An Advance Nature Based Algorithm with Hybridization : ALO with SA

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Abstract:
The proposed algorithm is an advance nature based algorithm with hybridization of Ant Lion Optimizer algorithm (ALO) with Simulated Annealing (SA). The algorithm will be tested by using hybridization technique with Ant Lion Optimizer algorithm (ALO)andSimulated Annealing (SA), targets to enhance best solution. Here, the 23 standard functions will be applied and tested to compare the hybridized algorithm. After testing, better results will be found by using functions.

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

1. Introduction

The Ant Lion Optimizer (ALO) mimics the hunting mechanism of ant lions in nature. Five main steps of hunting prey such as the random walk of ants, building traps, entrapment of ants in traps, catching preys, and re-building traps are implemented.[6]

The proposed algorithm targeted to improve these results. The algorithm was tested by using hybridization of Ant Lion Optimizer (ALO) with the Simulated Annealing (SA), focused to enhance best values. Here, among many techniques of improving the ALO algorithm's outcomes, the hybridization technique was used for obtaining better solutions. Here, the 23 benchmark functions were applied and compared the results with existing Algorithm. After testing, better results were found using functions. The hybridization technique proved the most promising.

2. Proposed Optimization Algorithm

The main inspiration of the Ant Lion Optimizer (ALO) originates from different behaviors.

The Ant Lion Optimizer (ALO) mimics the hunting mechanism of ant lions in nature. Five main steps of hunting prey such as the random walk of ants, building traps, entrapment of ants in traps, catching preys, and re-building traps are implemented. The purpose of choosing this (ALO) algorithm was its results were very impressive. To overcome the problems in the original ALO algorithm, the hybridization of Ant Lion Optimizer (ALO) with the Simulated Annealing (SA) focused to enhance best values. The nature inspired algorithms were of four main categories which includes Physics-based, Human-behavior based, Evolution-based and Swarm based. These algorithms used Physics-based techniques, Human-related techniques, Evolutionary techniques and Swarm intelligence techniques respectively.

2.1 Classification of Algorithms

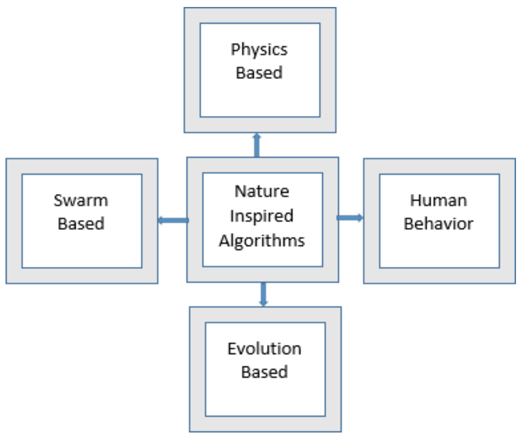

Fig 1. Classification of Nature-inspired algorithms [6]

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Sr. No.	Algorithm Name	Author Name	Year
1.	Ant Colony Optimization	Marco Dorigo	1992
2.	Firefly Algorithm	Xin-She Yang	2008
3.	Evolution Strategy	Ingo Rechenberg et al	1960
4.	Genetic Programming	John R. Koza	1992
5.	Human Learning Optimization	Xianbing Meng et al	2014
6.	Brain Storm Optimization	Yuhui Shi	2011
7.	Water Cycle Algorithm	Eskandar et al	2012
8.	Gravitational Search Algorithm	Esmat Rashedi et al	2009

2.2 Algorithms & Authors

Table 1: Algorithms and Authors [6]

2.3 Steps

1. Original algorithm (ALO) used with 23 benchmark functions.
2. Iterations were carried out for each function.
3. Obtained optimal values for ALO using 23 benchmark functions.
4. Hybridized (ALO) algorithm with (SA) algorithm for obtaining best optimal solution using 23 benchmark functions.
5. Results were found best in 12 benchmark functions.

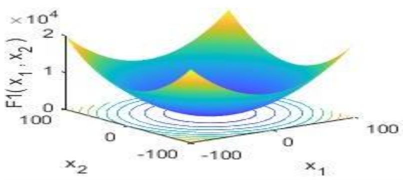
3. Functions & Equations

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]

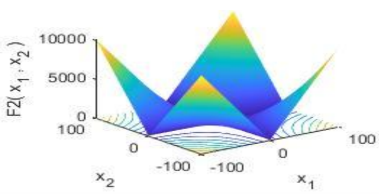
4. Result & Discussion

- Function 1:



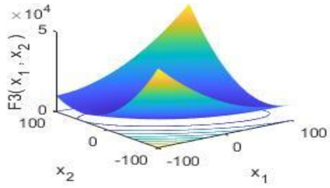
The best optimal value of the objective function F-1 after hybridization of ALO with SA was found as7.6832e-09.

