E-HHO: An Enhanced Harris Hawks Optimizer with improved Local Search Capability for Multi-Disciplinary Engineering Design and Optimization Problems

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Abstract: Recently developed Harris hawks optimizer has natural performance for discovery the optimum solution in global search space region without getting trapped into earlier convergence though the exploitation stage of the current Harris hawks optimization algorithm is underprivileged. In this research paper hybrid form of Harris hawks optimization algorithm mutual with canis lupus which is basically grey wolf optimization algorithm has established to find the different types of solution of optimization problem, non-convex, nonlinear and multidisciplinary engineering design problem. In this proposed research paper the exploitation stage of the present algorithm HHO has been further improved using grey wolf optimizer to expand its local and global search capability. The effectiveness of the proposed optimizer has been tested for various engineering design and optimization problems and it has been found that the proposed algorithm yields better results for multi-disciplinary design and optimization problems, as compared to others heuristics and meta-heuristics search algorithms.

Keywords: Harris Hawks Optimization, Meta-Heuristics Search Algorithm, Multidisciplinary Engineering Design Problem.

Introduction

Artificial intelligence and Deep Learning have problem solving ability to deal with problems, which are related to real world and have continuous and discrete behavior and constrained and unconstrained in nature [1][2]. For this kinds of attributes, there are happened a few challenges to handle a few sorts of issues utilizing traditional methodologies with scientific techniques[3][4]. There are a few sorts of research have tried that the seal strategies are insufficient viable or effective to bargain numerous kinds of non-continuous problem and non-differentiable problem and further more in such huge numbers of real world problem [5].In this way Metaheuristics algorithm is considered and it used to handling such a significant number of problem which is generally basic in nature and easily executed. In streamlining occupants based systems are fundamentally used to discover some arrangement dependent on imperfect and ideal which can similar with the specific ideal worth that arranged to it close by neighborhood or point. By creating populace set of the individuals, the enhancement procedure of the optimization surprise and in the populace every individual speak to applicant arrangement of the issue dependent on techniques. By supplanting the number of inhabitants for the best situation of present area, the populace can altered respectively and produce another populace utilizing a few administrators that's behavior is stochastic in nature [6][7].The procedure of optimization technique is proceeded till this can fulfill the most extreme iteration. Presently days the developing mindfulness and enthusiasm for effective, economical and fruitful utilization of such kinds of meta-heuristic calculation in the ongoing currents or examine.

Nonetheless, after No Free Lunch Theorem (NFL) [8], wide range for optimization dependent through enhancement methods prescribed and show normal equal execution on the off chance that it is applied to every likely so dependent on optimization technique. As indicated by NFL hypothesis, it can't consider hypothetically a calculation as all around best sort of optimizer agent as a rule reason. Thus, NFL hypothesis persuades for entering and rising progressively successful calculation and dependent on improvement method.

In the proposed research about paper, another enhancement method, hHHO-GWO algorithm which is essentially founded on nature-propelled to contend with different sorts of enhancer. The fundamental impression behind this sort of proposed streamlining procedure is supported from the helpful regular conduct for the upmost clever fowl known as Harris Hawks and the characteristic of this bird is chasing conduct and getting away or maintaining as strategic distance from behavior of the victim (rabbit) [9]. Hence an innovative scientific technique that’s nature like stochastic and meta-heuristic for handle various sorts of problems in the field of optimization is executed right now.

Literature Review

The scientists are accomplishing proceeds with chip away at various problems so as to execute different sorts of new methods on various issues and are skilled to discover the outcomes effectively. The effort is gainful to locate novel optimization techniques and furthermore this method by that hybrid structure for relieve some sorts disadvantage including existing methods in the leaving techniques. For the suggested inquire about research works have been chosen to explore deficits of current methods.

The scientists are accomplishing proceeds with chip away at various problems so as to execute different sorts of new methods on various issues and are skilled to discover the outcomes effectively. The effort is gainful to locate novel optimization techniques and furthermore this method by that hybrid structure for relieve some sorts disadvantage including existing methods in the leaving techniques. The other existing optimization techniques has good development prospect, but their research are still at initial stage and it includes too many problems, which need be solved or other instance there are several uncertainties such as: how to adequately stay away from nearby or local optimum? The most effective method to consummately consolidate the upsides of distinctive enhancement calculations? How to successfully set the boundaries or parameter of a calculation? What are the compelling cycle of iteration stop conditions? Etc. The most significant issues is that it comes up short on a bound together and complete hypothetical framework. In the proposed research, the authors has tried to resolve these problems by combining two efficient algorithms heuristically for better exploration and exploitation and for better search capability. The following research works have been chosen to explore deficits of current methods. Specific of those research work includes CBO [9], CEA [10], DA [11], DP [12], EMA [13], EHO [14], EOA [15], EFO [16], FOA [17], FFA [18], GSA [19], FPA [20], HGO [21], FA [22], GOA [23], GWO [24], GA[25], LSA [26], MIP [27], [28], KHA [29], Imperialist Competitive Algorithm (ICA) [30], League Championship Algorithm (LCA) [31], Interior search algorithm (ISA) [32], Monarch Butterfly Optimization (MBO) [33], Mine Blast Algorithm (MBA) [34], Sine Cosine Algorithm (SCA) [35] Particle Swarm Optimization (PSO) [36], Optics Inspired Optimization (OIO) [37], Simulated Annealing (SA) [38], Runner-Root Algorithm (RRA) [39], Stochastic Fractal Search (SFS) [40], Search Group Algorithm (SGA) [41], Shuffled Frog-Leaping Algorithm (SFLA) [42], [43], Symbiotic Organisms Search (SOS) [44], Tabu Search (TS)[45], Salp Swarm Algorithm (SSA) [46], Virus Colony Search (VCS) [47], Water Wave Optimization (WWO) [48], Whale Optimization Algorithm (WOA) [49], WCA [50], Weighted Superposition Attraction (WSA) [51], Teaching-Learning-Based

Optimization (TLBO) [52], Wind Driven Optimization (WDO) [53], Harris Hawks optimization (HHO) [54].

Mathematical Strategy of Hybrid Harris Hawks optimizer

Right now component of HHO is talked about. Considering the ordinary chasing methodology of Harris birds of prey, they identify the track and prey it by utilizing the predominant eyes over which the injured individual can't be acknowledge it no problem at all. Presently considering the equivalent possibility w for each adjusting system which depends upon areas for additional individuals from to approach sufficient while confronting as a prey, follow in eqn. (1)

$$X(iteration+1) = \{X_{rand}(iteration) - r_1 \times abs(X_{rand}(iteration) - 2 \times r_2 \times X(iteration)); \quad w \geq .5 \tag{1}$$

$$X(iteration+1) = \{(X_{rabbit}(iteration) - X_m(iteration)) - r_3 \times (LB + r_4 \times (UB - LB)); \quad w < .5 \tag{2}$$

$$X_m(iteration) = \frac{1}{N}\left(\sum_{i=1}^{N} X_i(iteration)\right) \tag{3}$$

Where, $r_{1,} r_{2,} r_{3,} r_{4,}$ & w are random records in the middle of (0, 1) those are upgraded in every cycle, $X(iteration+1)$ is denoted as Rabbit's position and N is defined as total amount of Harris hawks

Normal area for Harris Hawks accomplish with utilizing in eqn. (3).

Change after the period for investigation of the period of exploitation is shown;

$$E = 2 \times E_0 \times \left(1 - \frac{iteration}{iter\max}\right) \tag{4}$$

Where, E is avoidance energy for rabbit, E_0, the early condition for energy and $iter\max$ = maximum iteration

$$X(iteration+1) = \Delta X(iteration) - E \times abs(JX_{rabbit}(iteration) - X(iteration)) \tag{5}$$

$$\Delta X(iteration) = (X_{rabbit}(iteration) - X(iteration)) \tag{6}$$

$$X(iteration+1) = X_{rabbit}(iteration) - E \times abs(\Delta X(iteration)) \tag{7}$$

$$Y = X_{rabbit}(iteration) - E \times abs(JX_{rabbit}(iteration) - X(iteration)) \tag{8}$$

$$Z = Y + S \times LF(D) \tag{9}$$

Along these lines, to find out the better solution of a soft enclose, the Hawks birds of prey be able to choose their following development Y that depends upon standard that is shown eqn. (8)

Established upon Lf (D) patterns constructed which track the given instruction in eqn. (10)

Where, D = Problem's dimension, S = Dimension of random vector with size $1 \times D$

$$LF(x) = 0.01\left(\frac{\mu \times \sigma}{|v|^{\frac{1}{\beta}}}\right) \tag{10}$$

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2\left(\frac{\beta-1}{2}\right)} \right)^{\frac{1}{\beta}} \quad (11)$$

Where, μ, σ are denoted as such kind of value randomly in between (0, 1) and β set to 1.5 which is a constant known as default.

In this way, including these the final and actual technique for update the real area of Hawks sells through that period for soft enclose with accomplished through Eqn. (12) and (13) that is shown

$$X(iteration+1) = \begin{cases} Y; & if \quad F(Y) < F(X(iteration)) \\ Z; & if \quad F(Z) < F(X(iteration)) \end{cases} \quad (12)$$

$$Y = X_{rabbit}(iteration) - E \times abs(JX_{rabbit}(iteration) - X_m(iteration)) \quad (13)$$

$$Z = Y + S \times Lf(D) \quad (14)$$

Where, $X_m(iteration)$ can obtain from eqn. (3). X_m $(iteration)$ can obtain from eqn. (5).

