Enhancing Whale Optimization Algorithm with Pso: A Hybrid Benchmark Study

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Abstract
Whale Optimization Algorithm (WOA) is known for its exploration ability while Particle Swarm Optimization (PSO) is known for its exploitation ability. Hybridizing them helps to improve convergence speed and solution accuracy. This paper presents a hybrid WOA-PSO algorithm which is evaluated on twenty-three benchmark functions and compared its performance with the original WOA and is able to show better results. Hybrid WOA-PSO algorithm giving better optimal solutions than the original one. Experimental results between WOA and PSO enhances balance between exploration and exploitation.

Keywords:
Optimization, Hybridization, algorithm, benchmark, WOA

1. Introduction

Optimization Algorithm plays a major role in solving real word problems, where finding the best possible solution efficiently. Many practical applications such as machine learning, industrial automation, logistics, engineering design, and resource allocation, require robust optimization techniques to achieve better performance and efficiency. Among the widely used metaheuristic algorithm, The Whale Optimization Algorithm (WOA) it commonly known for its powerful exploration ability, it allows to find the vast solution space effectively. instead, the Particle Swarm Optimization (PSO) algorithm excellent in exploration, allowing it to clarify solution to achieve faster convergence [5].

To take the advantages of both techniques, this paper offers a hybrid WOA-PSO algorithm, which aims to improve the combination of speed and solution accuracy. The performance of hybrid algorithm is improved by using twenty-three benchmark functions compared to original WOA. The Experimental Result demonstrate that the hybrid approach achieves the better optimal solution [7].

By merging the global search capability of WOA with the local refinement power of PSO, the hybrid WOA-PSO algorithm offers a more effective optimization technique. This study provides valuable insight it how hybridization can improve the metaheuristic algorithms, making them more suitable for solving real world optimization problems [6].

2. Literature Review

Optimization Algorithms are classified into four categories: Nature-based, Swarm-based, Physics-based, and Human-based. Nature-based algorithm is an optimization technique inspired by natural phenomena, such as evolution, natural selection, or biological processes. Nature-based algorithms, like Genetic Algorithm (GA). Swarm-based algorithm is an optimization technique that simulates the collective behaviour and social interaction of swarms or groups of agents. Physics-based algorithm is an optimization technique that models physical processes

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and natural laws to find optimal solutions. Physics-based methods, such as Simulated Annealing (SA), use physical processes like energy minimization. Human-based algorithm is an optimization technique inspired by human behaviour, culture, or social dynamics. Human-based algorithms, like Cultural Algorithm (CA), replicate social and cultural interactions [3].

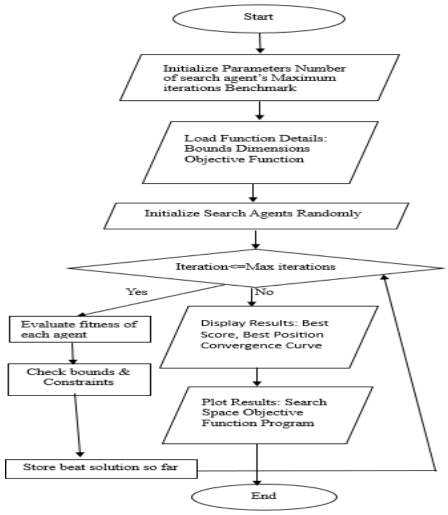
Category	Algorithms	Description
Physics-based	**Sine Cosine Algorithm, Equilibrium Optimizer, Gravitational Search Algorithm**	**Inspired by physical phenomena such as gravitational forces, equilibrium states, and sinusoidal motion.**
Swarm- based	**Particle Swarm Optimization, Ant Colony Optimization, Slime Mould Algorithm**	**Based on the collective behavior of biological groups like birds, ants and grasshoppers.**
Evolution-based	**Genetic Algorithm, Differential Evolution, Backtracking Search Algorithm**	**Mimics the principles of natural selection and evolution.**
Human Behaviour-based	**1brain Storm Optimization, Battle Royale Optimization Algorithm, Social Engineering Learning Optimization**	**Inspired by human learning, teaching, brainstorming, and strategic behaviours.**

Table 1: Classification of Metaheuristic Algorithm

Sr. No.	Name of Algorithm	Name of Author
1.	**Particle Swarm Optimization**	**James Kennedy and Russell Eberhart (1995)**
2.	**An idea Based on Honey Bee Swarm for Numerical Optimization**	**Dervis Karaboga (2005)**
3.	**A New Metaheuristic Bat-Inspired Algorithm**	**Xin-She Yang (2010)**
4.	**Cuckoo Search via Levy Flights**	**Xin-She Yang and Suash Deb (2009)**
5.	**Grey Wolf Optimizer**	**Seyedali Mirjalili et. al. (2014)**
6.	**Elephant Herding Optimization**	**Liang Wang et. al. (2015)**

Table 2: Metaheuristic Algorithms

1. FLOW CHART



2. 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
$F_2(S) = \sum_{m=1}^{z} \|S_m\| + \prod_{m=1}^{z} \|S_m\|$	(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
$F_4(S) = max_m\{\|S_m\|, 1 \leq m \leq z\}$	(10,30,50,100)	[-100 , 100]	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
$F_5(S) = \sum_{m=1}^{z-1}[100(S_{m+1} - S_m^2)^2 + (S_m - 1)^2]$	(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

