Hybrid Approach for Numerical Optimization using an Enhanced Sand Cat Swarm Algorithm

Deepa Barethiya; Kirti Modi;
Kanchan Hatwar; Anuradha Muttemwar
Department of Master in Computer Application
G H Raisoni College of Engineering and Management, Nagpur, India.

Abstract:
This study introduces a hybridization algorithm called Sand Cat Swarm Optimization (SCSO), which mimics the survival behaviors of sand cats in nature. The two types of phases are search and attack. The SCSO was tested in MATLAB 2023a using functions F1 to F23, and the results were compared with those of other effective hybridization algorithms. SCSO achieved the best solution of -3.39 for function F19 among the test functions. The improved results indicate that SCSO excels in convergence rate and effectively locates most, if not all, local and global optima, outperforming the other methods in comparison.

Keywords: Benchmark,Optimization, Hybridization, PSO, SCSO.

Introduction:
In everyday life, optimization involves reducing time and costs while increasing efficiency and quality. Heuristic and metaheuristic algorithms are two types used to find optimized solutions [1]. Heuristic algorithms are tailored to specific problems, while metaheuristic algorithms are more general and do not rely on a particular challenge they find optimal solutions through a random search within predefined boundaries. When solving an optimization challenge, it is important to define the relevant variable values according to the specific problem at hand [2]. The sand cat (Felis margarita) is a member of the Felis genus, which is part of the mammal family. This species thrives in harsh environments, such as sandy and stony deserts found in regions like Central Asia, the Sahara, and the Arabian Peninsula. The small, agile sand cat exhibits unique hunting and living behaviors that differ from those of domestic cats, despite their similar appearance [3]. Unlike many other felines, sand cats are solitary animals. Their paws and foot soles are covered with a dense layer of fur that ranges from sandy to light grey, providing insulation against the extreme temperatures of the desert [4].

Literature Review:
The Sand Cat Swarm Optimization (SCSO) algorithm is based on the behaviors of sand cats in the wild. Sand cats primarily engage in two activities: hunting for prey and attacking it [5]. This remarkable feature allows them to locate prey, whether it's on the surface or underground, enabling them to catch it quickly. Since sand cats are solitary animals in their natural habitat, the authors of the proposed algorithm treated them as a group to highlight the idea of swarm intelligence [6]. Therefore, during the initialization of the algorithm, the number of sand cats can be set to optimize either a minimization or maximization problem. There 4 types of classification there are Evolutionary-Based, Human-Inspired, Natural-Inspired, Physical-Based Algorithms [7].

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1. Evolutionary-Based Algorithms:
These are algorithms that are based on biological evolution, especially the ideas of natural selection and the concept of survival of the fittest.

2. Human-Inspired Algorithms:
These methods are based on human intelligence, behaviors, and decision-making strategies.

3. Natural-Inspired Algorithms:
These are algorithms that take cues from natural processes and phenomena. They often imitate the behaviors of living organisms and ecosystems to tackle optimization challenges.

4. Physical-Based Algorithms:
These algorithms that physical laws, forces, and mathematical models such as gravity, electromagnetism, and wave dynamics.

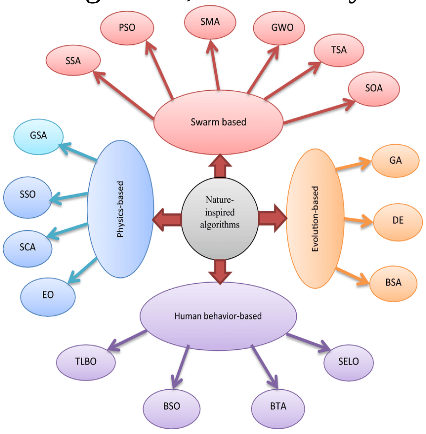

Fig-1: Classification of nature-inspired algorithms

Pseudocode:
1. Initialize the population of sand cats randomly within the search space.
2. Set maximum number of iterations and define the objective function.
3. Initialize velocity (for PSO) for each sand cat.
4. Evaluate fitness of each sand cat.
5. Identify the best-performing sand cat (global best solution).
6. Update velocity of sand cats using PSO velocity equations:

$$vi = w \cdot vi + c1 \cdot r1.\ (p\ best,\ i - xi) + c2 \cdot r2 \cdot (gbest - xi)$$

- Update the positions of sand cats using a combination of:
- SCSO Exploration: Random movement in the environment.
- SCSO Exploitation: Moving toward the best solution.
- PSO-inspired velocity-driven movement: Updating positions using velocity.

$$xi = xi + vi$$

- Evaluate the new fitness values.
- Update the best solution if a better one is found.
- Store the convergence curve (Best Fitness per iteration).

