The Improved Hybridized Version of Dragonfly Algorithm with PSO

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Abstract
The paper proposes a novel hybrid optimization algorithm, DA-PSO, which integrates a modified Dragonfly Algorithm (DA) with Particle Swarm Optimization (PSO) to enhance solution accuracy and convergence speed. To evaluate DA-PSO's performance, extensive experiments were conducted on a comprehensive suite of 23(twenty-three) established benchmark functions, encompassing unimodal, multimodal, separable, and non-separable problems. The Proposed hybrid approach mitigates the limitations of individual algorithms, combining the exploration capabilities of DA with the exploitation Capability of PSO. DA-PSO exhibited a notable enhancement in solution quality compared to the original DA and PSO algorithms, demonstrating the effectiveness of the hybrid approach. Experimental results and statistical analysis confirm the effectiveness of the proposed hybrid algorithm in addressing complex optimization problems.

Keywords—Benchmark functions, Optimization, Algorithm, Hybridization, DA-PSO.

1. Introduction

Inspired by the dynamic swarming characteristic of dragonflies, the Dragonfly Algorithm (DA) has shown promise in the exploration of intricate search areas. However, DA's capacity to accurately identify global optima may be limited by its susceptibility to premature convergence[1]. On the other hand, Particle Swarm Optimization (PSO), which is well-known for its effective social learning exploitation skills, could have trouble with exploration, especially when dealing with high-dimensional or multimodal challenges[8]. In light of these inherent drawbacks, this work suggests DA-PSO, a novel hybrid algorithm that combines the advantages of both DA and PSO in a synergistic way. The goal of DA-PSO is to more effectively balance these two essential optimization factors by fusing PSO's sophisticated exploitation tactics with DA's strong exploration capabilities[1]. The goal of this hybridization is to increase the accuracy of the solutions, speed up convergence, and increase the overall resilience of the optimization process. Using several benchmark function evaluations, the performance of DA-PSO is fully assessed, showing that it outperforms the independent DA and PSO algorithms and is capable of handling challenging optimization problems across a variety of domains.

2. Proposed Optimization Algorithm

The Dragonfly Algorithm (DA) is inspired by the static and dynamic swarming behaviours of dragonflies. The Algorithm is chosen due to its impressive performance in optimization tasks. DA effectively balances exploration and exploitation through key behaviours such as alignment, separation, cohesion, attraction to food sources, and repulsion from predators [1][8][9]. However, it struggles with premature convergence and getting trapped in local optima. To address this issue, hybridizing DA with Particle Swarm Optimization (PSO) integrates DA strong exploration ability with PSO robust exploitation mechanism, enhancing overall performance.

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The nature inspired algorithms are of four main types which are Physics-based, Human behaviour-based, Evolution-based and Swarm based.

2.1. Algorithm Classification

Nature-based algorithms are broadly classified into four major types: Human-based, Evolution-based, Swarm-based, and Physics-based.

I.**Human-based algorithm:** Human-based algorithms emulate human intelligence, learning processes, and decision-making strategies.

- Teaching-Learning-Based Optimization (TLBO)
- Group Search Optimization (GSO)

ii.Evolutionary-basedalgorithm:
Evolutionary algorithms draw inspiration from Darwinian evolution, where the strongest individuals endure and evolve over

Table-1: Algorithm, Authors & Year of publishing

- Genetic Algorithm (GA)
- Differential Evolution (DE)

iiiSwarm-based algorithms: Swarm-based algorithms are modelled after the cooperative behaviour of social creatures like ants and bees, illustrating how local interactions can result in effective global problem-solving.

