Studying the Convergence Behavior and Global Exploration Capabilities of Sailfish Optimizer Algorithm

Saboohi Naeem Ahmed[1,2]*, Muhammad Rizwan Tanweer[3], Adnan Ahmed Siddiqui[4]
[1]Graduate School of Engineering and Information Technology, Hamdard University, Karachi, Pakistan.
[2]College of Computing and Information Science, Karachi Institute of Economics and Technology, Karachi. Pakistan.
[3]Department of Computing, Karachi School of Business and Leadership, Karachi, Pakistan.
[4]Department of Computing, Hamdard University, Karachi, Pakistan.
*E-mail: saboohi@kiet.edu.pk

ABSTRACT

Sailfish Optimizer (SFO) is a recent nature inspired metaheuristic optimization algorithm belonging to the category of swarm intelligence algorithms. It represents Sailfish group hunting behavior mathematically. Although the algorithm claims to avoid local optima and explores global search space widely; the fact is due to the weak search behavior it gets stuck in local optima, and it also exhibits slow convergence in the search space. In this study, we have analyzed the convergence behavior and global exploration capabilities of SFO by comparing it with the state-of-the-art optimization algorithms on unimodal and multimodal benchmark problems. Results show that the algorithm's search ability is limited, and it slowly converges towards the optimal value in unimodal problems, while global exploration is slightly better than the compared algorithms except teaching learning-based optimizer (TLBO) which is better in every test problem used. Wilcoxon signed rank test results also verify that grey wolf optimizer (GWO) and TLBO are significantly better than SFO while whale optimization algorithm (WOA) is performing like the SFO on the employed benchmark problems.

Keywords: Swarm Intelligence, Sailfish Optimizer, limitations, Wilcoxon Signed Rank Test.

INTRODUCTION

Optimization algorithms inspired by nature are well-known stochastic methods which are most suitable for optimizing problems that cannot be solved through linear methods. This is a well-established research area since the inception of genetic algorithm (GA) (Holland 1992). These algorithms draw their inspiration from natural processes, for example, birds finding their food in groups (Kennedy and Eberhart 1995), ant colony behaviors (Dorigo and Di Caro 1999), or arithmetic rules (Abualigah et al. 2021). Such algorithms can be categorized in various ways, for example, evolutionary/ swarm intelligence (SI) based algorithms (Li et al. 2020), procedure/ equation based algorithms (Yang 2020) or Biology/Physics/ Chemistry/ Mathematics based algorithms (Rana et al. 2020).

Sailfish Optimizer algorithm (Shadravan, Naji, and Bardsiri 2019) belongs to the SI- based algorithms mimicking the group hunting behavior of sailfishes in the ocean. It uses two types of population, sailfish, and sardines (prey); sailfishes are the candidate solutions that are optimized in the process and sardines' population assist in finding optimal value quickly. The process also removes hunted sardines from the sardine population. Like other optimization problems, this algorithm also suffers from local optima stagnation and weak exploration capabilities (Issam et al. 2019; Zhang and Mo 2021). However, due to the simple nature of the algorithm, it is applied to various real world problems, including classification in deep learning models (Nagapavithra and Umamaheswari 2023; Alqahtani et al. 2023), wireless sensor networks (Amutha, Sivasankari, and Venugopal 2023; Rajoriya and Gupta 2023; Mehta and Saxena 2020), data mining (Hamza et al. 2022) and so on.

This study is conducted to experimentally observe the limitations of SFO and to compare it with the state-of-the-art metaheuristics including grey wolf optimizer (GWO), whale optimization algorithm (WOA), teaching-learning based optimizer (TLBO) and marine predator algorithm (MPA). Experimental analysis consists of various steps for studying the behavior of any optimization algorithms, including selection of the compared algorithms and test problems, initial population, and number of iterations for a single run. These details are provided in the experiments section and objectives are outlined in the next section.

OBJECTIVES

The main objective of this study is to find out the limitations of SFO experimentally in comparison with state-of-the-art algorithms and make suggestions on improving the local and global search capabilities of the algorithm. Specific objectives include:

- To optimize selected unimodal and multimodal benchmark functions using the GWO, WOA, MPA, TLBO and SFO.
- To calculate mean and standard deviation of the obtained results to observe the performance of SFO in exploration and exploitation phases.
- To visualize the convergence behavior through convergence curves.
- To prove the significance of the results using Wilcoxon signed-rank test.
- To suggest improvements in the search capabilities of the analyzed algorithm.

Experiments and Discussions

In this section we present the methodology of this study. First, benchmark problems are selected that are most suitable for testing exploration and exploitation capabilities of the algorithm. We have employed four unimodal functions that are sphere function (F1), Schwefel's problem 1.2 (F2), 2.21(F3), 2.22(F4) and one multimodal function namely generalized Schwefel's problem (F5). Unimodal functions are suitable for analyzing convergence behavior and multimodal functions uncover the divergence capabilities.