7. Return the best solution and the convergence curve.

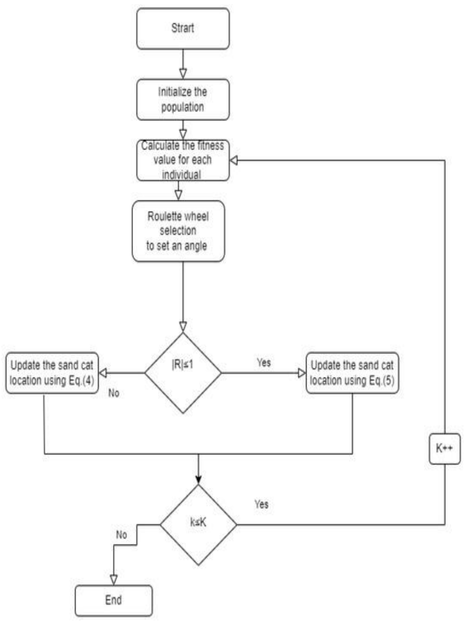

Table1: Benchmark Functions

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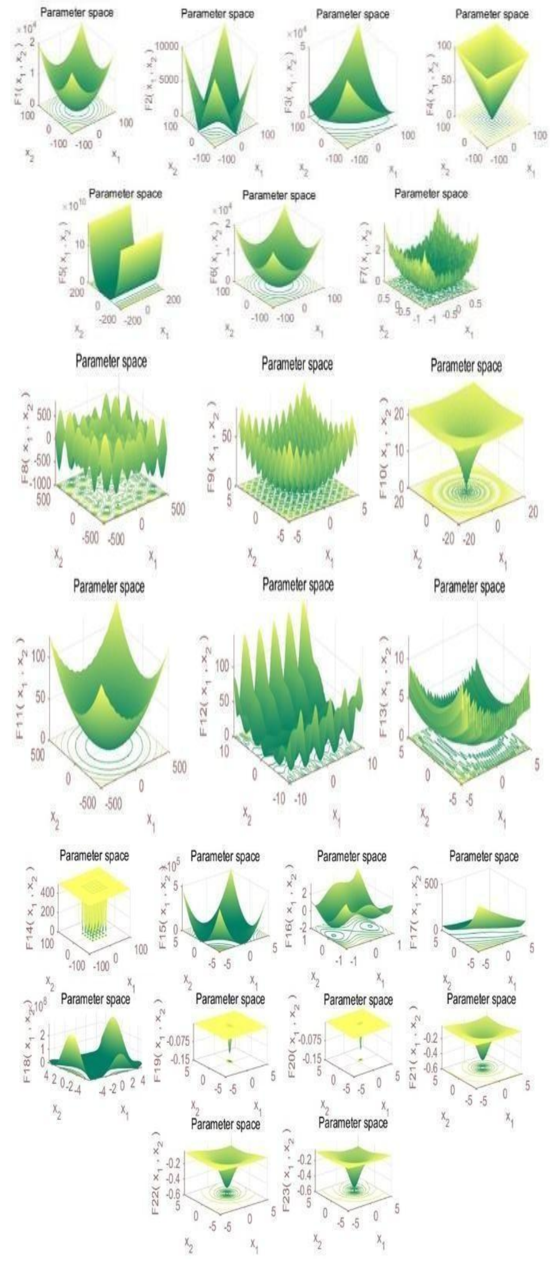
Table 2: Standard UM benchmark functions

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
$F_5(S) = \sum_{m=1}^{z-1} [100(S_{m+1}-S_m^2)^2 + (S_m - 1)^2]$	(10,30,50,100)	[-38 , 38]	0
$F_6(S) = \sum_{m=1}^{z} ([S_m + 0.5])^2$	(10,30,50,100)	[-100 , 100]	0
$F_7(S) = \sum_{m=1}^{z} mS_m^4 + random\,[0,1]$	(10,30,50,100)	[-1.28, 1.28]	0

Functions	Dimension	Range	f_{min}
$F_8(S) = \sum_{m=1}^{z} -S_m sin(\sqrt{\lvert S_m \rvert})$	(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

Functions	Dimensions	Range	f_{min}
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5\frac{1}{n + \sum_{m=1}^{z}(S_m - b_{mn})^6}]^{-1}$	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



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Results and Discussion:

The SCSO algorithm is implemented for each problem, and its results are compared with those obtained from other hybridization algorithms.

