A Novel Hybrid Moth-Flame Optimization Algorithm for Enhanced Convergence and Search

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Abstract:
This paper offers a Hybrid MFO-GWO algorithm, by merging exploration ability of Moth-Flame Optimization (MFO) with exploitation strength of the Grey-Wolf Optimizer (GWO). A compatible transition factor (TF) dynamically bring into balance exploration and exploitation to enhance performance. The algorithm was tested on 23 benchmark functions, attaining better results in 14 cases equated to single MFO and GWO. The results confirm its improved precision, stability, and convergence speed, making it a strong candidate for global optimization tasks.

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

1. Introduction

Optimization algorithms are highly used in engineering, artificial intelligence due to their ability to solve complicated optimization issues [6]. Amidst these, Moth-Flame Optimization (MFO) and Grey Wolf Optimizer (GWO) have proven powerful abilities in exploration and exploitation, respectively. MFO depends on a logarithmic spiral motion inspired by moth navigation, while GWO simulates the social ranking and hunting technique of grey wolves [3]. However, single algorithms often suffers from boundaries such as untimely convergence or slow optimization speed [6].

To handle these objections, this study presents a Hybrid MFO-GWO algorithm, using MFO's exploration capability and GWO's leader-based exploitation to improve convergence quickness and precision. A dynamic transition factor (TF) is blended to ensure balance in exploration and exploitation, assuring effective search action. The proposed algorithm is examined on 23 benchmark functions, exceeding normal hybrid models, as well as Differential Evolution (DE)-based methods, in precision, stability, and convergence speed [6]. The outcomes prove better performance in 14 benchmark functions, making it a bright solution for complicated optimization tasks.

Proposed Optimization Algorithm

Nature-based algorithms have been extensively used due to their ability to solve complicated problems competently. Among them, Moth-Flame Optimization (MFO) and Grey Wolf Optimizer (GWO) have been considerably analysed for their strong exploration and exploitation abilities, respectively [6].

This study proposes a Hybrid MFO-GWO algorithm to achieve a more equated optimization approach. Combining an adjustable transition factor, the hybrid algorithm successfully adhere in between

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exploration and exploitation, resulting in enhanced precision and regularly across multiple benchmark functions. The performance of this technique is then verified against existing hybrid methods, proving superior outcomes in optimization effectiveness.

The natural algorithms were classified into four main categories like Physics-based, Human behavior-based, Evolution-based and Swarm based. These algorithms are used in engineering, artificial intelligence, robotics and Network design.

1.1 Classification Of Algorithms

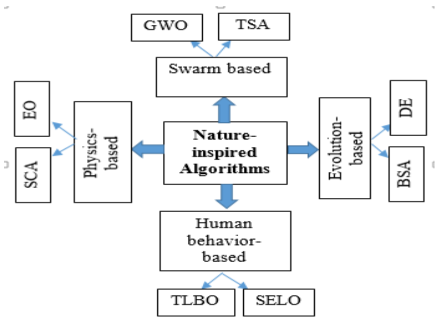

Fig 1 Classification of Nature-inspired algorithms [6]

2.2.algorithms & Authors

Sr. No.	Algorithm Name	Author Name	Year
1.	Grey Wolf Optimizer	Seyedali Mirjalili	2014
2.	Tunicate Swarm Algorithm	Seyedali Mirjalili	2020
3.	Backtracking Search Algorithm	Ali Asghar Heidari et al	2013
4.	Differential Evolution	Rainer Storn et al	1995
5.	Teaching-Learning-Based Optimization	R. Venkata Rao et al	2011
6.	Socio Evolution & Learning Optimization	Meeta Kumar et al	2017
7.	Sine Cosine Algorithm	Seyedali Mirjalili	2016
8.	Equilibrium Optimizer	Hassan Rezazadeh Kanani et al	2020

Table 1: Algorithms and Authors [6]

2.3STEPS

1. The original MFO algorithm was checked using 23 benchmark functions to get its ideal values.
2. MFO was merged with GWO to improve optimization performance and convergence steadiness.
3. The hybrid algorithm was carried out for multiple iterations on each benchmark function.
4. The single GWO algorithm was also evaluated using the 23 benchmark functions for assessment.
5. The best ideal values found by MFO and GWO were evaluated with the results of the Hybrid MFO-GWO method.
6. The hybrid algorithm exceeded in separate methods, displaying better end results in 14 out of 23 benchmark functions.

