ISSN (e): **2250 – 3005** || Volume, 08 || Issue, 2|| February – 2018 ||
International Journal of Computational Engineering Research (IJCER)

A Noveladaptive Multi-Verse Optimizer for Global Optimization Problems

Naveen Sihag[1]Ph.D. Scholar)
Department of Computer Engineering, Rajasthan Technical University Kota, Rajasthan 324002, India[1]
Corresponding author: Naveen Sihag1Ph.D

ABSTRACT
A novel bio-inspired optimization algorithm based on the theory of multi verse in physics known as Multi-verse optimizer (MVO) 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 MVO and exercised on unconstraint test benchmark function and localization of partial discharge in transformer like geometry. MVO algorithm has quality feature that it covers vast area as considers universes and uses terms like white, black and warm hole represents exploration, exploitation and local minimum in optimization problems. Integration of new randomization adaptive technique provides potential that AMVO algorithm to attain global optimal solution and faster convergence with less parameter dependency. Adaptive MVO (AMVO) solutions are evaluated and results shows its competitively better performance over standard MVO optimization algorithms.
KEYWORDS: Meta-heuristic; Multi-Verse optimizer; Adaptive technique; Global optimal; Inflation rate, PD localization.

I. INTRODUCTION

A novel nature –inspired, multi-verse optimizer algorithm [1] based on the theory of multi-verse in physics. In this reference it is assumed that there are more than one big bang [2, 3] and every big bang causes the birth of new universe. Each universe consists of inflation rate, main cause of formation of white, black, worm hole, stars, physical laws and planets. Only three holes are taken in consideration to reach targeted 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 MVO 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. MVO integrated with adaptive technique reduces the computational times for highly complex problems.

Paper under literature review are: Adaptive Cuckoo Search Algorithm (ACSA) [4] [5], QGA [6],Acoustic Partial discharge (PD)[7] [8], HGAPSO [9], PSACO [10], HSABA [11], PBILKH [12], KH-QPSO [13], IFA-HS [14], HS/FA [15], CKH [16], HS/BA [17], HPSACO [18], CSKH [19], HS-CSS [20], PSOHS [21], DEKH [22], HS/CS [23], HSBBO [24], CSS-PSO [25] etc.
Recently trend of optimization is to improve performance of meta-heuristic algorithms [26] 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 [27] that can accelerate its global convergence speed. Evolutionary constraint handling scheme is used in Interior Search Algorithm (ISA) [28] that avoid upper and lower limits of variables.
The remainder of this paper is organized as follows: The next Section describes the Multi-verse 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 5 PD localization by acoustic emission,, in

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

II. MULTI-VERSE OPTIMIZER

Three notions such as black hole, white hole and wormhole are the main motivation of the MVO algorithm. These three notions are formulated in mathematical models to evaluate exploitation, exploration and local search, respectively. The white hole assumed to be the main part to produce universe. Black holes are attracting all due to its tremendous force of gravitation. The wormholes behave as time/space travel channels in which objects can moves rapidly in universe. Main steps uses to the universes of MVO:

I. If the inflation rate is greater, the possibility of presence of white hole is greater.
II. If the inflation rate is greater, the possibility of presence of black hole is lower.
III. Universes having greater inflation rate are send the substances through white holes.
IV. Universes having lesser inflation rate are accepting more substances through black holes.
V. The substances/objects in every universe can create random movement in the direction of the fittest universe through worm holes irrespective to the inflation rate. The objects are move from a universe having higher inflation rate to a universe having lesser inflation rate. It can assure the enhancement of the average inflation rates of the entire cosmoses with the iterations. In each iteration, the universes are sorted according to their inflation rates and select one from them using the roulette wheel as a white hole. The subsequent stages are used for this procedure. Assume that

$$U = \begin{bmatrix} x_1^1 & x_1^2 & . & . & x_1^d \\ x_2^1 & x_2^2 & . & . & x_2^d \\ . & . & . & . & . \\ . & . & . & . & . \\ x_n^1 & x_n^2 & . & . & x_n^d \end{bmatrix} \quad (4)$$

Where, *d* shows the number of variables and *n* shows the number of candidate solutions:

$$x_i^j = \begin{cases} x_k^j & ; r1 < NI(Ui) \\ x_i^j & ; r1 \geq NI(Ui) \end{cases} \quad (5)$$

Where, x_i^j shows the j^{th} variable of i^{th} universe, U_i indicates the i^{th} universe, $NI(U_i)$ is normalized inflation rate of the i^{th} universe, *r1* is a random no. from [0, 1], and x_k^j shows the j^{th} variable of k$^{\text{th}}$ universe chosen through a roulette wheel. To deliver variations for all universe and more possibility of increasing the inflation rate by worm holes, suppose that worm hole channels are recognized among a universe and the fittest universe created until now. This mechanism is formulated as:

$$x_i^j = \begin{cases} \begin{cases} X_j + TDR \times ((ub_j - lb_j) \times r4 + lb_j); r3 < 0.5 \\ X_j - TDR \times ((ub_j - lb_j) \times r4 + lb_j); r3 \geq 0.5 \end{cases} ; r2 < WEP \\ x_i^j ; r2 \geq WEP \end{cases} \quad (6)$$

where X_j shows j^{th} variable of fittest universe created until now, lb_j indicates the min limit of j^{th} parameter, ub_j indicates max limit of j^{th} parameter, x_i^j shows the j^{th} parameter of i^{th} universe, and *r2, r3, r4* are random numbers from [0, 1]. It can be concluded by the formulation that wormhole existence probability (*WEP*) and travelling distance rate (*TDR*) are the chief coefficients. The formula for these coefficients are given by:

$$WEP = \min + l \times \left(\frac{\max - \min}{L} \right) \quad (7)$$

Where, *l* shows the present run, and *L* represent maximum run number/iteration.

