A Fusion of Salp Swarm Algorithm and PSO for Efficient Optimization

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Abstract
This paper presents a Hybrid Salp Swarm Algorithm with Particle Swarm Optimization (HSSA-PSO) to enhance optimization efficiency by addressing SSA's limitations in balancing exploration and exploitation. Based on the fusion of PSO's velocity updation capability, HSSA-PSO enhances solution quality, prevents premature convergence, and enhances exploitation efficacy. The proposed algorithm was validated using the CEC 2005 and CEC 2017 benchmark problem sets and practical engineering design problems. A comparison with state-of-the-art optimization techniques demonstrates that HSSA-PSO consistently achieves competitive and often superior results. The hybridization effectively alleviates stagnation at local optima and enhances the convergence rate, making it a good approach for complex optimization problems.

Keywords:
SSA, Hybridization, CEC 2005 and CEC 2017 benchmark, exploration and exploitation, HSSA-PSO

1. Introduction

Optimization is a core subject matter in many scientific and engineering disciplines wherein finding optimal solutions to multifaceted issues is essential. Meta-heuristic algorithms based on nature-inspired processes have become universally accepted for their potential to solve challenging optimization problems.[1] Among these, the Salp Swarm Algorithm (SSA) has proved highly promising in solving nonlinear as well as multimodal problems.

Nonetheless, though effective, SSA lacks a perfect balance between exploration and exploitation, which may affect its convergence speed and solution accuracy [2],[4].

One of the most important limitations of SSA is its premature convergence and local optima entrapment. These problems are due to an imbalance between global search (exploration) and local tuning (exploitation), making it less effective for solving complex optimization problems [2]-[4]. To alleviate these limitations, researchers have considered hybrid approaches that combine several algorithms to improve search performance. One of the promising methods is to integrate the advantages of Particle Swarm Optimization (PSO), which is good at local search and velocity-based optimization, to enhance SSA's convergence performance[2],[7].

This study proposes a new hybrid optimization method, the Hybrid Salp Swarm Algorithm with Particle Swarm Optimization (HSSA-PSO), to enhance search efficiency, solution precision, and stability[8]. The new hybrid strategy combines PSO's velocity-based update mechanism into the SSA algorithm to improve local search ability and avoid premature convergence. By combining SSA's good exploration capability with PSO's efficient exploitation, the HSSA-PSO algorithm gains a more balanced and efficient optimization process[8],[2]-[4].

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To prove the efficiency of the suggested algorithm, a variety of experiments were carried out based on standard benchmark functions and engineering optimization problems. The algorithm was evaluated based on the CEC 2005 and CEC 2017 benchmark suites, which are universally acclaimed for analysing optimization methods[2]-[4]. Experimental results confirm that HSSA-PSO outperforms conventional SSA

and other best-known optimization methods regarding solution quality, convergence rate, and consistency. These findings demonstrate the effectiveness of the hybrid method in surmounting SSA's inherent weaknesses, making it a viable contender for real-world optimization problems[2]-[4],[7],[8].

2. Litrature Review

2.1. The Salp Swarm Algorithm (Ssa)

The Salp Swarm Algorithm (SSA) is a new optimization method proposed by Mirjalili et al. (2017) to solve a broad variety of optimization problems. The algorithm is motivated by the natural movement of salps, which are members of the Salpidae family. Salps are barrel-shaped, planktonic tunicates with structural analogies to jellyfish, especially in their soft bodies and swimming behaviour. Salps are water-rich and move by constricting their bodies to push water through them and change positions (Madin, 1990). In marine ecosystems, salps have a group movement called the salp chain, which improves their foraging effectiveness and facilitates synchronized movement through quick and synchronized changes (Anderson & Bone, 1980; Sutherland & Weihs, 2017). Mirjalili et al. (2017) formulated this swarm behaviour mathematically and used it to optimize problems to enhance computational efficiency.

