

A Hybrid Model: Combining Ant Lion Optimizer and Genetic Algorithm for Solving Complex Numerical Optimization Problem

Deepa Barethiya ; Sandhya Dahake ;
Ghanshyam Rahangadale ; Aditya Gour

Department of MCA, G H Rasoni College of Engineering & Management
Nagpur, Maharashtra, India

Abstract-

Optimization algorithms play a key role in solving complex numerical optimization problems. In this paper, a new hybrid model that integrates the Ant Lion Optimizer (ALO) and the Genetic Algorithm (GA) for optimizing and increase performance. The new hybrid model integrates the exploration ability of ALO and the exploitation ability of GA with the expectation of better convergence and optimal solutions. This hybrid algorithm being tested on twenty-three benchmarking functions and the results indicate that the hybrid model is better than the individual ALO algorithm and generating smaller errors and scores in the area of optimization. The study indicates that the proposed hybrid model offers a feasible solution to solving complex numerical optimization problem.

Keywords: Ant Lion Optimizer (ALO), Hybridization, Benchmark Functions, Exploration, Exploitation

1. Introduction

Optimization is a fundamental mechanism for addressing the complex issues in the areas of science, engineering, and artificial intelligence. While metaheuristic algorithms have proven highly effective in dealing with extensive search spaces, individual algorithm stand to experience problems with premature convergence or poor exploitation [12]. In this paper hybrid methodology being implemented to blends the strengths of the Ant Lion Optimizer (ALO) [9] and the Genetic algorithm [10] to facilitate

effective search process. By utilizing the exploratory ability of ALO and the enhanced exploitation capabilities of GA, our proposed model optimizes both convergence rate and solution precision [3,4].

The hybrid model was being tested on twenty-three benchmarking functions, and the results were always exceptional to those of the individual ALO and GA, hence indicating an enhancement in optimization and efficiency. These findings syndicate those hybrid methodologies may effectively substitute for addressing complex optimization problems.

2. Literature Review

This figure classifies the meta-heuristics algorithm into four types: nature-based algorithm, evolutionary-based algorithm, physics-based algorithm and human-based algorithm [11]. Each type represents different methods for solving optimization problem effectively.

