A Hybridized Version of Dragonfly Algorithm

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Abstract:
The proposed algorithm is a hybridized and improved version of Dragonfly Algorithm. Algorithm will be tested by using hybridization technique with Grey Wolf Optimizer (GWO) and Dragonfly Algorithm (DA), aims to enhance accurate solution. Here, the 23 benchmark functions will be applied and tested to compare the hybridized algorithm with existing Dragonfly Algorithm. After testing, better results will be found in hybridized algorithm using functions.

Keywords:
Algorithm, Benchmark, Optimization, Hybridization, DA-GWO.

I.Introduction

The main inspiration of the Dragonfly Algorithm (DA) algorithm originates from static and dynamic swarming behaviours. These two swarming behaviours were very similar to the two main phases of optimization using meta-heuristics: exploration and exploitation. Dragonflies create sub swarms and fly over different areas in a static swarm, which was the main objective of the exploration phase in the static swarm. However, dragonflies fly in bigger swarms and along one direction, which was favourable.[6]

The proposed algorithm tried to improve these outcomes. The algorithm was tested by using hybridization technique with Grey Wolf Optimizer (GWO) and Dragonfly Algorithm (DA), aimed to enhance accurate solution. Here, among many techniques of improving the DA algorithm's outcomes, the most promising hybridization technique was used for obtaining better results. Here, the 23 benchmark functions were applied and tested to compare the hybridized algorithm with existing Dragonfly Algorithm. After testing, better results were found in 13 functions. The hybridization technique proved the most beneficial.

2. Proposed Optimization Algorithm

The main inspiration of the Dragonfly Algorithm (DA) algorithm originates from static and dynamic swarming behaviours. The agenda of choosing this Dragonfly algorithm was its results were found to be very impressive. DA was effective in both exploration and exploitation through behaviors like alignment, separation, attraction to food source, cohesion and repulsion from enemy. However, DA faces the problem of premature convergence and local optima trapping. To overcome this problem, the hybridization of DA with GWO seeks to combine strong exploration ability and robust exploitation mechanism.

The nature inspired algorithms were classified into four main categories like Physics-based, Human behavior-based, Evolution-based and Swarm based. These algorithms use Physics-based techniques, Human-related techniques, Evolutionary techniques and Swarm intelligence techniques respectively.

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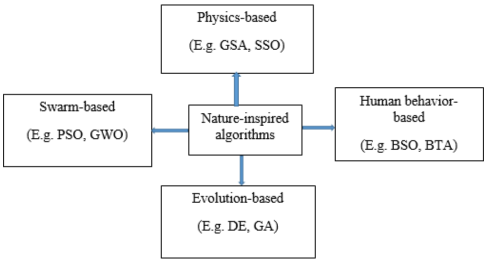
2.1. CLASSIFICATION OF ALGORITHMS



Sr. No.	Algorithm Name	Author Name	Year
1.	Gravitational Search Algorithm	Esmaeil Rashedi et al	2009
2.	Seagull Optimization Algorithm	Seyedali Mirjalili et al	2019
3.	Brain Storm Optimization	She Cheng et al	2013
4.	Butterfly Optimization Algorithm	Sarthak S. Majumder et al	2019
5.	Differential Evolution	Rainer Storn et al	1997
6.	Genetic Algorithm	John Holland	1975
7.	Particle Swarm Optimization	James Kennedy et al	1995
8.	Grey Wolf Optimizer	Seyedali Mirjalili et al	2014

2.2. ALGORITHMS & AUTHORS

Table 1: Algorithms and Authors [6]

2.3. STEPS

1. Obtained optimal value for original algorithm (DA) using 23 benchmark functions.
2. Hybridized original algorithm (DA) with another algorithm (GWO) for obtaining best optimal solution.
3. Iterations were carried out for each function.
4. Obtained optimal value for another algorithm (GWO) using 23 benchmark functions.
5. Compared the best optimal value of the objective function found by DA and the value after hybridization with the GWO.
6. Results were found to be best in 13 benchmark functions.