A suitable selection of state-of-the-art optimization algorithms is a crucial step for analyzing the performance of the target algorithm. In this study, SFO is compared with four state-of-the-art optimization algorithms namely, grey wolf optimizer (GWO) (Mirjalili, Mirjalili, and Lewis 2014), whale optimization algorithm (WOA), teaching-learning based optimization algorithm (TLBO) (Rao, Savsani, and Vakharia 2011) and Marine Predators Algorithm (MPA) (Rao, Savsani, and Vakharia 2011). GWO and WOA have a single parameter a which is set to 2 initially. The rest of the algorithms have random numbers that are used within the internal operation of the algorithms. For SFO, a=4 and $\epsilon = 0.0001$.

Randomness in the initial values promotes the search range of any optimization algorithm and due to these random initial seeds, the same algorithm can give different results each time. To properly analyze the behavior of an optimization algorithm, it is run several times (20, 30 or 50). We have studied the behavior of all algorithms initialized with random population and running each function 30 times independently with 5000 iterations. Code is implemented in MATLAB on a Windows operating system with a 2.4 GHz processor and 32 GB RAM. For the compared algorithms, code has been taken from their official websites and run in the same environment as mentioned. Mean and standard deviation of the mean results have been presented in Table 1 along with the z statistic and p-value obtained through Wilcoxon Signed rank test.

Table 1. Comparative results for five algorithms along with z-statistic and p-value in comparison with SFO.

	F1		F2		F3	
	Mean	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
SFO	5.2323E-21	1.75463E-20	3.97132E-11	4.59214E-11	4.4324E-20	8.23936E-20
GWO	0	0	2.0234E-178	0	3.90842E-88	2.02975E-87
TLBO	0	0	0	0	1.8157E-202	0
WOA	0	0	0	0	546.3778005	864.9673456
MPA	1.9311E-263	0	4.9084E-145	2.4603E-144	1.42676E-73	7.68335E-73
	F4		**F5**		**Wilcoxon Signed Rank Test**	
	Mean	**Std Dev**	**Mean**	**Std Dev**	**z statistic**	**p value**
SFO	1.52812E-11	2.08559E-11	6.28658E-05	9.66658E-05	N/A	
GWO	1.19259E-75	2.64427E-75	26.23677581	0.82717972	1.825741858	0.033944577
TLBO	0	0	1.250605336	0.977969333	2.022599587	0.021557223
WOA	10.46162521	17.94776099	25.30026949	0.432072594	1.603567451	0.054404715
MPA	1.5277E-99	4.0078E-99	18.2545823	1.380409739	2.022599587	0.021557223