$$TDR = 1 - \frac{l^{1/p}}{L^{1/p}} \quad (8)$$

Where, *p* states the accuracy of exploitation with the iterations. If the *p* is greater, the exploitation is faster and more precise. The complexity of the MVO algorithms based on the no. of iterations, no. of universes, roulette wheel mechanism, and universe arranging mechanism. The overall computational complexity is as follows:

$$O(MVO) = O(l(O(Quicksort) + n \times d \times (O(roulette\_wheel))))$$

$$O(MVO) = O(l(n^2 + n \times d \times \log n)) \quad (9)$$

Where, n shows no. of universes, l shows the maximum no. of run/iterations, and d shows the no. of substances.

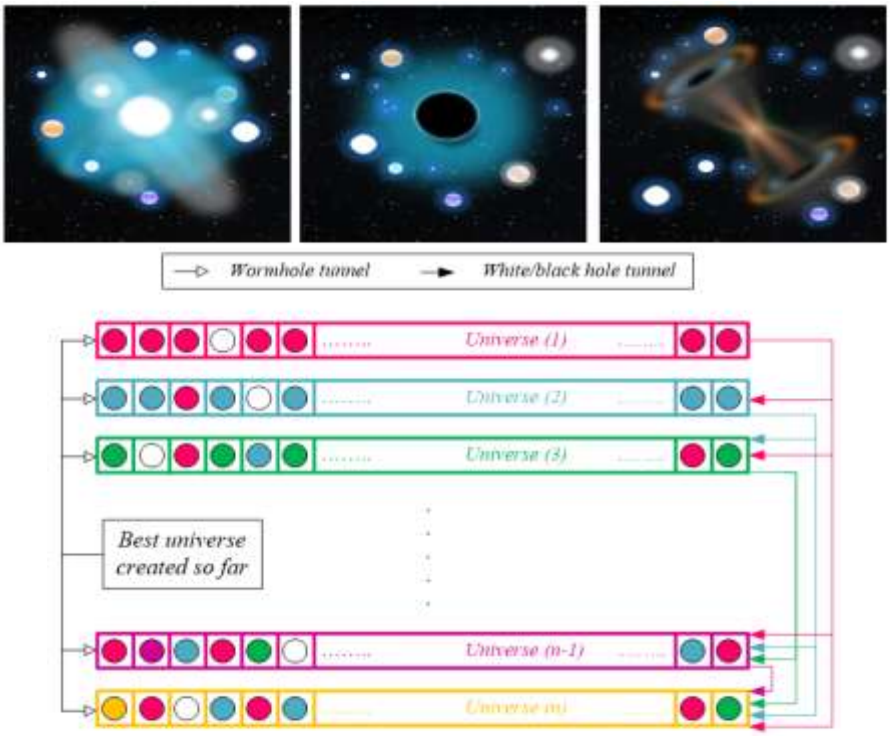


Fig. 1: Basic principle of MVO

III. ADAPTIVE MVO 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.

$$X_i^{t+1} = \left(\frac{1}{t}\right)^{\left|((bestf(t) - fi(t))/(bestf(t) - worstf(t)))\right|} \quad (10)$$

Where

X_i^{t+1} Step size 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	$f(x) = \sum_{i=1}^{n} \lvert x_i \rvert + \prod_{i=1}^{n} \lvert x_i \rvert * R(x)$	10	[-10, 10]	0

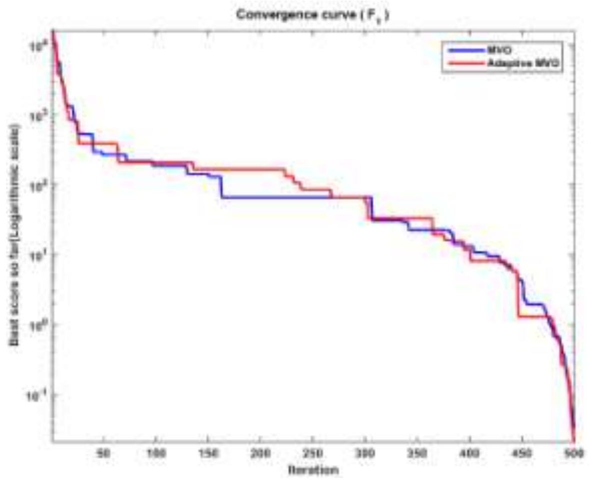
F3	Schwefel 1.2	$f\left(x\right)=\sum_{i=1}^{n}\left(\sum_{j-1}^{i}x_j\right)^2 * R\left(x\right)$	10	[-100, 100]	0
F4	Schwefel 2.21	$f\left(x\right)=\max_{i}\left\{\left\|x_i\right\|,1\leq i\leq n\right\}$	10	[-100, 100]	0
F5	Rosenbrock's Function	$f\left(x\right)=\sum_{i=1}^{n-1}\left[100\left(x_{i+1}-x_i^2\right)^2+\left(x_i-1\right)^2\right]*R$	10	[-30, 30]	0
F6	Step Function	$f\left(x\right)=\sum_{i=1}^{n}\left(\left[x_i+0.5\right]\right)^2 * R\left(x\right)$	10	[-100, 100]	0
F7	Quartic Function	$f\left(x\right)=\sum_{i=1}^{n} i x_i^4 + random\left[0,1\right) * R\left(x\right)$	10	[-1.28, 1.28]	0
F8	Schwefel 2.26	$F\left(x\right)=\sum_{i=1}^{n} - x_i sin\left(\sqrt{\left\|x_i\right\|}\right) *R\left(x\right)$	10	[-500, 500]	(-418.9829*5)
F9	Rastrigin	$F\left(x\right)=\sum_{i=1}^{n}\left[x_i^2-10cos\left(2\pi x_i\right)+10\right]*R(x$	10	[-5.12, 5.12]	0
F10	Ackley's Function	$F\left(x\right)=-20exp\left(-0.2\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-$ $exp\left(\frac{1}{n}\sum_{i=1}^{n}cos\left(2\pi x_i\right)\right)+20+e*R\left(x\right)$	10	[-32, 32]	0
F11	Griewank Function	$F\left(x\right)=\frac{1}{4000}\sum_{i=1}^{n}x_i^2-\prod_{i=1}^{n}cos\left(\frac{x_i}{\sqrt{i}}\right)+1*R($	10	[-600, 600]	0
F12	Penalty 1	$F\left(x\right)=\frac{\pi}{n}\begin{cases}10sin\left(\pi y_1\right)+\sum_{i=1}^{n-1}\left(y_i-1\right)^2 \\ \left[1+10sin^2\left(\pi y_{i+1}\right)\right]+\left(y_n-1\right)^2\end{cases}$ $y_i=1+\frac{x_i+1}{4},$ $u(x_i,a,k,m)=\begin{cases}k\left(x_i-a\right)^m & x_i \\ 0 & -a<x_i< \\ k\left(-x_i-a\right)^m & x_i<\end{cases}$	10	[-50, 50]	0