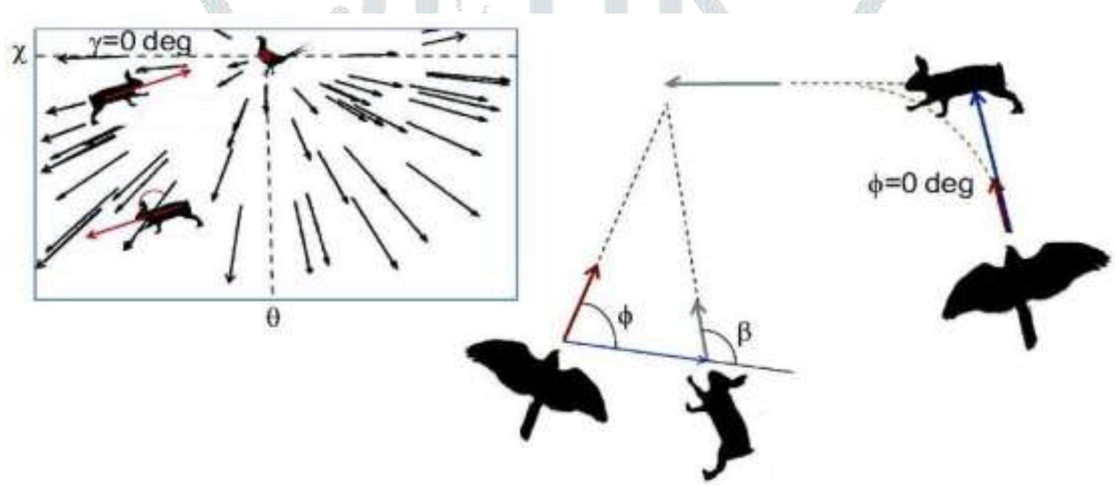


Fig.1: Surprise Attack by Harris Hawks

Mathematical Model for Grey Wolf Optimizer

Mostly established Grey Wolf Optimization Algorithm technique, is such type of algorithm which is basically constructed arranged by grey wolf which reconstruct the near of community and element use of hunting for grey wolves in the main point of three principle endeavors of hunting such as look over or scan for prey, surrounding the victim and attacking the target and which deductively method was considered for the purpose of near of chain of importance in various wolves. The adequate explanation to get the best fitness value which was selected as **a**, accordingly, another best fitness solutions are entitled as **b** and **c** independently. Whatever it is, the missing of the optimistic resolution are assumed to be **x**, **y** and **z**. To find out the fitness value design, the hunting procedure is directed through **a**, **b** and **c**. The **x**, **y** and **z** wolves track those wolves. For GWO, Enclosing or Catching of Victim accomplished with computing $\vec{G}$ and $\vec{W}_{gywolf}$ vectors defined through Eqn. (15) and (16).

$$\vec{G} = \left| \vec{C}.\vec{W}_{prey}(iter) - \vec{W}_{gywolf}(iter) \right| \quad (15)$$

$$\overrightarrow{W}_{gywolf}(iter+1) = \overrightarrow{W}_{prey}(iter) - \vec{A}.\vec{G} \tag{16}$$

$$\vec{A} = 2\vec{\alpha}.\vec{\gamma}_1 - \vec{\alpha} \tag{17}$$

$$\vec{C} = 2.\vec{\gamma}_2 \tag{18}$$

Here, $\vec{\gamma}_1, \vec{\gamma}_2 \in rand(0,1)$ and $\vec{\alpha}$ reduced linearly through 2 to 0. Chasing of the victim are accomplished through calculating the parallel score for fitness and locations of **a**, **b** and **c** wolves using equations numbers (19), (20) and (21) correspondingly and final location for attacking to the victim was designed by equation (24).

$$\vec{G}_a = abs(\vec{C}_1.\overrightarrow{W}_a - \overrightarrow{W}) \tag{19a}$$

$$\overrightarrow{W}_1 = \overrightarrow{W}_a - \vec{A}_1.\overrightarrow{W}_a \tag{19b}$$

$$\overrightarrow{W}_b = abs(\vec{C}_2.\overrightarrow{W}_b - \overrightarrow{W}) \tag{20a}$$

$$\overrightarrow{W}_2 = \overrightarrow{W}_b - \vec{A}_2.\overrightarrow{W}_b \tag{20b}$$

$$\vec{G}_c = abs(\vec{C}_3.\overrightarrow{W}_c - \overrightarrow{W}) \tag{21}$$

$$\overrightarrow{W}_3 = \overrightarrow{W}_c - \vec{A}_3.\vec{G}_c \tag{22}$$

$$\overrightarrow{W}(iter+1) = \frac{(\overrightarrow{W}_1 + \overrightarrow{W}_2 + \overrightarrow{W}_3)}{3} \tag{23}$$

In the projected hybrid Harris Hawks Optimization combined with Grey Wolf Optimizer (hHHO-GWO) algorithm can arbitrarily produce location vector $\vec{W}$ has been advance improved by Grey Wolf Optimization technique and the improved the position vector $\vec{W}$ which apply in grey wolves to estimate the scores of **a**, **b** and **c**. To hybridize the HHO and GWO, the procedure of heuristics search has been accepted. The phase of exploration in hHHO-GWO is like to standard HHO. In order to explore the space in searching global region the vector $\vec{A}$ and $\vec{C}$ used, which scientifically classic deviation. Absolute rate for $\vec{A}$ is more than 1 which services grey wolves for deviate after the target to optimistic discover a satisfactory prey.

In suggested hHHO-GWO method, for phases of GWO, pragmatic consecutively afterward HHO technique for increase exploration level and exploitation level through advance range. Pseudo code of suggested hybrid optimizer is displayed in Fig.2 (b). In the suggested hybrid Harris Hawks inspired grey wolves optimizer, mimetic sequential approach of hybridization has been used, in which the final position of Harris hawks has been delivered to the starting position of search agent in grey wolves optimizer, which further use the mechanism of encircling, harassing and trapping of prey using eqns. (16) through (24) to determine the final fitness value. The Pseudo code of Grey Wolf Optimizer has been shown in Fig. 2(a).

```
Initialization of the population of the grey wolves W_j, where j ∈ 1,2,3.....N
Initialization of a, C̄ and Ā
Calculation of the value of the fitness using objective function of the each search agents
Allot W_a → The best fitness value of search agent
      W_b → The second best fitness value of search agent
      W_c → The third best fitness value of search agent
Upgrade the location of W_j using the Harris Hawks method (PSEUDO code of HHO)
While (iter < iter_MAX)
      for the each search agents
            Upgrade the location of the present search agent by equation number (24)
      end for
            Upgrade the value of a, C̄ and Ā using the equation number (18) and (19)
            Upgrade the value of W_a, W_b and W_c
      iter = iter + 1
end while
Return W_a
```

Fig.2 (a): Pseudo code of grey wolf optimizer

INPUTS: The population size is taken as N and maximum iteration number is taken as $iter_{max}$.

OUTPUTS: The position of prey (rabbit) and its value of fitness

Initialization of random population $H_i (i = 1, 2, 3......., N)$

While (the stopping condition not met) **DO**

  Calculation of the fitness value of Harris hawks

  Set the parameter H_{rabbit} as the best position of the prey (rabbit)

  for (each Harris hawks (H_i)) DO

    $EG_0 = 2rand() - 1, K = 2(1 - rand())$ → Update energy at initial condition EG_0 and K

    Update EG using equation number (4)

   if $|EG| \geq 1$ **then** → **Phase of Exploration**

    Update the position vector using equation (1) and (2)

   if $|EG| \langle 1$ **then** → **Phase of Exploitation**

    if $(e_s \geq 0.5)$ and $|EG| \geq 0.5$ **then** → Soft encircle

     Location vector updated using equation number (5)

    else if $(e_s \geq 0.5)$ and $|EG| \langle 0.5$ **then** → **Hard encircle**

     Location vector updated using equation number (7)

   else if $(e_s \langle 0.5)$ and $|EG| \geq 0.5$ **then** → **Soft encircle with advanced fast dives**

     Location vector updated using equation number (12) and (13)

   else if $(e_s \langle 0.5)$ and $|EG| \langle 0.5$ **then** → **Hard encircle with advanced fast dives**

     Location vector updated using equation number (14) and (15)

HHO

Initialization of the population of the grey wolves W_j, where $j \in 1, 2, 3.....N$

Initialization of a, $\bar{C}$ and $\bar{A}$

Calculation of the value of the fitness using objective function of the each search agents

Allot W_a → The best fitness value of search agent

  W_b → The second best fitness value of search agent

  W_c → The third best fitness value of search agent

Upgrade the location of W_j using the Harris Hawks method (PSEUDO code of HHO)

While $(iter \langle iter_{MAX})$

  for the each search agents

    Upgrade the location of the present search agent by equation number (24)

  end for

    Upgrade the value of a, $\bar{C}$ and $\bar{A}$ using the equation number (18) and (19)

    Upgrade the value of W_a, W_b and W_c

  $iter = iter + 1$

end while

Return W_a

GWO

Fig.2 (b): Pseudo code of proposed hybrid hHHO-GWO algorithm

RESULTS AND DISCUSSION

In order to test the efficiency of the algorithm for multi-disciplinary design and optimization problems, the 11 engineering design and optimization problems from different domain has been taken into consideration and corresponding results has been shown in Table-2 through Table-14.