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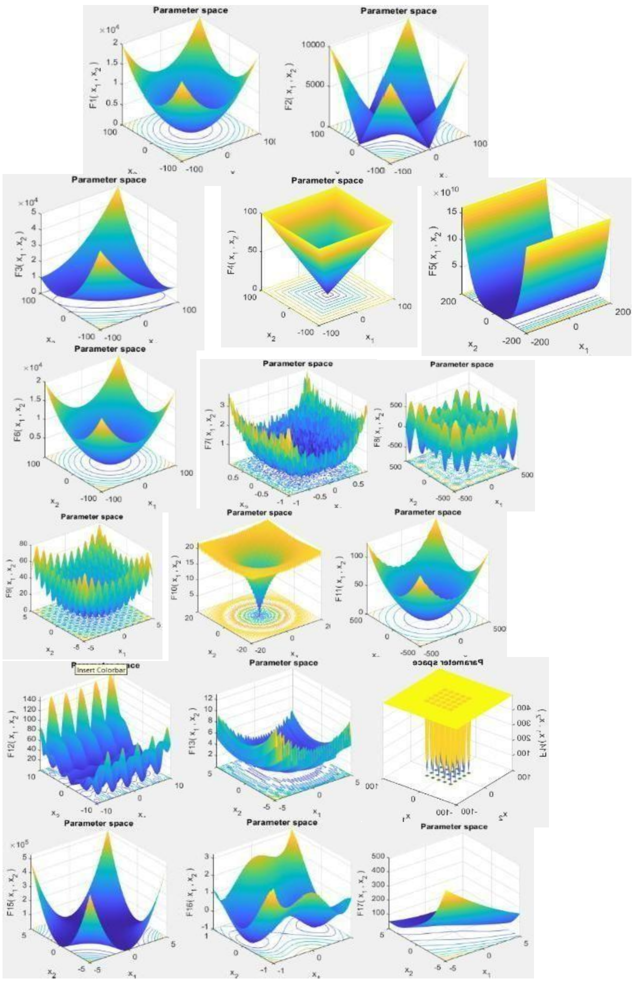
Functions	Dimension	Range	f_{min}
$F_8(S) = \sum_{m=1}^{z} -S_m sin(\sqrt{\|S_m\|})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z} [S_m^2 - 10cos(2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp\left(-0.2\sqrt{\left(\frac{1}{z}\sum_{m=1}^{z} S_m^2\right)}\right) - exp\left(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m)\right) + 20 + d$	(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

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

Table 3: Benchmark Functions



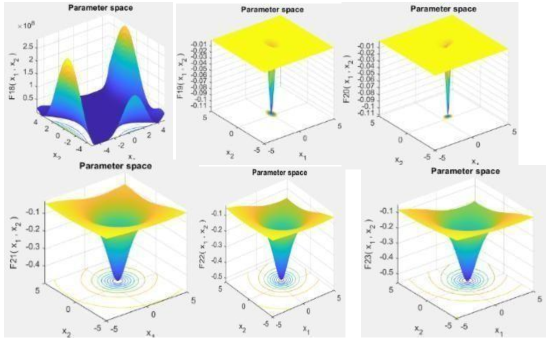


Fig. 1: Search Space

3. Result and Discussion

From the below table this paper concludes that, hybrid WOA-PSO giving more relevant and small value as compared to original algorithm. Some values are remained unchanged and some are showing fluctuation in values. Results of hybrid WOA-PSO are impressive. Some function shows (F4, F6, F7, F12, etc) enhancement in values. For ex., function 1 reduced from 6.8019e-80 to 1.143e-78.

Function No.	Original Value	Hybrid Value
Function 1	**6.8019e-80**	**1.143e-78**
Function 2	**6.6784e-55**	**2.8055e-53**
Function 3	**43708.8272**	**27734.5375**
Function 4	**4.0715**	**0.28816**
Function 5	**27.8255**	**27.7161**
Function 6	**0.13273**	**0.0973**
Function 7	**0.0032022**	**0.002682**
Function 8	**-11672.6931**	**-11405.443**
Function 9	**0**	**0**
Function 10	**3.9968e-15**	**3.9968e-15**
Function 11	**0**	**0**
Function 12	**0.011364**	**0.0057713**
Function 13	**0.5374**	**0.23443**
Function 14	**0.998**	**0.998**
Function 15	**0.00051**	**0.00033736**
Function 16	**-1.0316**	**-1.0316**
Function 17	**0.39789**	**0.39789**
Function 18	**3**	**3**
Function 19	**-3.8411**	**-3.7808**
Function 20	**-3.3122**	**-3.1869**
Function 21	**-10.1101**	**-10.0871**
Function 22	**-10.3895**	**-10.3755**
Function 23	**-2.8052**	**-1.6752**

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4. Conclusion

The proposed hybrid WOA-PSO algorithm combines the strengths of Whale Optimization and Particle Swarm Optimization, it leads to improve accuracy. Out of twenty-three benchmarks functions, the sixteen functions achieved better optimal values compared to the original one which demonstrating an improvement in WOA's performance.

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