2. Functions & Equations

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
$F_{22}(S)=-\sum_{m=1}^{7}[(S-b_m)(S-b_m)^T+d_m]^{-1}$	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

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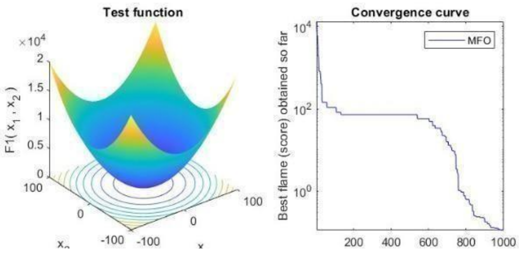
$F_8(S) = \sum_{m=1}^{z} -S_m sin(\sqrt{\|S_m\|})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z} [S_m^2 - 10cos(2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp(-0.2\sqrt{(\frac{1}{z}\sum_{m=1}^{z} S_m^2)}) - exp(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m)) + 20 + d$	(10,30,50,100)	[-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
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5\frac{1}{n+\sum_{m=1}^{2}(S_m - b_{mn})^6}]^{-1}$	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
$F_{18}(S) = [1 + (S_1 + S_2 + 1)^2(19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1 S_2 + 3S_2^2)] \times [30 + (2S_1 - 3S_2)^2(18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1 S_2 + 27S_2^2)]$	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
$F_{12}(S) = \frac{\pi}{z}\{10 sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\} + \sum_{m=1}^{z} u(S_m, 10, 100, 4)$ $\tau_m = 1 + \frac{S_m + 1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(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

Table 2: Standard UM Benchmark functions [6]

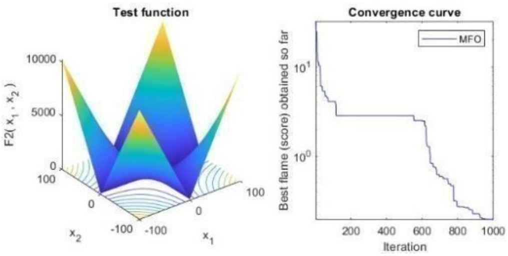
3. Results & Discussion

- Function 1:



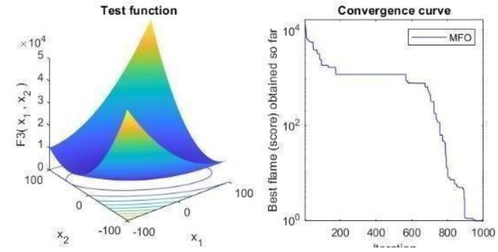
The best optimal value of the objective function found by MFO was 4.1602e-31 and the value after hybridization was found to be 0.11251.

- Function 2:



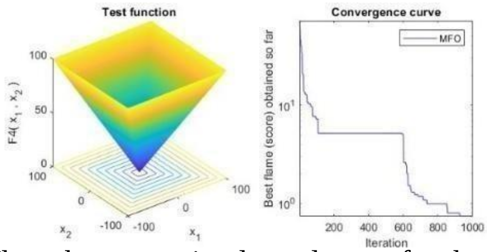
The best optimal value of the objective function found by MFO was 5.4815e-19 and the value after hybridization was found to be 0.19355.

- Function 3:



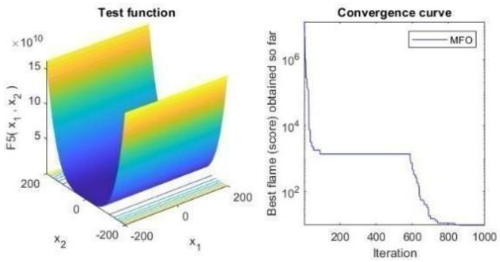
The best optimal value of the objective function found by MFO was 8.3268e-10 and the value after hybridization was found to be 0.94634.