Table-2: Name and Abbreviation of Engineering Design Problems

Engineering Problem Abbreviation	ENGG 1	ENGG 2	ENGG 3	ENGG 4	ENGG 5	ENGG 6	ENGG 7	ENG G 8	ENGG 9	ENGG 10	ENGG 11
Problem Name	Three-bar truss problem	Pressure Vessel	Spring Design	Welded Beam	Cantilever Beam Design	Gear Train	Speed Reducer problem	Belleville Spring	Rolling Element Bearing	Multiple Disk Clutch Brake (Discrete variables)	I beam design
Objective Function	@SPECIAL1	@SPECIAL2	@SPECIAL3	@SPECIAL4	@SPECIAL5	@SPECIAL6	@SPECIAL7	@SPECIAL8	@SPECIAL9	@SPECIAL10	@SPECIAL11

Table-3: Outcomes of Eng. Design Problems by **hHHO-GWO** method

ENGG DESIGN PROBLEM	ENGG 1	ENGG 2	ENGG 3	ENGG 4	ENGG 5	ENGG 6
Mean value Suitability	264.03669	3953.101	6932.5203	0.0135819	2.0432051	-70713.316
Std	0.1886716	756.71767	449.18682	0.0008347	0.2764923	14183.039
Best fitness	263.89589	3036.2349	6136.2708	0.0126693	1.7574094	-83035.681
Worst Fitness	264.67785	5453.2625	7873.643	0.0160809	2.7544306	-42284.194
Median	263.94733	3940.9188	6941.543	0.0133738	1.9353975	-79525.277
p-Value	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06	1.73E-06
ENGG PROBLEM	**ENGG 7**	**ENGG 8**	**ENGG 9**	**ENGG 10**	**ENGG 11**	
Mean value Suitability	0.4478391	0	2.65E+22	1.3074168	0.006625958	
Std	0.0501119	0	2.70E+22	0.0024859	3.12E-17	
Best fitness	0.3896541	0	1.9999278	1.3039803	0.006625958	
Worst Fitness	0.5710398	0	5.30E+22	1.3144023	0.006625958	
Median	0.4334583	0	2.65E+22	1.3069923	0.006625958	
p-Value	1.73E-06	1	1.57E-06	1.73E-06	1.50E-06	

Table-5: Computational time for Eng. Problems

Engineering Design Problems	ENGG 1	ENGG 2	ENGG 3	ENGG 4	ENGG 5	ENGG 6
Best Time	2.21875	3.28125	2.234375	2.40625	2.78125	4.15625
Mean Time	2.3328125	3.3546875	2.3057292	2.4692708	2.8453125	4.2182292
Worst Time	3.078125	3.546875	2.6875	2.5625	3.0625	4.328125
Engineering Problem	**ENGG 7**	**ENGG 8**	**ENGG 9**	**ENGG 10**	**ENGG 11**	
Best Time	3.25	1.53125	3.109375	2	2.21875	
Mean Time	3.5640625	1.7052083	3.6494792	2.2244792	2.556770833	
Worst Time	5.09375	2.078125	5.046875	2.703125	3.265625	

Table-6: Assessment with others technique for SPECIAL 1

Optimized Methods	Optimum value for variable		Optimal weight
	x1	***x2***	
hHHO-GWO	**0.79596**	**0.38803**	**263.8958877**
CS [55]	0.789	0.409	263.972
TSA [56]	0.788	0.408	263.68
Ray and Sain [56]	0.795	0.395	264.3

Table-7: Assessment with others technique for SPECIAL 2

Optimized Methods	Optimum value for variable				Optimum Cost
	Ts	***Th***	***R***	***L***	
hHHO-GWO	**0.901977**	**0.445349**	**46.68205**	**127.0593**	**6136.270795**
GWO [24]	0.8125	0.4345	42.0892	176.7587	6051.564
GSA[19]	1.125	0.625	55.9887	84.4542	8538.84
PSO [57]	0.8125	0.4375	42.0913	176.7465	6061.078
GA [58]	0.8125	0.4345	40.3239	200	6288.745
GA (Deb and Gene) [58]	0.9375	0.5	48.329	112.679	6410.381
DE [59]	0.8125	0.4375	42.0984	176.6377	6059.734
ACO [60]	0.8125	0.4375	42.1036	176.5727	6059.089
Lagrangian Multiplier [61]	1.125	0.625	58.291	43.69	7198.043
Branch-bound [62]	1.125	0.625	47.7	117.701	8129.1

Table-8: Assessment with others technique for SPECIAL 3

Optimized Methods	Optimum value for variable			Optimum weight
	d	*D*	*N*	
hHHO-GWO	**.0512**	**.34554**	**11.9758**	**.01266929**
GSA[19]	.0503	.3237	13.5254	.0127
GWO[24]	.0516	.3567	11.2889	.01267
ES [63]	.052	.364	10.8905	.01268
PSO[57]	.0517	.3576	11.2445	.01267
HS[64]	.0512	.3499	12.0764	.01267
GA[58]	.0515	.3517	11.6322	.0127
DE[59]	.0516	.3547	11.4108	.01267
Constraint correction [5]	.05	.3159	14.25	.01283
Mathematical optimization [65]	.0534	.3992	9.1854	.01273

Table-9: Assessment with others technique for SPECIAL 4

Optimized Methods	Optimum value for variable				Optimal Cost
	h	l	t	b	
hHHO-GWO	**0.206512**	**3.525279**	**8.901249**	**.212035**	**1.7574094**
GSA[19]	.1821	3.857	10	.2024	1.88
GWO[24]	.2057	3.478	9.036	.205	1.726
GA[58]	.2489	6.173	8.178	.253	2.433
Random[66]	.4575	4.731	5.085	.66	4.118
Simplex [67]	.2792	5.625	7.751	.279	2.530
David [8]	.2434	6.255	8.291	.244	2.384
HS [64]	.2442	6.223	8.291	.244	2.380
APPROX [68]	.2444	6.218	8.291	.244	2.381

Table-10: Assessment with others technique for SPECIAL 5

Optimized Methods	Optimum value for variable					Optimum weight
	*x*1	*x*2	*x*3	*x*4	*x*5	
hHHO-GWO	**6.040644**	**4.775305**	**4.561**	**3.4209**	**2.1528**	**1.303980317**
ALO[69]	6.0181	5.3114	4.4884	3.4975	2.1583	1.33995
SOS[44]	6.0188	5.3034	4.4959	3.499	2.1556	1.33996
CS [70]	6.0089	5.3049	4.5023	3.5077	2.1504	1.33999
GCA_II [71]	6.01	5.3	4.49	3.49	2.15	1.34
MMA[71]	6.01	5.3	4.49	3.49	2.15	1.34
GCA_I [71]	6.01	5.304	4.49	3.498	2.15	1.34

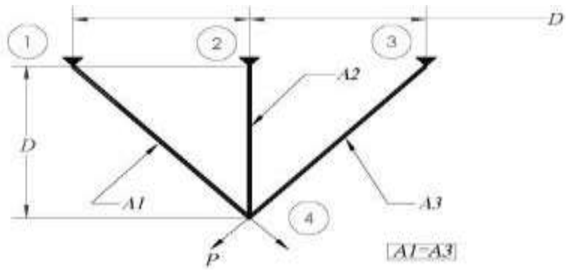
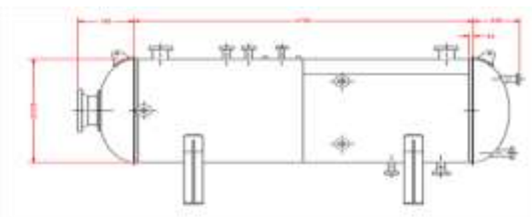
Table-11: Assessment with others technique for SPECIAL 6

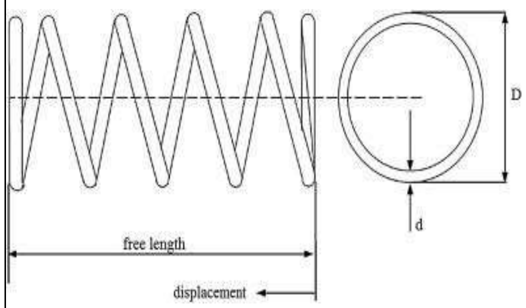
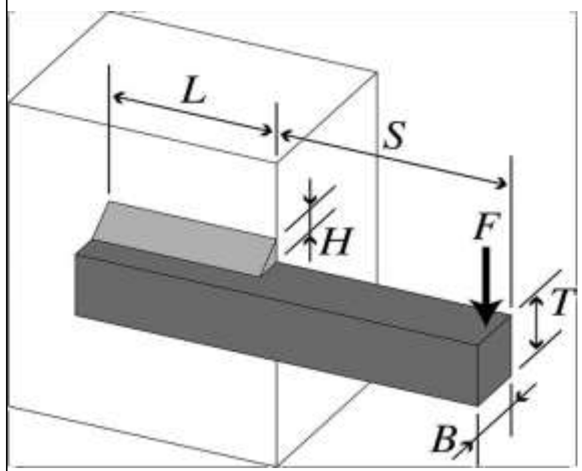
Optimized Methods	Optimum value for variable				Optimum fitness
	x1	*x2*	*x3*	*x4*	
hHHO-GWO	**51.8681**	**43.7593**	**21.36**	**15.33**	**0**
GeneAS [72]	50	33	14	17	0.144242
Kannan and Krame [72]	41	33	15	13	0.144124
Sandgren [72]	60	45	22	18	0.14667