F13	Penalty 2	$F(x)=0.1\begin{cases}sin^2(3\pi x_1)+\sum_{i=1}^{n}(x_i-1)^2\\ \left[1+sin^2(3\pi x_i+1)\right]\\ +(x_n-1)^2\left[1+sin^2(2\pi x_n)\right]\end{cases}$ $+\sum_{i=1}^{n}u(x_i,5,100,4)*R(x)$	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	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	$f(x)=\sum_{i=1}^{D-2}\begin{cases}(x_{i-1}+10x_i)^2+5(x_{i+1}-x_{i+2})^2-\\(x_i-2x_{i+1})^4+10(x_{i-1}-x_{i+2})^4\end{cases}$	4	[-30, 30]	0
F19	Beale Function	$f(x)=\begin{cases}(1.5-x_1+x_1x_2)^2+(2.25-x_1+x_1x_2\\+(2.625-x_1+x_1x_2^3)^2\end{cases}$	30	[-100, 100]	0
F20	levy13 function	$f(x)=\begin{cases}\sin^2(3\pi x_1)+(x_1-1)^2(1+\sin^2(3\pi\\+(x_2-1)^2(1+\sin^2(2\pi x_2))\end{cases}$	30	[-10, 10]	0

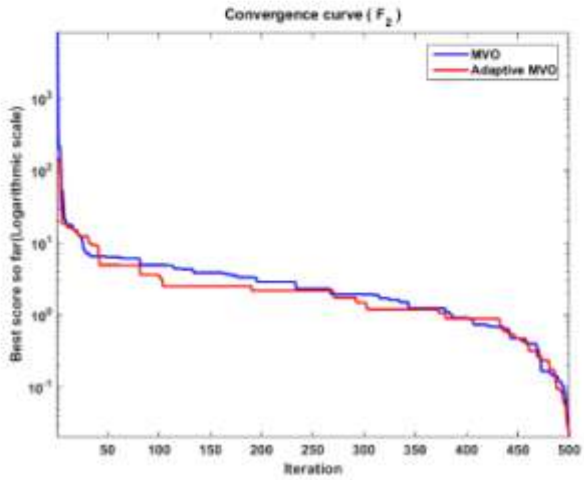
Table 2: Internal Parameters

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

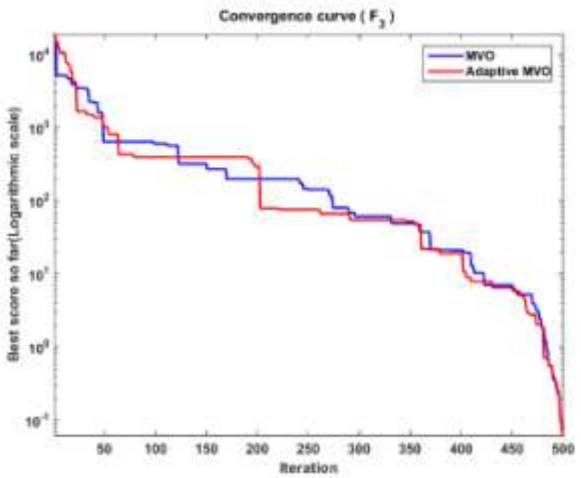
F₁



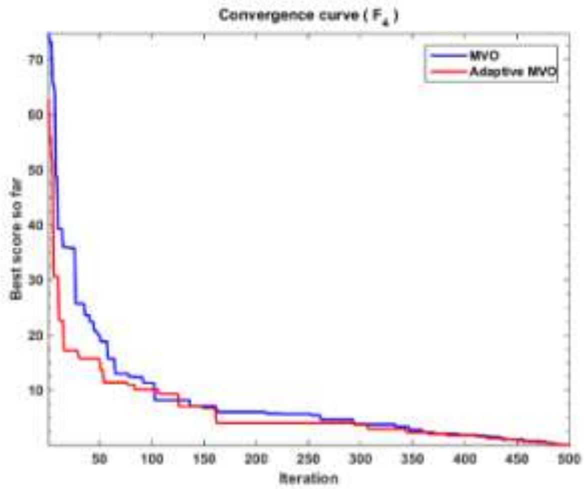
