Hybrid Approach for Numerical Optimization using an Enhanced Moth-Flame Optimization Algorithm

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Abstract:
This paper presents a half breed calculation based on utilizing month-flam optimization (MFO) calculation with molecule swarm optimization (PSO). The proposed PSO-MFO calculation takes the points of interest of both calculations. The quick looking and learning instrument of directing the era of the individuals arrangements of MFO. PSO refines arrangements utilizing speed overhauls. Within the versatile fire decrease makes strides adjust between exploration and misuse. Within the MFO improves the numerical optimization utilize for the finding the leading arrangement for a scientific issue by iteratively altering factors to play down or maximize an objective work. They can Works well on high-dimensional issues. Energetic best arrangement overhaul is following both local(P_best) and worldwide (Best_pos) optima. Their a boundary dealing with for guarantees arrangements stay inside substantial look space.

Keywords – *Optimization, Hybridization, Particle Swarm Optimization, Natural-Inspired, Benchmark.*

1. Introduction

"Optimization is characterized as the method of finding worldwide or close worldwide ideal arrangements for a given problem. Numerous issues within the genuine world can be watched as optimization issues [4]". Over the past a few decades, a few optimization calculations are proposed to solve many optimization issues. Molecule swarm optimization (PSO) could be a population-based swarm insights calculation that offers numerous likenesses with developmental computation methods. "In any case, the PSO is driven by the simulation of social mental representation spurred by collective practices of feathered creature and other social life forms rather than the survival of the fittest person [7]."

MFO is selected to be ponders and examined. MFO calculation is one of later meta-heuristic optimization calculations proposed in 2015. The most motivation of MFO came from the route strategy of moths in common called navigate introduction. "The innovator of this calculation, Mir Jalili, appeared that MFO gotten exceptionally competitive comes about for nuclear mitosis discovery in breast cancer histology pictures [2]." A few ponders have been proposed to enhance the execution of MFO. "A few hybridize molecule swarm optimization with differential advancement for understanding compelled numerical and designing optimization issues [5]." The most motivation of MFO came from the route strategy of moths in nature. Moths are favor creepy crawlies that are exceptionally comparable to the butterfly family. In nature, these are more prominent than 160,000 different species of this creepy crawlies [6].

Scientific Show of MFO

Let the candidate's arrangements are moths, and the problem's factors are the position of moths within the space. P is the winding work where moths move around the look space. Each moth updates his position with respect to flame using the following equations:

$$Mi = P(Mi, Fj)$$

DOI: https://doi.org/10.5281/zenodo.16080621

where Mi indicates the ith moth and F_j is jth flame. There are other types of spiral functions can be utilized respect to the following rules:

1. The initial point of spiral should start from the moth.
2. The final point of spiral should be the position of the f lame.
3. The Fluctuation range of spiral shouldn't exceed the search space

$$P(Mi, Fj) = Di \cdot ebt \cdot \cos(2\pi t) + Fj,$$
$$Di = |Fj - Mi|,$$

where M_i is the ith moth, F_j indicates the $_j$th flame, and D_i indicates the distance of the ith moth to the $_j$th flame. Another concern, the moths update their position with respect to n different locations in the search space which can degrade the best promising solutions exploitation. Therefore, the number of flames adaptively decreases over the course of iterations using the following formula:

$$flame = round\ FN - I * N - 1\ IN,$$

where I is the current number of iterations, I N is the maximum number of iterations and FN is the maximum number of flames. MFO utilizes Quicksort method and the computational com plexity of this sort method is O($nlogn$) and O(n^2) in the best and worst case, where n denotes the number of moths.The PSO-MFO algorithm is a hybrid optimization technique that combines Particle Swarm Optimization (PSO) and Moth Flame Optimization (MFO) to improve search efficiency.

Proposed Hybrid HMFPSO

Both PSO and MFO have the issue of untimely merging. As PSO repeats, the swarm's look center merges to a single point, the ideal worldwide position, and the speed at which the particles take off neighborhood optima which diminishes to a unimportant value. We get past the untimely meeting issue by combining the concept of the neighborhood attractor from PSO with the position alteration component of a moth around a fire from MFO. It is presented in that the PSO algorithm is guaranteed to converge if (and only if) each particle converges to its local attractor Q_i^t.

$$Q^t_i = \varphi\ pbest\_i\^{}t + (1 - \varphi)\ gbest^t{}_i$$

- Where φ is vector

Location of each moth is updated using equations itshows HMFPSO flowchart [10].