Table-12: Assessment with others technique for SPECIAL 7

Optimized Methods	Optimum value for variable							Optimum fitness
	x1	*x2*	*x3*	*x4*	*x5*	*x6*	*x7*	
hHHO- GWO	**3.534535**	**0.7**	**17**	**8.206115**	**8.206116**	**3.385823**	**5.286826**	**3036.234896**
HEAA [73]	3.500022	0.70000039	17.000012	7.300427	7.715377	3.35023	5.286663	2994.49911
PSO-DE [74]	3.5	0.7	17	7.3	7.8	3.350214	5.2866832	2996.34817
MDE [59]	3.50001	0.7	17	7.300156	7.800027	3.350221	5.286685	2996.35669
MBA[34]	3.5	0.7	17	7.300033	7.715772	3.350218	5.286654	2994.48245

Tabel-4: MULTIDISCIPLINARY ENGINEERING DESIGN OPTIMIZATION PROBLEMS

Problem Name with objective functions	Constraints	Diagram
SPECIAL 1 [47] Consider, $\bar{x} = [x_1, x_2] = [A_1, A_2]$, Minimize $f(\bar{x}) = \left(2\sqrt{2}x_1 + x_2\right) * l$	Subjected to, $g_1(\bar{x}) = \frac{\sqrt{2}x_1 + x_2}{\sqrt{2}x_1^2 + 2x_1x_2} P - \sigma \le 0$ $g_2(\bar{x}) = \frac{x_2}{\sqrt{2}x_1^2 + 2x_1x_2} P - \sigma \le 0$ $g_3(\bar{x}) = \frac{L}{\sqrt{2}x_2 + x_1} P - \sigma \le 0$ Where L = 100cm , P= 2KN/ , = 2 KN/cm^2	
SPECIAL 2 [47] Consider, $\bar{x} = [x_1 x_2 x_3 x_4] = [T_s T_h R L]$ Minimize $f(\bar{x}) = 0.6224x_1x_3x_4 + 1.7781x_2x_3^2 + 3.1661x_1^2x_4 + 19.84x_1^2x_3$	Subjected to, $g_1(\bar{x}) = -x_1 + 0.0193x_3 \le 0$ $g_2(\bar{x}) = x_3 + 0.00954x_3 \le 0$ $g_3(\bar{x}) = -\pi x_3^2 x_4 - \frac{4}{3}\pi x_3^3 + 1296000 \le 0$ $g_4(\bar{x}) = x_4 - 240 \le 0$, Variable range, $0 < X_1 < 99$, $0 < X_2 < 99$, $10 < X_3 < 99$, $10 < X_4 < 99$	

SPECIAL 3 [47] Consider, $\bar{x} = [x_1 x_2 x_3] = [dDN]$; Minimize $f(\bar{x}) = (x_3 + 2) x_2 x_1^2$	Subjected to, $g_1(\bar{x}) = 1 - \frac{x_2^3 x_3}{71785 x_1^4} \le 0$ $g_2(\bar{x}) = \frac{4x_2^2 - x_1 x_2}{12566(x_2 x_1^3 - x_1^4)} + \frac{1}{5108 x_1^2} \le 0$ $g_3(\bar{x}) = 1 - \frac{140.45 x_1}{x_2^2 x_3} \le 0$ $g_4(\bar{x}) = \frac{x_1 + x_2}{1.5} - 1 \le 0$, Variable range 0 .005< X_1 < 2, 0.25< X_2 < 1.3, 2 < X_3 < 15	
SPECIAL 4 [47] Consider, $\bar{x} = [x_1 x_2 x_3 x_4] = [hltb]$; Minimize $f(\bar{x}) = 1.10471 x_1^2 x_2 + 0.04811 x_3 x_4 (14.0 + x_2)$	Subjected to, $g_1(\bar{x}) = \tau(\bar{x}) - \tau_{max} \le 0$, $g_2(\bar{x}) = \sigma(\bar{x}) - \sigma_{max} \le 0$ $g_3(\bar{x}) = \delta(\bar{x}) - \delta_{max} \le 0$, $g_4(\bar{x}) = x_1 - x_4 \le 0$, $g_5(\bar{x}) = P - P_c(\bar{x}) \le 0$, $g_6(\bar{x}) = 0.125 - x_1 \le 0$ $g_7(\bar{x}) = 1.10471 x_1^2 + 0.04811 x_3 x_4 (14.0 + x_2) - 5.0 \le 0$ Variable range, 0.1< X_1 < 2, 0.1< X_2 < 10, 0.1 < X_3 < 10, 0.1< X_1 < 2	

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SPECIAL 5 [47]

Consider, $\bar{x}=[x_1 x_2 x_3 x_4 x_5]$;

Minimize, $f(\bar{x})=0.6224(x_1+x_2+x_3+x_4+x_5)$,

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Subjected to,

$g(\bar{x})=\frac{61}{x_1^3}+\frac{37}{x_2^3}+\frac{19}{x_3^3}+\frac{7}{x_4^3}+\frac{1}{x_5^3}\le 1$

Variable range $0.01\le x_1,x_2,x_3,x_4,x_5\le 100$

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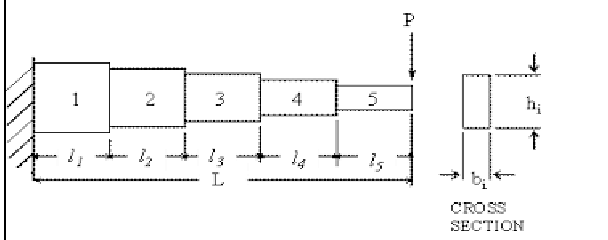

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SPECIAL 6 [47]

Consider, $\bar{g}=[g_1 g_2 g_3 g_4]=[M_A M_B M_C M_D]$

Minimize, $f(\bar{g})=\left(\frac{1}{6.931}-\frac{g_3 g_4}{g_1 g_4}\right)^2$

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Subjected to; $12\le g_1, g_2, g_3, g_4\le 60$

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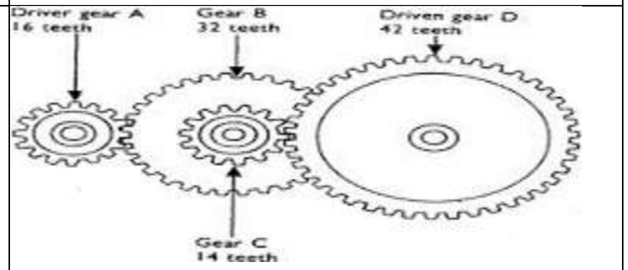

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SPECIAL 7 [47]

Minimize,

$f(\bar{s})=0.7854s_1s_2(3.3333s_3^2+14.9334s_3-43.0934)-1.508s_1(s_6^2+s_7^2)+7.4777(s_6^3+s_7^3)+0.7854(s_4s_6^2+s_5s_7^2)$

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Subjected to,

$g_1(\bar{s})=\frac{27}{s_1s_2^2s_3}-1\le 0$, $g_2(\bar{s})=\frac{397.5}{s_1s_2^2s_3^2}-1\le 0$

$g_3(\bar{s})=\frac{1.93s_4^3}{s_2s_3s_6^4}-1\le 0$, $g_4(\bar{s})=\frac{1.93s_5^3}{s_2s_3s_7^4}-1\le 0$,

$g_5(\bar{s})=\frac{1}{110s_6^3}\sqrt{(\frac{745.0s_4}{s_2s_3})^2+16.9\times10^6}-1\le 0$

$g_6(\bar{s})=\frac{1}{85s_7^3}\sqrt{(\frac{745.0s_5}{s_2s_3})^2+157.5\times10^6}-1\le 0$

$g_7(\bar{s})=\frac{s_2s_3}{40}-1\le 0$, $g_8(\bar{s})=\frac{5s_2}{s_1}-1\le 0$, $g_9(\bar{s})=\frac{s_1}{12s_2}-1\le 0$

$g_{10}(\bar{s})=\frac{1.5s_6+1.9}{12s_2}-1\le 0$, $g_{11}(\bar{s})=\frac{1.1s_7+1.9}{s_5}-1\le 0$

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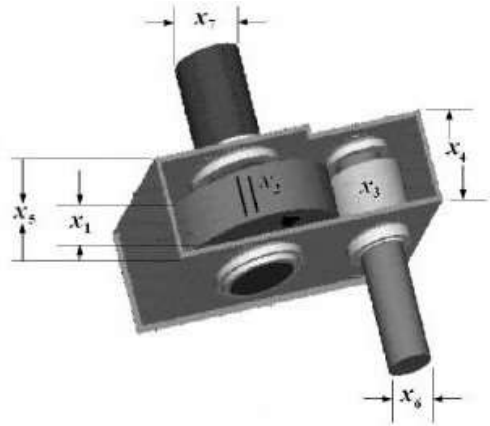

