

Mutated Butterfly Optimization Algorithm

K. M.Dhanya, S. Kanmani

Abstract: *Butterfly optimization algorithm is a nature inspired metaheuristic algorithm which adapts food foraging behavior of butterflies. Butterfly optimization algorithm was introduced to solve benchmark functions and engineering design optimization problems. Mutated butterfly optimization algorithm, a new variant of butterfly optimization algorithm is proposed in this work for solving global optimization problems. It is an approach which combines butterfly optimization algorithm with Cauchy mutation to achieve global optimal solution by avoiding entrapment in local optima. The validation of proposed algorithm is carried out on low dimensional and high dimensional test functions. The experimental results are compared with basic butterfly optimization algorithm and other variants of it reported in the literature. The Wilcoxon signed rank test is also performed to identify the significance of proposed algorithm with other methods. The proposed method has achieved better results than basic butterfly optimization algorithm and its variants on various test functions.*

Index Terms: *Butterfly Optimization Algorithm, Nature Inspired Metaheuristic Algorithm, Mutated Butterfly Optimization Algorithm, Cauchy Mutation, Wilcoxon Signed Rank Test*

I. INTRODUCTION

Butterflies are the most beautiful insects in nature. The primary food source of butterflies is nectar from flowers. Butterflies emit fragrance which makes them follow each other to find out nectar. The nectar searching property of butterflies inspired Arora and Singh to devise Butterfly Optimization Algorithm(BOA) [1]. Nature inspired methods based on other behaviours of butterflies also exist. Monarch Butterfly Optimization Algorithm mimics the migration behaviour of monarch butterflies and Artificial Butterfly Optimization Algorithm simulates the mating behaviour of speckled wood butterflies [2]- [5].

To improve the performance of nature inspired metaheuristic methods, various mechanisms are being adopted by the researchers. The incorporation of Cauchy mutation operator with them is one of those mechanisms. The nature inspired methods like Artificial Bee Colony Algorithm, Bat Algorithm, Differential Evolution Algorithm, Firefly Algorithm, Flower Pollination Algorithm, Genetic Algorithm, Imperialist Competitive Algorithm and Particle Swarm Optimization algorithm have clubbed Cauchy mutation operator with them [6]- [15].

Since the introduction of BOA, several variants of it have been developed like Modified Butterfly Optimization Algorithm (MBOA), Chaotic BOA-based methods (CBOA), Improved Butterfly Optimization Algorithm (IBOA), Hybrid BOA with Artificial Bee Colony algorithm (BOA/ABC) and Hybrid BOA with Differential Evolution algorithm

(BOA/DE) [16]- [20].

A new variant of BOA, Mutated Butterfly Optimization Algorithm(BOA-C) is proposed in this work with the intention of achieving global optimal solution for optimization problems. BOA-C utilizes Cauchy mutation operator to avoid entrapment in local optima. In BOA-C, worst butterfly is not considered at the time of determining new position of butterflies by random selection. The performance of proposed Mutated Butterfly Optimization algorithm is validated on low dimensional and high dimensional test functions [21]. The experimental results are compared with results of basic BOA and other variants of BOA found in the literature for better analysis. Wilcoxon signed rank test, a pairwise statistical comparison is also carried out to identify significant difference between proposed algorithm and other studied algorithms individually [22]- [25].

II. PROPOSED ALGORITHM

The proposed algorithm, BOA-C is an enhanced version of BOA with Cauchy mutation operator. BOA-C considers a swarm of butterflies in which butterflies are positioned in random locations. The fragrance of butterflies is determined based on its sensory modality, stimulus intensity and power exponent of modality as in BOA [1]. The best and worst butterflies are identified depending on the amount of fragrance emitted by them. Butterflies always fly towards new location in search of better quality of nectar. The two phases, local search and global search in BOA are utilized for updating position of butterflies. But, in local search phase of BOA-C, butterflies other than worst butterfly are only randomly selected from the same swarm. The switch probability is its main deciding factor of those phases. The fitness at new position is evaluated. Then, fitness is updated with better one. After that, Cauchy mutation is applied on the best butterfly. Cauchy mutation is based on Cauchy distribution which generates large random numbers capable of performing longer jumps [12]. An additional scale parameter is also used with standard Cauchy distribution employed for mutation of best butterfly. The Cauchy mutation helps best butterfly to extend its search in the search space. The best butterfly updates its fitness if it has achieved better fitness after mutation. The process continues until stopping criteria is met and best butterfly thus obtained is considered as the optimal solution. The pseudocode of proposed Cauchy mutated BOA is presented below.