- Function 2:



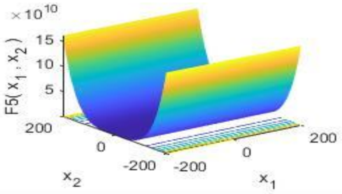
The best optimal value ofthe objective function F-2after hybridization of ALO with SA was found as4.1762e-05.

- Function 3:



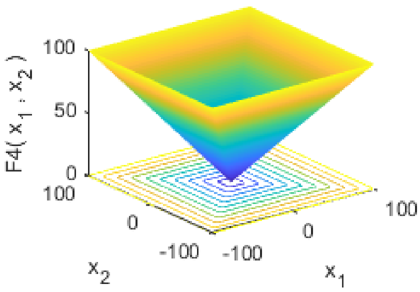
The best optimal value ofthe objective function F-3 after hybridization of ALO with SA was found as0.035858.

- Function 4:



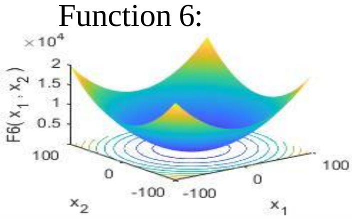
The best optimal value ofthe objective function F-4 after hybridization of ALO with SA was found as0.00013128.

- Function 5:



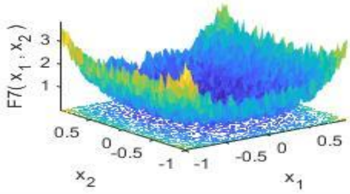
The best optimal value of the objective function F-5 after hybridization of ALO with SA was found as5.0457.

- Function 6:



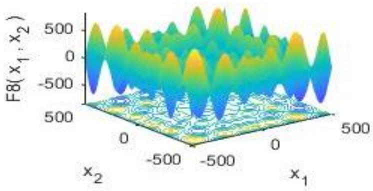
The best optimal value of the objective function F-6 after hybridization of ALO with SA was found as3.2805e-09.

- Function 7:



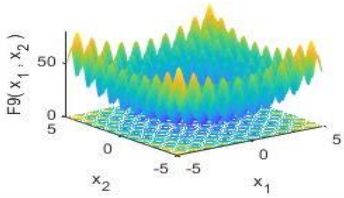
The best optimal value of the objective function F-7 after hybridization of ALO with SA was found as0.012528.

- Function 8:



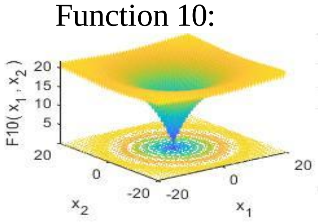
The best optimal value of the objective function F-8 after hybridization of ALO with SA was found as-3617.3413.

- Function 9:



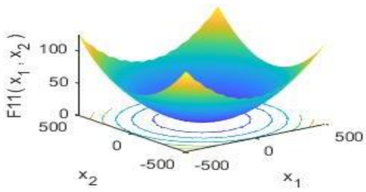
The best optimal value of the objective function F-9 after hybridization of ALO with SA was found as27.8588.

- Function 10:



The best optimal value of the objective function F-10 after hybridization of ALO with SA was found as1.1551.

- Function 11:



The best optimal value of the objective function F-11 after hybridization of ALO with SA was found as0.11311.

- Function 12:

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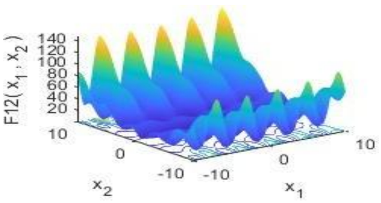
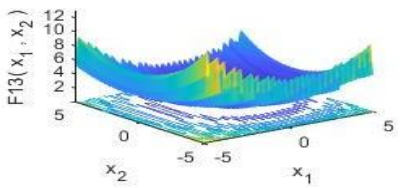


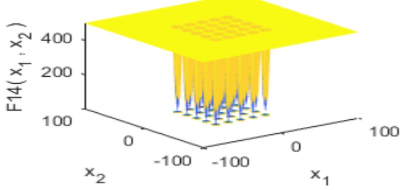
The best optimal value of the objective function F-12 after hybridization of ALO with SA was found as0.2056.