Functions & Equation

Functions	Dimensions	Range	f_{min}
$F_1(S) = \sum_{m=1}^{z} S_m^2$	(10,30,50,100)	[-100 , 100]	0
$F_2(S) = \sum_{m=1}^{z} \lvert S_m\rvert + \prod_{m=1}^{z} \lvert S_m\rvert$	(10,30,50,100)	[-10 ,10]	0
$F_3(S) = \sum_{m=1}^{z} (\sum_{n-1}^{m} S_n)^2$	(10,30,50,100)	[-100 , 100]	0
$F_4(S) = max_m\{\lvert S_m\rvert, 1 \le m \le z\}$	(10,30,50,100)	[-100 , 100]	0
$F_8(S) = \sum_{m=1}^{z} -S_m sin(\sqrt{\lvert S_m\rvert})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z} [S_m^2 - 10cos(2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp(-0.2\sqrt{(\frac{1}{z}\sum_{m=1}^{z} S_m^2)}) - exp(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(10,30,50,100)	[-32,32]	0
$F_{11}(S) = 1 + \sum_{m=1}^{z} \frac{S_m^2}{4000} - \Pi_{m=1}^{z} cos\frac{S_m}{\sqrt{m}}$	(10,30,50,100)	[-600, 600]	0
$F_{12}(S) = \frac{\pi}{z}\{10 sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_{m+1}}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(10,30,50,100)	[-50,50]	0
$F_{13}(S) = 0.1\{sin^2(3\pi S_m) + \sum_{m=1}^{z}(S_m - 1)^2[1 + sin^2(3\pi S_m + 1)] + (x_z - 1)^2[1 + sin^2 2\pi S_z)]$	(10,30,50,100)	[-50,50]	0
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5\frac{1}{n+\sum_{m=1}^{z}(S_m - b_{mn})^6}]^{-1}$	2	[-65.536, 65.536]	1
$F_{15}(S) = \sum_{m=1}^{11}[b_m - \frac{S_1(a_m^2 + a_m S_2)}{a_m^2 + a_m S_3 + S_4}]^2$	4	[-5, 5]	0.00030
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1S_2 - 4S_2^2 + 4S_2^4$	2	[-5, 5]	-1.0316
$F_{17}(S) = (S_2 - \frac{5.1}{4\pi 2}S_1^2 + \frac{5}{\pi}S_1 - 6)^2 + 10(1 - \frac{1}{8\pi})cosS_1 + 10$	2	[-5, 5]	0.398
$F_{18}(S) = [1 + (S_1 + S_2 + 1)^2(19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1S_2 + 3S_2^2)] \times [30 + (2S_1 - 3S_2)^2(18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1S_2 + 27S_2^2)]$	2	[-2,2]	3
$F_{19}(S) = -\sum_{m=1}^{4} d_m exp(-\sum_{n=1}^{3} S_{mn}(S_m - q_{mn})^2)$	3	[1, 3]	-3.32
$F_{20}(S) = -\sum_{m=1}^{4} d_m exp(-\sum_{n=1}^{6} S_{mn}(S_m - q_{mn})^2)$	6	[0, 1]	-3.32
$F_{21}(S) = -\sum_{m=1}^{5}[(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0,10]	-10.1532
$F_{22}(S) = -\sum_{m=1}^{7}[(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.4028
$F_{23}(S) = -\sum_{m=1}^{7}[(S - b_m)(S - b_m)^T + d_m]^{-1}$	4	[0, 10]	-10.5363

Table 2: Standard UM Benchmark functions [6]

3. RESULTS & DISCUSSION

- Function 1:

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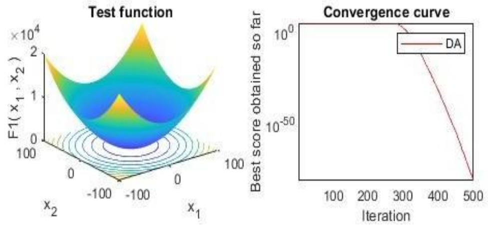
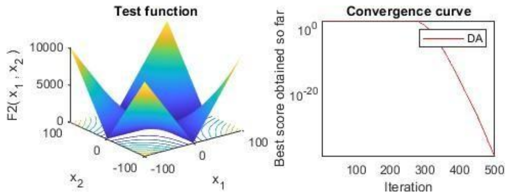


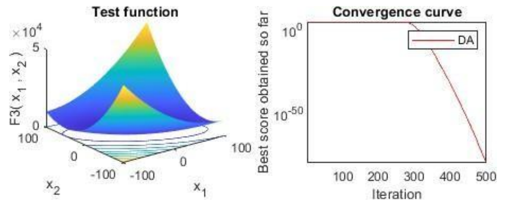
The best optimal value of the objective function found by DA was 0.015355 and the value after hybridization was found to be 4.5664e-81.

- Function 2:



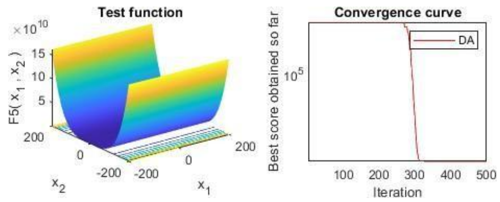
The best optimal value of the objective function found by DA was 1.6312 and the value after hybridization was found to be 4.1255e-40.