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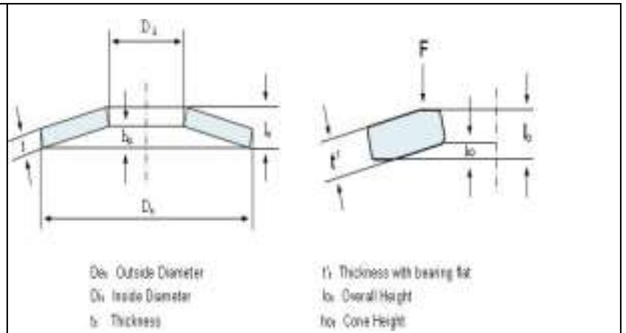
<td>SPECIAL 8 [47]

Minimize, $f(x) = 0.07075\pi(DIM_E^2 - DIM_I^2)t$</td>
<td>Subjected to,

$b_1(x) = G - \frac{4P\lambda_{max}}{(1-\delta^2)\alpha DIM_E}\left[\delta(S_H - \frac{\lambda \max}{2}) + \mu t\right] \geq 0$

$b_2(x) = (\frac{4P\lambda_{max}}{(1-\delta^2)\alpha DIM_E}\left[(S_H - \frac{\lambda}{2})(S_H - \lambda)t + t^3\right])_{\lambda_{max}} - P_{MAX} \geq 0$

$b_3(x) = \lambda_1 - \lambda_{max} \geq 0,\ b_4(x) = H - S_H - t \geq 0,$
$b_5(x) = DIM_{MAX} - DIM_E \geq 0,$
$b_6(x) = DIM_E - DIM_I \geq 0,\ b_7(x) = 0.3 - \frac{S_H}{DIM_E - DIM_I} \geq 0$</td>
<td>
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<td>SPECIAL 9 [47]

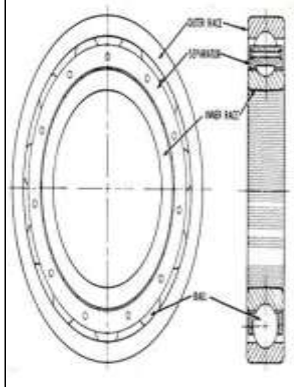
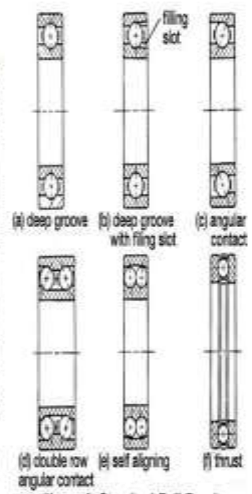
Maximize, $C_D = f_c N^{2/3} DIM_B^{1.8}$ if $DIM \leq 25.4mm$
$C_D = 3.647 f_C N^{2/3} DIM_B^{1.4}$ if $DIM \geq 25.4mm$</td>
<td>Subjected to,
$r_1(x) = \frac{\theta_0}{2\sin^{-1}\left(\frac{DIM_B}{DIM_{MAX}}\right)} - N + 1 \geq 0$
$r_2(x) = 2DIM_B - K_{DIM_{MIN}}(DIM - \mathrm{dim}) \geq 0$
$r_3(x) = K_{DIM_{MAX}}(DIM - \mathrm{dim}) \geq 0$
$r_4(x) = \beta B_W - DIM_B \leq 0;$
$r_4(x) = DIM_{MAX} - 0.5(DIM + \mathrm{dim}) \geq 0$
$r_5(x) = DIM_{MAX} - 0.5(DIM + \mathrm{dim}) \geq 0$
$r_6(x) = (0.5 + re)(DIM + \mathrm{dim}) \geq 0$
$r_7(x) = 0.5(DIM - DIM_{MAX} - DIM_B) - \alpha DIM_B \geq 0$
$r_8(x) = f_I \geq 0.515,\ r_9(x) = f_0 \geq 0.515$</td>
<td>
Figure 1 Typical High-Speed Ball Bearing


Figure 2 Standard Ball Bearing</td>
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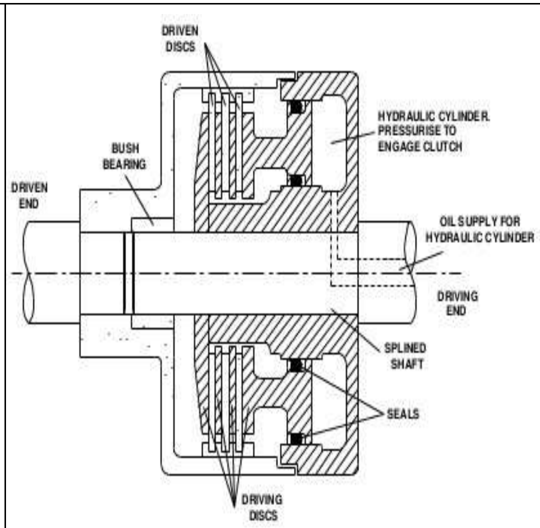
SPECIAL 10 [47] Minimize, $f\left(R_{in}, R_O, S_f, Th\right) = \pi Th\gamma\left(R_0^2 - R_{in}^2\right)\left(S_f + 1\right)$	Subjected to, $m_1 = R_0 - R_{in} - \Delta R \geq 0$ $m_2 = L_{MAX} - (S_f + 1)(Th + \alpha) \geq 0$ $m_3 = PM_{MAX} - PM_{\pi} \geq 0$ $m_4 = PM_{MAX} Y_{MAX} + PM_{\pi} Y_{SR} \geq 0$ $m_5 = Y_{SR_{MAX}} - Y_{SR} \geq 0$ $m_6 = t_{MAX} - t \geq 0$ $m_7 = DC_h - DC_f \geq 0$ $m_8 = t \geq 0$	

Table-13: Assessment with others technique for SPECIAL 8

Optimized Methods	Optimum value for variable				Optimum fitness
	x1	*x2*	*x3*	*x4*	
hHHO- GWO	**11.7423**	**9.691076**	**0.20466**	**0.20003**	**1.999927791**
TLBO [52]	12.01	10.03047	0.204143	0.2	0.198966
MBA[75]	12.01	10.030473	0.204143	0.2	0.198965

Table-14: Assessment with others technique for SPECIAL 10

Optimized Methods	Optimum value for variable					Optimum fitness
	*x*1	*x*2	*x*3	*x*4	*x*5	
hHHO- GWO	**70**	**90**	**2.312787**	**1.5**	**1000**	**0.389654109**
NSGA-II	70	90	3	1.5	1000	0.4704
TLBO[52]	70	90	3	1	810	0.3136566
MADE [59]	70	90	3	1	810	0.3136566

For the dynamic examination of impact of results of hybrid HHO-GWO has assessed to 30 trial runs and non-parametric test i.e. Wilcoxon rank sum test has been taken into consideration. The multi-disciplinary engineering design problems are checked including regard of worst value, p-value, standard deviation, best value additionally indicated the varieties best time and most noticeably worst time. The outcomes are likewise appeared through above table. The consequences of the multi-disciplinary engineering design problems are unequivocally sign for characteristics in the hybrid HHO-GWO technique to take care of those issues. Main outcomes for the suggested optimization technique likewise displays the viability for those issues with discrete as well as continuous type. The trial run through box plot for engineering optimization problems are presented in the Fig.3 (a) to Fig. 3 (j).

CONCLUSION

In the proposed research, the authors has improved the exploration and exploitation phase of the existing Harris Hawks Optimizer using Grey Wolf optimization algorithm and developed a hybrid meta-heuristics search algorithm i.e. hHHO-GWO. The effectiveness of the proposed optimizer has been tested for various engineering design and optimization problem and it has been experimentally found that the outcome of hHHO-GWO is much better than other recently proposed optimizer such as Ant Lion Optimization algorithm, Sine-Cosine optimizer algorithm and Moth Flame Optimizer algorithm. Hence, the proposed optimizer can be applied to solve other engineering optimization problems including power system optimization problems.

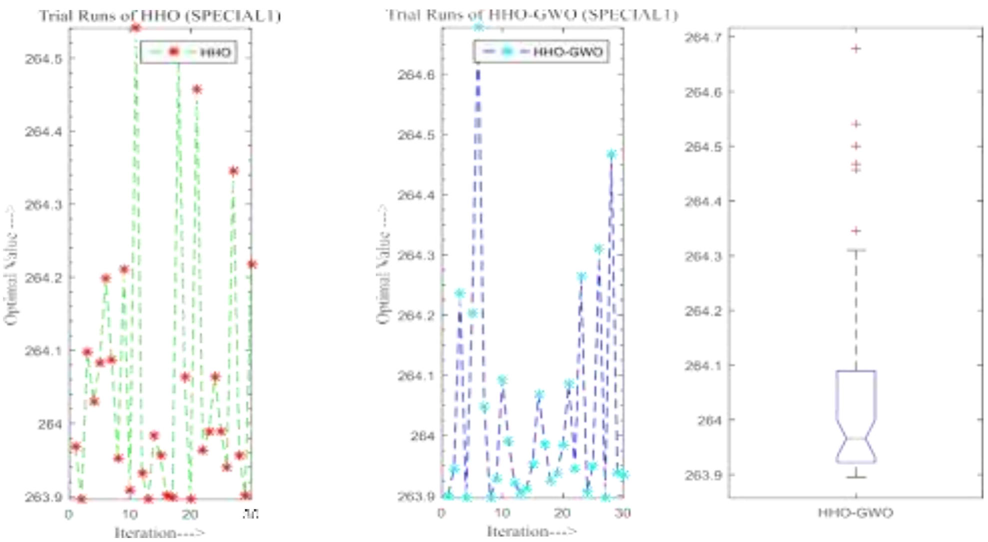


Fig.3 (a). Trail run of multidisciplinary engineering design problem (SPECIAL1)