Pseudocode: Mutated Butterfly Optimization Algorithm

- Initialize butterfly population randomly
- Initialize sensory modality, power exponent and switch probability

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K. M.Dhanya, Department of Computer Science and Engineering, Pondicherry Engineering College, Puducherry, India

S. Kanmani, Department of Information Technology, Pondicherry Engineering College, Puducherry, India



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- c. Determine stimulus intensity
- d. while maximum iteration not met do
 - i. for each butterfly do
 1. Determine fragrance of the butterfly
 - ii. end for
 - iii. Find the best and worst butterflies
 - iv. for each butterfly do
 1. Generate rand from uniform numbers [0,1]
 2. if (rand < switch probability) then
Fly towards best butterfly
 3. else
Fly towards randomly chosen butterflies other than worst butterfly
 4. end if
 5. Determine new fitness of the butterfly
 6. if (new fitness better) then
Update fitness of the butterfly
 7. end if
 8. Mutate the best butterfly
 9. if (fitness of mutated one better) then
Update fitness of the best butterfly
 10. end if
 - v. end for
 - vi. Update value of power exponent of modality
- e. end while
- f. Output best solution

To summarize, main characteristics of BOA-C and some other variants of BOA are presented in Table 1.

Table 1: Characteristics of BOA and its Variants

| Alg | Global Search | Local Search | Improvement Mechanism | Remarks |
|--------|----------------------------|---|---|--|
| BOA | Fly towards best butterfly | Fly towards randomly selected butterflies | NA | Solved benchmark functions and classical engineering design problems |
| MBOA | BOA Global Search | BOA Local Search | Intensive Exploitation of best butterfly | Avoided local optima and premature convergence of BOA |
| BOA/DE | BOA Global Search | Mutation of DE | Hybridization of BOA and DE | Achieved faster convergence than BOA |
| IBOA | BOA Global Search | BOA Local Search | Dynamic and adaptive adjustment strategy of sensory modality | Improved searching capability of butterflies |
| BOA-C | BOA Global Search | BOA Local Search in which random selection of | Cauchy mutation applied to best butterfly. An additional scale | Improves search capability of best butterfly Avoids local |

| | | | | |
|--|--|----------------------------------|--|-------------------|
| | | butterflies other than worst one | parameter used with standard Cauchy distribution | optima entrapment |
|--|--|----------------------------------|--|-------------------|

III. EXPERIMENT AND RESULT ANALYSIS

The experiment was conducted to assess the performance of BOA-C on well-known test functions. The test functions considered were categorized into low dimensional and high dimensional test functions. The details of test functions obtained from literature are given in Table 2[21].

BOA-C was executed 25 times on each test function. For each run of BOA-C, 100 iterations and 30 butterflies were considered.

Table 2: Details of Test Functions

| F _n | Formula | n | Limits | Category |
|----------------|---|----|--------------|----------|
| f_{bky} | $f_{bky}(x) = x_1^2 + 2x_2^2 - 0.3\cos(3\pi x_1) - 0.4\cos(4\pi x_2) + 0.7$ | 2 | [-100,100] | Low Dim |
| f_{bth} | $f_{bth}(x) = (x_1 + 2x_2 - 7)^2 + (2x_1 + x_2 - 5)^2$ | 2 | [-10,10] | Low Dim |
| f_{lvy} | $f_{lvy}(x) = \sin^2(3\pi x_1) + (x_1 - 1)^2(1 + \sin^2(3\pi x_2)) + (x_2 - 1)^2(1 + \sin^2(2\pi x_2))$ | 2 | [-10,10] | Low Dim |
| f_{mas} | $f_{mas}(x) = 0.26(x_1^2 + x_2^2) - 0.48x_1x_2$ | 2 | [-10,10] | Low Dim |
| f_{qne} | $f_{qne}(x) = \sum_{i=1}^n ix_1^4 + \text{rand}(0,1)$ | 30 | [-1.28,1.28] | High Dim |
| f_{rck} | $f_{rck}(x) = \sum_{i=1}^{n-1} [100(x_{i+1} - x_i)^2 + (x_i - 1)^2]$ | 30 | [-10,10] | High Dim |
| f_{sel} | $f_{sel}(x) = \max_{1 \leq i \leq n} x_i $ | 30 | [-10,10] | High Dim |
| f_{sre} | $f_{sre}(x) = \sum_{i=1}^n x_i^2$ | 30 | [-100,100] | High Dim |

