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A Novel Adaptive Dragonfly Algorithm for Global Optimization Problems

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ABSTRACT:A novel bio-inspired optimization algorithm based on the swarming behavior of Dragonflies in nature named as Dragonfly Algorithm (DA) 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 DA and exercised on unconstraint test benchmark function andlocalization of partial discharge in transformer like geometry. DA algorithm has quality feature that it uses static and dynamic swarming process covers vast area in exploration phase and step position changes over each iteration towards targeted destination or towards optimal solution. Integration of new randomization adaptive technique provides potential that ADA algorithm to attain global optimal solution and faster convergence with less parameter dependency. Adaptive DA (ADA) solutions are evaluated and results shows its competitively better performance over standard DA optimization algorithms.

KEYWORDS: Meta-heuristic; Dragonfly Algorithm; Adaptive technique; Global optimal; Acoustic;Sensor.

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I. Introduction

A novel nature –inspired, Dragonfly algorithm [1] based on the swarming behavior. A dragonfly in nature consists of two type swarming behavior Static swarm and dynamic swarm. In static swarm Dragonflies makes small groups and fly in search of food similar exploration phase and dynamic swarm at the time of attack on food and for migration to other place shows exploitation phase in optimization problem.

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 DA 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. DA 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 Dragonfly 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 emissionin section 6conclusion is drawn. Finally, acknowledgment gives regards detail and at the end, references are written.

II. Dragonfly Algorithm

Dragonfly Algorithm proposed by Seyedali Mirjalili, inspired from natural swarming behavior of Dragonflies which makes small group and fly different direction covers vast area in search of food technically term in optimization is exploration phase and makes large group to shift other place termed similar exploitation phase, called static and dynamic swarm.