- Particle Swarm Optimization (PSO)

ivPhysics-based algorithm: Physics-based algorithms utilize principles from natural forces such as gravity, electromagnetism, and thermodynamics, applying mathematical frameworks to represent these physical

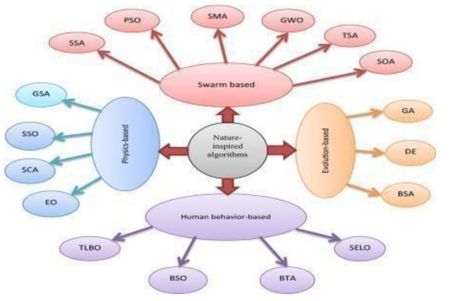

Fig-1. Nature-inspired algorithm classification

Figure1 obtained from: [https://www.researchgate.net/figure/Classification-of nature-inspired-algorithms_fig1_355084180](https://www.researchgate.net/figure/Classification-of-nature-inspired-algorithms_fig1_355084180)

2.2. Algorithms and Authors

The Table-1 represents nature-inspired optimization algorithms developed by various researchers over the years. These algorithms are used in solving complex optimization problems by mimicking natural phenomena, biological behaviors, or physical principles.

Sr. No.	Algorithm Name	Author Name	Year
1.	Sine Cosine Algorithm	Seyedali Mirjalili	2016
2.	Equilibrium Optimizer	Abdollah Asghari Varzaneh et al	2020
3.	Sunflower Evolutionary Optimization Algorithm	Osman K. Erol	2021
4.	Teaching Learning Based Optimization	Rao et al	2011
5.	Differential Evolution	Rainer Storn et al	1997
6.	Backtracking Search Algorithm	P. Civicioglu	2013
7.	Particle Swarm Optimization	James Kennedy et al	1995
8.	Slime Mould Algorithm	Mohammed H. Saremi	2020

2.3. Flowchart

DA-PSO (Dragonfly Algorithm - Particle Swarm Optimization) is a hybrid optimization technique that combines the exploration ability of the Dragonfly Algorithm (DA) with the exploitation ability of Particle Swarm Optimization (PSO). Below is a flowchart and a brief explanation of its process.

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- DA-PSO is effective in solving complex optimization problems due to its adaptive search strategy.
- The dragonfly-inspired movements enhance diversity in the search space, while PSO ensures convergence towards the best solution.
- This hybrid technique has been successfully applied in engineering design, machine learning, and multi-objective optimization tasks.

2.4. Functions and Equations

Table 2: Standard UM Benchmark

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
$F_3(S)=\sum_{m=1}^{z}\left(\sum_{n=1}^{m} S_n\right)^2$	(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
$F_{15}(S)=\sum_{m=1}^{11}[b_m-\frac{S_1(a_m^2+a_mS_2)}{a_m^2+a_mS_3+S_4}]^2$	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
$F_{18}(S)=\left[1+(S_1+S_2+1)^2\left(19-14S_1+3S_1^2-14S_2+6S_1S_2+3S_2^2\right)\right]\times\left[30+(2S_1-3S_2)^2\left(18-32S_1+12S_1^2+48S_2-36S_1S_2+27S_2^2\right)\right]$	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

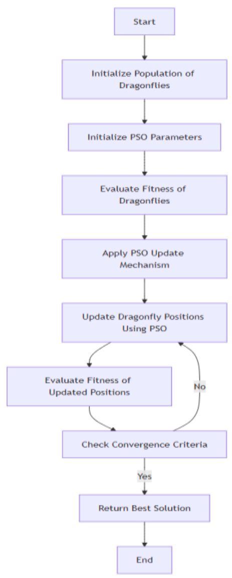

Fig-2. Flowchart of DA-PSO Algorithm [1]

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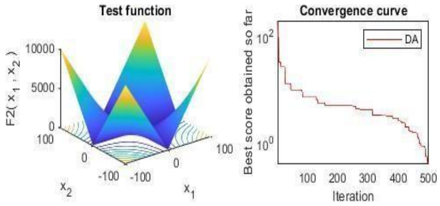
3. Results & Discussion

The DA-PSO algorithm underwent extensive testing on a diverse set of 23 (twenty-three) widely recognized benchmark functions. The results confirm the effectiveness of the proposed hybridization technique. To offer a comprehensive evaluation of DA-PSO's performance across various benchmark functions, the key findings from these tests are summarized below.