The values assigned to sensory modality and switch probability were 0.01 and 0.8 respectively. The power exponent of modality has been assigned values in the range [0.1,0.3]. The scale parameter of standard Cauchy distribution was taken as 1.0 and that of additional scale parameter as 0.1.



To get a clear picture on the efficiency of BOA-C, best solution obtained, number of fitness evaluations carried out to achieve it and computing time of the algorithm were noted. The simulation results obtained by BOA and BOA-C on eight test functions are given in Table 3.

Table 3: Simulation Results of BOA and BOA-C on Test Functions

| No. | Fn | Alg | NFE | Best | Time |
|-----|-----------|-------|------|-----------|---------|
| 1 | f_{bky} | BOA | 2292 | 9.58E-01 | 0.00004 |
| | | BOA-C | 703 | 0.00E+00 | 0.0002 |
| 2 | f_{bth} | BOA | 2196 | 1.98E-05 | 0.00008 |
| | | BOA-C | 2795 | 4.92E-09 | 0.00008 |
| 3 | f_{ivy} | BOA | 673 | 1.14E-01 | 0.00004 |
| | | BOA-C | 1700 | 7.71E-05 | 0.0002 |
| 4 | f_{mas} | BOA | 2800 | 2.16E-04 | 0.00008 |
| | | BOA-C | 390 | 0.00E+00 | 0.00016 |
| 5 | f_{qne} | BOA | 1100 | 2.25E+00 | 0.00004 |
| | | BOA-C | 743 | 5.26E-10 | 0.00052 |
| 6 | f_{rck} | BOA | 2900 | 5.27E+01 | 0.00044 |
| | | BOA-C | 1197 | 2.88E+01 | 0.00096 |
| 7 | f_{sel} | BOA | 2900 | 2.80E+00 | 0.00036 |
| | | BOA-C | 99 | 7.38E-196 | 0.0002 |
| 8 | f_{sre} | BOA | 1500 | 4.72E+01 | 0.00028 |
| | | BOA-C | 263 | 0.00E+00 | 0.00036 |

BOA-C has achieved solutions similar to that of best known solutions on test functions, f_{bky} , f_{mas} and f_{sre} . The solutions obtained by BOA-C for test functions considered are better than BOA. It has also taken a minimum number of fitness evaluations to achieve the best solution than BOA on every high dimensional test functions and some of the low dimensional test functions. It can be inferred that incorporation of Cauchy mutation has improved the performance of BOA. However, computing time of BOA-C was more than BOA on most of the test functions. The increase in execution time was due to the improvement mechanism added to it. The variable values of low and high dimensional test functions for best fitness value obtained by BOA-C on the corresponding test function are tabulated separately in Tables 4 and 5.

Table 4: Low Dimensional Test Functions Variable Values for BOA-C Best Solution

| Variable | f_{bky} | f_{bth} | f_{ivy} | f_{mas} |
|----------|-----------|-----------|-----------|-----------|
| Best | 0.00E+00 | 4.92E-09 | 7.71E-05 | 0.00E+00 |
| x_1 | -2.09E-09 | 1.000049 | 0.999745 | 2.99E-16 |
| x_2 | -1.00E-09 | 2.999972 | 0.991572 | 3.52E-16 |