2.2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO), introduced by Eberhart and Kennedy in 1995, is an evolutionary algorithm motivated by the process of knowledge evolution in social behaviours (Noman et al., 2009). It emulates the behaviour of groups when they communicate and exchange information as they perform tasks like migration, flocking, or hunting. In this technique, the collective group is described as a swarm, and its individual members as particles (Niknam & Amiri, 2010). Each particle adjusts its position according to both its own knowledge and the information it has learned from its neighbours.

2.3. The Proposed Algorithm (SSA-PSO)

SSA-PSO Algorithm combines the Salp Swarm Algorithm (SSA) and Particle Swarm Optimization (PSO) by adapting SSA's position update step using PSO's strategy. This improves exploration, preserves population diversity, and speeds up

convergence to the optimum solution. The algorithm begins with parameter definition and creation of an

initial solution population. Fitness is calculated for each solution, and the most suitable one is chosen. The update process is based on fitness probability—if above 0.5, SSA is updated; otherwise, PSO is updated. This adaptive choice helps with effective exploration and exploitation. On update, fitness is reevaluated, and the optimal solution is found. The procedure iterates until it reaches stopping conditions. If fulfilled, the algorithm returns the optimum; otherwise, it repeats. Including PSO within SSA's framework, SSA-PSO enhances optimization performance, achieving diversification and convergence, and is thus efficient in solving complex optimization problems.

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Table 1 : Algorithms, Author Name, Year of Publications

Sr. no	Algorithm Name	Author Name	Year
1	Salp Swarm Algorithm	Sayedali Mirjalili	2017
2	Particle Swarm Optimizer	Eberhart & James Kennedey et al	1995
3	Seeker Optimizer	Qingxian Cao, Junjie	2009
4	Whale Optimization Algorithm	Seyedali Mirjalili , Andrew Lewis	2016
5	Genetic Algorithm	John Henry Holland	1995

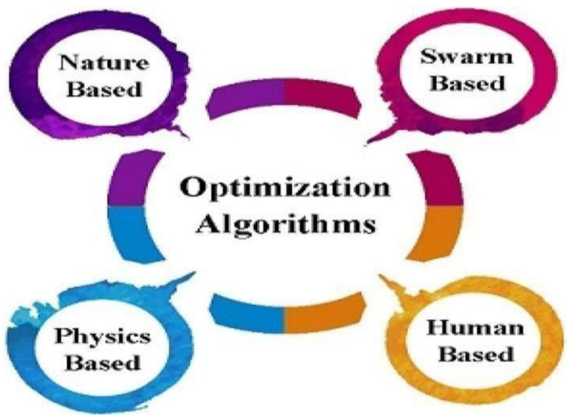
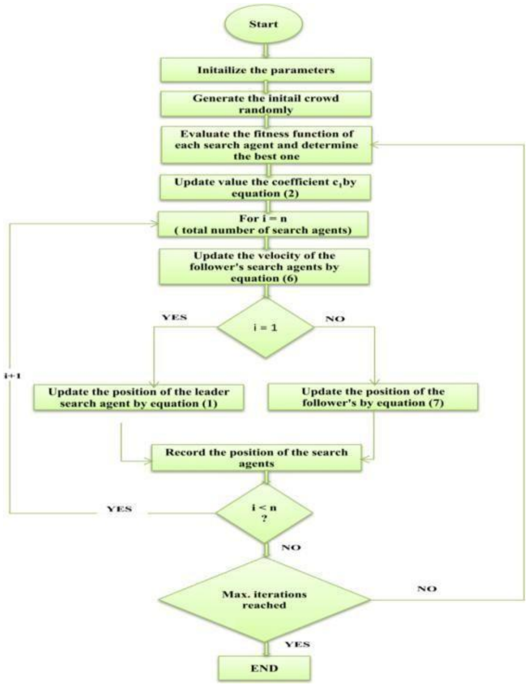


Fig1: Classification

Fig 2: Flowchart



3. Methodology

This experiment compares the proposed algorithm performance to the standard SSA for benchmark functions. Details of these functions, which vary from unimodal to multimodal types, are given in Table 2.