- Function No. 1:

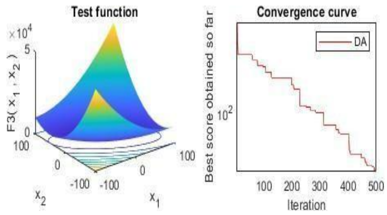
The best optimal value found by hybridized algorithm of DA with PSO was 0.058229.



- Function No. 2:

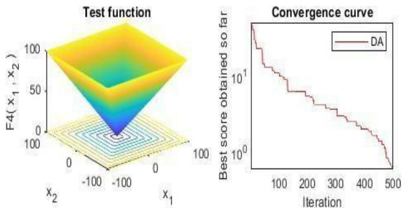
The best optimal value found by hybridized algorithm of DA with PSO was 0.340544.

- Function No. 3:



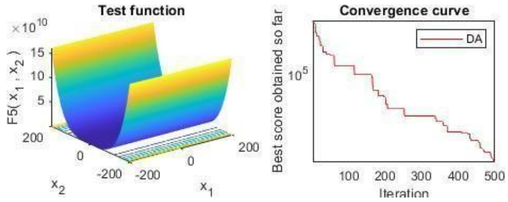
The best optimal value found by hybridized algorithm of DA with PSO was 10.042291.

- Function No. 4:



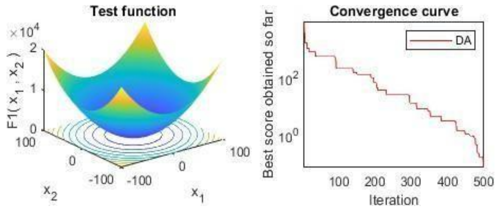
The best optimal value found by hybridized algorithm of DA with PSO was 0.519186.

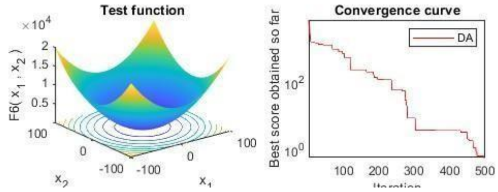
- Function No. 5:



The best optimal value found by hybridized algorithm of DA with PSO was 18.901004.

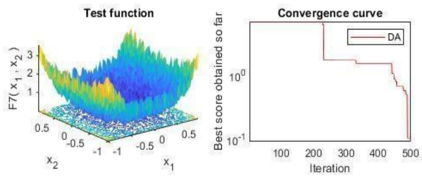
- Function No. 6:





The best optimal value found by hybridized algorithm of DA with PSO was 0.483904.

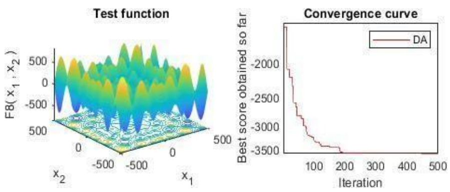
- Function No. 7:



The best optimal value found by hybridized algorithm of DA with PSO was 0.053382.

- Function No. 8:

The best optimal value found by hybridized



algorithm of DA with PSO was -3474.644082.

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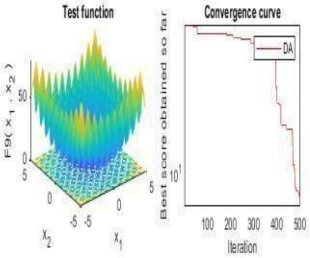
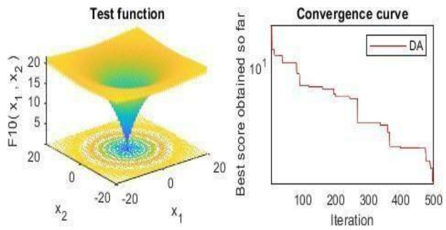


- Function No. 9:

The best optimal value found by hybridized algorithm of DA with PSO was 32.167953.