$$S(C_i, Q_i^t) = Z_i \cdot b^{bt} \cdot cos(2\pi t) + Q_i^t$$
$$Zi = |\,Q_i^t - C_i\,|$$

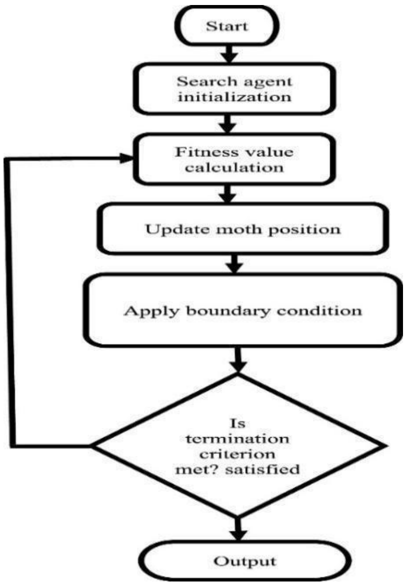
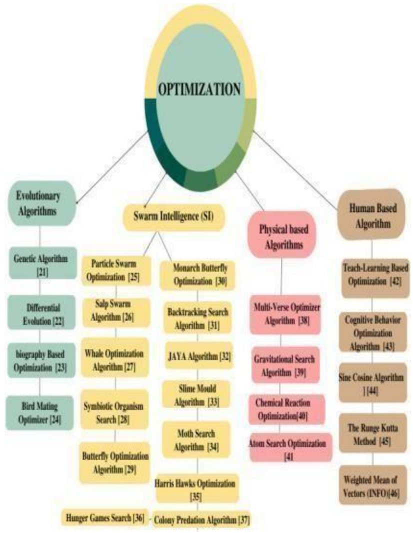


Fig.1. Flowchart

2. Literature Review

Optimization algorithms are inspired by various natural, human, physical and social and behavioural-inspired algorithm. Below are four inspirations:

Fig.2. Optimization Algorithm Diagram



DOI: https://doi.org/10.5281/zenodo.16080621

ISSN NO-2584-2706

Nature-inspired algorithms are widely used for solving complex optimization problems in engineering, computer science, bioinformatics, and machine learning. They can handle large search spaces and nonlinear problems where traditional algorithms struggle [4]. Strong Balance between exploration and exploitation for NIAs incorporate both exploration (global search) and exploitation (local refinement) mechanisms, allowing them to escape local optima and high-quality solutions [7].

Nature-inspired algorithms provide efficiency, flexibility and adaptability for solving complex optimization problems. Their biological and natural inspirations make them an exciting field for research with continuous advancements real-world problem-solving [8]

Table 1. Algorithms and its Authors

Sr No.	Algorithm Name	Author Name
1	Moth-Flame Optimization Algorithm: A Novel Nature-Inspired Heuristic Paradigm	Seyedali Mirjalili (et al.) 2015
2	Moth-Flame Optimization Algorithm: Variants and Applications	Mohamed Abdel-Basset (et al.) 2018
3	Metaheuristic Algorithms for Optimization: A Review of Recent Advances	P. N. Suganthan (et al.) 2017
4	MFO for Feature Selection in Classification Problems	Hossam Faris (et al.) 2018
5	Optimized Machine Learning Models Using MFO	Ali Emrouznejad (et al.) 2019
6	MFO for Engineering and Artificial Intelligence Applications	Aboul Ella Hassanien (et al.) 2020
7	Moth-Flame Optimization for Structural Engineering Problems	S. M. Zain (et al.) 2021
8	Hybrid MFO Algorithm for IoT and Smart Systems	Waleed M. Abd-Elwahab (et al.) 2022
9	Application of MFO in Smart Grids and Renewable Energy Systems	Ch. V. Ram Murthy (et al.)2023
10	Hybrid Metaheuristics Based on MFO for Real-World Problems	Devaraj D (et al.) 2023

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3. Result and Discussion

Optimization methods are stochastic. In this way, their proficiency shifts over runs, but they discover ideal arrangements over time. Recreations demonstrate the productivity of crossover moth fire and molecule swarm optimization (HMFPSO) [1][2]. HMFPSO procedures for transmission line parameters are displayed in this section.