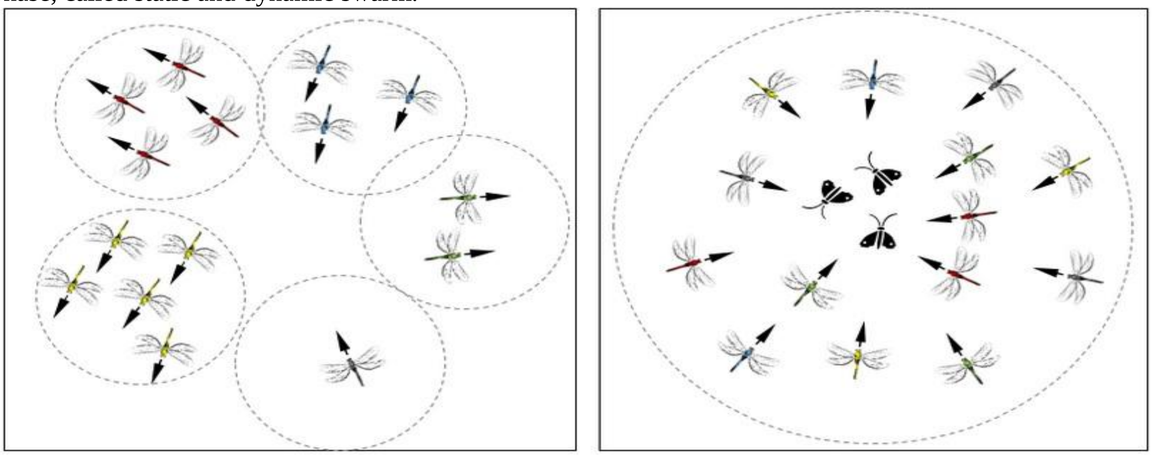


Fig. 1: Dynamic versus Static dragonfly swarms

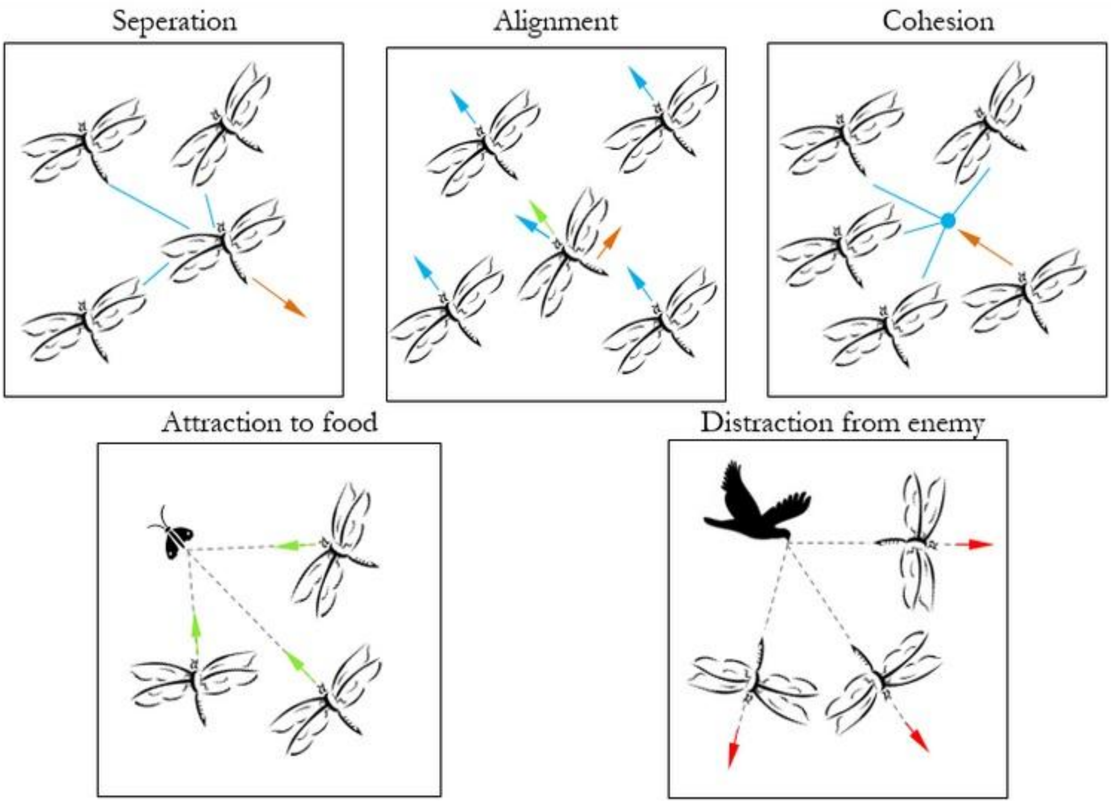


Fig. 2: Dragonfly Algorithm principle

Each portion of Dragonfly Algorithm is formulated by algebraic equations are:

1. For Separation part formulating equation:

$$S_i=-\sum_{j=1}^{N} X - X_j \quad (1)$$

2. For Alignment part formulating equation:

$$A_i=\frac{\sum_{j=1}^{N} X_j}{N} \quad (2)$$

3. For cohesion part formulating equation:

$$C_i = \frac{\sum_{j=1}^{N} X_j}{N} - X \tag{3}$$

4. For Attraction towards a food source part formulating equation:

$$F_i = X^+ - X \tag{4}$$

5. For Attraction towards a food source part formulating equation:

$$E_i = X^- + X \tag{5}$$

6. Step vector is formulating equation:

$$\Delta X_{t+1} = (sS_i + aA_i + cC_i + fF_i + eE_i) + w\Delta X_t \tag{6}$$

7. Position vector is calculated using equation

$$X_{t+1} = X_t + \Delta X_{t+1} \tag{7}$$

8. Position of dragonfly updated using equation

$$X_{t+1} = X_t + \text{Levy}(x) * X_t \tag{8}$$

Where

Where *X*=Location of the current individuals, *N*= Neighboring individuals, X^+=positions of food source, X^-=positions of enemy, *s*=separation weight, *a*=alignment weight, *c*=cohesion weight, *f*=food weight, *e*=enemy weight, *w*=inertia weight, *t*=iteration counter and *d*=dimension of position vectors that levy flight step calculated.

III. Adaptive Dragonfly 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.

$$X_i^{t+1} = X_i^t + randn * \left(\frac{1}{t}\right)^{\left|((bestf(t) - fi(t))/(bestf(t) - worstf(t)))\right|} \tag{9}$$

Where

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

IV. 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	$f(x) = \sum_{i=1}^{n} \|x_i\| + \prod_{i=1}^{n} \|x_i\| * R(x)$	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	$f(x) = \max_i \{ \|x_i\|, 1 \le i \le n \}$	10	[-100, 100]	0

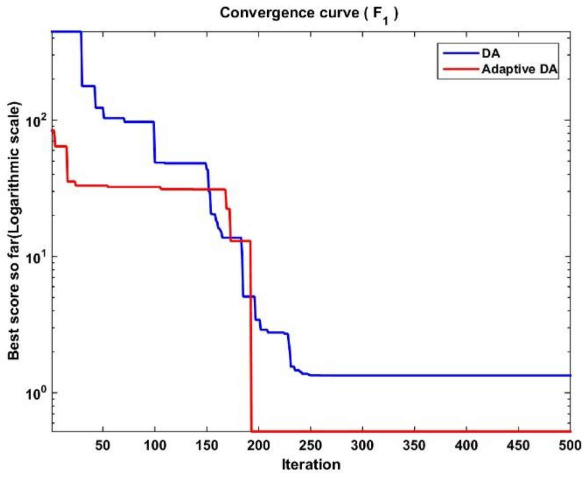
F5	Rosenbrock's Function	$f(x)=\sum_{i=1}^{n-1}\left[100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right]$	10	[-30, 30]	0
F6	Step Function	$f(x)=\sum_{i=1}^{n}\left(\left[x_i+0.5\right]\right)^2*R(x)$	10	[-100, 100]	0
F7	Quartic Function	$f(x)=\sum_{i=1}^{n}ix_i^4+random\left[0,1\right)*R(x)$	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	$F(x)=\sum_{i=1}^{n}\left[x_i^2-10cos\left(2\pi x_i\right)+10\right]*R$	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	$F(x)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}cos\left(\frac{x_i}{\sqrt{i}}\right)+1*$	10	[-600, 600]	0
F12	Penalty 1	$F(x)=\frac{\pi}{n}\begin{cases}10sin\left(\pi y_1\right)+\sum_{i=1}^{n-1}\left(y_i-1\right)^2\\ \left[1+10sin^2\left(\pi y_{i+1}\right)\right]+\left(y_n-\right.\end{cases}$ $y_i=1+\frac{x_i+1}{4},$ $u(x_i,a,k,m)=\begin{cases}k\left(x_i-a\right)^m & \\ 0 & -a< \\ k\left(-x_i-a\right)^m & \end{cases}$	10	[-50, 50]	0
F13	Penalty 2	$F(x)=0.1\begin{cases}sin^2\left(3\pi x_1\right)+\sum_{i=1}^{n}\left(x_i-1\right)^2\\ \left[1+sin^2\left(3\pi x_i+1\right)\right]\\ +\left(x_n-1\right)^2\left[1+sin^2\left(2\pi x_n\right.\right.\end{cases}$ $+\sum_{i=1}^{n}u\left(x_i,5,100,4\right)*R(x)$	10	[-50, 50]	0