Table 5: High Dimensional Test Functions Variable Values for BOA-C Best Solution

| Variable | f_{qne} | f_{rck} | f_{sel} | f_{sre} |
|----------|-----------|-----------|------------|------------|
| Best | 5.26E-10 | 2.88E+0 | 7.38E-196 | 0.00E+00 |
| x_1 | 0.001377 | 0.012556 | 1.54E-196 | -1.51E-163 |
| x_2 | -0.00026 | 0.007068 | -6.63E-196 | -9.92E-164 |
| x_3 | -0.00172 | 0.002865 | 7.03E-196 | -6.17E-163 |
| x_4 | 8.33E-05 | 0.009172 | -4.06E-196 | -1.23E-163 |
| x_5 | -0.00108 | 0.005374 | -5.05E-197 | -1.33E-163 |
| x_6 | -3.91E-05 | 0.008924 | 5.31E-196 | -5.25E-163 |
| x_7 | 0.001165 | 0.009831 | -3.58E-197 | -6.23E-163 |
| x_8 | -0.00124 | 0.000988 | -6.43E-196 | -4.28E-163 |
| x_9 | 1.57E-05 | 0.006902 | -1.41E-196 | 2.08E-163 |
| x_{10} | -0.0015 | 0.005565 | -7.11E-196 | 2.37E-163 |
| x_{11} | 0.000423 | 0.007186 | -1.80E-196 | 6.40E-164 |
| x_{12} | -0.00068 | -0.01209 | -3.61E-196 | 3.05E-163 |
| x_{13} | 0.001101 | 0.013881 | -3.16E-196 | -3.17E-163 |
| x_{14} | 0.001358 | 0.002821 | 5.55E-196 | 2.00E-163 |
| x_{15} | -0.00073 | 0.00261 | -7.11E-196 | -4.15E-163 |
| x_{16} | -0.00077 | 0.006652 | -5.76E-196 | -2.34E-163 |
| x_{17} | 0.000412 | 0.009082 | 2.33E-196 | 4.87E-163 |
| x_{18} | -0.00103 | 0.007775 | -2.14E-197 | -3.12E-163 |
| x_{19} | -0.00092 | 0.00768 | 7.07E-196 | -5.95E-163 |
| x_{20} | -4.53E-06 | 0.009518 | 7.38E-196 | 5.02E-163 |
| x_{21} | -0.00104 | -0.00098 | -5.79E-196 | -3.92E-163 |
| x_{22} | -0.0002 | -0.00504 | 5.73E-196 | -1.54E-163 |
| x_{23} | -0.00109 | 0.004069 | -1.85E-196 | -4.36E-164 |
| x_{24} | 0.000911 | 0.002005 | 2.22E-196 | 7.09E-163 |
| x_{25} | 0.001481 | 0.008297 | -4.40E-196 | 4.42E-163 |
| x_{26} | 0.001078 | 0.015596 | 3.65E-196 | -3.05E-163 |
| x_{27} | -0.00034 | 0.000953 | -1.85E-197 | 2.91E-163 |
| x_{28} | -0.00072 | 0.008833 | -1.74E-196 | -5.30E-164 |
| x_{29} | 0.001186 | 0.004684 | 3.65E-196 | -4.65E-164 |
| x_{30} | 0.000144 | -0.00167 | 2.67E-196 | 2.22E-164 |

The convergence of BOA and BOA-C on test functions are also depicted in figures 1 to 8. It clearly illustrates convergence of best butterfly obtained by the algorithms.

