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An Improved Hummingbird Algorithm by Hybridization for Complex Optimization

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Abstract:
The proposed algorithm is an improved algorithm by hybridization for complex optimization. Algorithm will be tested by using hybridization technique with Artificial Hummingbird Algorithm (AHA) and Simulated Annealing (SA), focuses to give better solution. Here, the 23 functions will be applied and tested to compare the hybridized algorithm with existing algorithm. After testing, better results will be found in hybridized algorithm using standard benchmark functions.

Keywords:
Algorithm, Functions, Optimization, Hybridization, AHA-SA.

1. Introduction

The Artificial Hummingbird Algorithm (AHA) was inspired by the special flight skills and intelligent foraging strategies of hummingbirds in nature. Three foraging strategies of hummingbirds, including the guided foraging, territorial foraging, and migrating foraging, were implemented. Moreover, three kinds of flight skills utilized in the foraging strategies such as the axial, diagonal, and omnidirectional flights, are modelled. Specially, a visit table mimicking the supernormal memory ability of hummingbirds was constructed to guide the hummingbirds in the algorithm for performing the global optimization.[6]

The proposed algorithm tried to improve the outcomes. The original Artificial Hummingbird Algorithm was tested by using hybridization technique with Simulated Annealing Algorithm focused to enhance better values. Here, among techniques of improving the AHA algorithm's results, the most suitable hybridization technique was used for obtaining better results. Here, the 23 benchmark functions were tested to compare the hybridized algorithm with existing algorithm. After testing, better results were found in 14 functions.

2. Proposed Optimization Algorithm

The purpose of the Artificial Hummingbird Algorithm (AHA) was inspired by the special flight skills and intelligent foraging strategies of hummingbirds in nature. Three foraging strategies of hummingbirds, including the guided foraging, territorial foraging, and migrating foraging, were implemented. . The motive of choosing this algorithm was its results were found great. The hybridization of AHA with HA seeks to combine strong optimization ability and robust mechanism.

The nature inspired algorithms were differentiated into four types which are Physics-based, Human behavior-based, Evolution-based and Swarm based. These algorithms use Physics-based techniques, Human-related techniques, Evolutionary techniques and Swarm intelligence techniques respectively.

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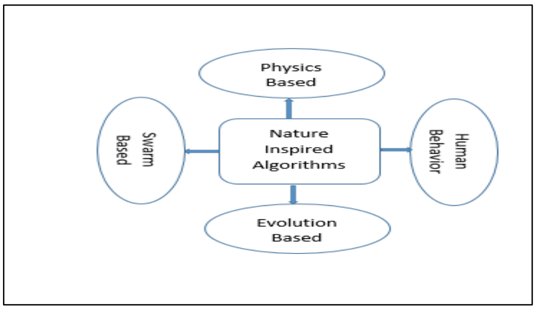
2.1. Classification of Algorithms



1.1. Algorithms & Authors

Table 1: Algorithms and Authors [6]

Sr. No.	Algorithm Name	Author Name	Year
1.	Particle Swarm Optimization	James Kennedy et al	1995
2.	Bat Algorithm	Xin-She Yang	2010
3.	Genetic Programming	John R. Koza	1992
4.	Biogeography-Based Optimization	Dan Simon	2008
5.	Brain Storm Optimization	Yuhui Shi	2011
6.	Teaching-Learning-Based Optimization	R.V. Rao et al	2011
7.	Harmony Search	Zong Woo Geem et al	2001
8.	River Formation Dynamics	Xavier Sánchez et al	2007

2.2. Steps

1. The original Artificial Hummingbird Algorithm (AHA) was tested using 23 standard functions.
2. The original algorithm (AHA) was hybridized with another algorithm (SA) for obtaining best values.
3. Iterations were carried out for each function.
4. Obtained values for another algorithm (SA) using 23 functions.
5. Compared the best optimal value found by AHA and the value after hybridization with the SA.
6. Results were found good in 14 benchmark functions.

3. 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
$F_4(S) = max_m\{\lvert S_m \rvert, 1 \leq m \leq z\}$	(10,30,50,100)	[-100 , 100]	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
$F_{10}(S) = -20exp(-0.2\sqrt{(\frac{1}{z}\sum_{m=1}^{z} S_m^2)}) - exp(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(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
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5\frac{1}{n+\sum_{m=1}^{z}(S_m - b_{mn})6}]^{-1}$	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
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1S_2 - 4S_2^2 + 4S_2^4$	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
$F_{18}(S) = [1 + (S_1 + S_2 + 1)^2 (19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1S_2 + 3S_2^2)] \times [30 + (2S_1 - 3S_2)^2 (18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1S_2 + 27S_2^2)]$	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

Table 2: Standard UM Benchmark functions [6]