- Function 3:



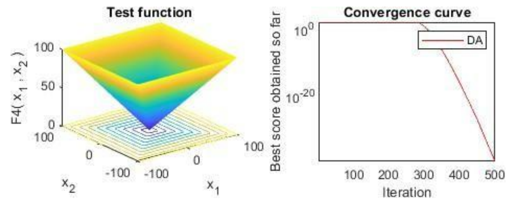
The best optimal value of the objective function found by DA was 6.0779 and the value after hybridization was found to be 3.9544e-80.

- Function 4:



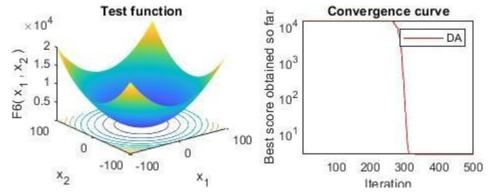
The best optimal value of the objective function found by DA was 1.8058 and the value after hybridization was found to be 2.6001e-40.

- Function 5:



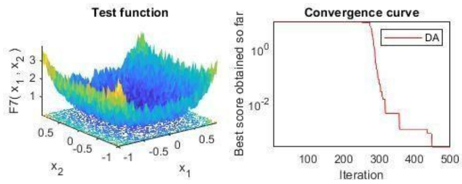
The best optimal value of the objective function found by DA was 11.0962 and the value after hybridization was found to be 9.

- Function 6:



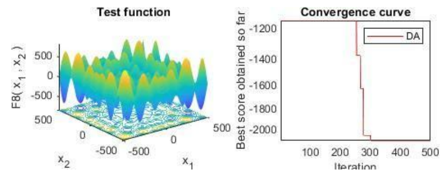
The best optimal value of the objective function found by DA was 5.1366 and the value after hybridization was found to be 2.5.

- Function 7:



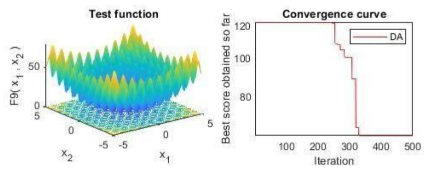
The best optimal value of the objective function found by DA was 0.069909 and the value after hybridization was found to be 0.00027381.

- Function 8:



The best optimal value of the objective function found by DA was -2821.0436 and the value after hybridization was found to be -2124.4057.

- Function 9:



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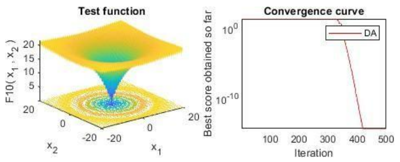
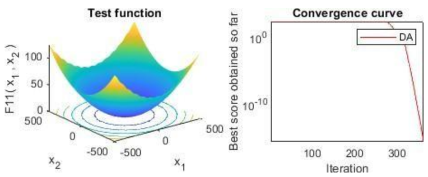
The best optimal value of the objective function found by DA was 10.7444 and the value after hybridization was found to be 63.9908.



- Function 10:

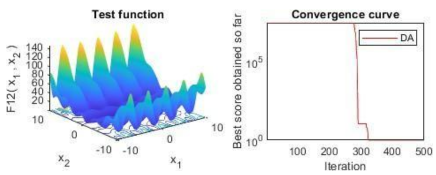
The best optimal value of the objective function found by DA was 4.2143 and the value after hybridization was found to be 3.9968e-15.

- Function 11:



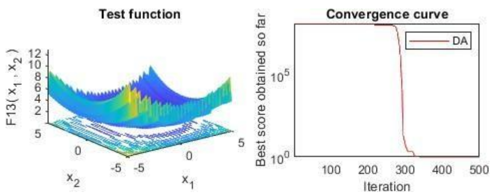
The best optimal value of the objective function found by DA was 0.16839 and the value after hybridization was found to be 0.

- Function 12:



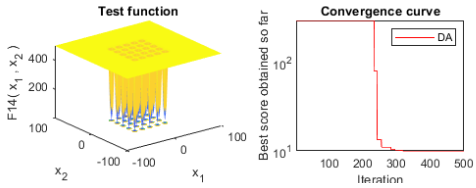
The best optimal value of the objective function found by DA was 1.1485 and the value after hybridization was found to be 0.96446.

- Function 13:



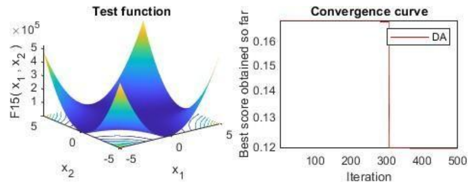
The best optimal value of the objective function found by DA was 0.019557 and the value after hybridization was found to be 1.

- Function 14:



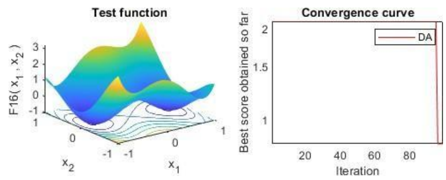
The best optimal value of the objective function found by DA was 0.998 and the value after hybridization was found to be 9.9308.