F₂



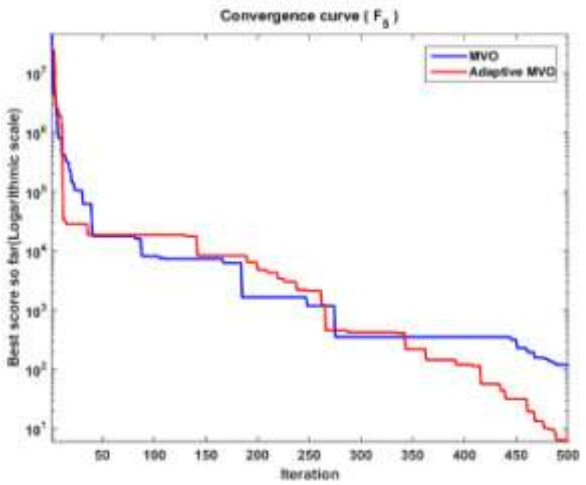
F₃



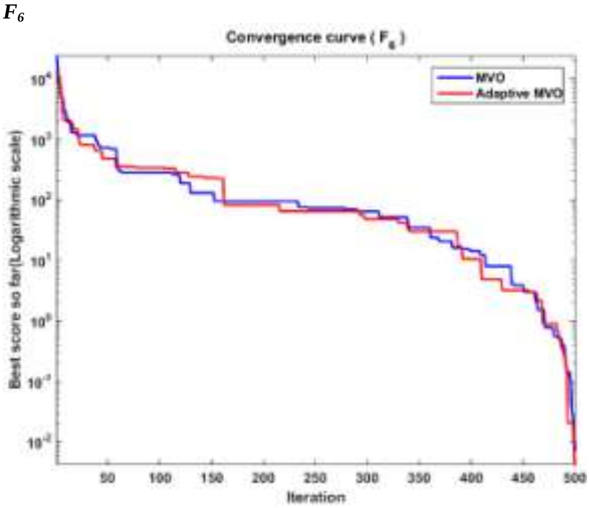
F₄



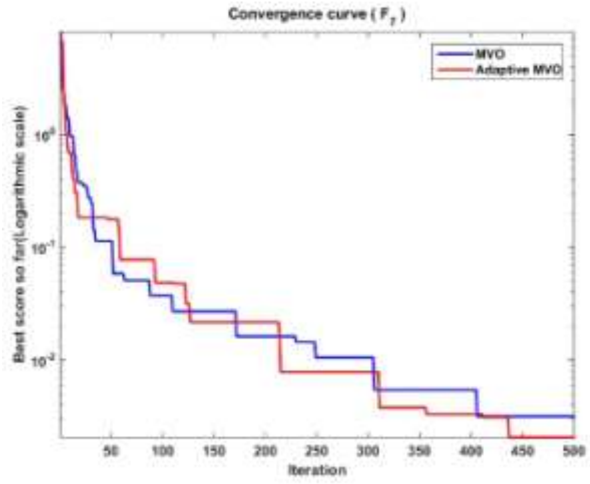
F₅



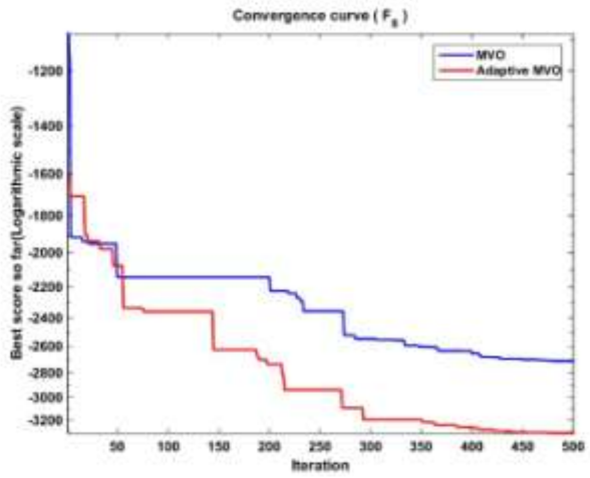
F₆



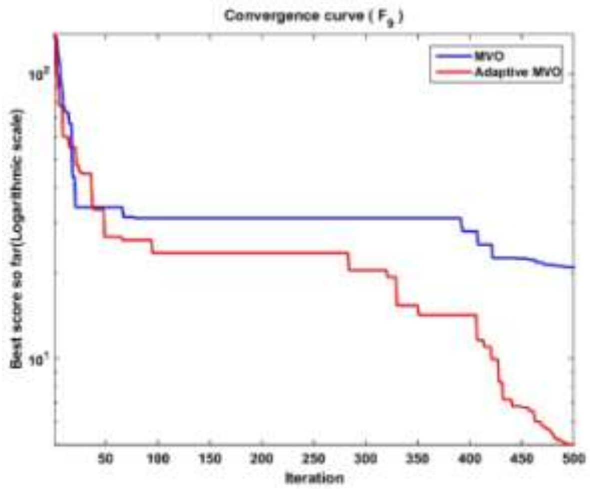
F$_7$



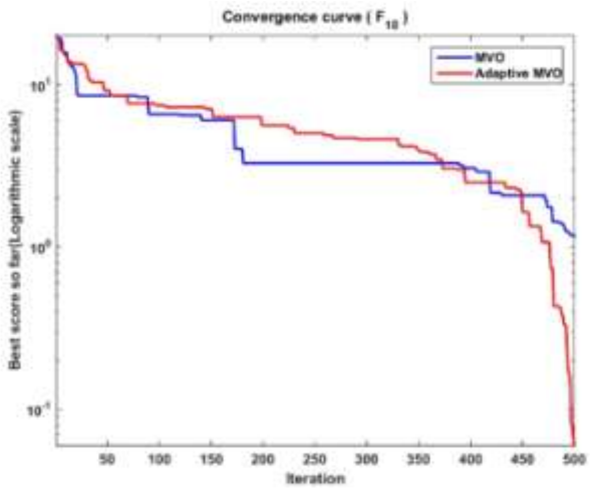
F$_8$



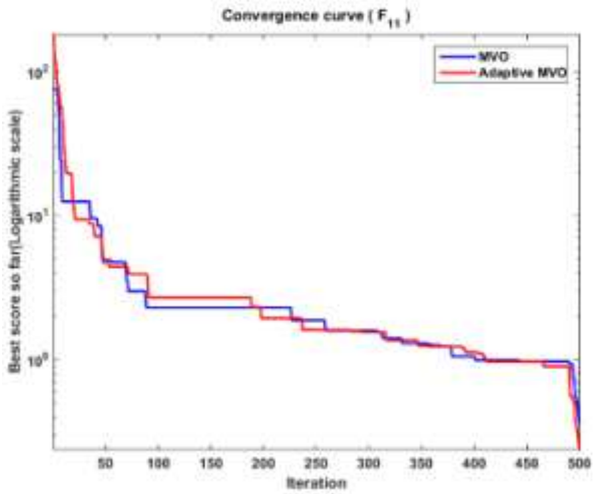
F$_9$



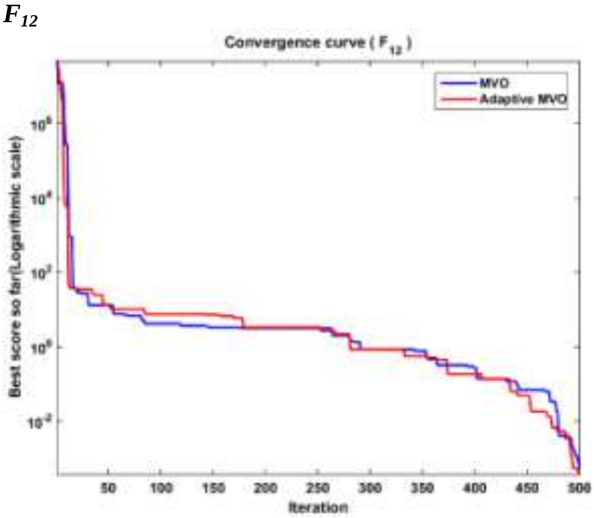
F$_{10}$



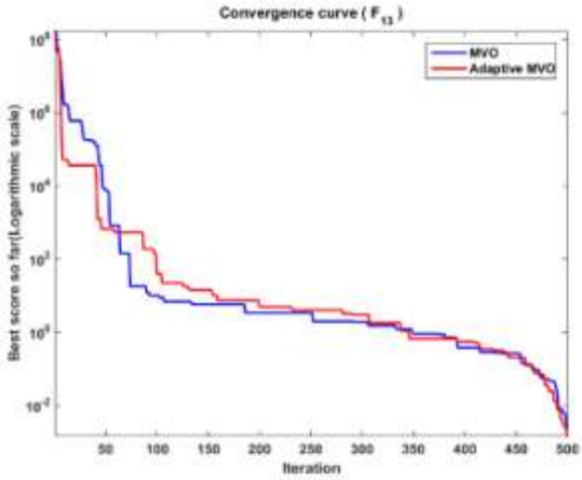
F$_{11}$



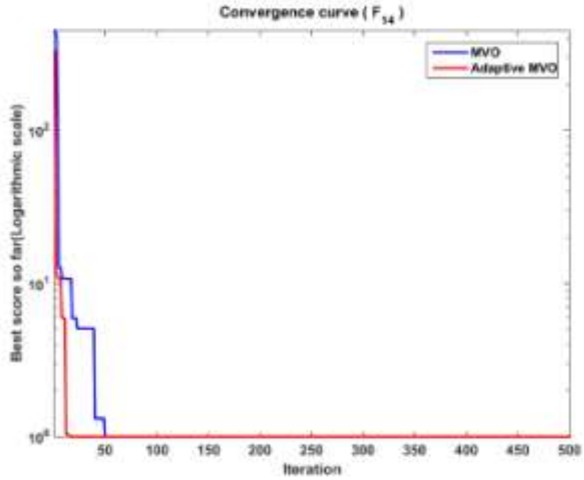
F$_{12}$



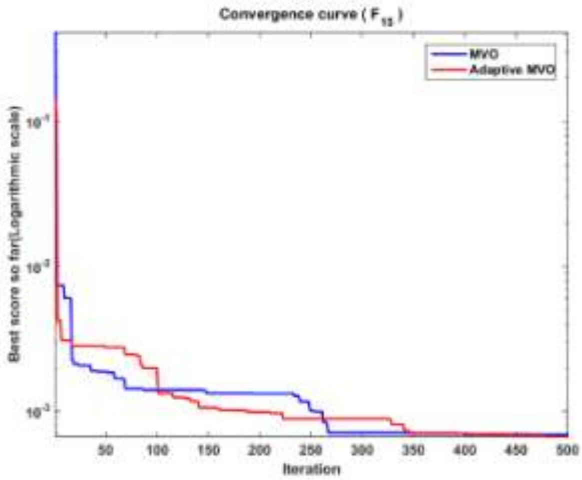
F_{13}



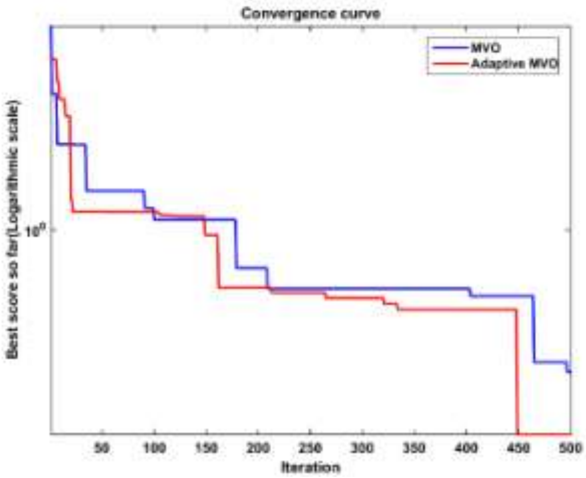
F_{14}



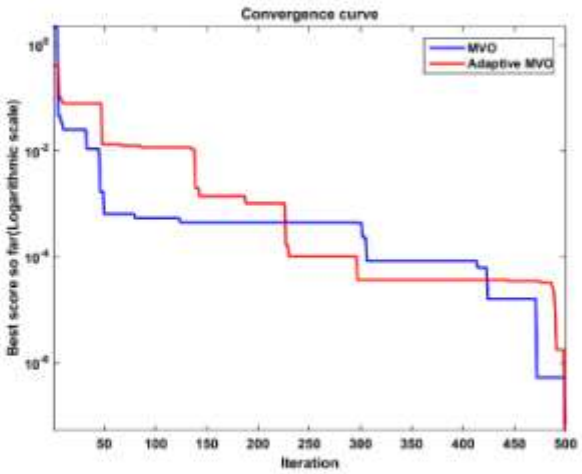
F_{15}



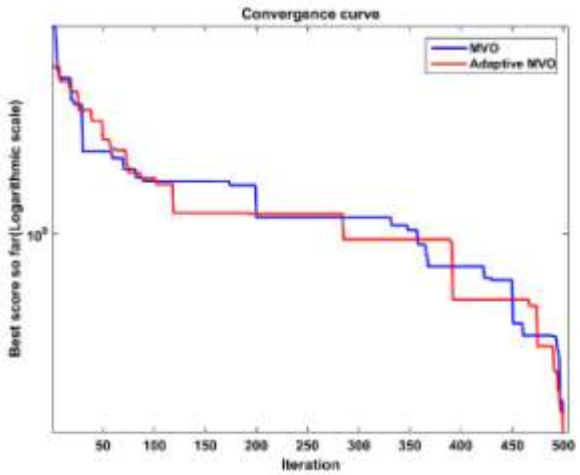
F_{16}



F_{17}



F_{18}



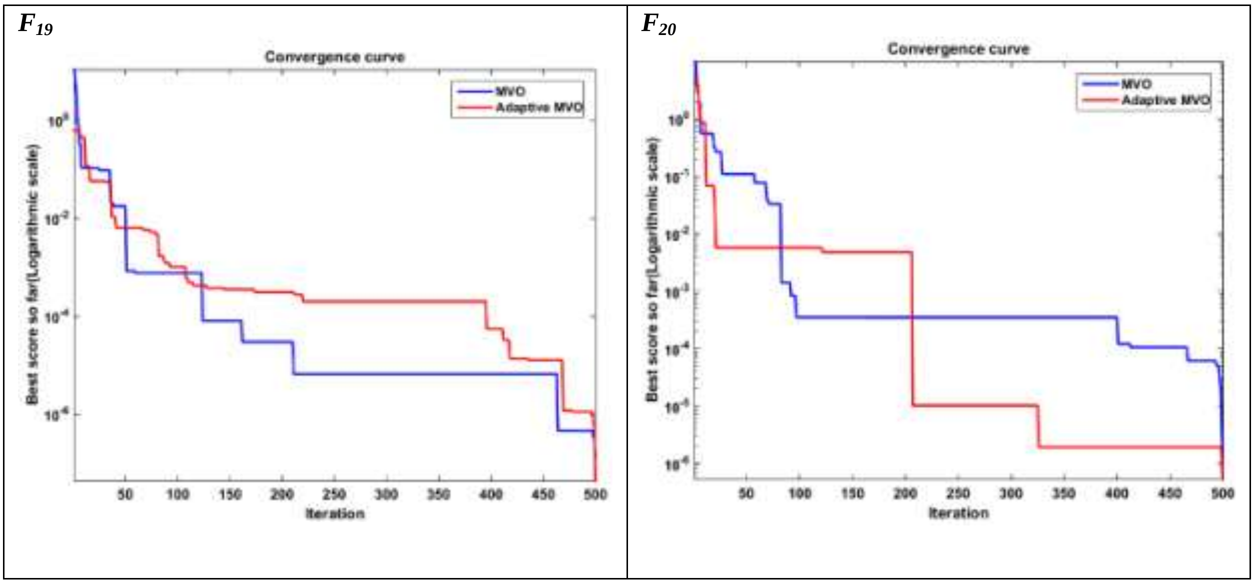


Fig. 2: Convergence Curve of Benchmark Test Function

Table 3: Result for benchmark functions

Function	**Multi-Verse optimizer (MVO)**			**Adaptive Multi-Verse optimizer (AMVO)**		