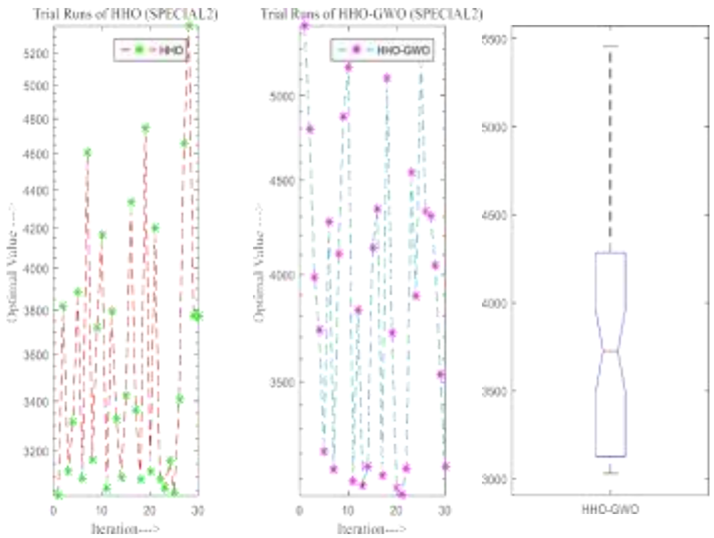


Fig.3 (b). Trail run of multidisciplinary engineering design problems (SPECIAL2)

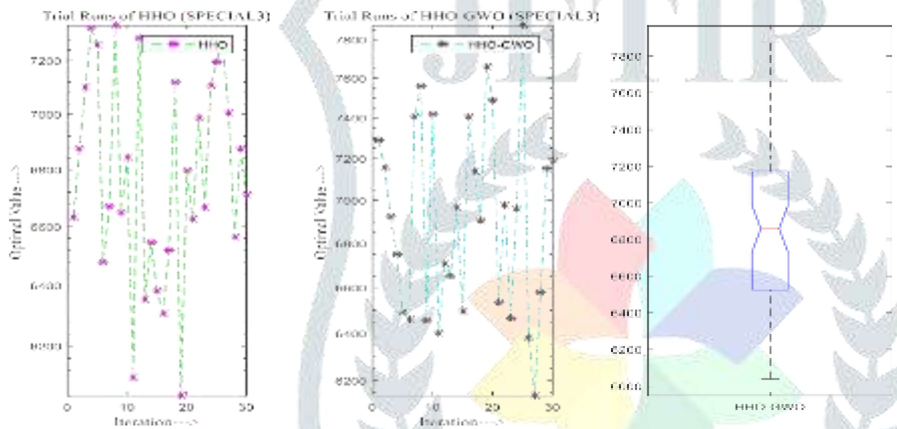


Fig.3 (c). Trail run of multidisciplinary engineering design problem (SPECIAL3)

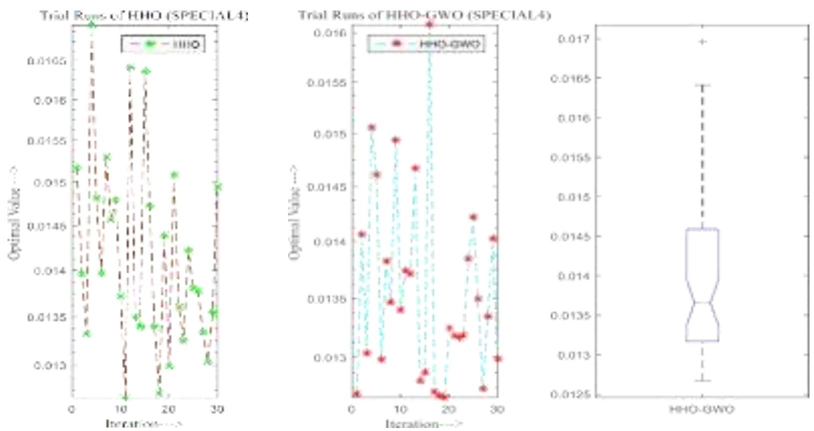


Fig.3(d). Trail run of multidisciplinary engineering design problems (SPECIAL4)

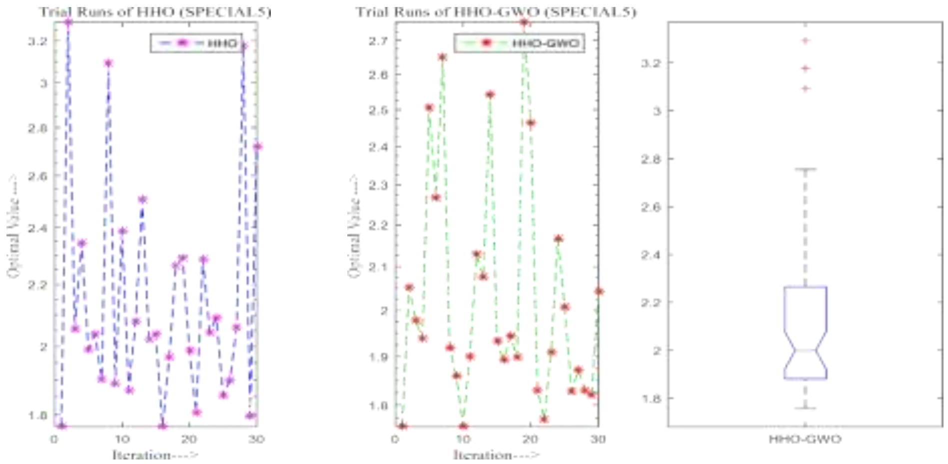


Fig.3 (e). Trail run of multidisciplinary engineering design problem (SPECIAL5)

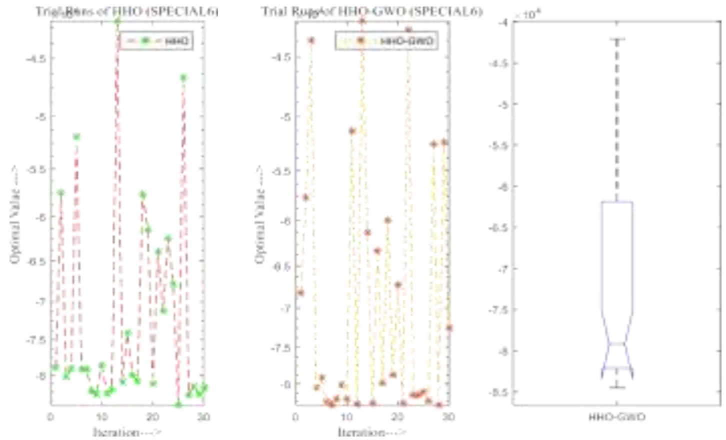


Fig.3 (f). Trail run of multidisciplinary engineering design problems (SPECIAL6)

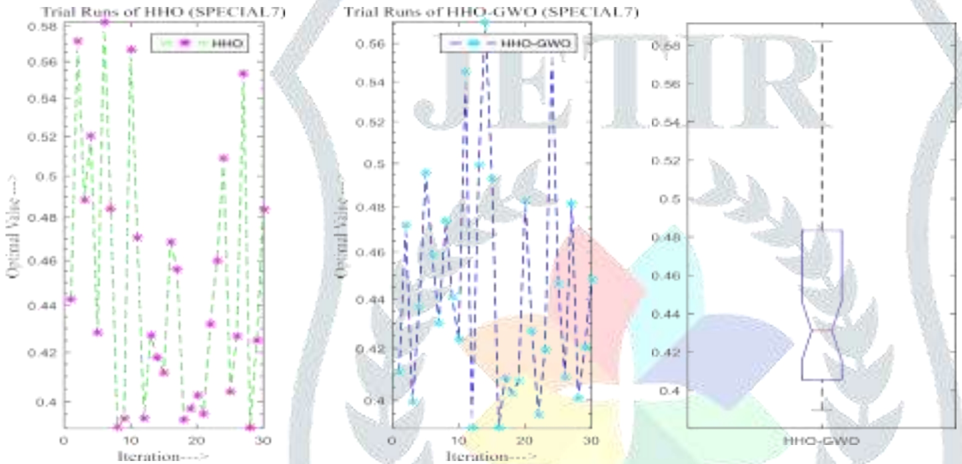


Fig.3 (g). Trail run of multidisciplinary engineering design problem (SPECIAL7)

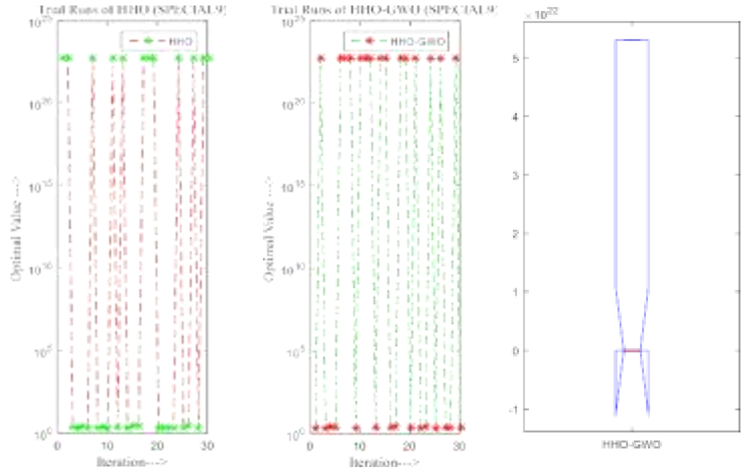


Fig.3 (h). Trail run of multidisciplinary engineering design problems (SPECIAL8)