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

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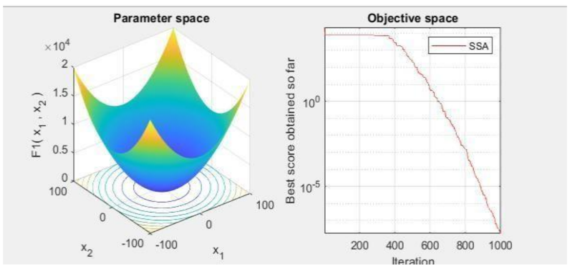
$F_8(S) = \sum_{m=1}^{z} -S_m sin(\sqrt{\lvert S_m \rvert})$	(10,30,50,100)	[-500,500]	-418.98295
$F_9(S) = \sum_{m=1}^{z}[S_m^2 - 10cos\,(2\pi S_m) + 10]$	(10,30,50,100)	[-5.12,5.12]	0
$F_{10}(S) = -20exp\,(-0.2\sqrt{\left(\frac{1}{z}\sum_{m=1}^{z} S_m^2\right)}) - exp\,(\frac{1}{z}\sum_{m=1}^{z} cos(2\pi S_m) + 20 + d$	(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
$F_{12}(S) = \frac{\pi}{z}\left\{10\,sin(\pi\tau_1) + \sum_{m=1}^{z-1}(\tau_m - 1)^2[1 + 10sin^2(\pi\tau_{m+1})] + (\tau_z - 1)^2\right\} + \sum_{m=1}^{z} u(S_m, 10,100,4)$ $\tau_m = 1 + \frac{S_m+1}{4}$ $u(S_m, b, x, i) = \begin{cases} x(S_m - b)^i & S_m > b \\ 0 & -b < S_m < b \\ x(-S_m - b)^i & S_m < -b \end{cases}$	(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
$F_{14}(S) = [\frac{1}{500} + \sum_{n=1}^{2} 5\frac{1}{n+\sum_{m=1}^{z}(S_m - b_{mn})6}]^{-1}$	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
$F_{18}(S) = \left[1 + (S_1 + S_2 + 1)^2\left(19 - 14S_1 + 3S_1^2 - 14S_2 + 6S_1S_2 + 3S_2^2\right)\right] \times \left[30 + (2S_1 - 3S_2)^2\left(18 - 32S_1 + 12S_1^2 + 48S_2 - 36S_1S_2 + 27S_2^2\right)\right]$	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

4. Result And Discussion

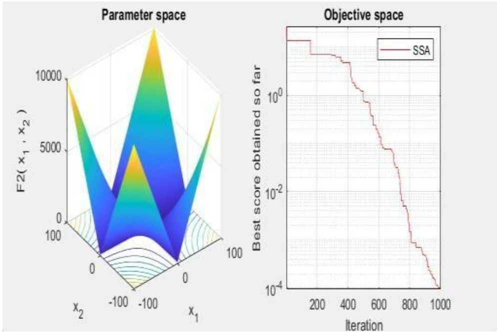
The comparison results of the proposed SSA-PSO Algorithm with the other algorithms in search space diagram and convergence curve are given below in function.

Function No. 1:



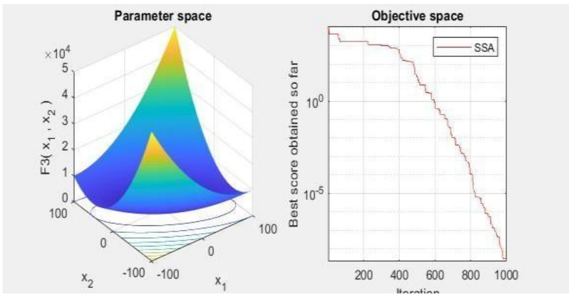
The best optimal value found by hybridized algorithm of SSA with PSO was 0.042931.