	Ave	**Best**	**S.D.**	**Ave**	**Best**	**S.D.**
F1	0.038988	0.035876	0.0044019	0.025255	**0.021229**	0.0044019
F2	0.037368	0.022524	0.020993	0.026381	**0.020761**	0.020993
F3	0.087611	0.078906	0.012311	0.080412	**0.06168**	0.012311
F4	0.12263	0.10546	0.024292	0.067436	**0.067181**	0.024292
F5	189.9745	119.2147	100.0695	57.7826	**6.1424**	100.0695
F6	0.010759	0.0074771	0.004641	0.010415	**0.0042417**	0.004641
F7	0.0031751	0.0031688	8.9653E-06	0.0022007	**0.0020565**	8.9653E-06
F8	-2687.7615	-2709.2547	30.3959	-3240.727	**-3319.6467**	30.3959
F9	22.3933	20.9002	2.1116	10.4546	**4.9825**	2.1116
F10	1.5932	1.169	0.5999	0.85717	**0.059874**	0.5999
F11	0.42588	0.36567	0.085154	0.33394	**0.23724**	0.085154
F12	0.00090205	0.00059359	0.0004362	0.00083938	**0.00037817**	0.000436
F13	0.0046441	0.0027507	0.0026777	0.015079	**0.0015104**	0.0026777
F14	0.998	**0.998**	5.1422E-11	0.998	**0.998**	5.1422E-11