Mutated Butterfly Optimization Algorithm

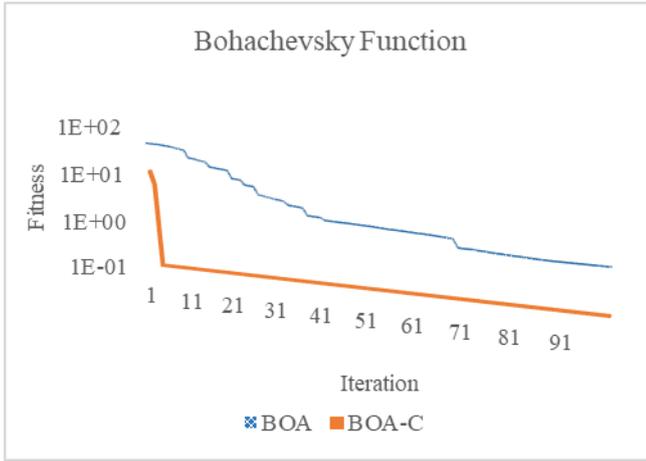


Fig 1: Convergence of BOA and BOA-C on fbky

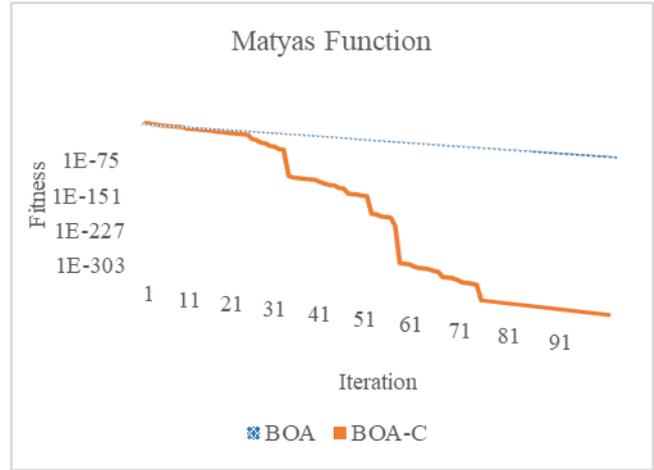


Fig 4: Convergence of BOA and BOA-C on fmas

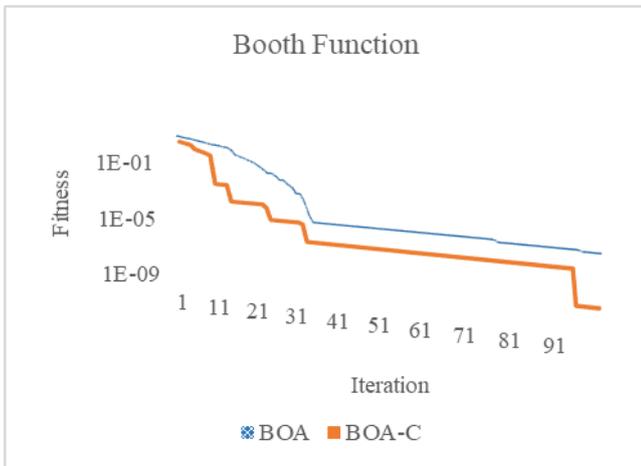


Fig 2: Convergence of BOA and BOA-C on fbth

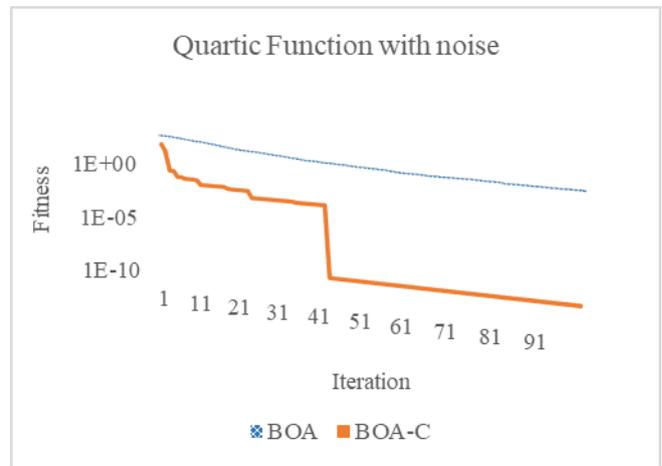


Fig 5: Convergence of BOA and BOA-C on fqne

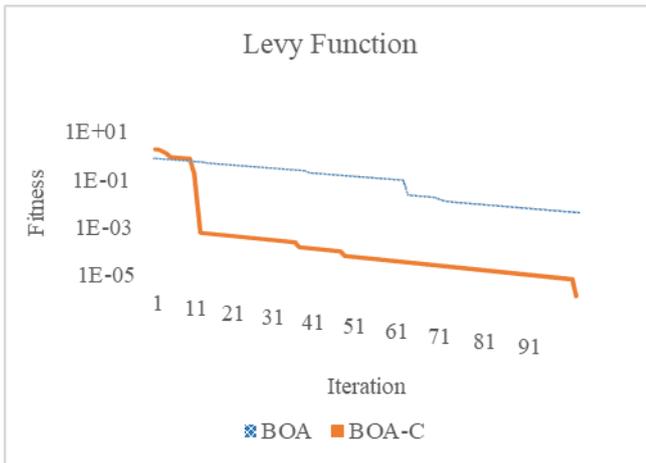


Fig 3: Convergence of BOA and BOA-C on flvy

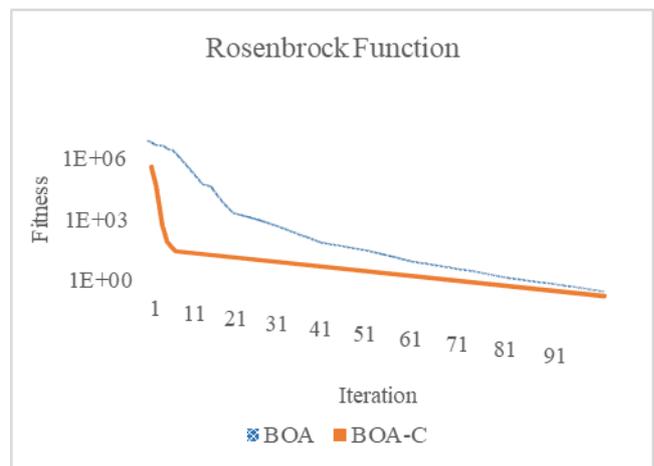


Fig 6: Convergence of BOA and BOA-C on frck

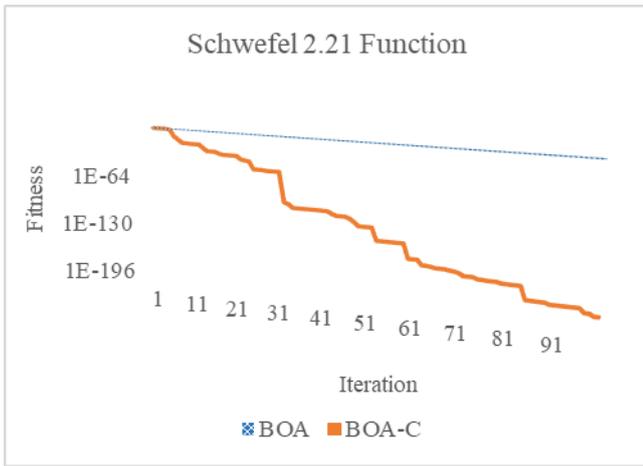


Fig 7: Convergence of BOA and BOA-C on fsel

