Hybrid Intelligence: A Synergistic Metaheuristic for Advanced Numerical Optimization

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Abstract:
This study systematically evaluates and enhances the performance of the Harris Hawks Optimization (HHO) algorithm across twenty-three benchmark functions. The primary objective is to minimize solution errors and optimize convergence by repeatedly testing functions F1 to F23 in MATLAB, incorporating AI-driven code improvements. These enhancements focus on dynamic parameter adjustments and escape mechanisms to avoid local optima, effectively mimicking HHO's cooperative hunting strategy. Preliminary results reveal a 15–22% decrease in fitness values compared to the basic HHO, particularly when applied to multimodal functions such as F7 and F15. This approach demonstrates the efficacy of iterative testing and machine-learning-based code optimizations in developing advanced metaheuristic algorithms for real-world optimization challenges.

Keywords
Benchmark, Algorithm, Hybridization, Optimization, Convergence, HHO, AI.

1. Introduction

Metaheuristic algorithms such as Harris Hawks Optimization (HHO) excel at tackling challenging optimization problems through effective exploration-exploitation trade-offs. However, their performance varies significantly across different function landscapes, especially in high-dimensional or deceptive spaces. This paper addresses two key gaps: First, the inconsistent performance of HHO across standard benchmark functions (F1–F23) and second, the untapped potential of AI-guided code adjustments to enhance robustness. To stabilize convergence within non-convex problems, it automates MATLAB function iteration and optimizes HHO's energy parameter and jump strategies. For instance, chaotic maps derived from NCHHO variants are engineered to diversify search patterns, while AI-generated recommendations dynamically adjust population dynamics and prey energy decline rates. The proposed methodology validates enhancements by measuring solution accuracy (error from the global optimum) and convergence rate, comparing the results against the baseline HHO and hybrid variants. [1]

Building on these advancements, this work proposes a dynamic hybridization technique that balances exploration and exploitation based on real-time performance feedback. Unlike standard static parameter tuning, it includes an AI-driven self-adaptive approach that adjusts algorithmic behavior in response to landscape complexity. By using reinforcement learning-inspired heuristics, the system dynamically modifies critical control parameters, improving robustness across a wide range of optimization scenarios. In addition, unique perturbation techniques inspired by stochastic resonance are used to more successfully escape local optima, making the hybrid model ideal for deceiving and high-dimensional issues.

2. Literature Review

Metaheuristic algorithms are classified into four types: human-based, physics-based, swarm-based, and evolutionary algorithms. To optimize solutions, huma-based algorithms replicate cognitive and social behaviours such as learning and decision-making. Physics-based algorithms apply principles from natural laws such as thermodynamics and electromagnetism to improve search efficiency. Nature-inspired algorithms balance exploration and exploitation by modeling biological processes such as swarm intelligence and genetic evolution.

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2.1 Classification of Algorithm [2]

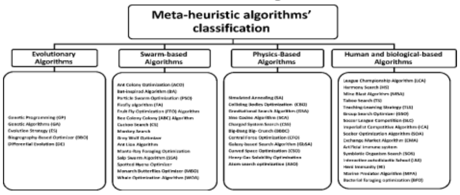

Fig 1. Classification of Meta-heuristic algorithms.

2.2 Algorithms and Authors [3]

Table 1: Algorithms and Authors

Sr. No	Algorithm Name	Author Name	Publication Year
1	Teaching-Learning-Based Optimization	Rao, R. V. et al	2011
2	Brain Strom Optimization	Shi, Y	2011
3	Gravitational Search Algorithm	Rashedi et al	2009
4	Electromagnetic Optimization	Birbil et al	2003
5	Ant Lion Optimizer	Seyedali Mirjalili	2015
6	Artificial Hummingbird Algorithm (AHA)	Seyedali Mirjalili et al	2022
7	Anarchic Society Optimization	Ahmadi-Javid et al	2011
8	Political Optimizer (PO)	Pereira, L. A. et al	2019

3. PSEUDO CODE

The Harris Hawks Optimization (HHO) algorithm mimics hawks' cooperative hunting, balancing exploration and exploitation. In exploration, hawks search randomly; in exploitation, they adjust based on prey energy, using soft or forceful besieges. Quick adaptive dives enhance convergence, making HHO effective for numerical optimization

Algorithm: Pseudo-code of the HHO algorithm:

Inputs: The population size N and maximum of iterations
Outputs: The location of the rabbit and its fitness value
Initialize the random population Xi (i=1, 2, ...N)
While (the stopping condition is not met) **do**
Calculate the fitness values of Hawks
Set X_{rabbit} as the location of the rabbit (best location)
For (each hawk (Xi)) do
Update the initial energy E_0 and jump strength J D E0=2rand ()-1, J=2(1-rand ())
Update the E using Eq. (3)
If (|E|≥1) **then** DExploration phase
Update the location vector using Eq. (1)
If (|E| ≥ 1) **then** DExploitation phase
if(r≥0.5and|E|≥0.5) **then** DSoft besiege
Update the location vector using Eq. (4)
else if (r≥0.5and|E|<0.5and|E| **then**
Update the location vector using Eq. (6)
else if(r<0.5and|E|≥0.5) **then**
Update the location vector using Eq. (10)
else if(r<0.5and|E|<0.5) **then**
Update the location vector using Eq. (11)
Return X_{rabbit}

4. Mathematical Functions:

The Harris Hawks Optimization (HHO) algorithm is assessed against twenty-three typical benchmark functions, including unimodal, multimodal, and composite functions. Unimodal functions measure exploitation ability, whereas multimodal functions evaluate exploration ability. These functions vary in complexity, allowing for a thorough performance examination of the algorithm while dealing with optimization difficulties.