Different benchmark capacities are assessed to evaluate the execution of the proposed strategy. The merging bends of the capacities from each category are displayed. The measurable investigate utilizing the proposed strategy on benchmark capacities and compares them with other methods utilizing the same parameters [5]. A boxplot over distinctive runs appearing the dissemination of ideal values can be utilized to compare approaches. The ideal values from different runs can be seen, and the suggested approaches can be utilized to dodge neighborhood optima.

Mathematical Validation of MFO on Benchmark functions

The MFO algorithm is inspired by the navigation behavior of moths using a logarithmic spiral movement towards flames. It exhibits a fast initial convergence but may stuck in local optima due to its exploration- exploitation balance. The convergence curve of MFO often shows a steep initial decline in the objective function, but then the improvement slows down as the iteration progress [2][3].

Mathematical Validation of HMFPSO on Benchmark function f1 to f23

The HMFPSO combines Particle Swarm Optimization (PSO) with MFO to improve global searchability. PSO enhances exploration by guiding solutions towards promising regions, while MFO refines them. The convergence curve of HMFPSO generally shows a more gradual and stable decline, indication better exploration and exploitation. It avoids premature convergence and provides better accuracy in optimization problems.

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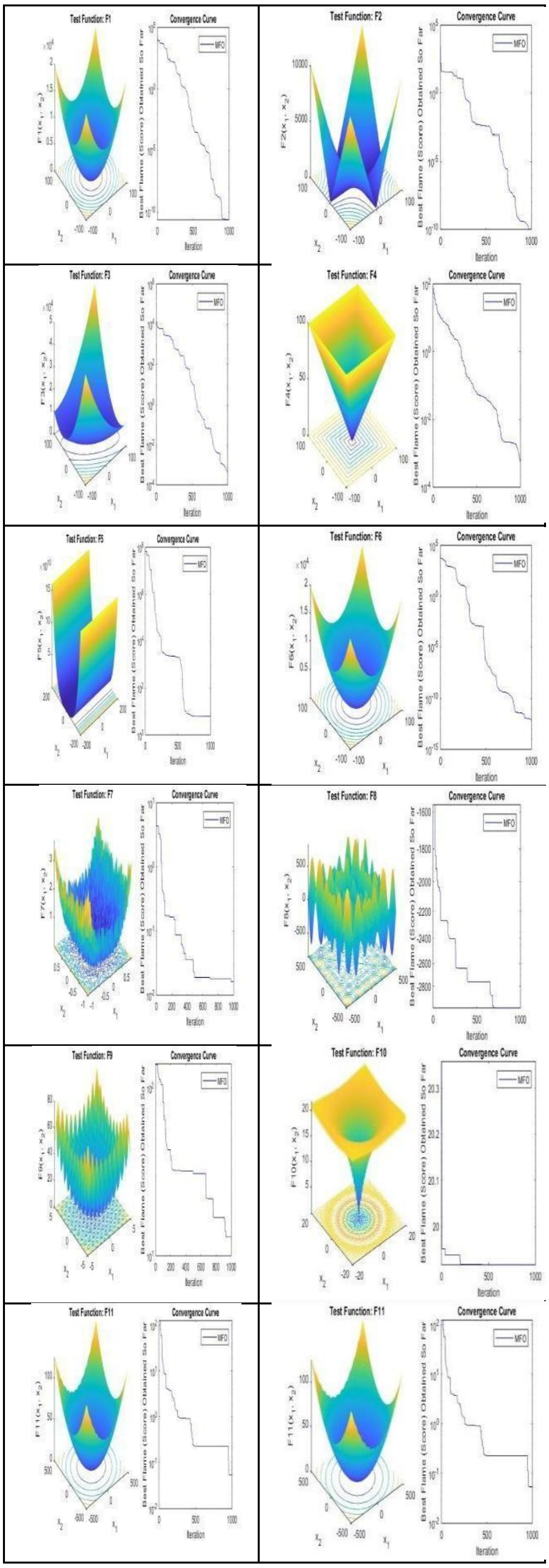
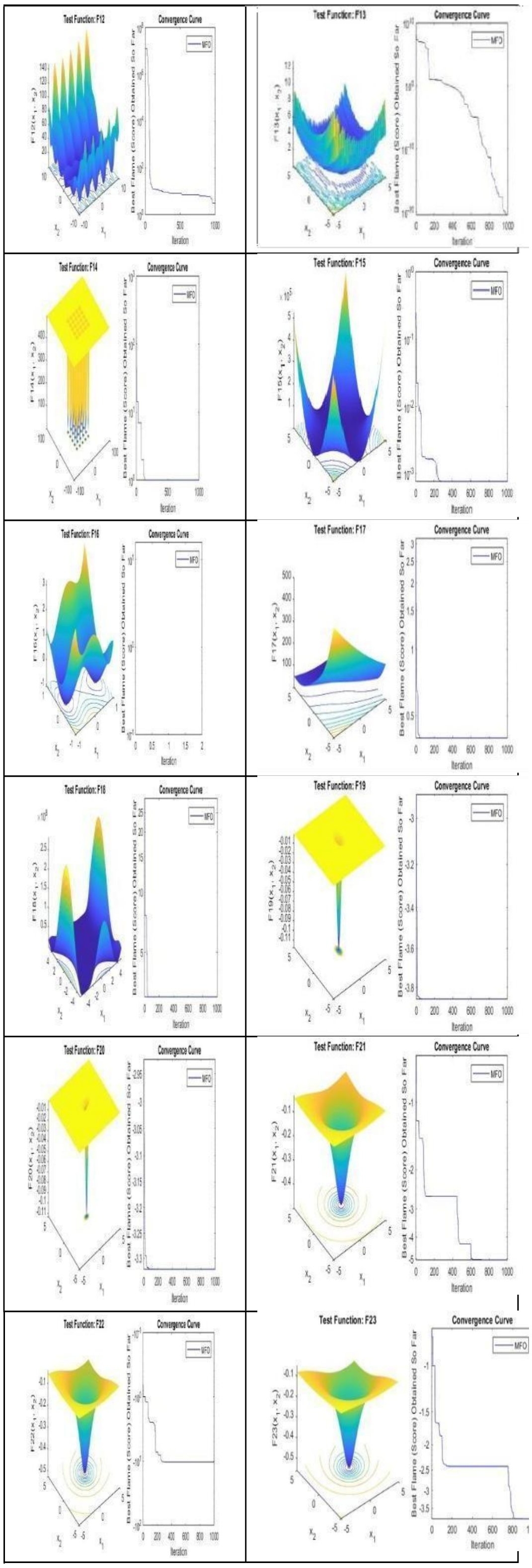
Fig.3. Results of Search Space