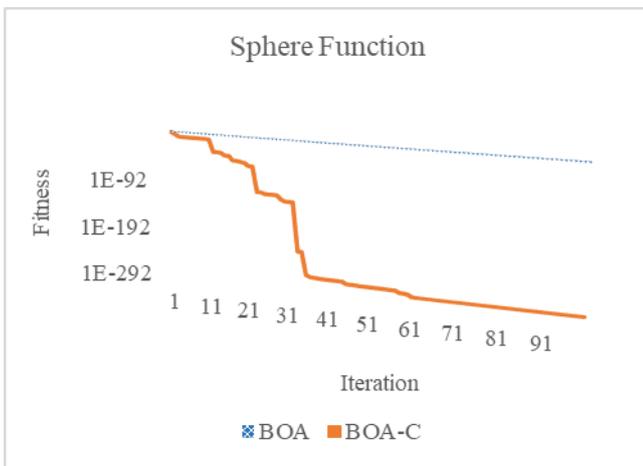


Fig 8: Convergence of BOA and BOA-C on fsre

BOA-C converges to solutions better than BOA on all the test functions. Cauchy mutation operator has enabled best butterfly in BOA-C to increase its search capability and attain global optimal solutions. In other words, BOA-C has improved quality of solutions by avoiding local optima.

The performance of BOA-C on test functions was further analyzed with that of basic BOA, MBOA, BOA/DE and IBOA. For comparison, performance mean and standard deviation values obtained by BOA and BOA-C are noted in Tables 6 and 7 along with values of BOA variants which are taken from the literature [16], [20].