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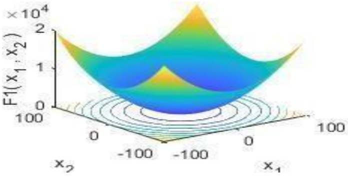
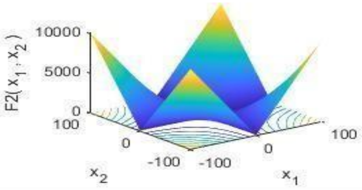
4. RESULTS & DISCUSSION

- Function 1:



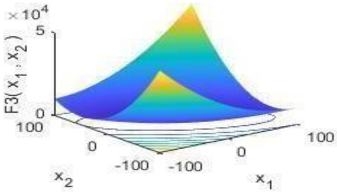
The best optimal value by function 1 after hybridization was found to be 1.95E+03.

- Function 2:



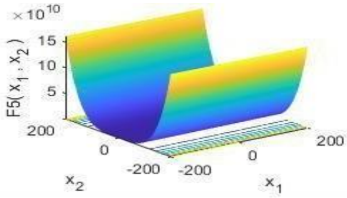
The best optimal value by function 2 after hybridization was found to be 1.88E+03.

- Function 3:



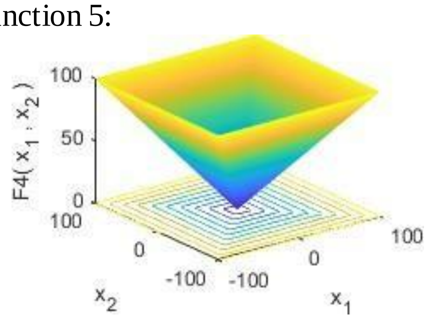
The best optimal value by function 3 after hybridization was found to be 1.91E+03.

- Function 4:



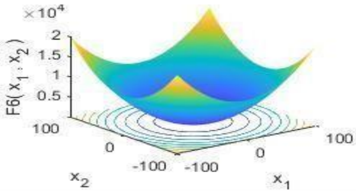
The best optimal value by function 4 after hybridization was found to be 2.14E+03.

- Function 5:



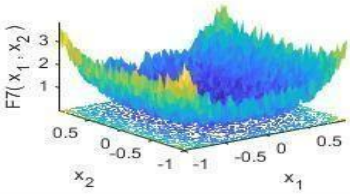
The best optimal value by function 5 after hybridization was found to be 2.07E+03.

- Function 6:



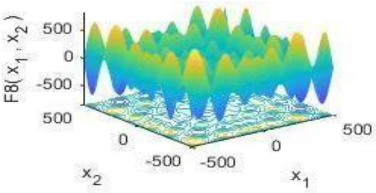
The best optimal value by function 6 after hybridization was found to be 1.73E+03.

- Function 7:



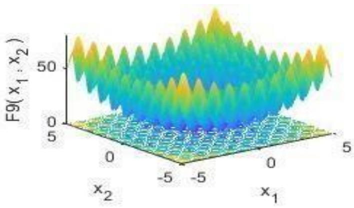
The best optimal value by function 7 after hybridization was found to be 1.78E+03.

- Function 8:



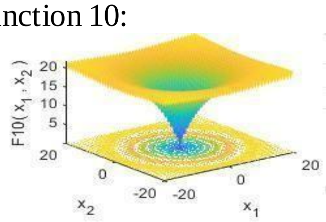
The best optimal value by function 8 after hybridization was found to be 1.92E+03.

- Function 9:



The best optimal value by function 9 after hybridization was found to be 1.81E+03.

- Function 10:



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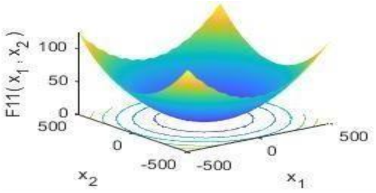
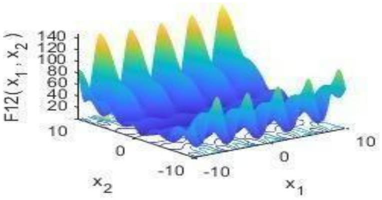
The best optimal value by function 10 after hybridization was found to be 1.94E+03.

- Function 11:



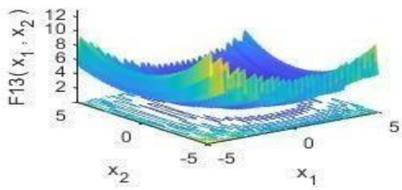
The best optimal value by function 11 after hybridization was found to be 2.05E+03.