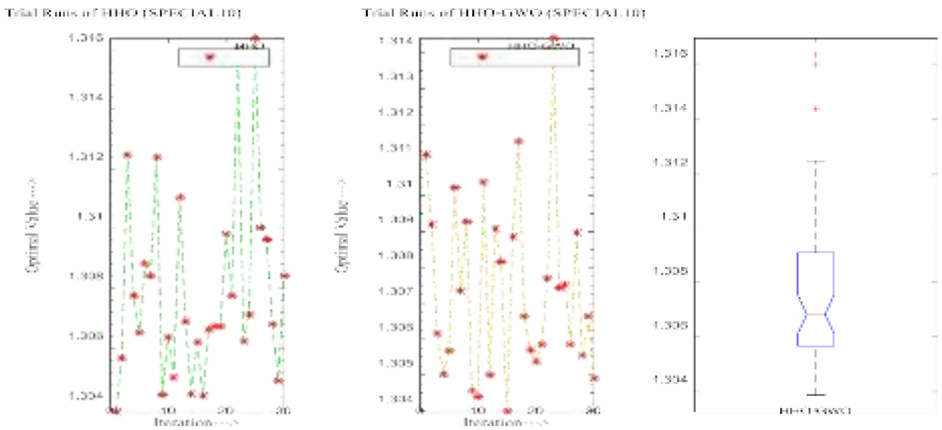


Fig.3 (i). Trail run of multidisciplinary engineering design problem (SPECIAL9)

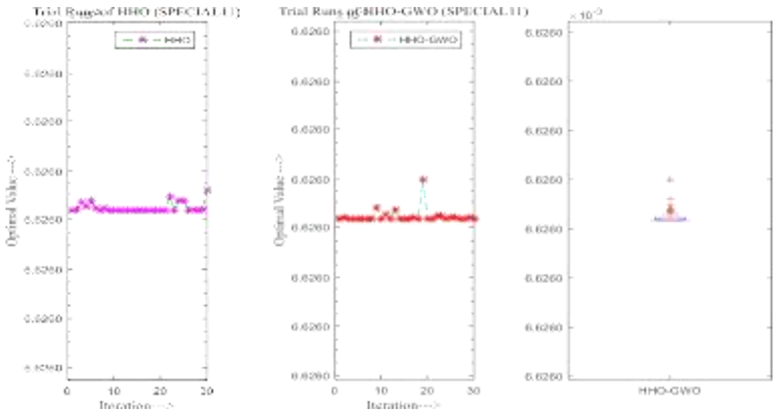


Fig.3(j). Trail run of multidisciplinary engineering design problems (SPECIAL10)

REFERRENCE

[1] R. Abbassi, A. Abbassi, A. Asghar, and S. Mirjalili, "An efficient salp swarm-inspired algorithm for parameters identification of photovoltaic cell models," *Energy Convers. Manag.*, vol. 179, no. August 2018, pp. 362–372, 2019.
[2] H. Faris, A. M. Al-Zoubi, A. A. Heidari, I. Aljarah, M. Mafarja, M. A. Hassonah, and H. Fujita, "An intelligent system for spam detection and identification of the most relevant features based on evolutionary Random Weight Networks," *Inf. Fusion*, vol. 48, pp. 67–83, 2019.
[3] J. F. McCarthy, "Block-conjugate-gradient method," *Phys. Rev. D*, vol. 40, no. 6, pp. 2149–2152, 1989.
[4] G. Wu, "Across neighborhood search for numerical optimization," *Inf. Sci. (Ny).*, vol. 329, no. 61563016, pp. 597–618, 2016.
[5] G. Wu, W. Pedrycz, P. N. Suganthan, and R. Mallipeddi, "A variable reduction strategy for evolutionary algorithms handling equality constraints," *Appl. Soft Comput. J.*, vol. 37, pp. 774–786, 2015.
[6] A. A. Heidari, R. Ali Abbaspour, and A. Rezaee Jordehi, "An efficient chaotic water cycle algorithm for optimization tasks," *Neural Comput. Appl.*, vol. 28, no. 1, pp. 57–85, 2017.
[7] M. Mafarja, I. Aljarah, A. A. Heidari, A. I. Hammouri, H. Faris, A. M. Al-Zoubi, and S. Mirjalili, "Evolutionary Population Dynamics and Grasshopper Optimization approaches for feature selection problems," *Knowledge-Based Syst.*, vol. 145, pp. 25–45, 2018.
[8] D. H. Wolpert and W. G. Macready, "No Free Lunch Theorems for Optimization 1 Introduction," *IEEE Trans. Evol. Comput.*, vol. 1, no. 1, pp. 67–82, 1997.
[9] A. Kaveh and V. R. Mahdavi, "Colliding bodies optimization: Extensions and applications," *Colliding Bodies Optim. Extensions Appl.*, pp. 1–284, 2015.
[10] H. C. Kuo and C. H. Lin, "Cultural evolution algorithm for global optimizations and its applications," *J. Appl. Res. Technol.*, vol. 11, no. 4, pp. 510–522, 2013.
[11] S. Mirjalili, "Dragonfly algorithm: a new meta-heuristic optimization technique for solving single-objective, discrete, and multi-objective problems," *Neural Comput. Appl.*, vol. 27, no. 4, pp. 1053–1073, 2016.
[12] W. L. Snyder, H. D. Powell, and J. C. Rayburn, "Dynamic programming approach to unit commitment," *IEEE Trans. Power Syst.*, vol. 2, pp. 339–347, 1987.
[13] N. Ghorbani and E. Babaei, "Exchange market algorithm," *Appl. Soft Comput. J.*, vol. 19, pp. 177–187, 2014.
[14] G. G. Wang, S. Deb, and L. D. S. Coelho, "Elephant Herding Optimization," *Proc. - 2015 3rd Int. Symp. Comput. Bus. Intell. ISCBI 2015*, pp. 1–5, 2016.
[15] G. G. Wang, S. Deb, and L. D. S. Coelho, "Earthworm optimization algorithm: a bio-inspired metaheuristic algorithm for global optimization problems," *Int. J. Bio-Inspired Comput.*, vol. 1, no. 1, p. 1, 2015.
[16] H. Abedinpourshotorban, S. Mariyam Shamsuddin, Z. Beheshti, and D. N. A. Jawawi, "Electromagnetic field optimization: A physics-inspired metaheuristic optimization algorithm," *Swarm Evol. Comput.*, vol. 26, pp. 8–22, 2016.
[17] M. Ghaemi and M. R. Feizi-Derakhshi, "Forest optimization algorithm," *Expert Syst. Appl.*, vol. 41, no. 15, pp. 6676–6687, 2014.
[18] X. S. Yang, "Firefly algorithm," *Eng. Optim. pp*, vol. 221, 2010.
[19] E. Rashedi, H. Nezamabadi-Pour, and S. Saryazdi, "GSA: a gravitational search algorithm," *Inf Sci*, vol. 179, p. 2232, 2009.
[20] Y. X-s., "Flower pollination algorithm for global optimization," in *Unconventional computation and natural computation*, ; p. 240-9: Springer, 2012.
[21] C. Dai, W. Chen, L. Ran, Y. Zhang, and Y. Du, "Human Group Optimizer with Local Search," pp. 310–320, 2011.
[22] Y. Tan, Y. Tan, and Y. Zhu, "Fireworks Algorithm for Optimization Fireworks Algorithm for Optimization," no. December, pp. 355–364, 2015.
[23] S. Saremi, S. Mirjalili, and A. Lewis, "Grasshopper Optimisation Algorithm: Theory and application," *Adv. Eng. Softw.*, vol. 105, pp. 30–47, 2017.
[24] S. Mirjalili, S. M. Mirjalili, and A. Lewis, "Grey Wolf Optimizer," *Adv. Eng. Softw.*, vol. 69, pp. 46–61, 2014.
[25] S. A. Kazarlis, "A genetic algorithm solution to the unit commitment problem, IEEE Transactions on Power Systems, pp. 83 - 92," 1996.
[26] H. Shareef, A. A. Ibrahim, and A. H. Mutlag, "Lightning search algorithm," *Appl. Soft Comput. J.*, 2015.
[27] M. Reza Norouzi, A. Ahmadi, A. Esmaeel Nezhad, and A. Ghaedi, "Mixed integer programming of multi-objective security-constrained hydro/thermal unit commitment," *Renew. Sustain. Energy Rev.*, vol. 29, pp. 911–923, 2014.
[28] S. Karimkashi, S. Member, and A. A. Kishk, "Invasive Weed Optimization and its Features in Electromagnetics," vol. 58, no. 4, pp. 1269–1278, 2010.
[29] A. H. Gandomi and A. H. Alavi, "Krill herd: A new bio-inspired optimization algorithm," *Commun. Nonlinear Sci. Numer. Simul.*, vol. 17, no. 12, pp. 4831–4845, 2012.
[30] E. Atashpaz-Gargari and C. Lucas, "Imperialist competitive algorithm: An algorithm for optimization inspired by imperialistic competition," *2007 IEEE Congr. Evol. Comput. CEC 2007*, pp. 4661–4667, 2007.
[31] A. H. Kashan, "League Championship Algorithm (LCA): An algorithm for global optimization inspired by sport championships," *Appl. Soft Comput. J.*, vol. 16, pp. 171–200, 2014.
[32] A. H. Gandomi, "Interior search algorithm (ISA): A novel approach for global optimization," *ISA Trans.*, vol. 53, no. 4, pp. 1168–1183, 2014.
[33] G. G. Wang, S. Deb, and Z. Cui, "Monarch butterfly optimization," *Neural Comput. Appl.*, 2015.
[34] A. Sadollah, A. Bahreininejad, H. Eskandar, and M. Hamdi, "Mine blast algorithm: A new population based algorithm for solving constrained engineering optimization problems," *Appl. Soft Comput. J.*, 2012.