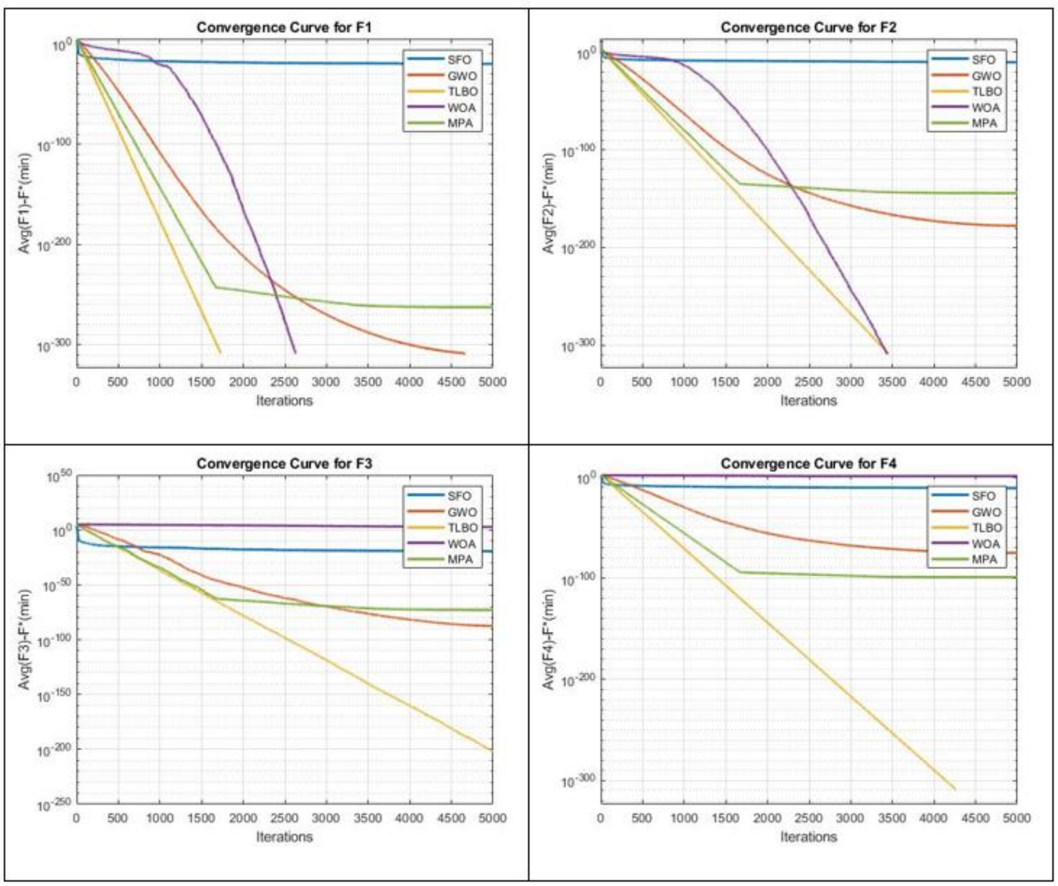

Figure 1. Convergence curves for unimodal functions (F1 - F4)

It can be observed from **Error! Reference source not found.** that SFO has the worst performance for F1 and F2 while WOA is performing worst for F3 and F4 (see Figure **1**). For F5, GWO is reaching to the worst mean value. It is also observed that TLBO is performing best in each of the functions employed. For this study, we are more interested in SFO behavior compared to the other state-of-the-art algorithms. For F3 and F4, SFO is performing second worst. Divergence behavior analysis needs further experimentation as from this study SFO has shown best results for F5.

It is already mentioned that F1 to F4 are used for testing exploitation and by looking at the convergence curves presented in Figure **1**, it is confirmed that SFO has limited exploitation capabilities as compared to the other algorithms. For all the unimodal test problems, SFO shows early convergence and hence reaching the optimal value is not possible for this algorithm. While for exploration, SFO is somewhat better than most of the other algorithms.

Comparative results show mixed behavior therefore by looking at these mean results, we are not sure about the SFO performance. For a more detailed comparison, we need to employ a statistical test that will identify the significant differences between the performances of different algorithms. For this purpose, Wilcoxon signed-rank test is used, and results are reported in Table 1 in last column. This test returns a z-statistic value and corresponding p-value is obtained from a precalculated normal distribution table. We have set $\alpha=0.05$ (i.e. 95% significance level) and if the calculated p-value is less than 0.05 then it means that results are significantly different. GWO, MPA and TLBO contain p-values of less than 0.05 hence they are significantly better than SFO. WOA is performing like SFO as both have a p-value approximately equal.

CONCLUSION

From experimental results, it is evident that the sailfish optimizer is not suitable for solving unimodal functions. It is also observed from the convergence curves that SFO has slow convergence speed; furthermore, it also suffers from local optima stagnation for the multimodal problem employed. Therefore, we can conclude that it has weak exploitation capabilities, and it is imperative to improve the local search capabilities of the considered algorithm. To identify the improvement method, a comprehensive survey of the variants of the other metaheuristic algorithms can be conducted later. A few techniques present in the literature to improve an existing optimization algorithm might include modification of the internal random parameters, updating search equation or hybridizing the algorithm with other techniques. It is essential to note that this study only uses one multimodal problem; therefore, in future, a more detailed study could analyze the exploration behavior of SFO in greater depth. Additionally, other state-of-the-art algorithms could be included for a thorough analysis.

REFERENCES

1. Abualigah, Laith, Ali Diabat, Seyedali Mirjalili, Mohamed Abd Elaziz, and Amir H. Gandomi. 2021. “The Arithmetic Optimization Algorithm.” Computer Methods in Applied Mechanics and Engineering 376: 113609. https://doi.org/10.1016/j.cma.2020.113609.
2. Alqahtani, Mazen Mushabab, Ashit Kumar Dutta, Sultan Almotairi, M. Ilayaraja, Amani Abdulrahman Albraikan, Fahd N. Al-Wesabi, and Mesfer Al Duhayyim. 2023. “Sailfish Optimizer with EfficientNet Model for Apple Leaf Disease Detection.” Computers, Materials and Continua 74 (1). https://doi.org/10.32604/cmc.2023.025280.
3. Amutha, R., G. G. Sivasankari, and K. R. Venugopal. 2023. “Node Clustering and Data Aggregation in Wireless Sensor Network Using Sailfish Optimization.” Multimedia Tools and Applications 82 (28). https://doi.org/10.1007/s11042-023-15225-z.
4. Dorigo, Marco, and Gianni Di Caro. 1999. “Ant Colony Optimization: A New Meta-Heuristic.” In Proceedings of the 1999 Congress on Evolutionary Computation, CEC 1999, 2:1470–77. https://doi.org/10.1109/CEC.1999.782657.