F15	0.010525	0.0006874	0.013913	0.00072527	**0.0006683**	0.013913
F16	15.6118	0.00034001	22.078	0.0049899	**1.0153E-05**	22.078
F17	1.4823E-07	7.1927E-08	1.079E-07	7.2133E-08	**5.2882E-08**	1.079E-07
F18	0.00017922	0.00015414	3.5469E-05	6.9524E-05	**5.6899E-05**	3.5469E-05
F19	2.1653E-07	1.3361E-07	1.1727E-07	5.8068E-08	**4.4165E-08**	1.1727E-07
F20	1.4931E-06	9.795E-07	7.2629E-07	3.9497E-06	**5.2568E-07**	7.2629E-07

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:

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

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).

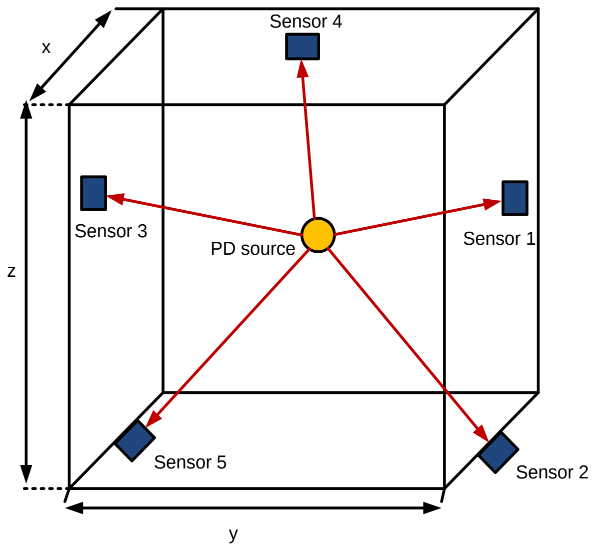


Fig. 3:Visualization of PD source and sensor arrangement

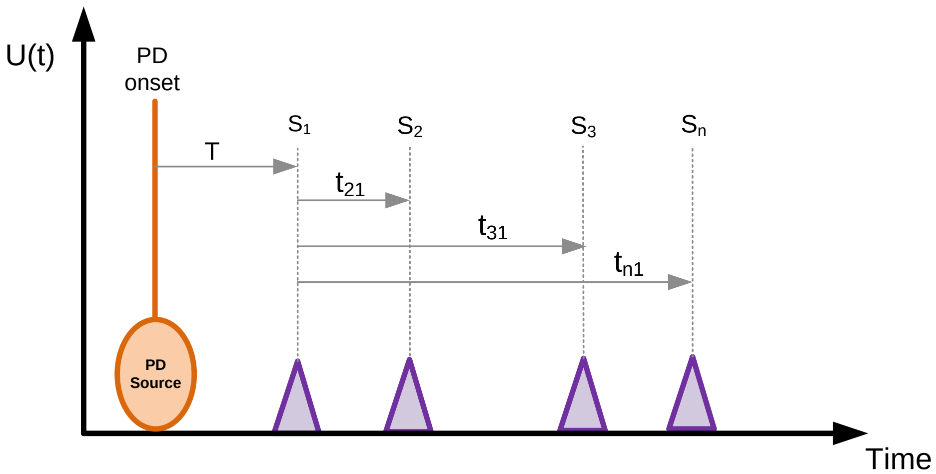


Fig. 4:Schematic of acoustic time differences in reference to electrical PD signal

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 [8].

Problem Formulation:

$$\begin{aligned} &\tau_{21} = -1000\times 10^{-03}, \tau_{31} = -1100\times 10^{-03}, \\ &\tau_{41} = -700\times 10^{-03}, \tau_{51} = -924.69\times 10^{-03}, \end{aligned} \quad (12)$$

$$P = \left[(x-x_1)^2 + (y-y_1)^2 + (z-z_1)^2 \right]^{0.5} \quad (13)$$

$$a = \left[(x-x_2)^2 + (y-y_2)^2 + (z-z_2)^2 \right]^{0.5} - P - \upsilon_e \tau_{21}; \quad (14)$$

$$b = \left[(x-x_3)^2 + (y-y_3)^2 + (z-z_3)^2 \right]^{0.5} - P - \upsilon_e \tau_{31}; \quad (15)$$

$$c = \left[(x-x_4)^2 + (y-y_4)^2 + (z-z_4)^2 \right]^{0.5} - P - \upsilon_e \tau_{41}; \quad (16)$$

$$d = \left[(x-x_5)^2 + (y-y_5)^2 + (z-z_5)^2 \right]^{0.5} - P - \upsilon_e \tau_{51}; \quad (17)$$

$$Min \quad \{D_f(x, y, z, \upsilon_e)\} = a^2 + b^2 + c^2 + d^2; \quad (18)$$

Subjected to

$$\left. \begin{aligned} &0 \le x \le x_{\max} \\ &0 \le y \le y_{\max} \\ &0 \le z \le z_{\max} \\ &1200 \le \upsilon_e \le 1500, \quad (m/s) \end{aligned} \right\} \quad (19)$$