- Function 4:



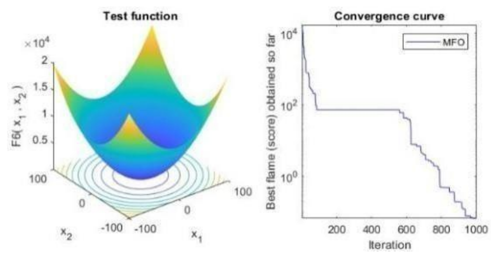
The best optimal value of the objective function found by MFO was 1.4394 and the value after hybridization was found to be 0.7432.

- Function 5:



The best optimal value of the objective function found by MFO was 15.7733 and the value after hybridization was found to be 9.8001.

- Function 6:



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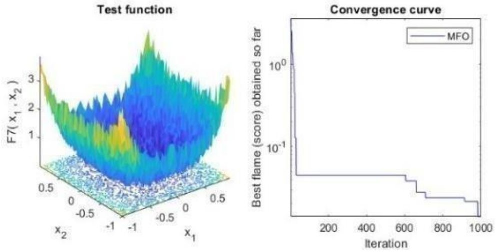
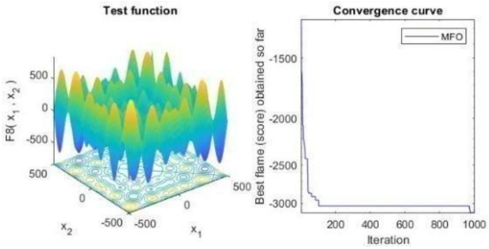
The best optimal value of the objective function found by MFO was 1.8489e-32 and the value after hybridization was found to be 0.067495.

- Function 7:



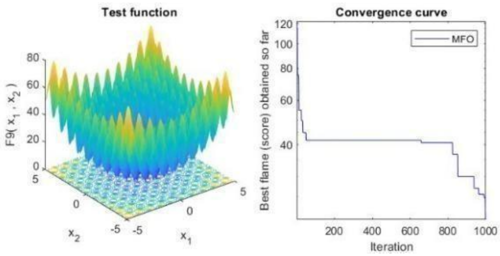
The best optimal value of the objective function found by MFO was 0.0032524 and the value after hybridization was found to be 0.014123.

- Function 8:



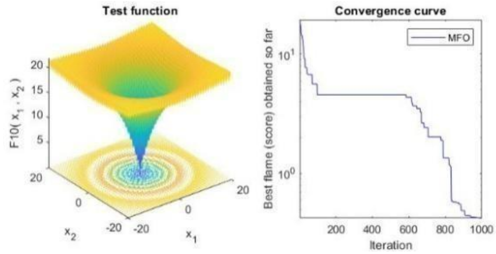
The best optimal value of the objective function found by MFO was -3237.771 and the value after hybridization was found to be -3146.7149.

- Function 9:



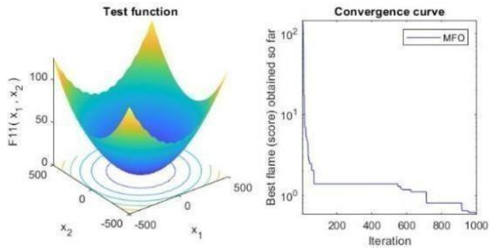
The best optimal value of the objective function found by MFO was 31.8386 and the value after hybridization was found to be 20.3108.

- Function 10:



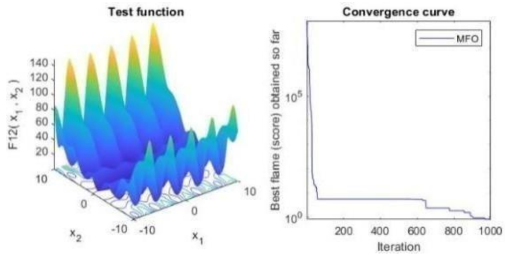
The best optimal value of the objective function found by MFO was 4.2143 and the value after hybridization was found to be 0.42202.