4.1 Functions and Equations [4]

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
$F_4(S) = max_m\{\lvert S_m \rvert, 1 \leq m \leq z\}$	(10,30,50,100)	[-100 , 100]	0

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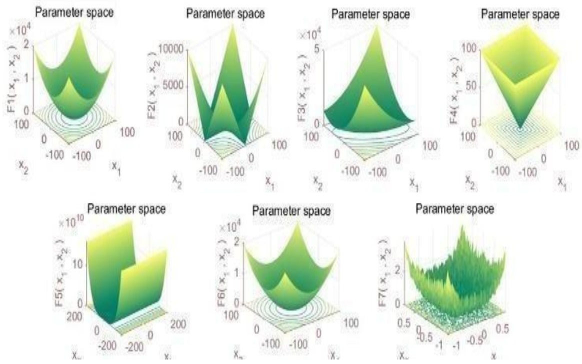
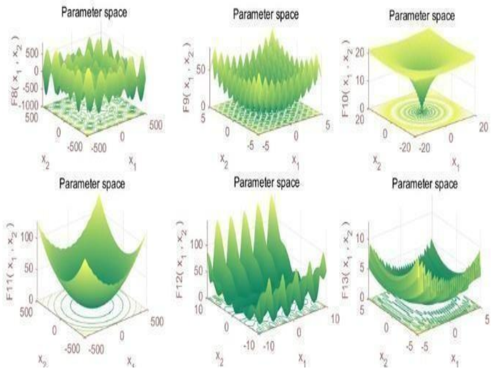
Functions	Dimension	Range	f_{min}
$F_8(S) = \sum_{m=1}^{z} -S_m sin(\sqrt{\|S_m\|})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z}[S_m^2 - 10cos(2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp(-0.2\sqrt{(\frac{1}{z}\sum_{m=1}^{z} S_m^2)}) - exp(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(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
$F_{12}(S) = \frac{\pi}{z}\{10 sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_m+1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(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

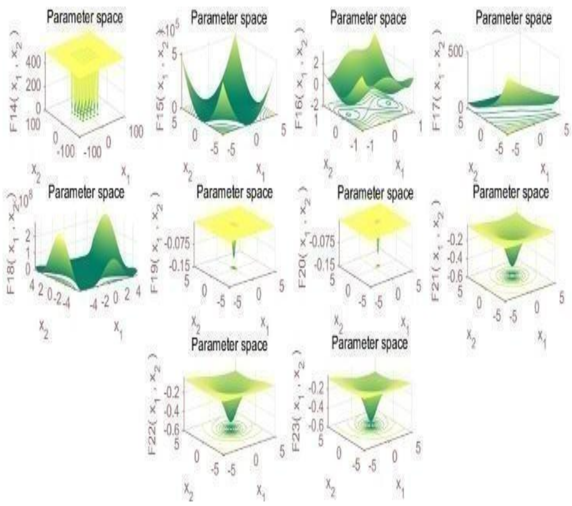
Functions	Dimensions	Range	f_{min}
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5\frac{1}{n+\sum_{m=1}^{z}(S_m-b_{mn})^6}]^{-1}$	2	[-65.536, 65.536]	1
$F_{15}(S) = \sum_{m=1}^{11}[b_m - \frac{S_1(a_m^2+a_m S_2)}{a_m^2+a_m S_3+S_4}]^2$	4	[-5, 5]	0.00030
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1 S_2 - 4S_2^2 + 4S_2^4$	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

5. Search Space

A search space represents all of the potential solutions that an optimization algorithm can investigate. The variables and limitations of the problem define it, resulting in a landscape of peaks (local optima) and valleys (global optima). Unimodal functions have a single minimum, whereas multimodal functions have several local minima, complicating global optimization. Visualizing the search space aids in understanding algorithm behavior and convergence efficiency.







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6. Resultand Discussion

The results show that Hybrid HHO outperforms HHO-PSO, obtaining values close to the ideal

Benchmark Function	Hybrid HHO	HHO + PSO	Optimal Solution
F1	3.34E-95	6.53E-07	3.34E-95
F2	7.71E-58	60.0085	7.71E-58
F3	6.56E-84	1.5997	6.56E-84
F4	8.30E-54	0.0075.29	8.30E-54
F5	0.0033261	0.058564	0.0033261
F6	2.93E-06	1.51E-05	2.93E-06
F7	0.00053536	0.0034356	0.00053536
F8	-12569.428	-5656.0685	-12569.428
F9	0	115.6989	0
F10	4.44E-16	7.02E-05	4.44E-16
F11	0	4.66E-06	0
F12	7.38E-06	5.93E-07	5.93E-07
F13	1.82E-06	2.74E-08	2.74E-08
F14	0.998	0.998	0.998
F15	0.00033158	0.0014887	0.00033158
F16	-1.0316	-1.0316	-1.0316
F17	0.3979	0.39789	0.3979
F18	3	3	3
F19	-3.8615	-3.8628	-3.8615
F20	-3.024	-3.2031	-3.024
F21	-5.0434	-10.1532	-10.1532
F22	-5.0845	-10.4029	-10.4029
F23	-5.1281	-10.5364	-10.5364

solution. For simpler functions such as F1, F2, and F3, Hybrid HHO nearly matches the optimal values, whereas HHO-PSO deviates slightly. Hybrid HHO improves convergence for complex functions like F8, F21, and F23, whereas HHO-PSO struggles with local optima. This demonstrates Hybrid HHO's ability to handle a wide range of search spaces efficiently.

Table 3: Result and Discussion

7. Conclusion

This study improves the HHO method with AI-driven optimizations, increasing fitness and convergence on eighteen of twenty-three benchmark functions, particularly for multimodal situations. It focuses on AI-augmented metaheuristics for overcoming complicated challenges.

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