F14	De Joung (Shekel's Foxholes)	$F(x)=\left(\frac{1}{500}+\sum_{j=1}^{25}\frac{1}{j+\sum_{i=1}^{2}\left(x_i-a_{ij}\right)^6}\right)^{-1}$	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	Shekel	$f(x)=-\sum_{i=1}^{10}\left[\left(X-a_i\right)\left(X-a_i\right)^T+c_i\right]^{-1}$	4	[0,10]	-10.5363
F17	Cube function	$f(x)=100(x_2-x_1^3)^2+(1-x_1)^2$	30	[-100, 100	0
F18	Matyas function	$f(x)=0.26(x_1^2+x_2^2)-0.48x_1x_2$	10	[-30, 30]	0
F19	Powell function	$f(x)=\sum_{i=1}^{D-2}\begin{cases}(x_{i-1}+10x_i)^2+5(x_{i+1}-x_{i+2}\\(x_i-2x_{i+1})^4+10(x_{i-1}-x_{i+2}\end{cases}$	4	[-30, 30]	0
F20	Beale Function	$f(x)=\begin{cases}\left(1.5-x_1+x_1x_2\right)^2+\left(2.25-x_1+\right.\\+\left(2.625-x_1+x_1x_2^3\right)^2\end{cases}$	30	[-100, 100]	0
F21	levy13 function	$f(x)=\begin{cases}\sin^2\left(3\pi x_1\right)+\left(x_1-1\right)^2\left(1+\sin^2\left(\right.\right.\\+\left(x_2-1\right)^2\left(1+\sin^2\left(2\pi x_2\right)\right)\end{cases}$	30	[-10, 10]	0

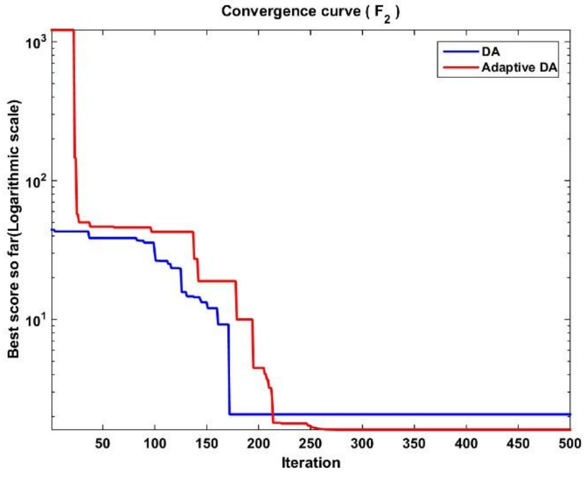
Table 2: Internal Parameters

Parameter Name	**Search Agents no.**	**Max. Iteration no.**	**No. of Evolution**
F1-F17, F20-F21	30	500	20-30
F18	10	100	20-30
F19	30	200	20-30
Acoustic PD Localization	40	200	20
Note:- Scale specified on axis, Not specified means axis are linear scale			