- Function 11:



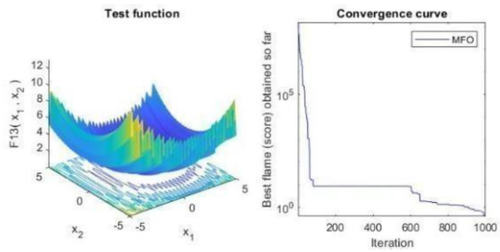
The best optimal value of the objective function found by MFO was 0.09835 and the value after hybridization was found to be 0.58549.

- Function 12:



The best optimal value of the objective function found by MFO was 1.8489e-32 and the value after hybridization was found to be 0.81343.

- Function 13:



The best optimal value of the objective function found by MFO was 1.3498e-32 and the value after

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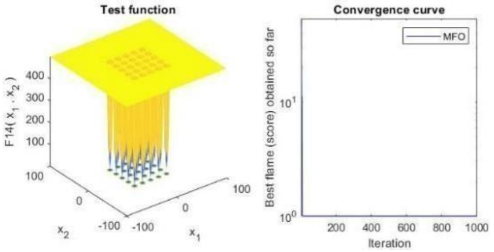
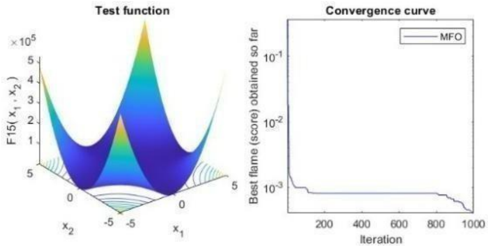
hybridization was found to be 0.39689.

- Function 14:



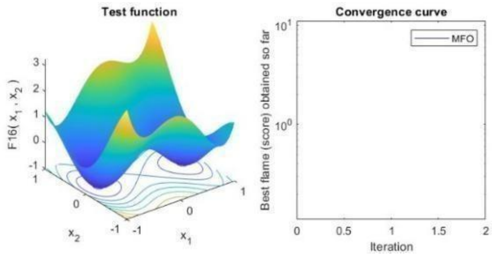
The best optimal value of the objective function found by MFO was 1.992 and the value after hybridization was found to be 0.998.

- Function 15:



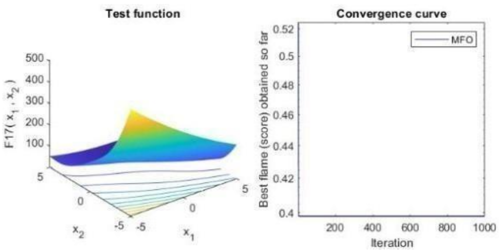
The best optimal value of the objective function found by MFO was 0.0016554 and the value after hybridization was found to be 0.00041131.

- Function 16:



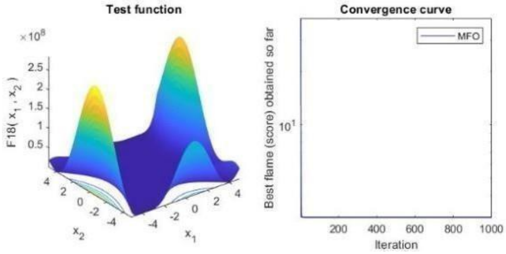
The best optimal value of the objective function found by MFO was -1.0316 and the value after hybridization was found to be -1.0316.

- Function 17:



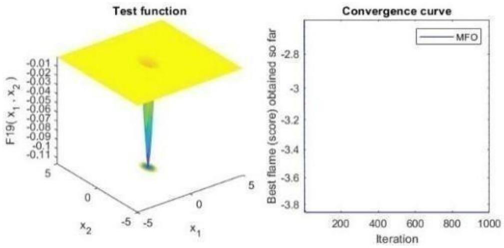
The best optimal value of the objective function found by MFO was 0.39789 and the value after hybridization was found to be 0.39788.