- Function 13:



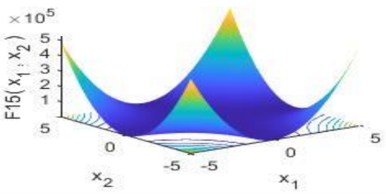
The best optimal value of the objective function F-13 after hybridization of ALO with SA was found as2.2729e-08.

- Function 14:



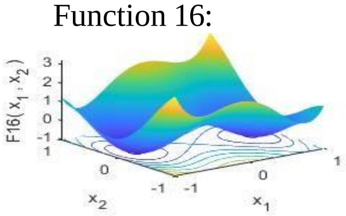
The best optimal value of the objective function F-14 after hybridization of ALO with SA was found as0.998.

- Function 15:



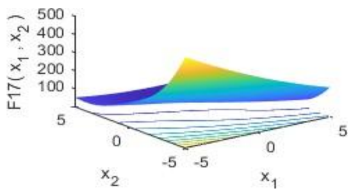
The best optimal value of the objective function F-15 after hybridization of ALO with SA was found as0.00075301.

- Function 16:



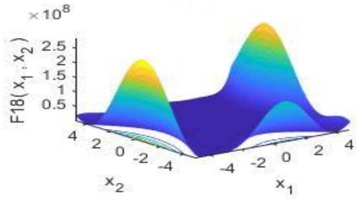
The best optimal value of the objective function F-16 after hybridization of ALO with SA was found as-1.0316.

- Function 17:



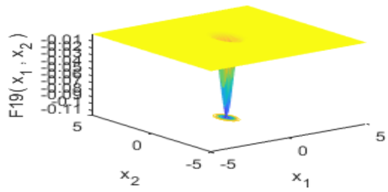
The best optimal value of the objective function F-17 after hybridization of ALO with SA was found as0.39789.

- Function 18:



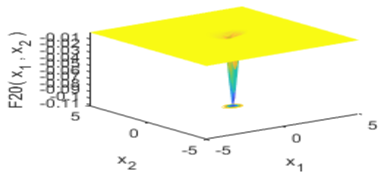
The best optimal value of the objective function F-18 after hybridization of ALO with SA was found as3.

- Function 19:



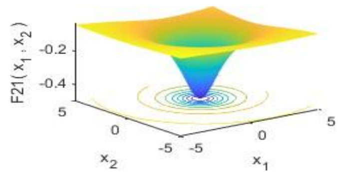
The best optimal value of the objective function F-19 after hybridization of ALO with SA was found as-3.8628.

- Function 20:



The best optimal value of the objective function F-20 after hybridization of ALO with SA was found as-3.322.

- Function 21:



The best optimal value of the objective function F-21 after hybridization of ALO with SA was found as-10.1532.

- Function 22:

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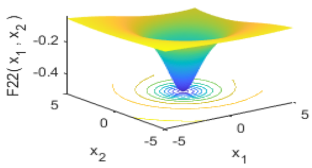
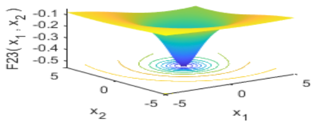


The best optimal value of the objective function F-22 after hybridization of ALO with SA was found as-5.1288.

- Function 23:



The best optimal value of the objective function F-23 after hybridization of ALO with SA was found as-10.5364.

Table 3: Results & Discussion

Benchmark Functions	**(ALO) Algorithm Values**	**(ALO-SA) Algorithm Values**
F1	3.17E-09	7.6832e-09
F2	7.73E-05	4.1762e-05
F3	1.91E-05	0.035858
F4	8.60E-05	0.00013128
F5	8.75E+02	5.0457
F6	1.46E-08	3.2805e-09
F7	1.60E-02	0.012528
F8	-2.04E+03	-3617.3413
F9	2.09E+01	27.8588
F10	1.16E+00	1.1551
F11	5.95E-01	0.11311
F12	8.58E-09	0.2056
F13	9.62E-09	2.2729e-08
F14	9.98E-01	0.998
F15	7.24E-04	0.00075301
F16	-1.03E+00	-1.0316
F17	3.98E-01	0.39789
F18	3.00E+00	3
F19	-3.86E+00	-3.8628
F20	-3.20E+00	-3.322
F21	-5.06E+00	-10.1532
F22	-3.72E+00	-5.0877
F23	-2.42E+00	-10.5364

5. Conclusion

The hybridization of the Ant Lion Optimizer (ALO) with the Simulated Annealing (SA) successfully combined the strong capability of exploration of ALO with exploitation and genetic features of SA.The hybridized algorithm of ALO with SA was tested with 23 benchmark functions and in 12 functions best values were found and considered as great results.

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