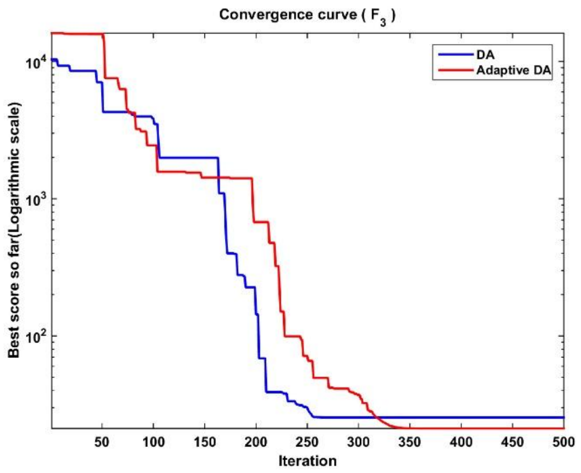
F₁



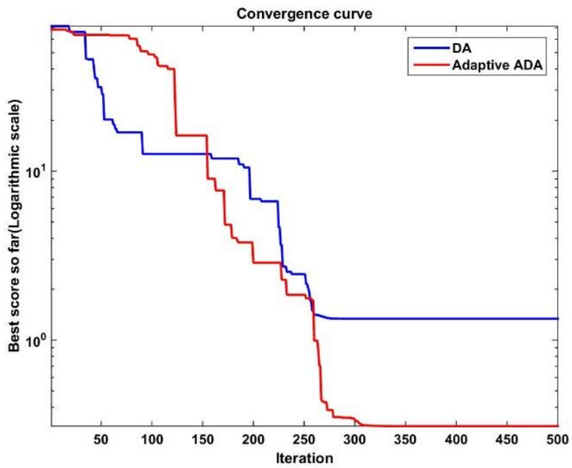
F₂



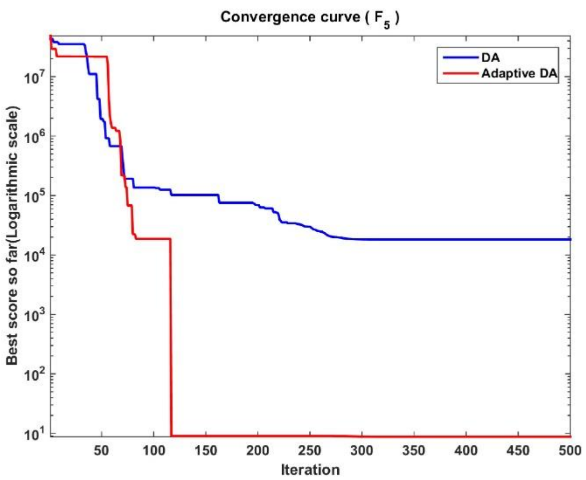
F₃



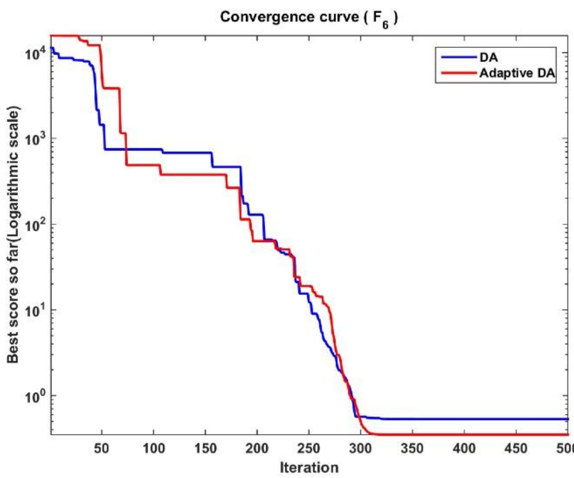
F₄



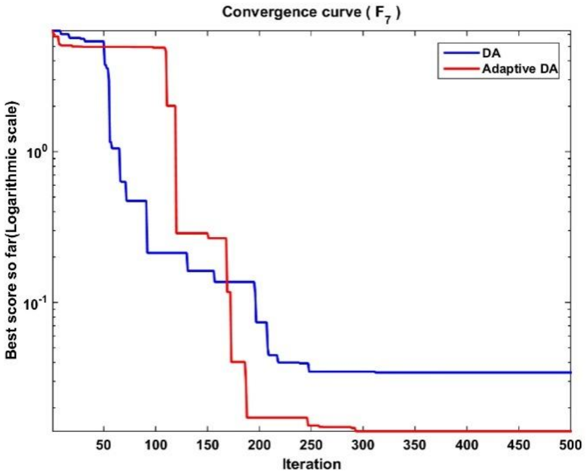
F₅



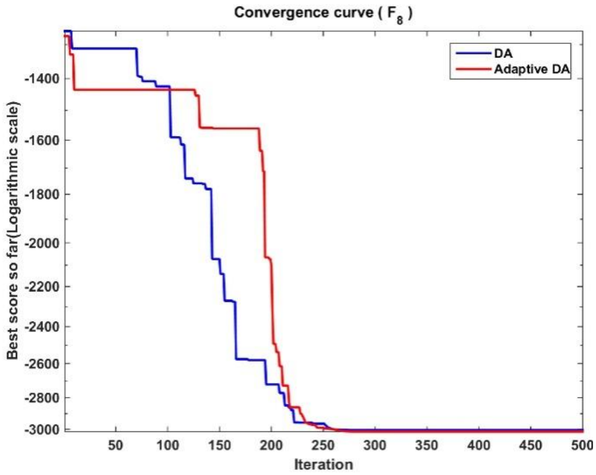
F₆



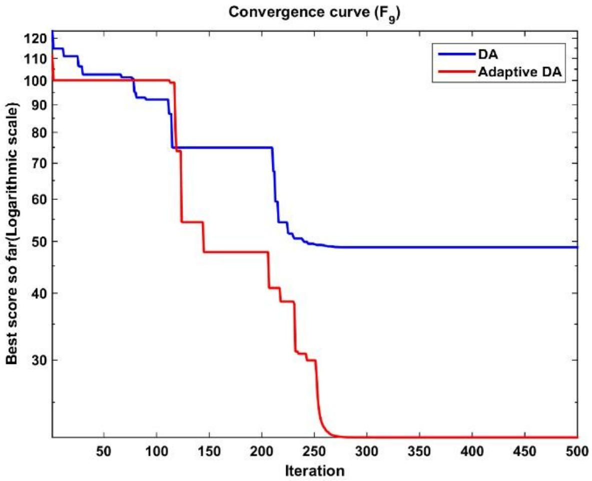
F_7



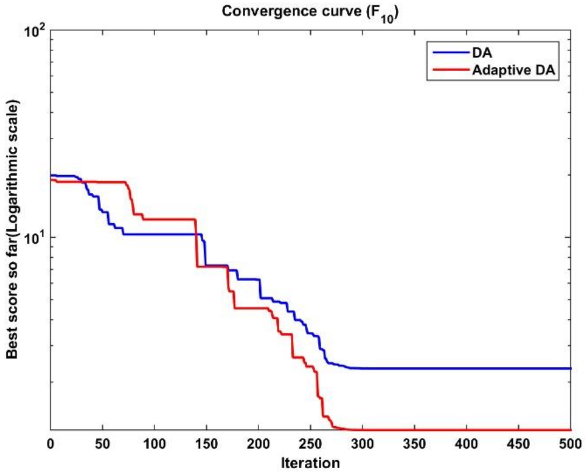
F_8



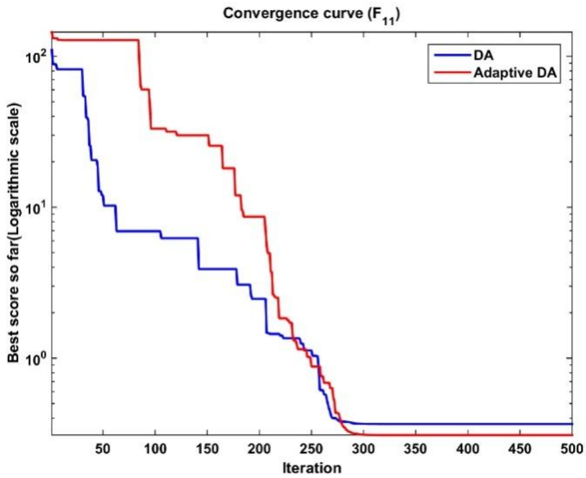
F_9



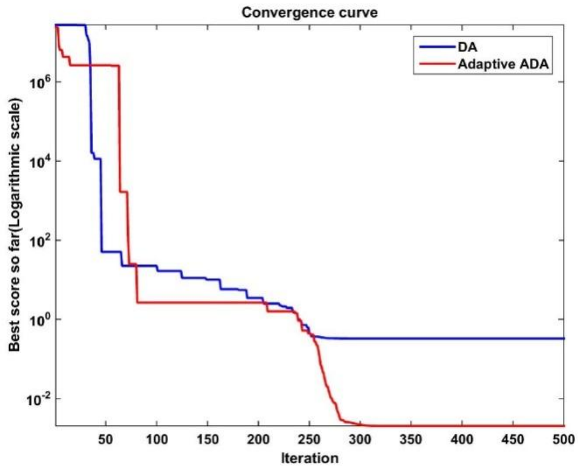
F_{10}



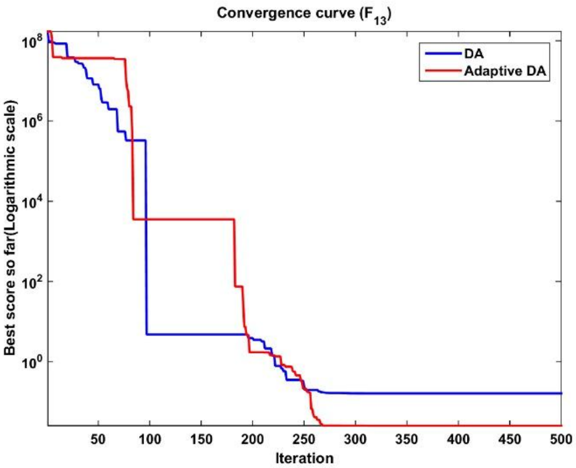
F_{11}



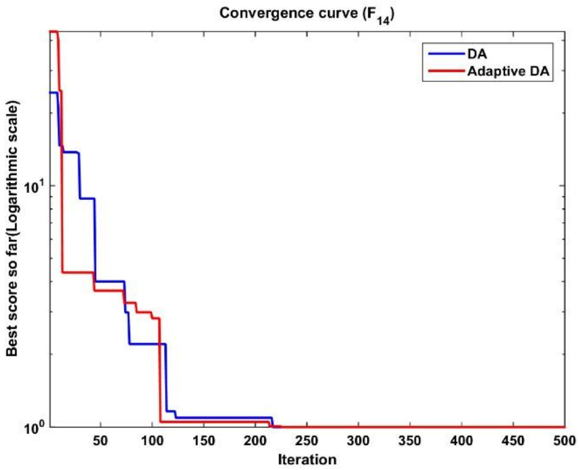
F_{12}



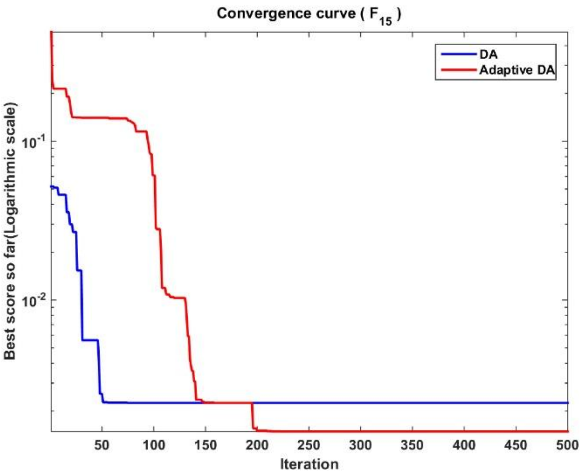
F_{13}



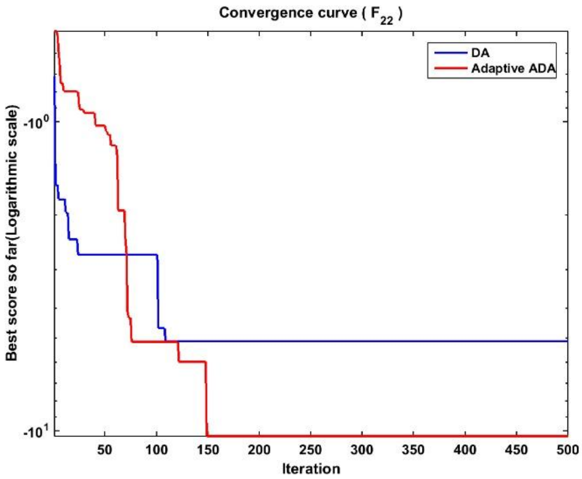
F_{14}



