-1985.6903	-2069.077	117.9266	-1972.6406	**-2083.7554**	157.1401
F9	1.6053e-05	6.6446e-07	2.1763e-05	0.02279	**4.2483e-10**	0.032231
F10	3.7458e-07	1.7164e-07	2.8699e-07	2.8647e-07	**3.702e-09**	3.9989e-07
F11	0.25018	0.065937	0.26056	0.16032	**7.6143e-06**	0.22672
F12	0.12648	0.11063	0.022422	0.070762	**0.070649**	0.00015947
F13	0.46522	0.4481	0.024212	0.26267	**0.23023**	0.045889
F14	2.9821	2.9821	9.2755e-09	1.0066	**1**	0.0093312
F15	0.001196	0.00083446	0.000511	0.0011316	**0.0007462**	0.00054495
F16	0.40079	0.39819	0.003682	0.40015	**0.4001**	7.8362e-05
F17	3.0002	**3**	0.000287	3.0001	**3**	8.5167e-05
F18	-3.851	-3.8518	0.001083	-3.8568	**-3.8597**	0.0040662
F19	-2.7927	-2.9917	0.2814	-2.9949	**-2.9951**	0.0003133
F20	-3.6866	-4.712	1.4501	-7.3322	**-8.001**	0.94579
F21	-4.033	-4.8214	1.1149	-3.6175	**-4.9149**	1.8349
F22	-2.9039	-3.0035	0.14096	-1.9953	**-3.0464**	1.4866
F23	0.0025187	0.00091794	0.0022638	0.00051534	**0.0003917**	0.00017479

F24	4.0003e-59	4.238e-61	5.5973e-59	1.4976e-61	**1.4385e-66**	2.1179e-61
F25	5.3868e-08	9.2165e-12	7.6168e-08	2.2212e-10	**1.6589e-19**	3.1412e-10
F26	0.00034411	0.00028346	8.577e-05	0.00034544	**0.0001207**	0.00031783
F27	0.0027642	0.0021221	0.00090814	0.0012886	**0.0012011**	0.00012384

Table 3: Result for Benchmark Functions

V. 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. 4. Each sensor will capture acoustic signals at different time as shown in Fig. 5. Time Difference of Arrival (TDOA) algorithm has been implemented to find location of partial discharge source.

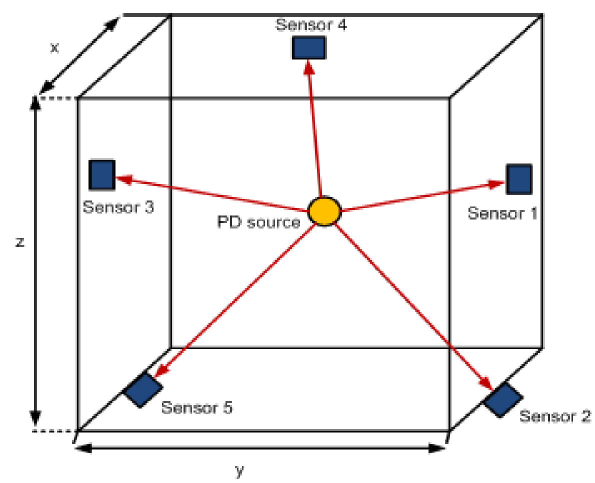


Fig. 4:Visualization of PD Source and Sensor Arrangement

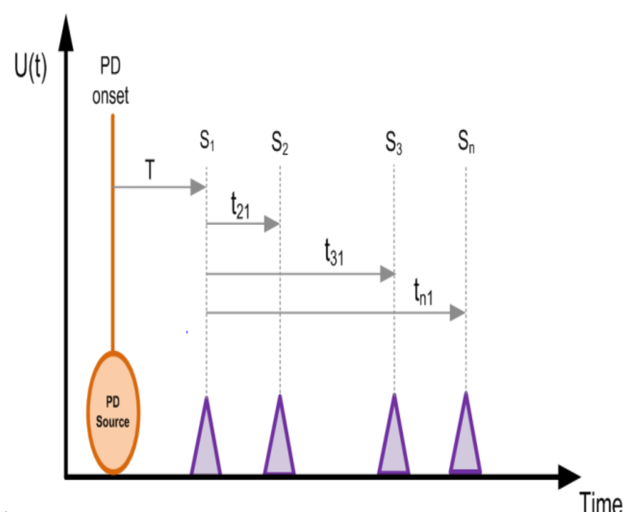


Fig. 5: Schematic of Acoustic Time Differences In Reference To Electrical PD signal

