Optimizing Dragonfly Algorithm using Ant Lion Algorithm for Solving Complex Numerical Optimization Problems

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Abstract:
Optimization algorithms play a key role in solving complex computational problems across various disciplines. In this paper, we introduce a new hybrid model that integrates the Dragonfly Algorithm (DA) and the Ant Lion Optimizer (ALO) for optimization performance enhancement. The new hybrid model integrates the exploration ability of DA and the exploitation ability of ALO with the expectation of better convergence and optimal solutions. We applied the model to optimize 23 benchmarking functions, and the results indicate that the hybrid model is better than the traditional algorithm approach in generating smaller errors and scores in the area of optimization. The study indicates that the proposed hybrid model offers a feasible solution to solving high-dimensional optimization problems.

Keywords:
Dragonfly Algorithm (DA), Hybridization, Benchmark, Exploration, Exploitation

Introduction:-
Optimization is a basic mechanism for addressing complicated problems in the areas of science, engineering, and artificial intelligence. Although metaheuristic algorithms have proven highly effective in dealing with vast search spaces, individual algorithms tend to experience problems with premature convergence or poor exploitation. This paper presents a hybrid methodology that blends the strengths of the Dragonfly Algorithm (DA)[16] and the Ant Lion Optimizer (ALO)[17] to facilitate a more uniformly distributed and effective search process. By utilizing the exploratory ability of DA and the enhanced exploitation capabilities of ALO, our proposed model optimizes both convergence rate and solution precision. The hybrid algorithm was evaluated on 23 benchmark functions, and the results were always superior to those of the individual DA and ALO, hence indicating an enhancement in optimization efficiency and stability. These findings imply that hybrid metaheuristic methodologies may be an effective substitute for addressing complicated optimization problems.

Literature Review:-

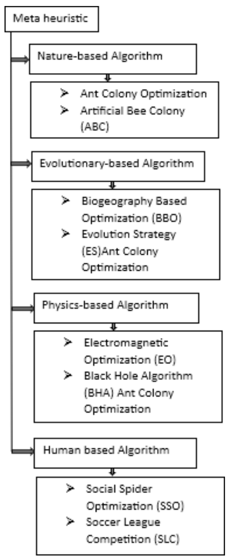
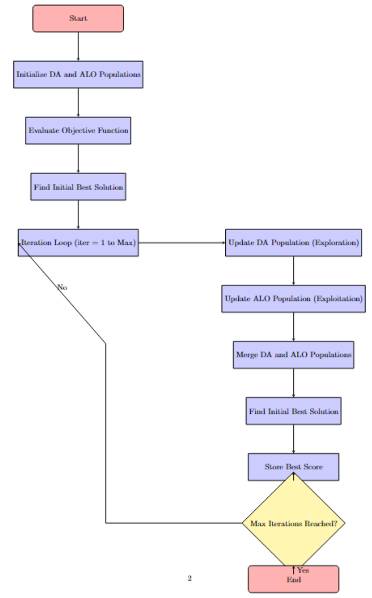


Fig1: Classification of Algorithms

DOI: https://doi.org/10.5281/zenodo.15619533

Tabel 1: Publication Details
Flowchart:- [16][17]