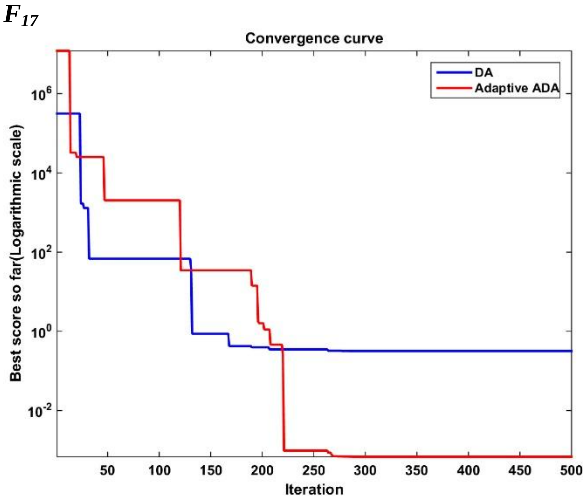
F_{15}



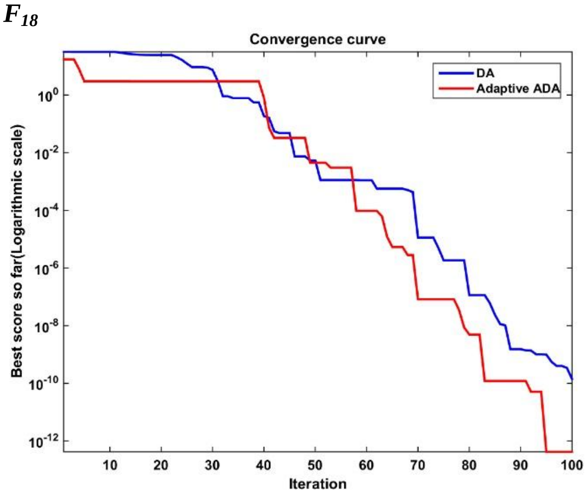
F_{16}



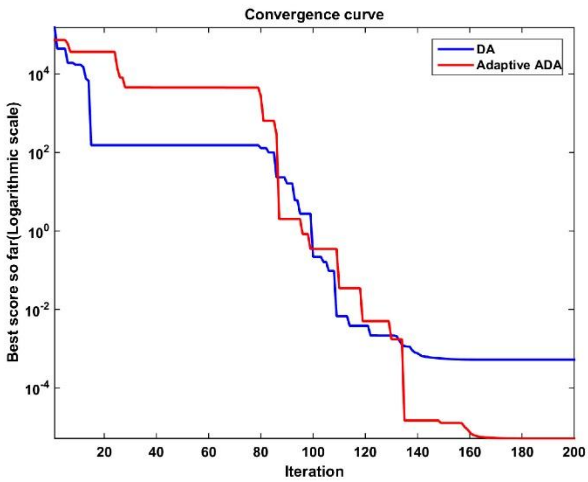
F_{17}



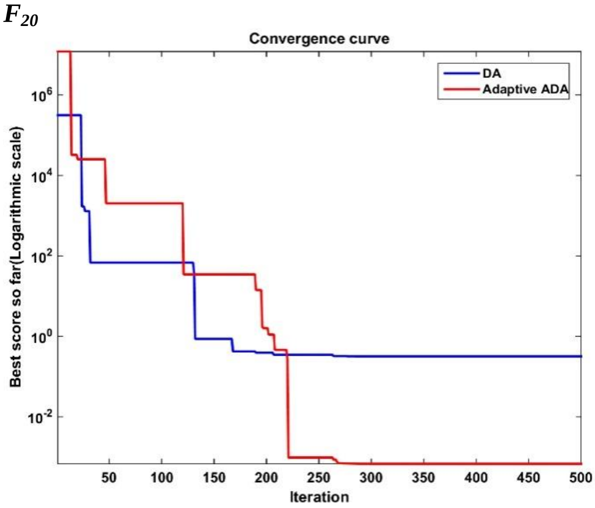
F_{18}



***F*$_{19}$**



***F*$_{20}$**



F$_{21}$

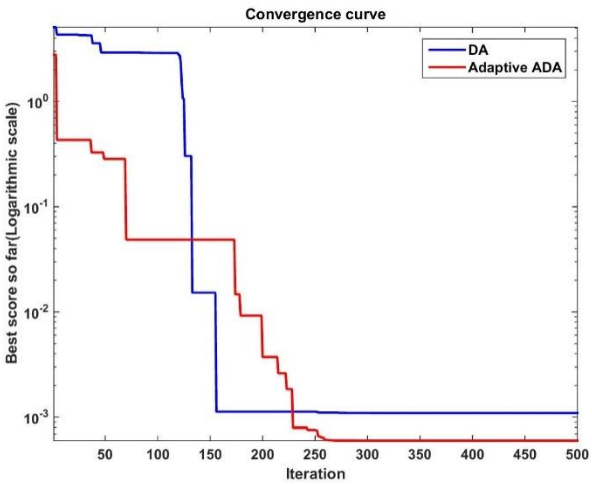


Fig. 3: Convergence Curve of Benchmark Test Function

Table 3: Result for benchmark functions

Fun.	**Dragonfly Algorithm (DA)**			**Adaptive Dragonfly Algorithm (ADA)**		
	Ave	**Best**	**S.D.**	**Ave**	**Best**	**S.D.**
F1	1.6625	1.3402	0.45582	1.7522	**0.51981**	1.7429
F2	2.0871	2.0731	0.019856	2.052	**1.6064**	0.6301
F3	195.5395	25.4491	240.5442	52.0969	**21.1825**	43.7196
F4	2.2896	1.3361	1.3485	2.8441	**0.30896**	3.5853