PDE equation in homogeneous medium for propagation of acoustic wave:

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

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

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)			

Table 4: Transformer Dimension and Co-Ordination Position of Sensor

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

- **Problem Formulation:**

$$\begin{aligned} &\tau_{21} = -1000\times10^{-03}, \tau_{31} = -1100\times10^{-03}, \\ &\tau_{41} = -700\times10^{-03}, \tau_{51} = -924.69\times10^{-03}, \end{aligned} \quad (5)$$

$$P = \left[(x - x_1)^2 + (y - y_1)^2 + (z - z_1)^2 \right]^{0.5} \; ... (6)$$

$$a = \left[(x - x_2)^2 + (y - y_2)^2 + (z - z_2)^2 \right]^{0.5} - P - \upsilon_e \tau_{21}; \quad (7)$$

$$b = \left[(x - x_3)^2 + (y - y_3)^2 + (z - z_3)^2 \right]^{0.5} - P - \upsilon_e \tau_{31}; \quad (8)$$

$$c = \left[(x - x_4)^2 + (y - y_4)^2 + (z - z_4)^2 \right]^{0.5} - P - \upsilon_e \tau_{41}; \quad (9)$$

$$d = \left[(x - x_5)^2 + (y - y_5)^2 + (z - z_5)^2 \right]^{0.5} - P - \upsilon_e \tau_{51}; \quad (10)$$

$$Min \quad \{D_f(x, y, z, \upsilon_e)\} = a^2 + b^2 + c^2 + d^2; \quad (11)$$

Subjected to

$$\left.\begin{aligned} &0 \le x \le x_{\max} \\ &0 \le y \le y_{\max} \\ &0 \le z \le z_{\max} \\ &1200 \le \upsilon_e \le 1500, \quad (m/s) \end{aligned}\right\} \quad (12)$$

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

$$\Delta R = \left[(x - x_c)^2 + (y - y_c)^2 + (z - z_c)^2 \right]^{0.5} \quad (13)$$

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

$$\in_r = \left| \frac{L_{act} - L_{cal}}{L_{act}} \right| \times 100\% \quad (14)$$

- **Maximum deviation D_{max}**

$$D_{\max} = \max\begin{Bmatrix} |x_{act} - x_{cal}| \\ |y_{act} - y_{cal}| \\ |z_{act} - z_{cal}| \end{Bmatrix} \quad \text{...... (15)}$$

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

Coordinate (mm)	**Actual PD source**	**SCA**	**ASCA**	**GA [4]**	**PSO [4]**	**Linear PSO [4]**	**SA [4]**	**QGA [4]**
x	4500	4357.3097	**4365.7179**	4223.76	4383.32	4382.14	4387.78	4394.77
y	2600	2394.7626	**2519.1891**	2391.71	2470.53	2469.99	2470.01	2475.98
z	3700	3634.2807	**3695.3759**	3503.04	3649.16	3648.11	3666.64	3656.17

Table 5: Comparison of the Results of PD localization

Error	**SCA**	**ASCA**	**GA [4]**	**PSO [4]**	**Linear PSO [4]**	**SA [4]**	**QGA [4]**
Error of x%	3.170	2.984	6.14	2.59	2.62	2.49	2.34
Error of y%	7.893	3.10	8.01	4.98	5.00	5.00	4.77
Error of z%	1.776	.0125	5.32	1.37	1.40	0.90	1.18
D_{max} /mm	205.2374	134.2831	276.24	129.47	130.01	129.99	124.02
Comprehensive Error(ΔR/mm)	258.4607	**156.7920**	398.10	181.55	182.99	174.94	168.45

Table 6: Error Analysis

VI. CONCLUSION

Sine Cosine Algorithm 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 exists to converse towards optimal solution. Acoustic PD source localization method based on ASCA is feasible. PD localization by ASCA gives better result than SCA and alsoaccurate in compare to GA, PSO and linear PSO, SA and QGA algorithm.The ASCA result of various unconstrained problems proves that it is also an effective method in solving challenging problems with unknown search space.

VII. ACKNOWLEDGMENT

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

REFERENCES

1. SeyedaliMirjalili, “Sine Cosine Algorithm”, “Knowledge-Based System”, 22 DEC. (2015). http://www.alimirjalili.com/SCA.html. doi: 10.1016/j.knosys.2015.12.022.
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.
26. Gandomi A.H. “Interior Search Algorithm (ISA): A Novel Approach for Global Optimization.” ISA Transactions, Elsevier, 53(4), 1168–1183, 2014.