- Function 15:



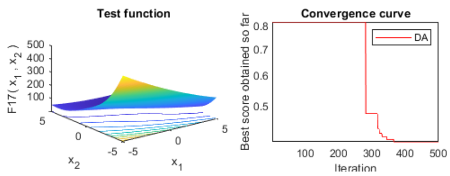
The best optimal value of the objective function found by DA was 0.00054487 and the value after hybridization was found to be 0.11934.

- Function 16:



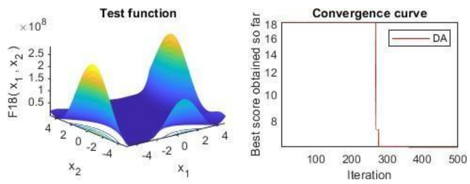
The best optimal value of the objective function found by DA was -1.0316 and the value after hybridization was found to be -1.031.

- Function 17:



The best optimal value of the objective function found by DA was 0.39789 and the value after hybridization was found to be 0.40387.

- Function 18:



The best optimal value of the objective function found by DA was 3 and the value after hybridization was found to be 6.3976.

- Function 19:

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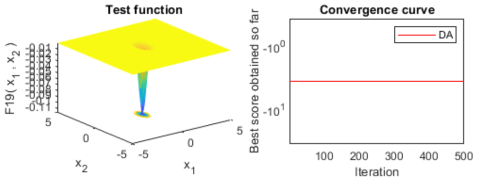
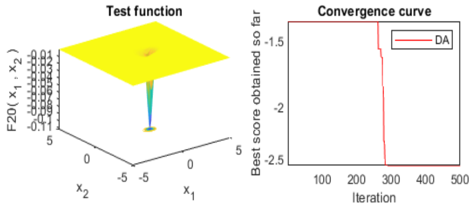
Function No.	Original Algorithm Values	Hybrid Algorithm Values
F1	0.015355	4.5664e-81
F2	1.6312	4.1255e-40
F3	6.0779	3.9544e-80
F4	1.8058	2.6001e-40
F5	11.0962	9
F6	5.1366	2.5
F7	0.069909	0.00027381
F8	-2821.0436	-2124.4057
F9	10.7444	63.9908
F10	4.2143	3.9968e-15
F11	0.16839	0
F12	1.1485	0.96446
F13	0.019557	1
F14	0.998	9.9308
F15	0.00054487	0.11934
F16	-1.0316	-1.031
F17	0.39789	0.40387
F18	3	6.3976
F19	-3.8628	-3.6516
F20	-2.9535	-2.5721
F21	-10.1532	-3.204
F22	-10.4029	-8.778
F23	-10.5364	-5.7215



The best optimal value of the objective function found by DA was -3.8628 and the value after hybridization was found to be -3.6516.

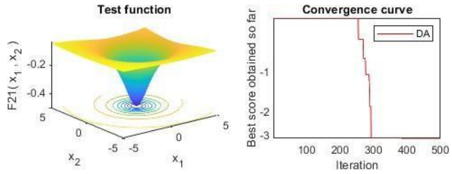
- Function 20:



Algorithm	Exploration	Exploitation	Convergence Speed
DA	High	Moderate	Slow
GWO	Moderate	High	Fast
Hybrid DA-GWO	High	High	Faster

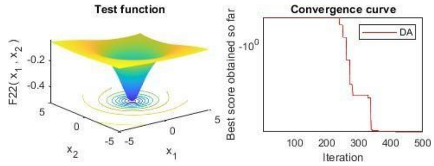
The best optimal value of the objective function found by DA was -2.9535 and the value after hybridization was found to be -2.5721.

- Function 21:



The best optimal value of the objective function found by DA was -10.1532 and the value after hybridization was found to be -3.204.

- Function 22:



The best optimal value of the objective function found by DA was -10.4029 and the value after hybridization was found to be -8.778.

- Function 23:

The best optimal value of the objective function found by DA was -10.5364 and the value after hybridization was found to be -5.7215.

The Table 3 Results & Discussion shows:
The first column shows the function numbers which are the 23 Standard UM Benchmark Functions that are used in both original algorithm (DA) and hybridized algorithm (DA with GWO). The second column shows the values found by original algorithm (DA) by using benchmark functions. The last column shows the values found by hybridized algorithm (DA with GWO) by using benchmark functions.

Table 3: Results & Discussion

4. CONCLUSION

The hybridized algorithm of DA with GWO was tested with 23 benchmark functions and in 13 functions best values were found in functions like F5, F6, F7, F8, F10, F12, F16, F19, F20, F21, F22, F23 and in function F11 the resultant value found was 0 which was best.

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