- Function No. 10
- The best optimal value found by hybridized algorithm of DA with PSO was 0.24726

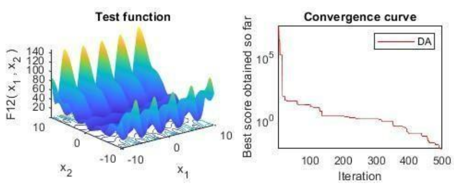


The best optimal value found by hybridized algorithm of DA with PSO was 0.247263.

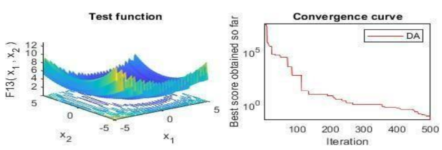
- Function No. 11:

The best optimal value found by hybridized algorithm of DA with PSO was 0.767261.

- Function No. 12:



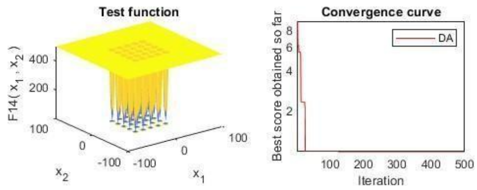
The best optimal value found by hybridized algorithm of DA with PSO was 0.002257.



- Function No. 13:

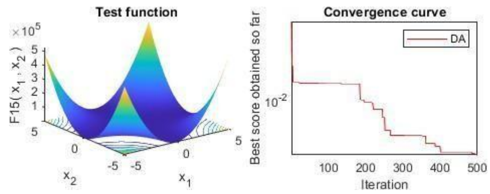
The best optimal value found by hybridized algorithm of DA with PSO was 0.027575.

- Function No. 14:



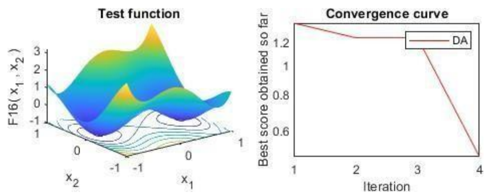
The best optimal value found by hybridized algorithm of DA with PSO was 0.998004.

- Function No. 15:



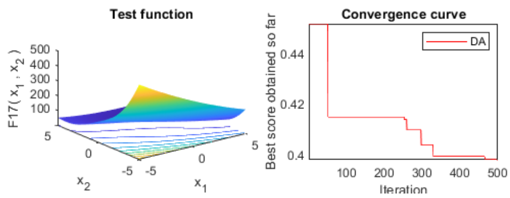
The best optimal value found by hybridized algorithm of DA with PSO was 0.001604.

- Function No. 16:



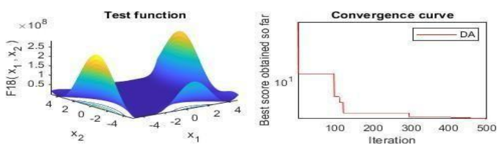
The best optimal value found by hybridized algorithm of DA with PSO was -1.031609.

- Function No. 17:



The best optimal value found by hybridized algorithm of DA with PSO was 0.39612.

- Function No. 18:



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The best optimal value found by hybridized algorithm of DA with PSO was 3.000715.