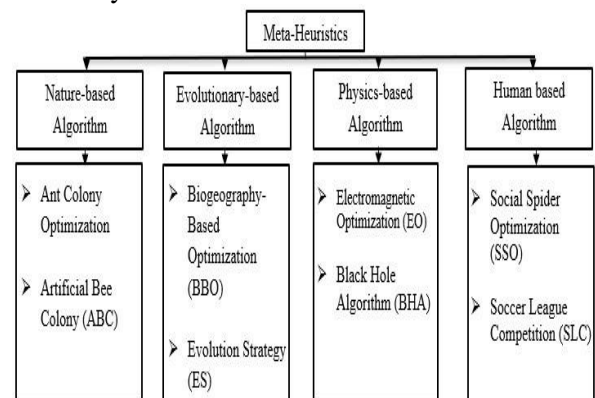


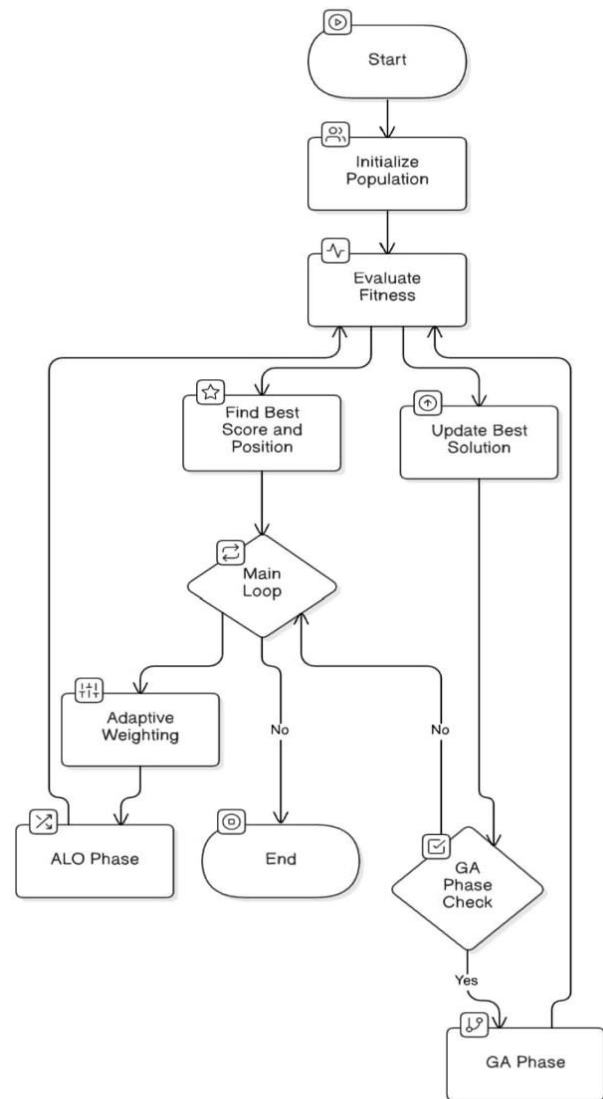
Fig-1: Classification of Algorithms

Tabel-1: Algorithm Details

| Sr No. | Algorithm | Author Name |
|--------|---------------------------------------|--|
| 1 | Ant Colony Optimization (ACO) | Dorigo & Gambardella Et al. (1997) |
| 2 | Artificial Bee Colony (ABC) | Karaboga Et al. (2005) |
| 3 | Biogeography-Based Optimization (BBO) | Simon Et al. (2008) |
| 4 | Evolution Strategy (ES) | Rechenberg Et al. (1973) |
| 5 | Electromagnetic Optimization (EO) | Birbil& Fang Et al. (2003) |
| 6 | Black Hole Algorithm (BHA) | Hatamlou Et al. (2013) |
| 7 | Social Spider Optimization (SSO) | Cuevas, Cienfuegos, Zaldívar Et al. (2013) |
| 8 | Soccer League Competition (SLC) | Moosavian& Gholipour Et al. (2015) |

The abovetable shows details of various meta-heuristics algorithms developed to solve complex optimization problems.

2.1 Flowchart



2.2 Benchmark Functions

Benchmark function is the mathematical test function which is used to analyze the performance of an algorithm. Each function test algorithm in different aspects.

Table 2: Standard UM benchmark functions

| Functions | Dimensions | Range | f_{min} |
|---|----------------|---------------|------------|
| $F_1(S) = \sum_{m=1}^n S_m^2$ | (10,30,50,100) | [-100, 100] | 0 |
| $F_2(S) = \sum_{m=1}^n S_m + \prod_{m=1}^n S_m $ | (10,30,50,100) | [-10, 10] | 0 |
| $F_3(S) = \sum_{m=1}^n (\sum_{n=1}^m S_n)^2$ | (10,30,50,100) | [-100, 100] | 0 |
| $F_4(S) = \max_n \{S_m, 1 \leq m \leq z\}$ | (10,30,50,100) | [-100, 100] | 0 |
| $F_5(S) = \sum_{m=1}^{n-1} [100(S_m + S_{m+1}^2)^2 + (S_m - 1)^2]$ | (10,30,50,100) | [-38, 38] | 0 |
| $F_6(S) = \sum_{m=1}^n ([S_m + 0.5])^2$ | (10,30,50,100) | [-100, 100] | 0 |
| $F_7(S) = \sum_{m=1}^n m S_m^4 + \text{random}[0,1]$ | (10,30,50,100) | [-1.28, 1.28] | 0 |
| $F_8(S) = \sum_{m=1}^n S_m \sin(\sqrt{ S_m })$ | (10,30,50,100) | [-500, 500] | -418.98295 |
| $F_9(S) = \sum_{m=1}^n [S_m^2 - 10 \cos(2\pi S_m) + 10]$ | (10,30,50,100) | [-5.12, 5.12] | 0 |
| $F_{10}(S) = -20 \exp(-0.2 \sqrt{\frac{1}{n} \sum_{m=1}^n S_m^2}) - \exp(\frac{1}{n} \sum_{m=1}^n \cos(2\pi S_m)) + 20 + d$ | (10,30,50,100) | [-32, 32] | 0 |
| $F_{11}(S) = 1 + \sum_{m=1}^n \frac{S_m^2}{4000} - \prod_{m=1}^n \cos \frac{S_m}{\sqrt{m}}$ | (10,30,50,100) | [-600, 600] | 0 |
| $F_{12}(S) = \frac{\pi}{n} \left\{ 10 \sin^2(\pi \tau_1) + \sum_{m=1}^{n-1} (\tau_m - 1)^2 [1 + 10 \sin^2(\pi \tau_{m+1})] + (\tau_n - 1)^2 \right\} + \sum_{m=1}^n u(S_m, 10, 100, 4)$ $\tau_m = 1 + \frac{S_m + 1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$ | (10,30,50,100) | [-50, 50] | 0 |
| $F_{13}(S) = 0.1 \{ \sin^2(3\pi S_m) + \sum_{m=1}^n (S_m - 1)^2 [1 + \sin^2(3\pi S_m + 1)] + (x_n - 1)^2 [1 + \sin^2(2\pi S_n)] \}$ | (10,30,50,100) | [-50, 50] | 0 |

