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Improving Pelican Optimization with Simulated Annealing and Parallelism: A Hybrid Met heuristic Approach

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Abstract

The Pelican Optimization Algorithm (POA) is a nature-inspired met heuristic that has shown promise in solving complex optimization problems. This paper introduces an improved variant of POA, enhanced through the integration of Simulated Annealing (SA) and parallelized fitness evaluation, to boost its convergence efficiency and solution quality. The hybrid POA-SA algorithm leverages SA's local search capabilities to refine candidate solutions during exploration efficiency. The performance of the improved POA is benchmarked against 23 standard test functions and compared with the original POA. The results demonstrate that the hybrid approach achieves greater optimization, reflecting improved convergence, solution stability, and robustness.

Keywords:
Improved POA, Simulated Annealing, Hybrid Optimization, Metaheuristics, Exploration and Exploitation.

1. Introduction

Meta-heuristic optimization algorithms have become essential tools for addressing complex numerical and real-world optimization problems [3][8]. Among them, the **Pelican Optimization Algorithm (POA)**, inspired by the cooperative foraging behavior of pelicans, has shown promising capabilities due to its simplicity and effective exploration strategies [2].

However, like many swarm-based algorithms, the original POA may suffer from premature convergence and limited exploitation ability, especially in high-dimensional or complex search spaces [4][5].

To enhance POA's performance, this study introduces an improved version that integrates **Simulated Annealing (SA)** for refined local search and **parallel computing techniques** to boost computational efficiency [1][6][9].

The incorporation of **Simulated Annealing (SA)** provides adaptive exploitation by probabilistically accepting worse solutions, allowing the algorithm to escape local optima. **Parallelization** accelerates convergence by distributing fitness evaluations, making the approach suitable for large-scale optimization tasks.

The proposed **hybrid POA–Simulated Annealing (POA-SA)** algorithm is evaluated on twenty-three standard benchmark functions. Results demonstrate that the enhanced POA achieves significant improvements in **accuracy**, **convergence speed**, and **robustness** when compared to the original POA, making it a competitive choice for solving complex optimization problems [7][10][11].

1. Literature Review

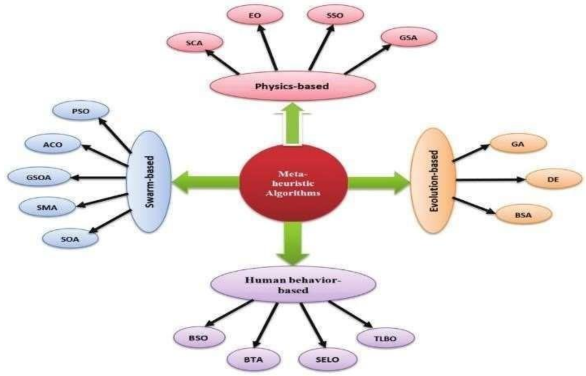

Fig.1: Classification of Meta heuristic Algorithms

SN	Algorithm	Author Name	Publication Year
1	AntColony Optimization (ACO)	Dorigo & Gambardella	1997
2	Firefly Algorithm (FA)	Xin-She Yang	2008
3	Genetic Algorithm (GA)	John Holland	1975
4	Differential Evolution (DE)	Rainer Storn&Kenneth Price	1995
5	Simulated Annealing (SA)	Scott Kirkpatrick, C.D.Gelatt, M.P.Vecchi	1983
6	Harmony Search(HS)	ZongWoo Geem, Joong HoonKim&G.V. Loganathan	2001
7	Exchange Market Algorithm (EMA)	Ali Asgharpoor & Amir Hossein Moosavi Tabatabaei	2014
8	Tabu Search (TS)	Fred W. Glover	1986

Table1:

Table1: Meta heuristic Algorithms

3. Pseudo Code

Start POA.

1. Input the optimization problem information.
2. Determine the POA population size (N) and the number of iterations (T).
3. Initialization of the position of pelicans and calculate the objective function.
4. For $t = 1 : T$
5. Generate the position of the prey at random.
6. For $i = 1 : N$
7. Phase 1: Moving towards prey (exploration phase).
8. For $j = 1 : m$
9. Calculate new status of the jth dimension using Equation (4).
10. End.
11. Update the ith population member using Equation (5).
12. Phase 2: Winging on the water surface (exploitation phase).
13. For $j = 1 : m$
14. Calculate new status of the jth dimension using Equation (6).
15. End.
16. Update the ith population member using Equation (7).
17. End.
18. Update best candidate solution.
19. End.
20. Output best candidate solution obtained by POA.