Function No. 2:



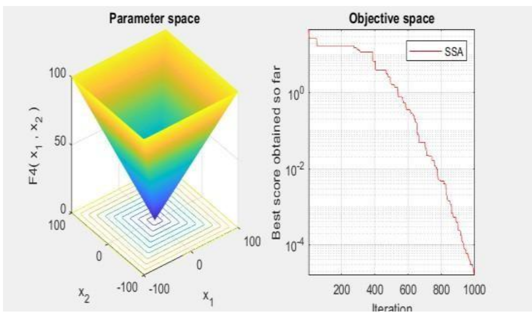
The best optimal value found by hybridized algorithm of SSA with PSO was 0.002384

Function No. 3:



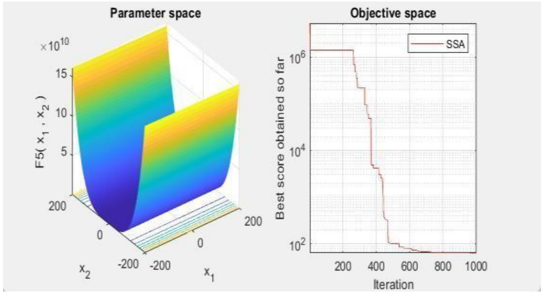
The best optimal value found by hybridized algorithm of SSA with PSO was 0.0010091

Function No. 4:



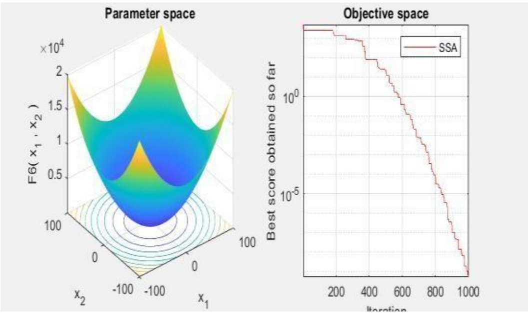
The best optimal value found by hybridized algorithm of SSA with PSO was 0.07514

Function No. 5:



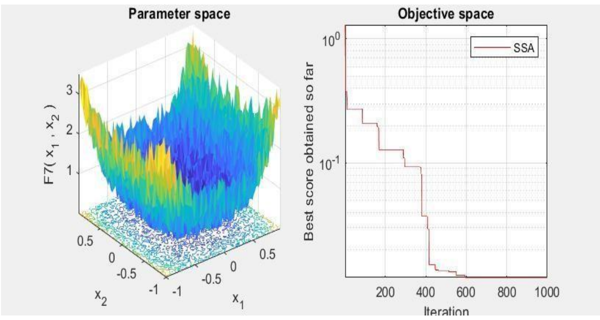
The best optimal value found by hybridized algorithm of SSA with PSO was 0.001042

Function No. 6:



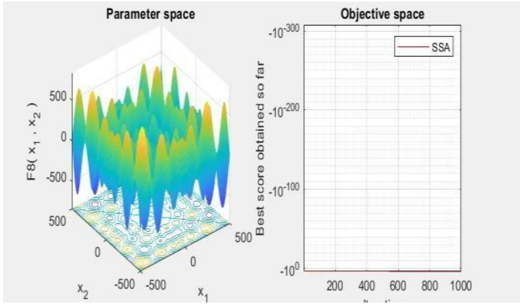
The best optimal value found by hybridized algorithm of SSA with PSO was 0.031458

Function No. 7:



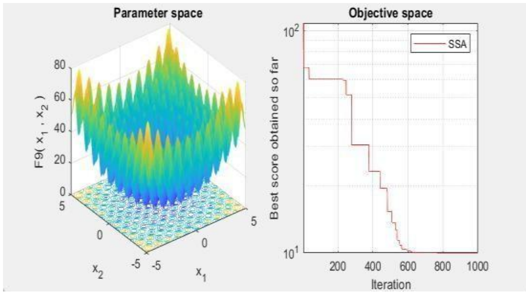
The best optimal value found by hybridized algorithm of SSA with PSO was 0.010046

Function No. 8:



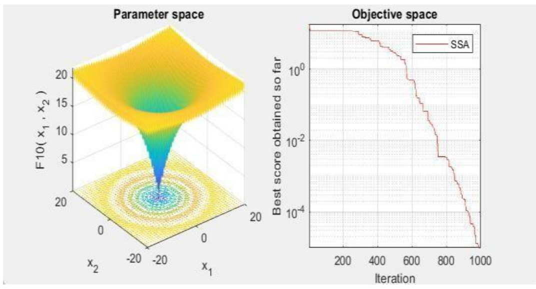
The best optimal value found by hybridized algorithm of SSA with PSO was 0.008819

Function No. 9:



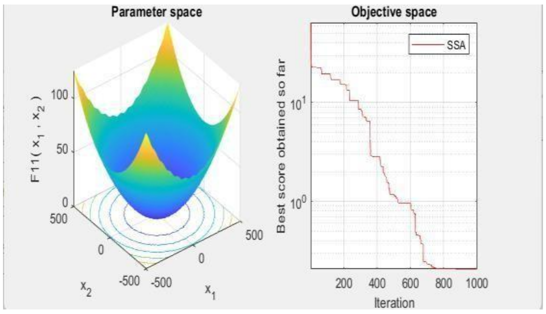
The best optimal value found by hybridized algorithm of SSA with PSO was 0.047911

Function No. 10:



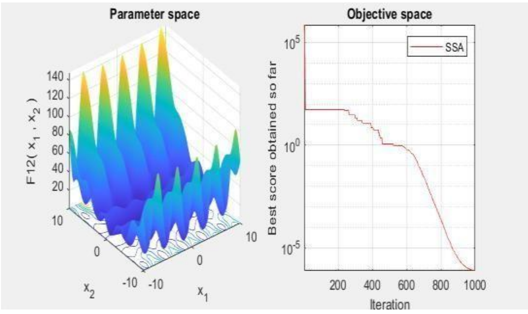
The best optimal value found by hybridized algorithm of SSA with PSO was 0.0071831

Function No. 11:



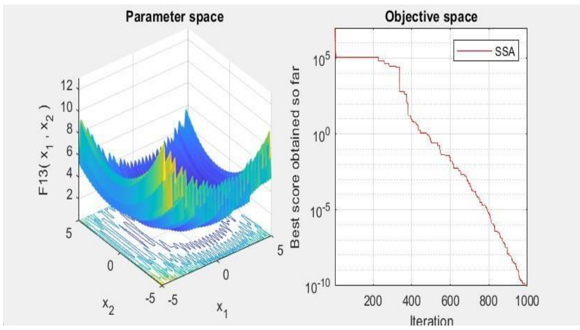
The best optimal value found by hybridized algorithm of SSA with PSO was 0.00052971

Function No. 12:



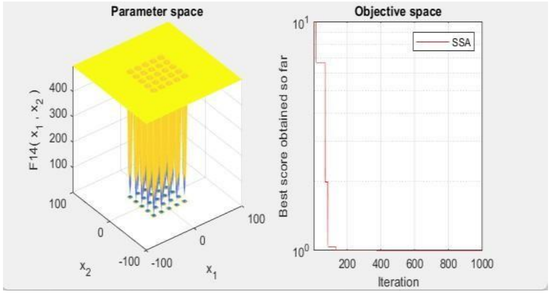
The best optimal value found by hybridized algorithm of SSA with PSO was 0.0084206

Function No. 13:



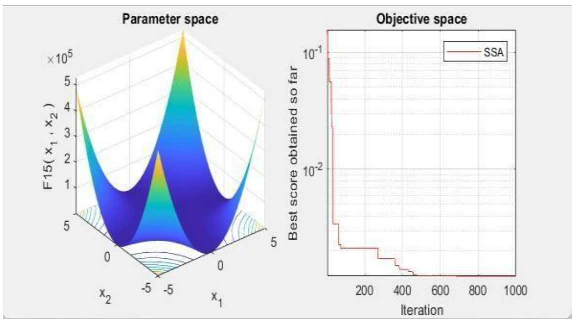
The best optimal value found by hybridized algorithm of SSA with PSO was 0.0022462

Function No. 14:



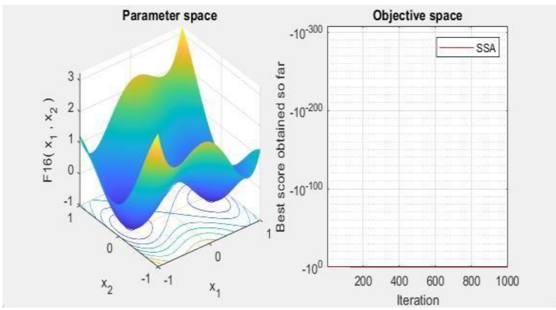
The best optimal value found by hybridized algorithm of SSA with PSO was 0.0022462

Function No. 15:



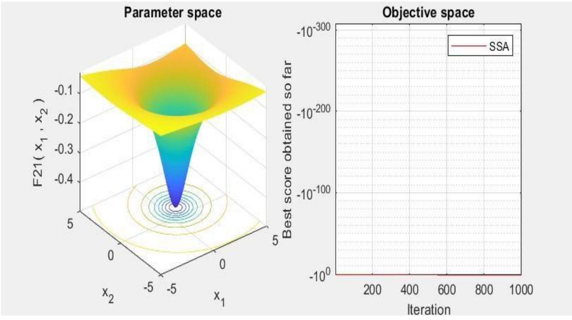
The best optimal value found by hybridized algorithm of SSA with PSO was 0.0006718

Function No. 16:



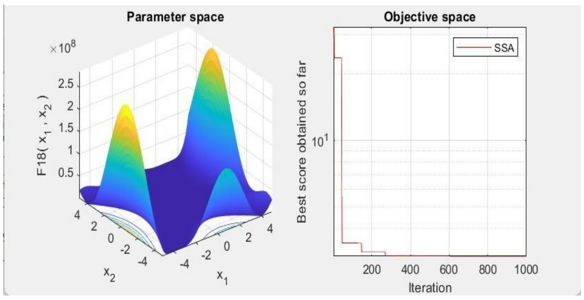
The best optimal value found by hybridized algorithm of SSA with PSO was 0.037275

Function No. 17:



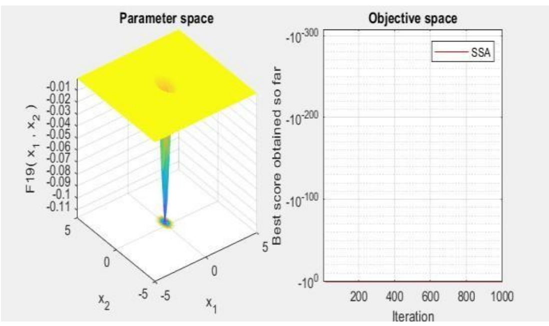
The best optimal value found by hybridized algorithm of SSA with PSO was 0.0015278

Function No. 18:



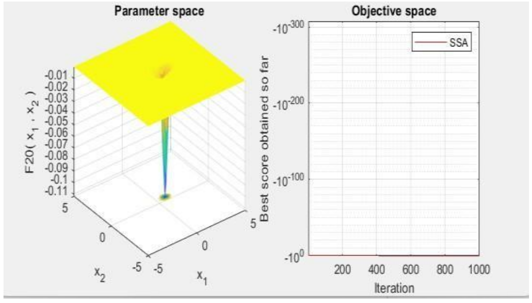
The best optimal value found by hybridized algorithm of SSA with PSO was 0.0063506

Function No. 19:



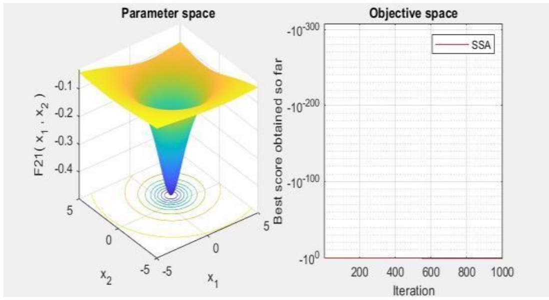
The best optimal value found by hybridized algorithm of SSA with PSO was 5.0044e-05