- Function 18:



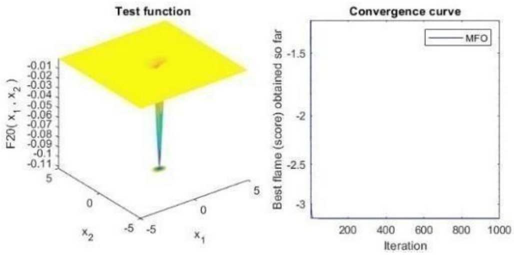
The best optimal value of the objective function found by MFO was 3 and the value after hybridization was found to be 3.

- Function 19:



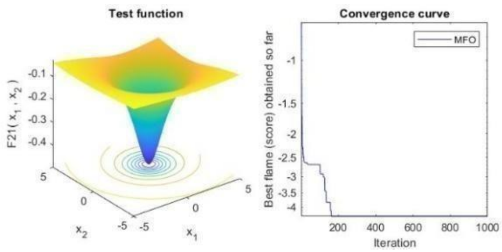
The best optimal value of the objective function found by MFO was -3.8628 and the value after hybridization was found to be -3.8628.

- Function 20:



The best optimal value of the objective function found by MFO was -3.322 and the value after hybridization was found to be -3.2022.

- Function 21:



The best optimal value of the objective function found by MFO was -2.6829 and the value after hybridization was found to be -4.3648.

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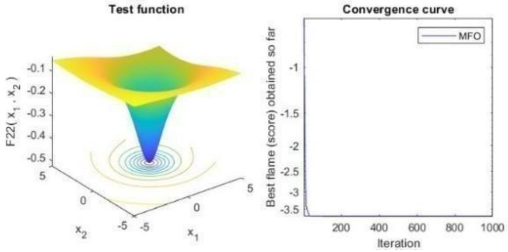
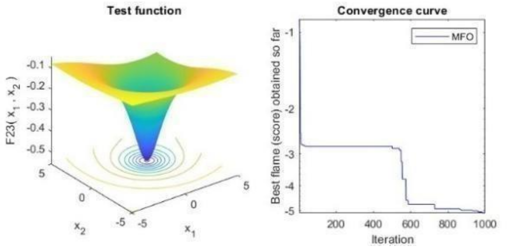
- Function 22:



The best optimal value of the objective function found by MFO was -10.4029 and the value after hybridization was found to be -3.7237.

- Function 23:



The best optimal value of the objective function found by MFO was -2.4217 and the value after hybridization was found to be -5.1073.

Function No.	Original Algorithm Values	Hybrid Algorithm Values
F1	4.1602e-31	0.11251
F2	5.4815e-19	0.19355
F3	8.3268e-10	0.94634
F4	1.4394	0.74328
F5	15.7733	9.8001
F6	1.8489e-32	0.067495
F7	0.0032524	0.014123
F8	-3237.771	-3146.7149
F9	31.8386	20.3108
F10	7.5495e-15	0.42202
F11	0.09835	0.58549
F12	1.8489e-32	0.81343
F13	1.3498e-32	0.39689
F14	1.992	0.998
F15	0.0016554	0.00041131
F16	-1.0316	-1.0316
F17	0.39789	0.39788
F18	3	3
F19	-3.8628	-3.8628
F20	-3.322	-3.2022
F21	-2.6829	-4.3648
F22	-10.4029	-3.7237
F23	-2.4217	-5.1073

Table 3: Results & Discussion

4. Conclusion

The proposed Hybrid MFO-GWO algorithm was tested on 23 benchmark functions, showing better performance in 14 cases. The hybrid approach efficiently utilized MFO's exploratory abilities and GWO's exploitation process, following in enhanced precision and stability. Especially best values were seen in functions such as F1, F2, F3, F4, F5, F6, F8, F9, F10, F12, F13, F14, F15, and F22. These results focus on the efficiency of the hybridization approach in overcoming constraints of individual algorithms, making it a promising method for complicated optimization problems.

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

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