5. Hamza, Manar Ahmed, Siwar Ben Haj Hassine, Ibrahim Abunadi, Fahd N. Al-Wesabi, Hadeel Alsolai, Anwer Mustafa Hilal, Ishfaq Yaseen, and Abdelwahed Motwakel. 2022. “Feature Selection with Optimal Stacked Sparse Autoencoder for Data Mining.” Computers, Materials and Continua 72 (2). https://doi.org/10.32604/cmc.2022.024764.
6. Holland, John H. 1992. “Genetic Algorithms.” Scientific American 267 (1): 66–72. https://doi.org/10.1038/scientificamerican0792-66.
7. Issam, El Hammouti, Azza Lajjam, Mohamed El Merouani, and Yassine Tabaa. 2019. “A Modified Sailfish Optimizer to Solve Dynamic Berth Allocation Problem in Conventional Container Terminal.” International Journal of Industrial Engineering Computations 10 (4): 491–504. https://doi.org/10.5267/j.ijiec.2019.4.002.
8. Kennedy, James, and Russell Eberhart. 1995. “Particle Swarm Optimization.” In Proceedings of ICNN’95 - International Conference on Neural Networks, 4:1942–48. IEEE. https://doi.org/10.1109/ICNN.1995.488968.
9. Li, Hui, Xiao Liu, Zhiguo Huang, Chenbo Zeng, Peng Zou, Zhaoyi Chu, and Junkai Yi. 2020. “Newly Emerging Nature-Inspired Optimization-Algorithm Review, Unified Framework, Evaluation, and Behavioural Parameter Optimization.” IEEE Access 8: 72620–49. https://doi.org/10.1109/ACCESS.2020.2987689.
10. Mehta, Deepak, and Sharad Saxena. 2020. “MCH-EOR: Multi-Objective Cluster Head Based Energy-Aware Optimized Routing Algorithm in Wireless Sensor Networks.” Sustainable Computing: Informatics and Systems 28: 100406. https://doi.org/10.1016/j.suscom.2020.100406.
11. Mirjalili, Seyedali, Seyed Mohammad Mirjalili, and Andrew Lewis. 2014. “Grey Wolf Optimizer.” Advances in Engineering Software 69 (March): 46–61. https://doi.org/10.1016/j.advengsoft.2013.12.007.
12. Nagapavithra, S., and S. Umamaheswari. 2023. “Detection and Classification of Sugarcane Billet Damage Using Aquila Sailfish Optimizer Based Deep Learning.” Artificial Intelligence Review 56. https://doi.org/10.1007/s10462-023-10574-5.
13. Rajoriya, Manisha Kumari, and Chandra Prakash Gupta. 2023. “Sailfish Optimization-Based Controller Selection (SFO-CS) for Energy-Aware Multi-Hop Routing in Software Defined Wireless Sensor Network (SDWSN).” International Journal of Information Technology (Singapore) 15 (7). https://doi.org/10.1007/s41870-023-01426-0.
14. Rana, Nadim, Muhammad Shafie Abd Latiff, Shafi’i Muhammad Abdulhamid, and Haruna Chiroma. 2020. “Whale Optimization Algorithm: A Systematic Review of Contemporary Applications, Modifications and Developments.” Neural Computing and Applications 32 (20): 16245–77. https://doi.org/10.1007/s00521-020-04849-z.
15. Rao, R. V., V. J. Savsani, and D. P. Vakharia. 2011. “Teaching-Learning-Based Optimization: A Novel Method for Constrained Mechanical Design Optimization Problems.” CAD Computer Aided Design 43 (3). https://doi.org/10.1016/j.cad.2010.12.015.
16. Shadravan, S., H. R. Naji, and V. K. Bardsiri. 2019. “The Sailfish Optimizer: A Novel Nature-Inspired Metaheuristic Algorithm for Solving Constrained Engineering Optimization Problems.” Engineering Applications of Artificial Intelligence 80: 20–34. https://doi.org/10.1016/j.engappai.2019.01.001.
17. Yang, Xin She. 2020. “Nature-Inspired Optimization Algorithms: Challenges and Open Problems.” Journal of Computational Science 46: 101104. https://doi.org/10.1016/j.jocs.2020.101104.
18. Zhang, Yuedong, and Yuanbin Mo. 2021. “Dynamic Optimization of Chemical Processes Based on Modified Sailfish Optimizer Combined with an Equal Division Method.” Processes 9 (10): 1806.