- Function 12:



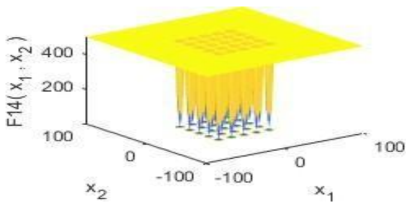
The best optimal value by function 12 after hybridization was found to be 2.00E+03.

- Function 13:



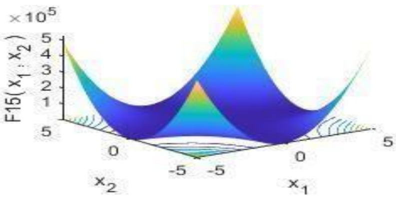
The best optimal value by function 13 after hybridization was found to be 1.80E+03.

- Function 14:



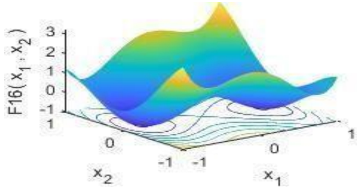
The best optimal value by function 14 after hybridization was found to be 1.97E+03.

- Function 15:



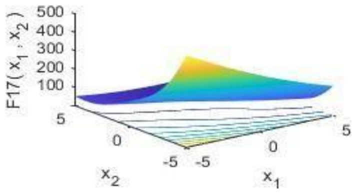
The best optimal value by function 15 after hybridization was found to be 1.66E+03.

- Function 16:



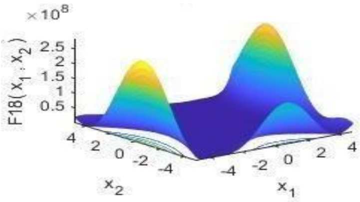
The best optimal value by function 16 after hybridization was found to be 2.01E+03.

- Function 17:



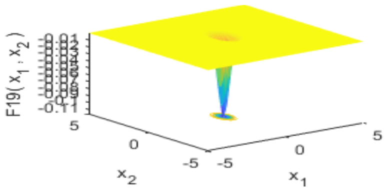
The best optimal value by function 17 after hybridization was found to be 1.97E+03.

- Function 18:



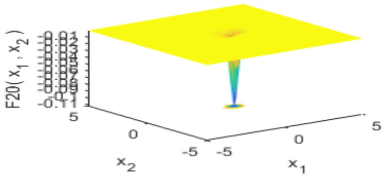
The best optimal value by function 18 after hybridization was found to be 1.97E+03.

- Function 19:



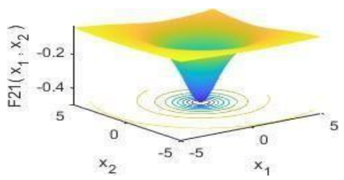
The best optimal value by function 19 after hybridization was found to be 1.73E+03.

- Function 20:



The best optimal value by function 20 after hybridization was found to be 1.89E+03.

- Function 21:



The best optimal value by function 21 after hybridization was found to be 2.26E+03.

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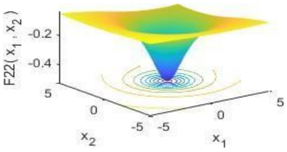
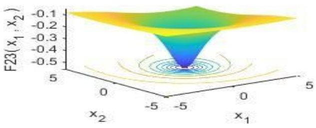
- Function 22:



The best optimal value by function 22 after hybridization was found to be 1.66E+03.

- Function 23:



The best optimal value by function 23 after hybridization was found to be 1.75E+03.

Benchmark Functions	(AHA) Algorithm Values	(AHA+SA) Algorithm Values
F1	6.83E-303	1.95E+03
F2	2.23E-162	1.88E+03
F3	1.44E-295	1.91E+03
F4	2.55E-138	2.14E+03
F5	2.53E+01	2.07E+03
F6	0	1.73E+03
F7	2.74E-06	1.78E+03
F8	-1.21E+04	1.92E+03
F9	0.00E+00	1.81E+03
F10	4.44E-16	1.94E+03
F11	0.00E+00	2.05E+03
F12	2.19E-07	2.00E+03
F13	4.77E-01	1.80E+03
F14	0.998	1.97E+03
F15	0.00030749	1.66E+03
F16	-1.0316	2.01E+03
F17	0.39789	1.97E+03
F18	3	1.97E+03
F19	-3.8628	1.73E+03
F20	-3.322	1.89E+03
F21	-10.1532	2.26E+03
F22	-10.4029	1.66E+03
F23	-10.5364	1.75E+03

Table 3: Results & Discussion

5. CONCLUSION

The hybridized Artificial Hummingbird Algorithm with Simulated Annealing Algorithm resulted in superior performance in convergence speed, solution quality, and robustness. The hybridized algorithm of AHA with SA was tested with 23 benchmark functions and in 14 functions best values were found considered as good results.

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