| | | | |
|--|---|-------------------|----------|
| $F_{14}(S) = \left[\frac{1}{500} + \sum_{n=1}^n 5 \frac{1}{n + \sum_{m=1}^n (S_m - b_{mn})^4} \right]^{-1}$ | 2 | [-65.536, 65.536] | 1 |
| $F_{15}(S) = \sum_{m=1}^{11} \left[b_m - \frac{S_1(a_m^2 + a_m b_m)}{a_m^2 + a_m b_m + S_4} \right]^2$ | 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 |
| $F_{17}(S) = (S_2 - \frac{81}{482}S_1^2 + \frac{5}{\pi}S_1 - 6)^2 + 10(1 - \frac{1}{8\pi})\cos S_1 + 10$ | 2 | [-5, 5] | 0.398 |
| $F_{18}(S) = \left[I + (S_1 + S_2 + 1)^4 (19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1S_2 + 3S_2^2) \right]^4 \times \left[30 + (2S_1 - 3S_2)^4 (18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1S_2 + 27S_2^2) \right]$ | 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 |
| $F_{21}(S) = -\sum_{m=1}^5 [(S - b_m)(S - b_m)^2 + d_m]^{-1}$ | 4 | [0, 10] | -10.1532 |
| $F_{22}(S) = -\sum_{m=1}^7 [(S - b_m)(S - b_m)^2 + d_m]^{-1}$ | 4 | [0, 10] | -10.4028 |
| $F_{23}(S) = -\sum_{m=1}^7 [(S - b_m)(S - b_m)^2 + d_m]^{-1}$ | 4 | [0, 10] | -10.5363 |

2.3 Search Spaces

The following figures present the search spaces for the twenty-three benchmarking function.