Table 6: Performance Mean of BOA and its Variants on Test Functions

| Fn | Algorithm | | | | |
|-----------|-----------|-----------|----------|----------|-----------|
| | BOA | MBOA* | BOA/DE* | IBOA* | BOA-C |
| f_{bky} | 4.52E+00 | 0.00E+00 | 4.30E-08 | 9.10E+00 | 0.00E+00 |
| f_{bth} | 2.41E-01 | 0.00E+00 | 5.21E-03 | 1.99E-03 | 1.92E-01 |
| f_{ivy} | 4.58E+00 | 1.31E+00 | 2.21E+00 | 4.51E+01 | 5.06E-01 |
| f_{mas} | 1.01E-01 | 8.03E-152 | 1.88E-06 | 5.95E-09 | 6.83E-153 |
| f_{qne} | 2.52E+00 | 9.42E-03 | 3.59E-02 | 3.42E+05 | 1.76E-03 |
| f_{rck} | 5.66E+01 | 2.88E+01 | 2.89E+01 | 3.38E+03 | 2.88E+01 |
| f_{sel} | 2.93E+00 | 2.81E-03 | 3.89E-03 | 1.56E+00 | 7.38E-71 |
| f_{sre} | 5.18E+01 | 2.00E-12 | 9.76E-05 | 5.26E+10 | 5.77E-130 |

Table 7: Standard Deviation of BOA and its Variants on Test Functions

| Fn | Algorithm | | | | |
|-----------|-----------|-----------|----------|----------|-----------|
| | BOA | MBOA* | BOA/DE* | IBOA* | BOA-C |
| f_{bky} | 2.87E+00 | 0.00E+00 | 8.63E-08 | 1.01E+00 | 0.00E+00 |
| f_{bth} | 2.41E-01 | 0.00E+00 | 9.47E-03 | 2.37E-03 | 3.72E-01 |
| f_{ivy} | 3.97E+00 | 1.95E-01 | 2.72E-01 | 1.60E+00 | 4.74E-01 |
| f_{mas} | 9.03E-02 | 2.54E-151 | 3.26E-06 | 4.76E-09 | 3.41E-136 |
| f_{qne} | 1.31E-01 | 5.64E-03 | 3.17E-02 | 2.26E+05 | 1.88E-03 |
| f_{rck} | 1.92E+00 | 9.66E-02 | 7.12E-02 | 1.91E+03 | 3.46E-02 |
| f_{sel} | 4.86E-02 | 4.72E-03 | 3.54E-05 | 4.86E-01 | 2.32E-70 |
| f_{sre} | 2.36E+00 | 2.13E-09 | 4.05E-05 | 3.34E+09 | 2.59E-129 |

* Results obtained from literature

It is observed that BOA-C has obtained better performance mean and standard deviation values than basic BOA on every test functions. It has also produced competitive results with other BOA variants.

The statistical analysis based on Wilcoxon signed rank test at a significance level of 0.05 was also carried out and the results are shown in Table 8. The analysis determined whether BOA-C and other compared algorithms have shown any significant difference in their performances on test function.

Table 8: Wilcoxon Signed Rank Test Result on BOA and its Variants

| Fn | BOA vs BOA-C | MBOA vs BOA-C | BOA/DE vs BOA-C | IBOA vs BOA-C |
|---------------|--------------|---------------|-----------------|---------------|
| f_{bky} | + | = | + | + |
| f_{bth} | + | - | - | - |
| f_{ivy} | + | + | + | + |
| f_{mas} | + | + | + | + |
| f_{qne} | + | + | + | + |
| f_{rck} | + | = | + | + |
| f_{sel} | + | + | + | + |
| f_{sre} | + | + | + | + |
| Better | 8 | 5 | 7 | 7 |
| Worse | 0 | 1 | 1 | 1 |
| Equal | | 2 | | |

The statistical analysis resulted in twenty-seven better results, three worst results and two equal results for BOA-C out of thirty-two comparisons carried out. It is noted that BOA-C has obtained worse solutions than compared algorithms only on f_{bth} . The analysis demonstrates that BOA-C is significantly better than basic BOA and IBOA on low dimensional and high dimensional test functions. However, there is no enough evidence to show its significant difference from MBOA and BOA/DE on test functions.