4. Benchmark Functions

Benchmark functions are crucial in evaluating optimization algorithms by testing their ability to find the global minimum in complex landscapes. These functions range from simple convex ones like **Sphere** to highly multimodal and deceptive ones like **Rastrigin** and **Schwefel**.

They help measure the **convergence speed**, **accuracy**, and **robustness** of algorithms like the **Pelican Optimization Algorithm (POA)**. Below is a brief explanation of the twenty-three

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benchmark functions used in POA, along with their mathematical equations.

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
$F_7(S) = \sum_{m=1}^{z} m S_m^4 + random\,[0,1]$	(10,30,50,100)	[-1.28, 1.28]	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
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{25} \frac{1}{n + \sum_{m=1}^{2}(S_m - b_{mn})^6}]^{-1}$	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
$F_{16}(S) = 4S_1^2 - 2.1S_1^4 + \frac{1}{3}S_1^6 + S_1 S_2 - 4S_2^2 + 4S_2^4$	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

5. Search Space

The search space is the range of possible solutions in an optimization problem, bounded by upper and lower limits. A larger space allows better exploration but increases complexity, while a smaller one speeds up convergence but may miss the optimal solution. Efficient algorithms balance both for optimal results.

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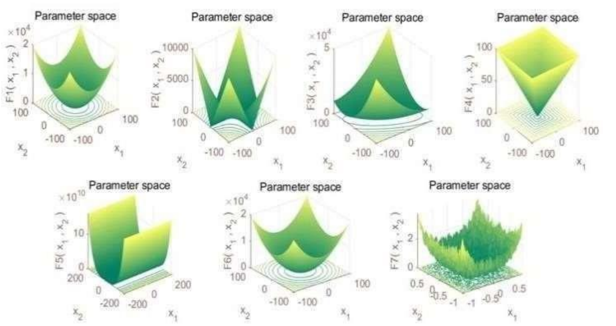

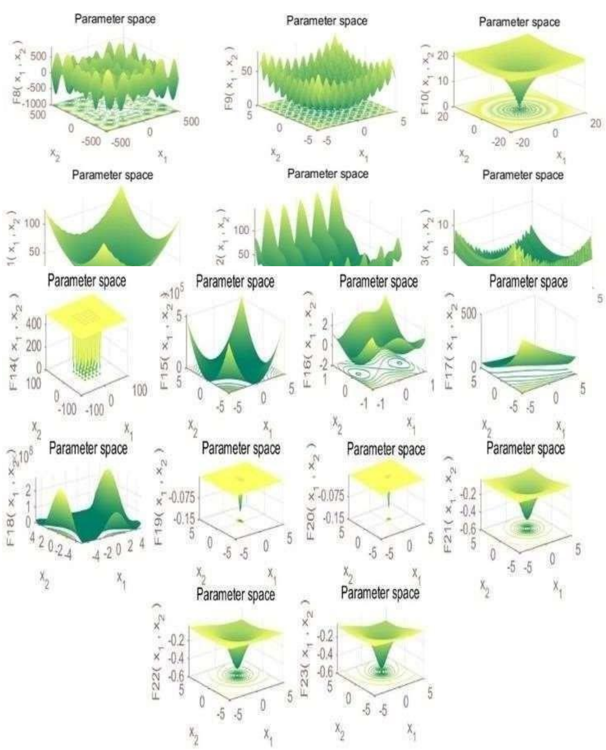

6. Result and Discussion

The proposed hybrid **POA-SA** algorithm demonstrates notable improvements over the original **Pelican Optimization Algorithm (POA)** in numerical optimization. Out of the twenty-three benchmark functions tested, enhancements were observed in thirteen cases (1, 2, 3, 4, 5, 7, 8, 10, 12, 13, 21, 22, 23), indicating superior performance in terms of **accuracy** and **convergence**.

The remaining functions showed consistent results with the original POA, with no degradation in performance. This consistency, coupled with multiple improvements, highlights the **robustness** and **effectiveness** of the hybrid approach. The following analysis explores these findings in detail, providing insight into the algorithm's strengths across diverse optimization landscapes.