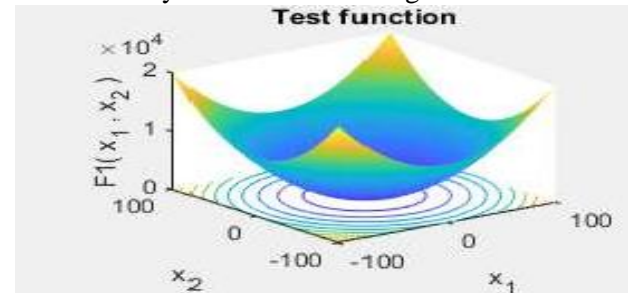


Fig. 1: Function 1

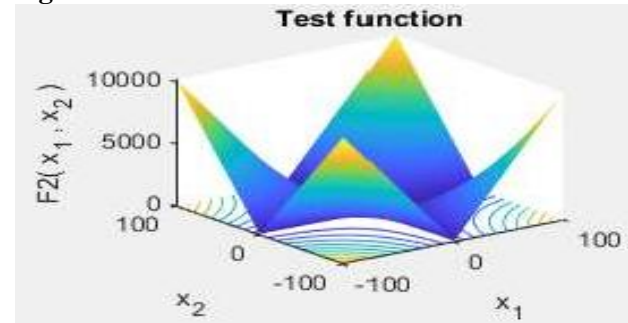


Fig. 2: Function 2

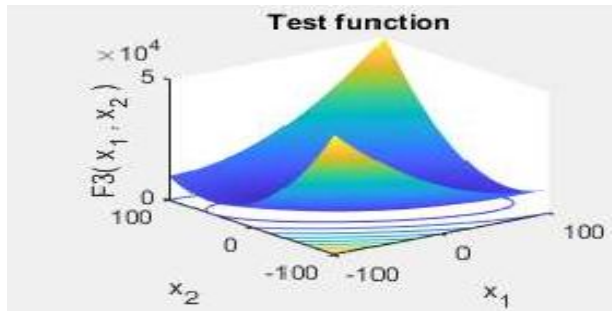


Fig. 3: Function 3

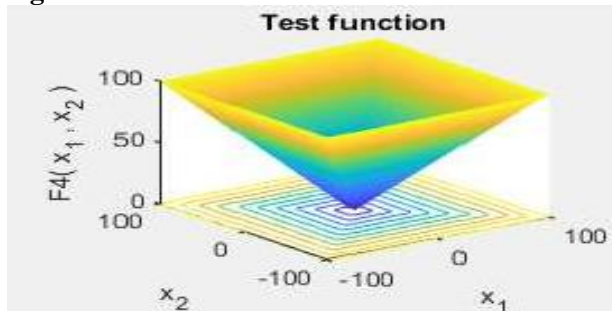


Fig. 4: Function 4

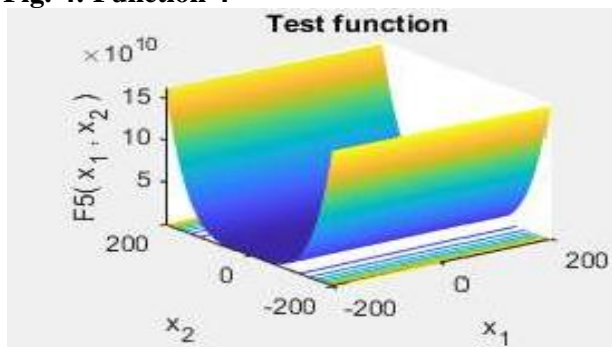


Fig. 5: Function 5

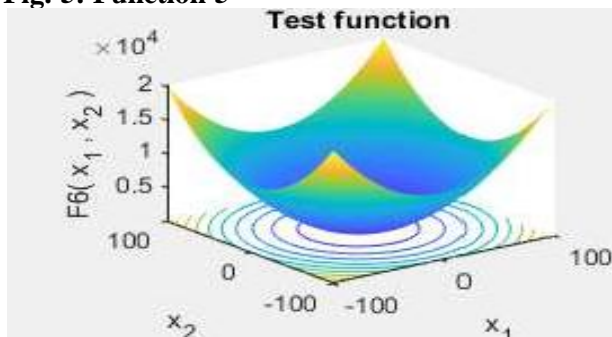


Fig.6: Function 6

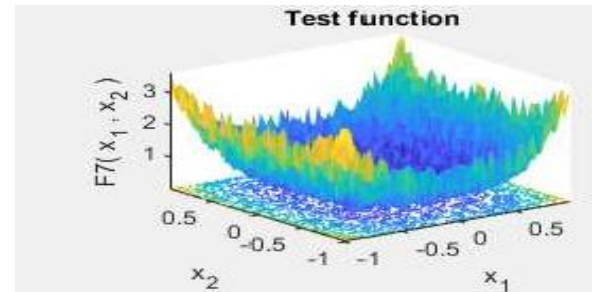


Fig. 7: Function 7

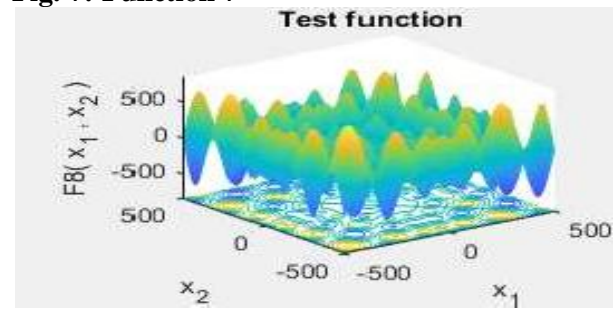


Fig. 8: Function 8

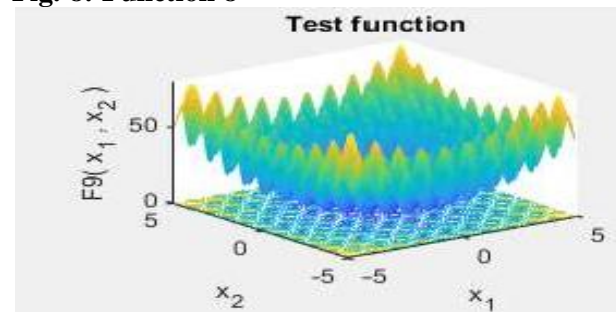


Fig. 9: Function 9

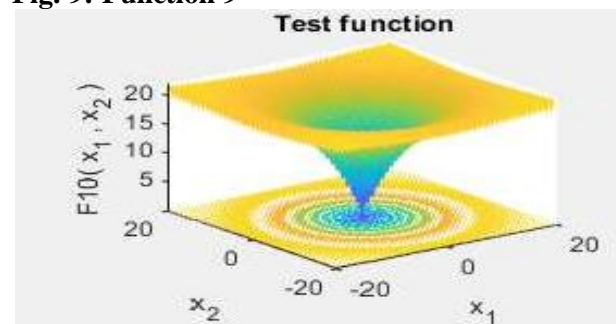


Fig. 10: Function 10

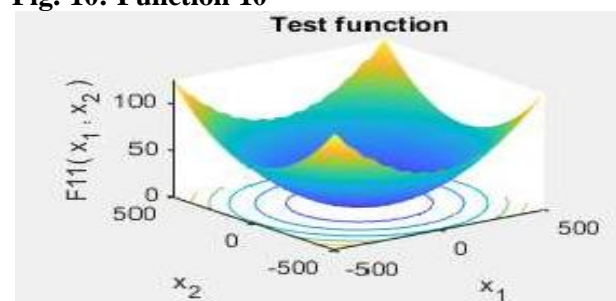


Fig. 11: Function 11

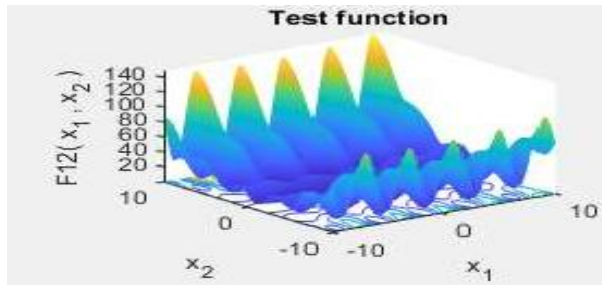


Fig. 12: Function 12