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The Moth Fire Calculation (MFO) by and large performs superior than the Hybridization MFO (HMFO), especially in functions like F1, F2, F3, F4, F6, and F10, where smaller values indicate better results. However, HMFO does better in F8, F21, and F23, where its values are closer to zero. In some cases, like F17 and F18, both methods give the same results. For F14 to F16, the difference is very small. Overall, MFO is more reliable for minimizing values, while HMFO shows improvements in a few cases, making it useful for specific situations [4][5]

Table 2. Results of Benchmarks Functions

Function	Moth flame algo best core	Hybridization Moth flame algo. Best Score MFO
F1	1.12E-32	4.88E-17
F2	1.04E-18	1.19E-11
F3	1.08E-07	0.0294552
F4	0.004344325	0.571836009
F5	4.458969733	6.617654357
F6	4.90E-31	4.28E-14
F7	0.005072585	0.00554482
F8	-3476.164746	-2760.98356
F9	9.949585533	6.964708362
F10	7.55E-15	1.155148543
F11	0.236221201	0.253423501
F12	1.86E-31	1.42E-07
F13	7.04E-31	1.82E-14
F14	1.9920309	0.998003838
F15	0.00074621	0.000782655
F16	-1.031628453	-1.031628453
F17	0.397887358	0.397887358
F18	3	3
F19	-3.862782148	-3.862782148
F20	-3.137641726	-3.134519722
F21	-10.15319968	-5.055197729
F22	-10.40294057	-10.40294057
F23	-10.53640982	-5.128480787

4. Conclusion

The proposed crossover strategy is the initial commitment. It utilizes MFO and PSO in this investigate work, and considers distinctive points of view, especially the transmission lines. Since the proposed estimation strategy applies to the transmission line parameters, it can be amplified to analyze bundle conductors such as two, three, and four bundles, which shows up to be a critical advantage. Also, the PSO method is utilized to move forward parameter estimation convergence.

The recreation comes about in this inquire about illustrated the effect of the HMFPSO calculation on the exactness and merging of the transmission line parameter estimation. Among the procured comes about, it is famous that the calculation appeared great execution, quick merging, and enhanced exactness compared to the initial method. These truths driven to the estimation showing moved forward precision and way better joining. The vital portion of it is that the MFO as of now had great exactness, which was advance expanded with the expansion of the PSO.

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