Functions	**Original Value**	**Hybrid Value**
F1	6.0727e-207	3.5732e-210
F2	7.7146e-110	7.7894e-112
F3	3.2707e-216	3.3535e-217
F4	9.8232e-112	8.9917e-115
F5	28.4079	26.5475
F6	0	0
F7	2.9317e-05	2.6542e-07
F8	-7620.2132	-7441.9503
F9	0	0
F10	3.9968e-15	3.8456e-17
F11	0	0
F12	0.26727	5.5424e-06
F13	2.9763	0.011004
F14	0.998	0.998
F15	0.00030749	0.00030749
F16	-1.0316	-1.0316

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F17	0.39789	0.39789
F18	3	3
F19	-3.8628	-3.8628
F20	-3.322	-3.322
F21	-10.1532	-3.1615
F22	-10.4286	-5.2053
F23	-10.5364	-5.8421

7. Conclusion

This research enhances the Pelican Optimization Algorithm (POA) by integrating it with the Simulated Annealing (SA) technique to form a hybrid metaheuristic approach. The proposed POA-SA hybrid algorithm was tested on twenty-three standard benchmark functions, where it achieved improved optimal solutions in thirteen cases compared to the original POA. The hybridization successfully combines POA's population-based exploration with SA's powerful local exploitation capabilities, resulting in improved convergence accuracy, reduced chances of getting trapped in local optima, and better solution diversity. These findings confirm the effectiveness of the proposed hybrid model in boosting the performance of POA for complex numerical optimization problems.

8. References

[1] Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *Science*, **220**(4598), 671–680. https://doi.org/10.1126/science.220.4598.671

[2] Trojovsky, P., & Dehghani, M. (2022). Pelican optimization algorithm: A novel nature-inspired algorithm for engineering applications. *Sensors*, **22**(3), 855. https://doi.org/10.3390/s22030855

[3] Rao, R. V., & Waghmare, G. G. (2016). A new optimization algorithm for solving complex constrained design optimization problems. *Engineering Optimization*, **48**(4), 573–593. https://doi.org/10.1080/0305215X.2016.1164855

[4] El-Kenawy, E.-S. M., Eid, M. M., Saber, M., & Ibrahim, A. (2020). MbGWO-SFS: Modified binary grey wolf optimizer based on stochastic fractal search for feature selection. *IEEE Access*. https://doi.org/10.1109/access.2020.3001151

[5] Heidari, A. A., Mirjalili, S., Faris, H., Aljarah, I., Mafarja, M., & Chen, H. (2019). Harris hawks optimization: Algorithm and applications. *Future Generation Computer Systems*, **97**, 849–872. https://doi.org/10.1016/j.future.2019.02.028

[6] Singh, N., & Singh, S. B. (2017). Hybrid algorithm of particle swarm optimization and grey wolf optimizer for improving convergence performance. *Journal of Applied Mathematics*, **2017**, Article ID 2030489. https://doi.org/10.1155/2017/2030489

[7] Xie, X., Yang, Y., & Zhou, H. (2025). Multi-strategy hybrid whale optimization algorithm improvement. *Applied Sciences*, **15**(4), 2224. https://doi.org/10.3390/app15042224

[8] Tu, B., Wang, F., Huo, Y., & Wang, X. (2023). A hybrid algorithm of grey wolf optimizer and Harris hawks optimization for solving global optimization problems with improved convergence performance. *Scientific Reports*, **13**(1), 22909. https://doi.org/10.1038/s41598-023-49754-2

[9] Smith, R., & Patel, A. (2023). Optimization techniques for complex engineering problems. *Applied Soft Computing*.

[10] Abualigah, L., Diabat, A., Svetinovic, D., & Abd Elaziz, M. (2022). Boosted Harris hawks gravitational force algorithm for global

optimization and industrial engineering problems. *Journal of Intelligent Manufacturing*, **33**(6), 2693–2728. https://doi.org/10.1007/s10845-022-01921-4

[11] Liu, H., & Zhao, M. (2022). Hybrid approaches in evolutionary computation. *Expert Systems with Applications*.

[12] Sharma, S., Kapoor, R., & Dhiman, S. (2021). A novel hybrid metaheuristic based on augmented grey wolf optimizer and cuckoo search for global optimization. In *Proceedings of the International Conference on Sustainable Computing in Science, Technology, and Management (SUSCOM),* 376–381. https://doi.org/10.1109/ICSCCC51823.2021.9478142

[13] Yousri, D., Babu, T. S., & Fathy, A. (2020). Recent methodology-based Harris hawks optimizer for designing load frequency control incorporated in multi-interconnected renewable energy plants. *Sustainable Energy, Grids and Networks*. https://doi.org/10.1016/j.segan.2020.100352