F5	24058.9814	18222.1745	18222.174	9.4869	**8.7653**	1.0205
F6	2.425	0.53177	2.6774	4.3229	**0.35012**	5.6183
F7	0.036	0.034331	0.0023597	0.021189	**0.014004**	0.010162
F8	-2940.1704	-3005.11	91.8386	-2526.0036	**-3014.8973**	691.4002
F9	49.9072	48.7586	1.6244	22.6842	**21.4892**	1.69
F10	2.574	2.3276	0.34844	2.1084	**1.1751**	1.3199
F11	0.48509	0.36625	0.16807	0.45095	**0.30942**	0.20017
F12	1.2058	0.32764	1.2419	1.3524	**0.002022**	1.9098

F13	0.57324	0.16349	0.57948	3.7987	**0.025623**	5.3359
F14	0.998	**0.998**	1.5701E-16	0.998	**0.998**	1.0943E-11
F15	0.0052928	0.0022519	0.0043004	0.0014887	**0.0014887**	1.1208E-07
F16	-3.7751	-5.1285	1.914	-7.856	**-10.5364**	3.7906
F17	1.5413	0.094384	2.0463	0.356	**0.054492**	0.42639
F18	1.679E-10	1.4179E-10	3.6931E-11	1.1675E-10	**4.2141E-13**	1.6452E-10
F19	0.0014206	0.0010947	0.00046089	0.0010075	**0.00060453**	0.00056983
F20	0.55184	0.31861	0.32983	0.021091	**0.00067904**	0.028867
F21	0.0011043	0.00052501	0.00081919	4.0946	**5.1662E-06**	5.7906

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. 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:

$$\frac{\partial^2 P}{\partial t^2} = v^2 \nabla^2 P = v^2 \left(\frac{\partial^2 P}{\partial x^2} + \frac{\partial^2 P}{\partial y^2} + \frac{\partial^2 P}{\partial z^2} \right) \quad (10)$$

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*).