Function	Original	Purpose
F1	0	5.98E+03
F2	0	3.84E+01
F3	0	1.02E+04
F4	0	2.73E+01
F5	28.800247	2.58E+06
F6	2.228888	6.08E+03
F7	0.000115	1.02E+00
F8	-7064.684071	-3.63E+03
F9	0	2.08E+02
F10	0	1.30E+01
F11	0	4.88E+01
F12	0.179116	1.12E+04
F13	2.287431	1.94E+06
F14	2.982105	1.04E+00
F15	0.000307	1.59E-03
F16	-1.031628	-1.03E+00
F17	0.397887	4.01E-01
F18	3.000008	3.01E+00
F19	-3.861573	-3.39E+00
F20	-3.136492	-3.01E+00

Conclusion:

The Sand Cat Swarm Optimization (SCSO) algorithm is inspired by the hunting behaviors, of sand cats. Effectively balances exploration and exploitation in optimization problems. It enhances performance by adapting movement strategies, reducing local optima entrapment, and improving convergence speed. Integrating hybrid techniques like PSO further refines its efficiency, making it a robust metaheuristic for complex problem-solving. The result is original function better than hybridization.

References:

[1] Sand Cat swarm optimization Amir Seyyedabbasi1 · Farzad Kiani1Received: 20 February 2021 /Accepted: 10January 2022EngineeringwithComputershttps://doi.org/10.1007/s00366-022-01604x

[2] Y. Cheng, S. Zhao, B. Cheng, S. Hou, Y. Shi, and J. Chen, “Modeling and optimization for collaborative business process towards IoT applications,” Mob. Inf. Syst., 2018, doi: 10.1155/2018/9174568.

[3] X. Wang, T. M. Choi, H. Liu, and X. Yue, “A novel hybrid ant colony optimization algorithm for emergency transportation problems during post-disaster scenarios,” IEEE Trans. Syst. Man, Cybern. Syst., 2018, doi: 10.1109/TSMC.2016.2606440.

[4] I E. Grossmann, Global Optimization in Engineering Design (Nonconvex Optimization and Its Applications), vol. 9. 1996.

[5] R. V. Rao and G. G. Waghmare, “A new optimization algorithm for solving complex constrained design optimization problems,” vol. 0273, no. April, 2016, doi: 10.1080/0305215X.2016.1164855.

[6] E.-S. M. El-Kenawy, M. M. Eid, M. Saber, and A. Ibrahim, “MbGWO-SFS: Modified Binary Grey Wolf Optimizer Based on Stochastic Fractal Search for Feature Selection,” IEEE Access, 2020, doi: 10.1109/access.2020.3001151.

[7] Maroua Nouiri · Abdelghani Bekrar · Abderezak Jemai · Smail Niar · Ahmed Chiheb Ammari Received: 17 July 2014 / Accepted: 17 January 2015 © Springer Science+Business Media New York 2015

[8] Y. Li, J. Wang, D. Zhao, G. Li, and C. Chen, “A two-stage approach for combined heat and power economic emission dispatch: Combining multi-objective optimization with integrated decision making,” Energy, 2018, doi: 10.1016/j.energy.2018.07.200.

[9] D. Yousri, T. S. Babu, and A. Fathy, “Recent methodology based Harris hawks optimizer for designing load frequency control incorporated in multi-interconnected renewable energy plants,” Sustain. Energy, Grids Networks, 2020, doi: 10.1016/j.segan.2020.100352.

[10] R. Al-Hajj and A. Assi, “Estimating solar irradiance using genetic programming technique and meteorological records,” AIMS

DOI: https://doi.org/10.5281/zenodo.15676455

Energy, 2017, doi: 10.3934/energy.2017.5.798.
[11] R. Al-Hajj, A. Assi, and F. Batch, “An evolutionary computing approach for estimating global solar radiation,” in 2016 IEEE International Conference on Renewable Energy Research and Applications, ICRERA 2016, 2017. doi: 10.1109/ICRERA.2016.7884553.
[12] R. A. Meyers, “Classical and Nonclassical Optimization Methods Classical and Nonclassical Optimization Methods 1 Introduction 1 1.1 Local and Global Optimality 2 1.2 Problem Types 2 1.3 Example Problem: Fitting Laser-induced Fluorescence Spectra 3 1.4 Criteria for Optimization 4 1.5 Multicriteria Optimization 4,” Encycl. Anal. Chem., pp. 9678–9689, 2000, [Online]. Available: https://pdfs.semanticscholar.org/5c5c/908bb00a54439dcee50ec1ada6b735694a94.pdf
[13] N. Steffan and G. T. Heydt, “Quadratic programming and related techniques for the calculation of locational marginal prices in distribution systems,” in 2012 North American Power Symposium (NAPS), 2012, pp. 1–6. doi: 10.1109/NAPS.2012.6336310.
[14] M. Mafarja et al., “Evolutionary Population Dynamics and Grasshopper Optimization approaches,” Knowledge-Based Syst., vol. 145, pp. 25–45, 2018, doi: 10.1016/j.knosys.2017.12.037.
[15] A. A. Heidari, R. Ali Abbaspour, and A. Rezaee Jordehi, “An efficient chaotic water cycle algorithm for optimization tasks,” Neural Comput. Appl., vol. 28, no. 1, pp. 57–85, 2017.

DOI: https://doi.org/10.5281/zenodo.15676455