- Function No. 19:

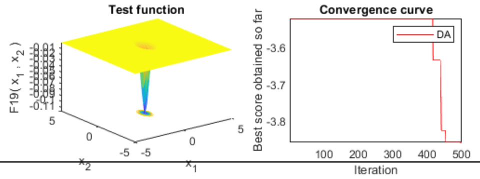
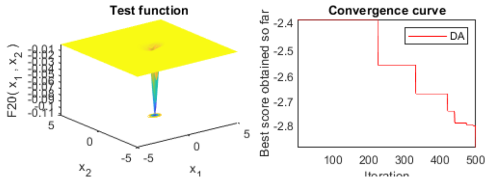


Table 3: Outcomes

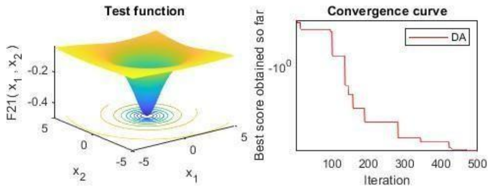
The best optimal value found by hybridized algorithm of DA with PSO was -3.894628.

- Function No. 20:



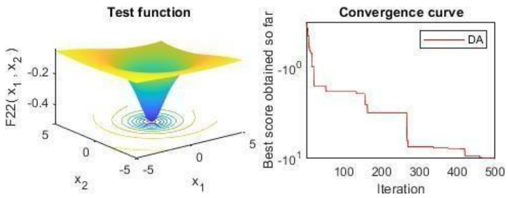
The best optimal value found by hybridized algorithm of DA with PSO was -3.129204.

- Function No. 21:



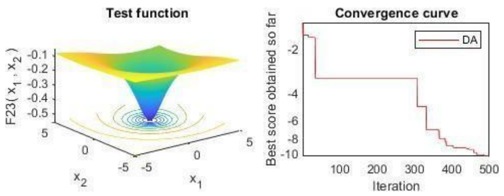
The best optimal value found by hybridized algorithm of DA with PSO was -10.129206.

- Function No. 22:



The best optimal value found by hybridized algorithm of DA with PSO was -11.369889.

- Function No. 23:



The best optimal value found by hybridized algorithm of DA with PSO was -11.478877.

Function No.	DA Algorithm	Hybrid DA-PSO Algorithm	Optimal Solution
F1	0.015355	0.058229	DA
F2	1.6312	0.340544	DA-PSO
F3	6.0779	10.042291	DA-PSO
F4	1.8058	0.519186	DA-PSO
F5	11.0962	18.901004	DA-PSO
F6	5.1366	0.483904	DA-PSO
F7	0.069909	0.053382	DA-PSO
F8	-2821.0436	-3474.644082	DA-PSO
F9	10.7444	32.167953	DA-PSO
F10	4.2143	0.247263	DA-PSO
F11	0.16839	0.767261	DA
F12	1.1485	0.002257	DA-PSO
F13	0.019557	0.027575	DA
F14	0.998	0.998004	DA-PSO
F15	0.00054487	0.001604	DA
F16	-1.0316	-1.031609	DA-PSO
F17	0.39789	0.39612	DA-PSO
F18	3	3.000715	DA-PSO
F19	-3.8628	-3.894628	DA-PSO
F20	-2.9535	-3.129204	DA-PSO
F21	-10.1532	-10.129206	DA
F22	-10.4029	-11.369889	DA-PSO
F23	-10.5364	-11.478877	Depends on Goal

CONCLUSION

The Proposed hybridized algorithm DA-PSO's performance is thoroughly tested and extensive experiments were conducted on a comprehensive suite of 23 benchmark functions, encompassing a wide range of complexities and characteristics. The superiority of DA-PSO over both standalone DA and PSO was demonstrated by the experimental results. Notably, optimal solutions were achieved by DA-PSO in [F2, F3, F4, F5, F6, F7, F8, F9, F10, F12, F14, F16, F17, F18, 19, F20, F22] out of the 23 benchmark functions, Function F8 resultant value was found -3474.644082 which was best because it achieves a much lower result than other functions, making it a strong candidate for

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optimality in a minimization task+. The optimal solutions were achieved by DA-PSO in 17 out of the 23 benchmark functions. This outcome highlights the effectiveness of the proposed DA-PSO hybridization in escaping local optima and converging towards global optima.

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