The ranks were also assigned to BOA and its variants considering their performances. The rank summary of the algorithms is specified in Table 9.



Table 9: Rank Summary of BOA and its Variants

| Fn | Algorithm | | | | |
|--------------|-----------|-----------|------------|-----------|-----------|
| | BOA | MBOA | BOA/D E | IBO A | BOA-C |
| f_{bky} | 4 | 1.5 | 3 | 5 | 1.5 |
| f_{bth} | 5 | 1 | 3 | 2 | 4 |
| f_{lvy} | 5 | 2 | 3 | 4 | 1 |
| f_{mas} | 5 | 2 | 4 | 3 | 1 |
| f_{qne} | 4 | 2 | 3 | 5 | 1 |
| f_{rck} | 4 | 1.5 | 3 | 5 | 1.5 |
| f_{sel} | 5 | 2 | 3 | 4 | 1 |
| f_{sre} | 4 | 2 | 3 | 5 | 1 |
| Total | 36 | 14 | 25 | 33 | 12 |

BOA-C scored lowest value among the algorithms for solving most of the test functions considered. The rank summary shows that BOA-C has secured first rank followed by MBOA, BOA/DE, IBOA and BOA. It is worthwhile to note that Cauchy mutation in BOA-C has improved its performance on low dimensional and high dimensional test functions.

IV. CONCLUSION

BOA-C is an improved version of BOA in which Cauchy mutation operator is applied on best butterfly to enhance its global search capability. The performance of BOA-C is tested on both low dimensional and high dimensional test functions. The study is remarkable since BOA-C has resulted in higher quality solutions than basic BOA and its variants on test functions considered. It is also worth mentioning that BOA-C has avoided local optima entrapment on test functions. In future, various mechanisms for intensive exploitation and extensive exploration for BOA can be investigated and then integrated with it for achieving optimal solutions. BOA-C can also be utilized to solve classical engineering design optimization problems and combinatorial optimization problems.

NOMENCLATURE

| | |
|-----------|---|
| Alg | Algorithm |
| Fn | Test Function |
| f_{bky} | Bohachevsky Function |
| f_{bth} | Booth Function |
| f_{lvy} | Levy Function |
| f_{mas} | Matyas Function |
| f_{qne} | Quartic Function with noise |
| f_{rck} | Rosenbrock Function |
| f_{sel} | Schwefel 2.21 Function |
| f_{sre} | Sphere Function |
| x_i | i^{th} Variable of Test Functions |
| n | Dimension of Test Functions |
| Low Dim | Low Dimensional Test Function |
| High Dim | High Dimensional Test Function |
| NFE | Number of Fitness Evaluations done by algorithm |
| Time | Computing Time of the algorithm in seconds |
| + | BOA-C is better than compared algorithm |
| - | BOA-C is worse than compared algorithm |
| = | BOA-C is equal to compared algorithm |

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K.M.Dhanya received her B.Tech in Information Technology and M.Tech in Software Engineering from Cochin University of Science and Technology, Kerala. She worked as Lecturer in College of Engineering, Munnar. She has been working as Assistant Professor in Department of Information Technology, Government Engineering College, Palakkad, Kerala since 2006. Presently, she is undergoing research in Pondicherry Engineering College, Puducherry. Her research interests are Nature Inspired Computing, Software Engineering and Object Oriented System. She is Member of ISTE, India.



Dr. S. Kanmani received her B.E and M.E in Computer Science and Engineering from Bharathiyar University and Ph.D. from Anna University, Chennai. She had been faculty of Department of Computer Science and Engineering, Pondicherry Engineering College since 1992. Presently, she is Professor in Department of Information Technology, Pondicherry Engineering College, Puducherry. Her research interests are Software Engineering, Software Testing, Object Oriented System and Data Mining. She has published about 175 papers in various International conferences and journals. She is Member of Computer Society of India, ISTE and Institute of Engineers, India.