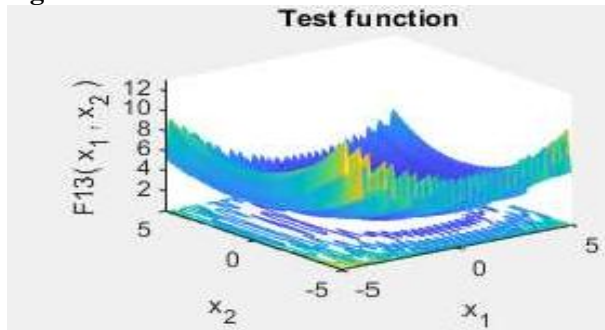


Fig. 13: Function 13

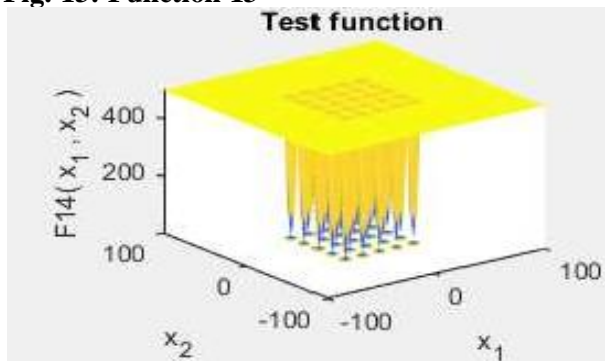


Fig. 14: Function 14

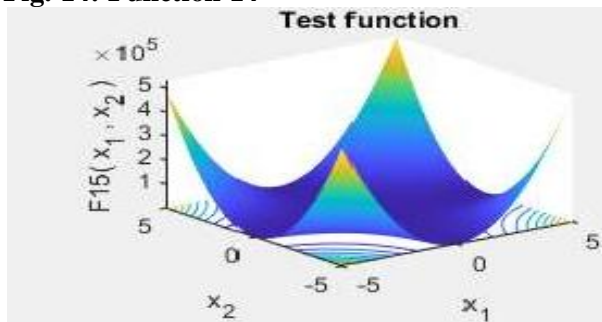


Fig. 15: Function 15

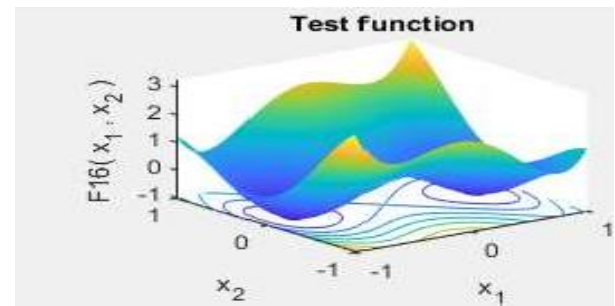


Fig.16: Function 16

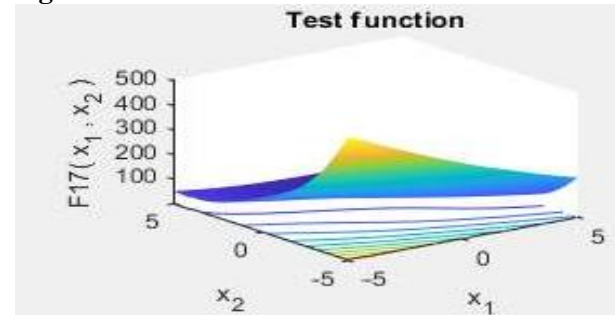


Fig. 17: Function 17

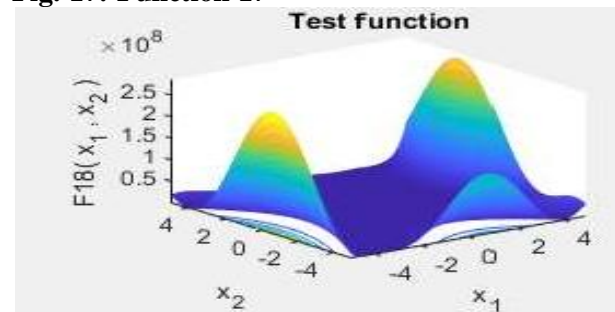


Fig. 18: Function 18

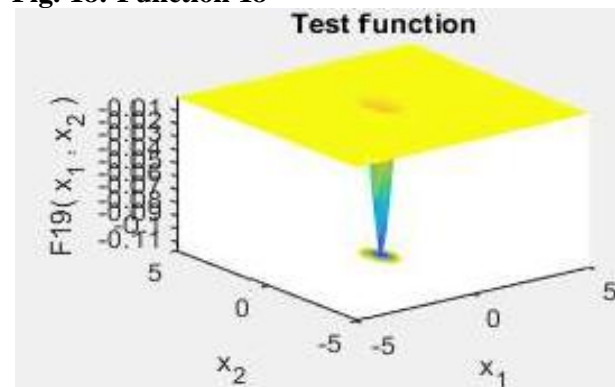


Fig. 19: Function 19

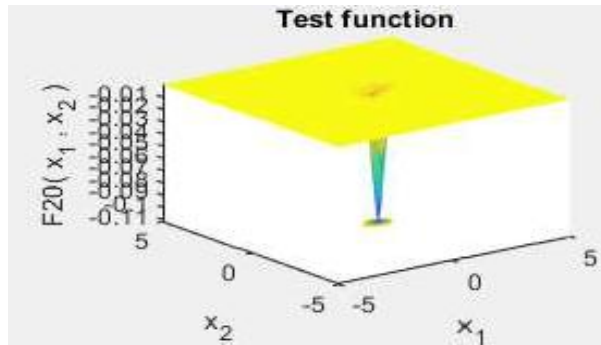


Fig.20: Function 20

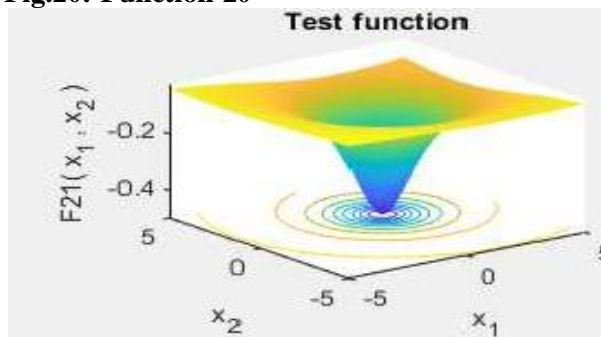


Fig. 21: Function 21

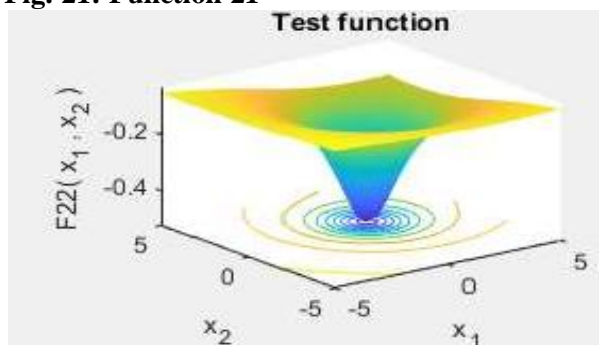


Fig. 22: Function 22

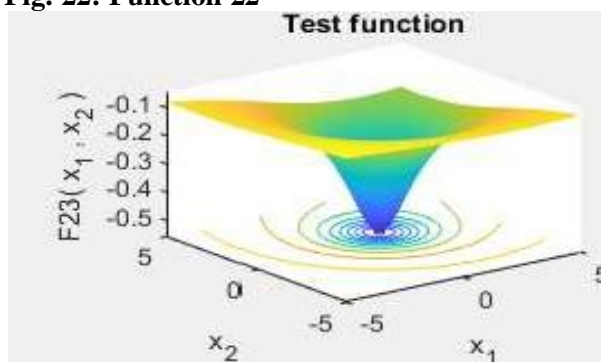


Fig. 23: Function 23

3. Results and Discussion

The proposed hybrid algorithm being tested on twenty-three benchmarking functions to determine its performance.