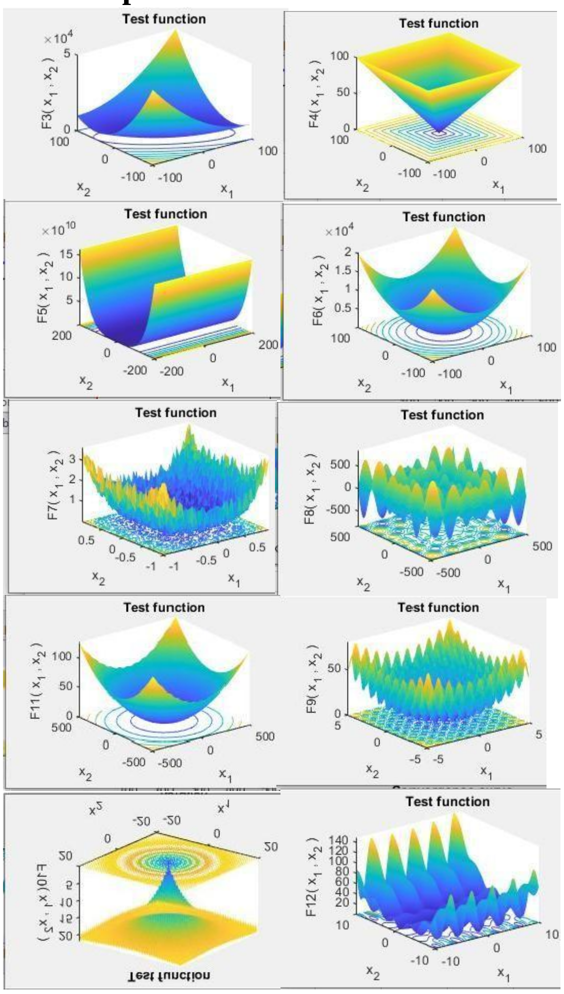
Benchmark Function:-

Table 2: Standard UM benchmark functions

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
$F_5(S) = \sum_{m=1}^{z-1} [100(S_{m+1}-S_m^2)^2 + (S_m - 1)^2]$	(10,30,50,100)	[-38 , 38]	0
$F_6(S) = \sum_{m=1}^{z} ([S_m + 0.5])^2$	(10,30,50,100)	[-100 , 100]	0
$F_7(S) = \sum_{m=1}^{z} mS_m^4 + random\ [0,1]$	(10,30,50,100)	[-1.28, 1.28]	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
$F_{10}(S) = -20exp\left(-0.2\sqrt{\left(\frac{1}{z}\sum_{m=1}^{z} S_m^2\right)}\right) - exp\left(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m)\right) + 20 + d$	(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
$F_{12}(S) = \frac{\pi}{z}\left\{10 sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\right\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_m+1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(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
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1 S_2 - 4S_2^2 + 4S_2^4$	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

Sr.no	Algorithm	Author Name
1	Ant Colony Optimization (ACO)	Dorigo & Gambardella Et al. (1997)
2	Artificial Bee Colony (ABC)	Karaboga Et al. (2005)
3	Biogeography-Based Optimization (BBO)	Simon Et al. (2008)
4	Evolution Strategy (ES)	Rechenberg Et al. (1973)
5	Electromagnetic Optimization (EO)	Birbil & Fang Et al. (2003)
6	Black Hole Algorithm (BHA)	Hatamlou Et al. (2013)
7	Social Spider Optimization (SSO)	Cuevas, Cienfuegos, Zaldívar Et al. (2013)
8	Soccer League Competition (SLC)	Moosavian & Gholipour Et al.(2015)

Search Space:-



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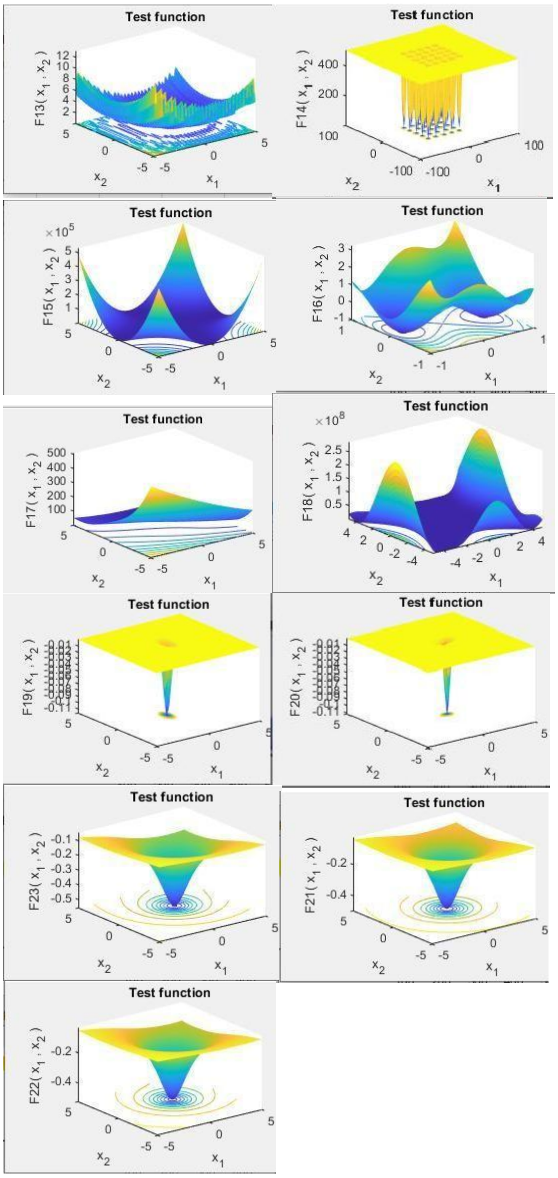

Results & Discussions:-

Function	Original Algorithm Value	Hybrid Algorithm Value
F1	0.010844	0.17057
F2	0.41577	0.17384
F3	16.3224	3.8555
F4	5.0088	0.80819
F5	9.4514	9.5206
F6	3.8895	0.18766
F7	0.039007	0.015949
F8	-2491.2016	-3221.5408
F9	9.0597	8.0225
F10	3.9508	1.7239
F11	0.33914	0.72508
F12	0.65975	0.54286
F13	0.21484	0.20924
F14	0.998	0.998
F15	0.0016554	0.00062231
F16	-1.0316	0
F17	0.39789	0.39789
F18	3	3
F19	-3.8628	-3.8628
F20	-3.322	3.1801
F21	-10.1532	10.1526
F22	-10.4029	10.4027
F23	-2.8066	10.5334

From above table, conclude that hybrid DA-ALO giving more relevant and optimize value as compared to original algorithm. Some values are remained unchanged and some are showing fluctuation in values. Results of hybrid DA-ALO are impressive. Function such as F2, F3, F4, F6, F7, F8, F9, F10, F12, F13, F15 and F23 shows the enhancement in value.

Conclusion:-

This research improves the performance of DragonFly Algorithm using hybridization approach of (DA+ALO), The hybrid algorithm being tested on 23 benchmark functions out of which 12 functions provide a best optimal value compared to the original Algorithm which demonstrating an improvement in DragonFly Algorithm performance.

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