Function No. 20:



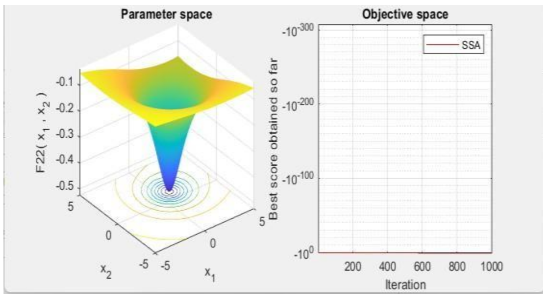
The best optimal value found by hybridized algorithm of SSA with PSO was 0.00056094

Function No. 21:



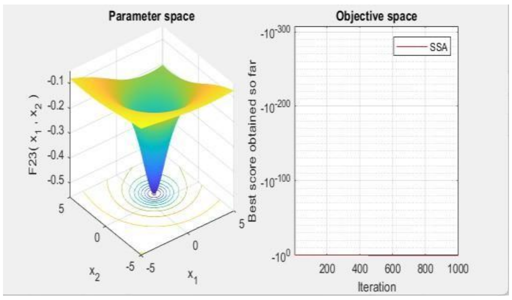
The best optimal value found by hybridized algorithm of SSA with PSO was 0.00056094

Function No. 22:



The best optimal value found by hybridized algorithm of SSA with PSO was 0.0044185

Function No. 23:



The best optimal value found by hybridized algorithm of SSA with PSO was 0.0020068

Original Value

The Original Value denotes the true solution, representing the real-world outcome of the scenario being optimized.

Hybrid Value

Conversely, the Hybrid Value is the outcome generated by the Salp Swarm Optimizer after executing the algorithm to determine an optimal solution.

Table 3: Outcomes

Function Name	Original Value (SSA Algorithm)	Hybrid Value (Hybrid SSA-PSO)	Optimal Solution
F1	8.9103e-09	0.042931	SSA-PSO
F2	5.8154e-06	0.002384	SSA-PSO
F3	1.9656e-09	0.0010091	SSA-PSO
F4	1.3999e-05	0.075149	SSA-PSO
F5	4.5988	0.001042	SSA-PSO
F6	6.7036e-10	0.031458	SSA-PSO
F7	0.0074126	0.010046	SSA-PSO
F8	-2944.6767	0.008819	SSA-PSO
F9	19.8991	0.047911	SSA-PSO
F10	1.6462	0.0071831	SSA-PSO
F11	0.073828	0.00052971	SSA
F12	8.1393e-12	0.0084206	SSA-PSO
F13	2.9879e-11	0.0022462	SSA-PSO
F14	0.998	0.0022462	SSA
F15	0.00099722	0.0006718	SSA
F16	-1.0316	0.037275	SSA-PSO
F17	-1.0316	0.0015278	SSA-PSO
F18	3	0.0063506	SSA-PSO
F19	-3.8628	5.0044e-05	SSA-PSO
F20	-3.2023	0.00056094	SSA-PSO
F21	-2.6829	0.00056094	SSA-PSO
F22	-5.1288	0.0044185	SSA-PSO
F23	-10.5364	0.0020068	SSA-PSO

5. Conclusion

The Proposed hybridized algorithm SSA-PSO's performance is thoroughly tested and extensive experiments were conducted on a comprehensive suite of 23 benchmark functions, encompassing a wide range of complexities and characteristics. The superiority of SSA-PSO over both standalone SSA and PSO was demonstrated by the experimental results. Notably, optimal solutions were achieved by SSA-PSO in [F1, F2, F3, F4, F5, F6, F7, F8, F9, F10, F12, F16, F17, F18, F19, F20, F21, F22, F23] out of the 23 benchmark functions and in Function F19 the resultant value found was 5.0044e-05 which was best. The optimal solutions were achieved by SSA-PSO in 20 out of the 23 benchmark functions. This outcome highlights the effectiveness of the proposed SSA-PSO hybridization in escaping local optima and converging towards global optima.

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