| Function | Ant Lion Optimizer | Hybrid of Ant Lion Optimizer with Genetic Algorithm |
|----------|--------------------|---|
| F1 | -1.03E+00 | 0.0014293 |
| F2 | 7.73E-05 | 0.014322 |
| F3 | 6.40E+00 | 0.0081235 |
| F4 | 8.60E-05 | 0.027812 |
| F5 | 8.75E+02 | 8.7406 |
| F6 | 1.46E-08 | 0.00056108 |
| F7 | 0.016035 | 0.012942 |
| F8 | -2039.08 | -3897.0635 |
| F9 | 20.8941 | 4.9801 |
| F10 | 1.1551 | 0.017075 |
| F11 | 0.5952 | 0.082671 |
| F12 | 8.58E-09 | 0.0003813 |
| F13 | 9.62E-09 | 0.00019925 |
| F14 | 0.998 | 0.998 |
| F15 | 0.00094243 | 0.00073664 |
| F16 | -1.0316 | -1.0316 |
| F17 | 0.39789 | 0.39789 |
| F18 | 3 | 3 |
| F19 | -3.8628 | -3.8628 |
| F20 | -3.2027 | -3.322 |
| F21 | -5.0552 | -10.1531 |
| F22 | -10.4029 | -10.4029 |
| F23 | -10.5364 | -10.5364 |

From above table, conclude that hybrid ALO-GA provide more relevant and optimize value as compared to individual ALO algorithm. Some values remained unchanged, and some are showing fluctuation in values and functions such as F3, F5, F7, F8, F9, F10, F11, F15, F20 and F21 give the optimized value.

4. Conclusion

This study evaluates and improves the performance of Ant Lion Optimizer using hybridization approach of (ALO+GA), the hybrid algorithm being tested on twenty-three benchmarking functions out of which 10 functions provide a best optimal value compared to the original algorithm which consider as an improvement in performance of Ant Lion Optimizer.

5. References

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