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

$$\Delta R = \left[(x-x_c)^2 + (y-y_c)^2 + (z-z_c)^2 \right]^{0.5} \quad (20)$$

Error of each co-ordinate is formulated:

$$\in_r = \left| \frac{L_{act} - L_{cal}}{L_{act}} \right| \times 100\% \quad (21)$$

Maximum deviation *D_{max}*

$$D_{\max} = \max \begin{Bmatrix} |x_{act} - x_{cal}| \\ |y_{act} - y_{cal}| \\ |z_{act} - z_{cal}| \end{Bmatrix} (22)$$

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	MVO	AMVO	GA [6]	PSO [6]	Linear PSO [6]
x	4500	4383.6498	**4384.2355**	4223.76	4383.32	4382.14
y	2600	2470.1037	**2471.0915**	2391.71	2470.53	2469.99
z	3700	3648.9165	**3650.0455**	3503.04	3649.16	3648.11

Table 6: Error analysis

Error	MVO	AMVO	GA [6]	PSO [6]	Linear PSO [6]
Error of x%	2.585	2.572	6.14	2.59	2.62
Error of y%	4.99	4.958	8.01	4.98	5.00
Error of z%	1.380	1.350	5.32	1.37	1.40
D_{max}/mm	129.8963	128.9085	276.24	129.47	130.01
Comprehensive Error(ΔR/mm)	181.7139	**180.3171**	398.10	181.55	182.99

VI. CONCLUSION

Multi-Verse 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 AMVO is feasible. PD localization by AMVO gives better result than MVO and alsoaccurate in compare to GA, PSO and linear PSO algorithm.
The AMVO result of various unconstrained problems proves that it is also an effective method in solving challenging problems with unknown search space.

ACKNOWLEDGMENT:

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

REFERENCES

[1]. Seyedali Mirjalili, Seyed Mohammad Mirjalili, Abdolreza Hatamlou,"Multi-Verse Optimizer: a nature-inspired algorith for global optimization", " The Natural Computing Applications Forum 2015", 17 March 2015 http://dx.doi.org/10.1007/s00521-015-1870-7
[2]. Khoury J, Ovrut BA, Seiberg N, Steinhardt PJ, Turok N (2002) From big crunch to big bang. Phys Rev D 65:086007.
[3]. Tegmark M (2004) Parallel universes. In: Barrow JD, Davies PCW, Harper CL Jr (eds) Science and ultimate reality: Quantum theory, cosmology, and complexity. Cambridge University Press, pp 459–491.
[4]. P. Ong, "Adaptive Cuckoo search algorithm for unconstrained optimization," The Scientific World Journal, Hindawi Publication, vol. 2014, pp.1-8, 2014.
[5]. 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.
[6]. 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.
[7]. Liu HL, Liu HD. Partial discharge localization in power transformers based on the sequential quadratic programming-genetic algorithm adopting acoustic emission techniques. Eur Phys J Appl Phys 2014;68(01):10801.
[8]. Yang Y, Wang BB. Application of unconstrained optimization in ultrasonic locating of transformer partial discharge. Mod Electron Techn 2007; 2007 (3):100–4.
[9]. 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.
[10]. 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.
[11]. Iztok Fister Jr., Simon Fong, Janez Brest, and Iztok Fister, 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.
[12]. Gai-Ge Wang, Amir H. Gandomi, Amir H. Alavi, Suash Deb, A hybrid PBIL-based Krill Herd Algorithm, December 2015.
[13]. 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.
[14]. A. Tahershamsi, A. Kaveh, R. Sheikholeslami and S. Kazemzadeh Azad, An improved _rey algorithm with harmony search scheme for optimization of water distribution systems, Scientia Iranica A (2014) 21(5), 1591{1607.
[15]. Lihong Guo, 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.
[16]. Gai-Ge Wang, Lihong Guo, Amir Hossein Gandomi, Guo-Sheng Hao, Heqi Wang. Chaotic krill herd algorithm. Information Sciences, Vol. 274, pp. 17-34, 2014.
[17]. GaigeWang and Lihong Guo, 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.

[18]. 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.
[19]. 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.
[20]. Ali Kaveh / Omid Khadem 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 Periodica Polytechnica 2012.
[21]. 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.
[22]. 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.
[23]. 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.
[24]. Gaige Wang, Lihong Guo, 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.
[25]. S. Talatahari, R. Sheikholeslami, B. Farahmand Azar, 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.
[26]. A.H. Gandomi, X.S. Yang, S. Talatahari, A.H. Alavi, Metaheuristic Applications in Structures and Infrastructures, Elsevier, 2013.
[27]. A.H. Gandomi, A.H. Alavi, Krill Herd: a new bio-inspired optimization algorithm, Common Nonlinear Sci. Numer. Simul. 17 (12) (2012) 4831–4845.
[28]. Gandomi A.H. “Interior Search Algorithm (ISA): A Novel Approach for Global Optimization.” ISA Transactions, Elsevier, 53(4), 1168–1183, 2014.

Naveen Sihag1Ph.D " A Noveladaptive Multi-Verse Optimizer for Global Optimization Problems” International Journal of Computational Engineering Research (IJCER), vol. 08, no. 02, 2018, pp. 08-20.