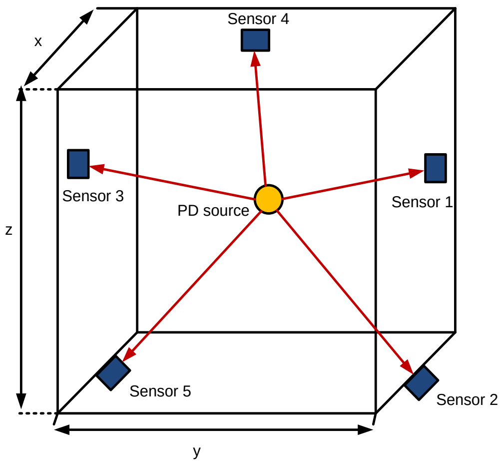


Fig. 4:Visualization of PD source and sensor arrangement

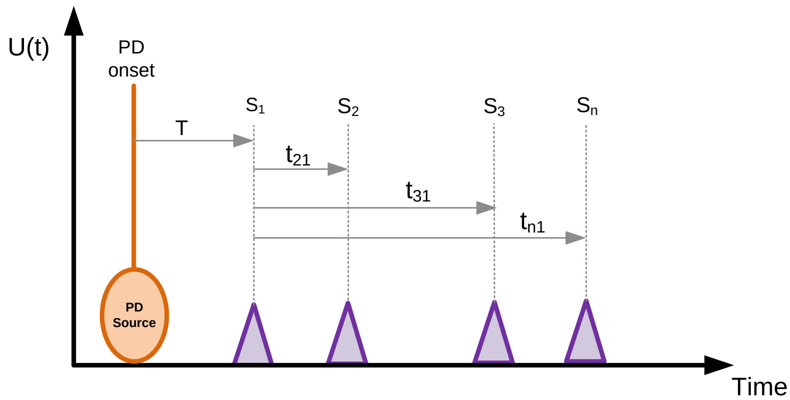


Fig. 5:Schematic of acoustic time differences in reference to electrical PD signal

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:

$$\begin{aligned}\tau_{21} &= -1000\times10^{-03}, \tau_{31} = -1100\times10^{-03},\\ \tau_{41} &= -700\times10^{-03}, \tau_{51} = -924.69\times10^{-03},\end{aligned} \tag{11}$$

$$P = \left[(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2\right]^{0.5} \tag{12}$$

$$a = \left[(x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2\right]^{0.5} - P - \upsilon_e\tau_{21}; \tag{13}$$

$$b = \left[(x-x_3)^2 + (y-y_3)^2 + (z-z_3)^2\right]^{0.5} - P - \upsilon_e\tau_{31}; \tag{14}$$

$$c = \left[(x-x_4)^2 + (y-y_4)^2 + (z-z_4)^2\right]^{0.5} - P - \upsilon_e\tau_{41}; \tag{15}$$

$$d=\left[\left(x-x_5\right)^2+\left(y-y_5\right)^2+\left(z-z_5\right)^2\right]^{0.5}-P-\upsilon_e\tau_{51}; \quad (16)$$

$$Min \quad \{D_f(x,y,z,\upsilon_e)\}=a^2+b^2+c^2+d^2; \quad (17)$$

Subjected to

$$\left.\begin{array}{l} 0\le x\le x_{\max} \\ 0\le y\le y_{\max} \\ 0\le z\le z_{\max} \\ 1200\le \upsilon_e \le 1500, \quad (m/s) \end{array}\right\} \quad (18)$$

Where:

x_{max} ,y_{max} ,z_{max} andυ_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

$$\Delta R=\left[\left(x-x_c\right)^2+\left(y-y_c\right)^2+\left(z-z_c\right)^2\right]^{0.5} \quad (19)$$

Error of each co-ordinate is formulated:

$$\in_r=\left|\frac{L_{act}-L_{cal}}{L_{act}}\right|\times 100\% \quad (20)$$

Maximum deviation D_{max}

$$D_{\max}=\max\left\{\begin{array}{l} \left|x_{act}-x_{cal}\right| \\ \left|y_{act}-y_{cal}\right| \\ \left|z_{act}-z_{cal}\right| \end{array}\right\} \quad (21)$$

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	DA	ADA	GA
X	4500	4381.7461	**4382.1807**	4223.76
Y	2600	2469.6028	**2469.8002**	2391.71
Z	3700	3647.4902	**3647.9569**	3503.04

Table 6:Error analysis

Error	DA	ADA	GA
Error of x%	2.627	2.618	6.14
Error of y%	5.015	5.007	8.01
Error of z%	1.419	1.406	5.32
D_{max}/mm	130.3972	130.1998	276.24
Comprehensive Error(ΔR/mm)	183.6972	**183.1443**	398.10

VI. Conclusion

Dragonfly 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 exits to converse towards optimal solution. Acoustic PD source localization method based on Adaptive Dragonfly Algorithm is feasible. PD localization by ADA gives better result than DA and alsoaccurate in compare to GA.The ADA 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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References

[1]. Seyedali Mirjalili, “Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective , discrete , and multi-objective problems”, “ The Natural Computing Applications Forum 2015”, 30 April 2015. http://dx.doi.org/10.1007/s00521-015-1920-1.

[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 / OmidKhadem Hosseini, 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.

Naveen Sihag." A Novel Adaptive Dragonfly Algorithm for Global Optimization Problems” International Journal Of Engineering Research And Development , vol. 14, no. 02, 2018, pp. 27–39.