[35] S. Mirjalili, “SCA: A Sine Cosine Algorithm for solving optimization problems,” *Knowledge-Based Syst.*, vol. 96, pp. 120–133, 2016.
[36] J. Kennedy and (1995) Eberhart R. C., “Particle Swarm Optimization,” in *Proceedings of the IEEE International Conference on Neural Networks*, pp. 1942–1948.
[37] A. Husseinzadeh Kashan, “A new metaheuristic for optimization: Optics inspired optimization (OIO),” *Comput. Oper. Res.*, vol. 55, pp. 99–125, 2014.
[38] S. Kirkpatrick, C. D. Gelatt, and M. P. Vecchi, “Optimization by simulated annealing.,” *Science*, vol. 220, no. 4598, pp. 671–80, May 1983.
[39] F. Merrikh-Bayat, “The runner-root algorithm: A metaheuristic for solving unimodal and multimodal optimization problems inspired by runners and roots of plants in nature,” *Appl. Soft Comput. J.*, vol. 33, pp. 292–303, 2015.
[40] H. Salimi, “Stochastic Fractal Search: A powerful metaheuristic algorithm,” *Knowledge-Based Syst.*, vol. 75, pp. 1–18, 2015.
[41] M. S. Gonçalves, R. H. Lopez, L. Fleck, and F. Miguel, “Search group algorithm : A new metaheuristic method for the optimization of truss structures,” vol. 153, pp. 165–184, 2015.
[42] J. M. Anita and I. J. Raglend, “Shuffled Frog Leaping Algorithm,” *Int. Conf. Comput. Electron. Electr. Technol.*, pp. 109–115, 2012.
[43] C. Dai, Y. Zhu, W. Chen, and C. Engineering, “Seeker Optimization Algorithm,” pp. 167–176, 2007.
[44] M. Y. Cheng and D. Prayogo, “Symbiotic Organisms Search: A new metaheuristic optimization algorithm,” *Comput. Struct.*, vol. 139, pp. 98–112, 2014.
[45] F. Glover, “Tabu search—Part I,” *ORSA J. Comput.*, vol. 1, p. 190, 1989.
[46] S. Mirjalili, A. H. Gandomi, S. Z. Mirjalili, S. Saremi, H. Faris, and S. M. Mirjalili, “Salp Swarm Algorithm: A bio-inspired optimizer for engineering design problems,” *Adv. Eng. Softw.*, vol. 114, pp. 163–191, 2017.
[47] M. D. Li, H. Zhao, X. W. Weng, and T. Han, “Advances in Engineering Software A novel nature-inspired algorithm for optimization : Virus colony search,” *Adv. Eng. Softw.*, vol. 92, pp. 65–88, 2016.
[48] Y. J. Zheng, “Water wave optimization: A new nature-inspired metaheuristic,” *Comput. Oper. Res.*, vol. 55, pp. 1–11, 2015.
[49] S. Mirjalili and A. Lewis, “The Whale Optimization Algorithm,” *Adv. Eng. Softw.*, vol. 95, pp. 51–67, 2016.
[50] H. Eskandar, A. Sadollah, A. Bahreininejad, and M. Hamdi, “Water cycle algorithm – A novel metaheuristic optimization method for solving constrained engineering optimization problems,” *Comput. Struct.*, vol. 110–111, pp. 151–166, 2012.
[51] A. Baykasoğlu and Ş. Akpinar, “Weighted Superposition Attraction (WSA): A swarm intelligence algorithm for optimization problems – Part 1: Unconstrained optimization,” *Appl. Soft Comput. J.*, vol. 56, pp. 520–540, 2017.
[52] S. C. Satapathy, A. Naik, and K. Parvathi, “A teaching learning based optimization based on orthogonal design for solving global optimization problems,” pp. 1–12, 2013.
[53] Z. Bayraktar, M. Komurcu, and D. H. Werner, “Wind Driven Optimization (WDO): A Novel Nature-Inspired Optimization Algorithm and its Application to Electromagnetics (1),” no. 1, pp. 0–3, 2010.
[54] A. A. Heidari, S. Mirjalili, H. Faris, I. Aljarah, M. Mafarja, and H. Chen, “Harris hawks optimization: Algorithm and applications,” *Futur. Gener. Comput. Syst.*, 2019.
[55] X.-S. Yang and S. Deb, “Cuckoo Search via Levey Flights,” *2009 World Congr. Nat. Biol. Inspired Comput. (NaBIC 2009)*, pp. 210–214, 2009.
[56] S. Mohanty, B. Subudhi, and P. K. Ray, “A New MPPT Design Using Grey Wolf Optimization Technique for Photovoltaic System Under Partial Shading Conditions,” *IEEE Trans. Sustain. Energy*, vol. 7, no. 1, pp. 181–188, Jan. 2016.
[57] L. C. Cagnina, S. C. Esquivel, U. Nacional, D. S. Luis, S. Luis, and C. A. C. Coello, “Solving Engineering Optimization Problems with the Simple Constrained Particle Swarm Optimizer 1 Introduction 2 Literature review 3 Our proposed approach : SiC-PSO,” vol. 32, pp. 319–326, 2008.
[58] H. John, *Holland, adaptation in natural and artificial systems*. Cambridge: MIT Press, 1992.
[59] R. Storn and K. Price, “Differential Evolution – A Simple and Efficient Heuristic for global Optimization over Continuous Spaces,” *J. Glob. Optim.*, vol. 11, no. 4, pp. 341–359, 1997.
[60] M. Dorigo, M. Birattari, and T. Stutzle, “Ant colony optimization,” *IEEE Comput. Intell. Mag.*, vol. 1, no. 4, pp. 28–39, 2006.
[61] D. Murtaza and S. Yamashiro, “Unit Commitment Scheduling by Lagrange Relaxation Method Taking into Account Transmission Losses, Electrical Engineering in Japan,” *Vol.*, vol. 152, no. 4, pp. 27–33, 2005.
[62] A. I. Cohen and M. Yoshimura, “A Branch-and-Bound Algorithm for Unit Commitment,” *IEEE Trans. Power Appar. Syst.*, vol. 102, no. 2, pp. 444–451, 1983.
[63] X. Yao, Y. Liu, and G. Lin, “Evolutionary programming made faster,” *IEEE Trans Evol Comput*, vol. 3, p. 82, 1999.
[64] V. Kumar and K. S. K. Bath, “Hybrid HS – random search algorithm considering ensemble and pitch violation for unit commitment problem,” *Neural Comput. Appl.*, 2015.
[65] M. Mahdavi, M. Fesanghary, and E. Damangir, “An improved harmony search algorithm for solving optimization problems,” vol. 188, pp. 1567–1579, 2007.
[66] S. Gupta and K. Deep, “A novel Random Walk Grey Wolf Optimizer,” *Swarm Evol. Comput.*, Jan. 2018.
[67] D. Wang, Y. Zhou, and S. Jiang, *A Simplex Method-Based Salp Swarm Algorithm for Numerical and Engineering Optimization*, vol. 2. Springer International Publishing, 2018.
[68] E. A. Jasmin, G. E. College, and G. E. College, “A FUNCTION APPROXIMATION APPROACH TO REINFORCEMENT LEARNING FOR SOLVING UNIT COMMITMENT PROBLEM WITH PHOTO VOLTAIC SOURCES.”
[69] S. Mirjalili, “The ant lion optimizer,” *Adv. Eng. Softw.*, vol. 83, pp. 80–98, 2015.
[70] Y. X-s and S. Deb, “Cuckoo search via Levy flights,” *World Congr. Nat. Biol. inspired Comput.*, vol. 2009, 2009.
[71] H. CHICKERMANE and H. C. GEA, “Structural Optimization Using a New Local Approximation Method,” *Int. J. Numer. Methods Eng.*, vol. 39, no. 5, pp. 829–846, 2002.

[72] K. Deb, "A Combined Genetic Adaptive Search (GeneAS) for Engineering Design," vol. 26, pp. 30–45, 1996.
[73] W. Zhao, Z. Zhang, and L. Wang, "Engineering Applications of Artificial Intelligence Manta ray foraging optimization : An effective bio-inspired optimizer for engineering applications," *Eng. Appl. Artif. Intell.*, vol. 87, no. October 2019, p. 103300, 2020.
[74] B. Niu and L. Li, "A Novel PSO-DE-Based Hybrid Algorithm for Global," pp. 156–163, 2008.
[75] A. Sadollah, A. Bahreininejad, H. Eskandar, and M. Hamdi, "Mine blast algorithm : A new population based algorithm for solving constrained engineering optimization problems," *Appl. Soft Comput. J.*, vol. 13, no. 5, pp. 2592–2612, 2013.