ISSN: 0971-1260
Vol-22-Issue-16-August-2019

An Ameliorated Salp Swarm Algorithm For Scalar Objective Numerical Optimization Problems

Vikram Kumar Kamboj[1]

[1]School of Electronics and Electrical Engineering, Lovely Professional University, India

Abstract: Salp Swam Algorithm is a new bio-inspired global search algorithm, which was inspired by the simulation behavior of salps in oceans during foraging and navigating and tested for 19 well known benchmark problems and 5 classical engineering design problems i.e. cantilever beam, welded beam, three-truss, I-beam, tension/compression designs problems and airfoil for aircrafts. In the proposed research, the author has developed the ameliorated variant of the classical salp swarm optimizer to improve its exploitation phase to further extent. The proposed optimizer has been tested for 23 well known benchmark problems, which consist of unimodal, multi-modal and fixed dimension numerical optimization problems. Experimental results reveals that the proposed ameliorated salp swarm optimizer performs much better than classical Salp swarm optimizer and such a powerful optimizer can be adopted to solve various engineering optimization problems and other real life problems.

Keywords: Numerical Optimization, Standard Benchmark functions, Salp Swarm Optimizer.

1. INTRODUCTION

Optimization has a wide scope in every field of research and technology it is not a concise term related to engineering only it find a wide use in each field of science as well as engineering. As the name optimization indicates it does not focuses only to optimize the problem in hand but to discover a new unconventional solution which is more cost effective and can be used to achieve high performance rating under the given restrictions which has to be taken in to account, and all this is done by exploring the desired factors and exploiting the undesired factors. Where exploration means to attain the maximum outcome from the problem and the exploitation refers to the minimum fatalities. When we exploits or reduce the problem the function value is termed as cost function and in case of exploration or expansion of problem the function value is called fitness. The major drawback of the optimization process is restriction of the optimization due to the time available to evaluate and lack of information available. Optimization is not only a technical term but it is also widely adopted in our day to day life, we accomplish various tasks by employing various optimization techniques to reduce our efforts. In engineering design problem if we talk about the manufacturing of some object, structure, or system there is need to choose the value of certain parameters which are subjected to some constraints uttering their range and interrelationship. The combination of parameters chosen determine the assessment of several other variables on which end product desirability depend which consist of parameters such as weight, reliability and cost. Therefore to attain the appropriate product there is need to have an optimized assessment of parameters which make the use of optimization an important step in the field of engineering and technology.

2. PROBLEM FORMULATION

The optimization problems are broadly divided in to two categories based on the type of problem

2.1 Scalar Objective Optimization

The scalar objective problem are simple and has only single objective to be calculated having only one solution as the global optimum. In scalar objective optimization the desired function is minimized under some specific constrained condition to be satisfied, the mathematical formulation of scalar objective optimization problem is given by

Minimize $f(x)$ $\quad$ 2.1[a]

Subjected to $x_i^{\min} \le x_i \le x_i^{\max}$ (i= 1, 2, 3……., N) $\quad$ 2.1[b]

where, X is the set of function variable and N is the number of variable

ISSN: 0971-1260
Vol-22-Issue-16-August-2019

2.2 Multi Objective Optimization

The multi-objective optimization problem is the one in which more than one objective has to be calculated simultaneously. These problems are complex in nature and require multi task handling the mathematical formulation of multi objective problem is given by

Minimize $f(X,U)$

2.2[a] Subjected to $g_i(X,U) \geq 0$ (i= 1, 2, 3……, q)

3.1 $h_j(X,U) \geq 0$ (j= 1, 2, 3……., p)

3.2 $x_i^{\min} \leq x_i \leq x_i^{\max}$ (i= 1, 2, 3……., n)

3.3 $u_i^{\min} \leq u_i \leq u_i^{\max}$ (j= 1, 2, 3……., m)

3.4

where $g_i(X,U) =$ Set of constraint of vector arguments X and U; $h_i(X,U) =$ Set of non-linear equality constraint;

3. SALP SWARM OPTIMIZER

The primary inspiration of salp swarm algorithm is the simulation behavior of salps in salp chain during navigating and foraging in an oceans. Salps are like jellyfishes with thick round body and a small tail. In the oceans Salps form a chain for achieving precise locomotion using coordinate changes. Salps are further classified into two groups one is leaders and the other is followers. In this chain leaders at the front side leads the chain and followers follow the leaders as in other swarm chains. The position of Salps in two dimensional matrix is saved in λ with n number of variables and F is food source in search target. In SSA algorithm the position of leaders is updated using following equation:

$$\lambda_j^i = \begin{cases} F_j + \alpha\big((ub_j - lb_j)\beta + lb_j\big), \gamma \geq 0 \\ F_j - \alpha\big((ub_j - lb_j)\beta + lb_j\big), \gamma \leq 0 \end{cases}$$

3.5

Where λ_j^i position of first salp, F_j is food position. ub_j, $lb_j$are upper and lower bounds in i^{th} dimension and α, β and γ are random numbers. The coefficient α is an imperative parameter as it maintains a balance between exploration and exploitation of an algorithm and is defined as:

$$\alpha = 2e^{-\left(\frac{4*i}{I}\right)^2}$$

3.6

Where i, indicates current and I is maximum number of iterations. The parameters β & γ are randomly generated numbers between 0 to 1 dictating the next position of Salp and step size of Salp. The position of followers is updated by using following equation (Newton's law of motion):

$$\lambda_j^i = \frac{1}{2}at^2 + v_0 t \qquad 3.7$$

Where $i \geq 2$, λ_j^i indicates the position of i^{th} followers in j^{th} dimension, t is time, v_0 is initial speed, and $a = \frac{v_{final}}{v_0}$

where $v = \frac{x - x_0}{t}$. Since the optimization time is iteration, the difference between iterations is equal to 1, and considering $v_0 = 0$, the above equation can be rewritten as follows.

$$\lambda_j^i = \frac{1}{2}\left(\lambda_j^i + \lambda_j^{i-1}\right)$$

3.8

where $i \geq 2$ and λ_j^i is position of i^{th} follower in salp chain in j^{th} dimension. By equations (3.5) and (3.8), the salps chain can be simulated. Figure 3.3 shows the PSEUDO code of Salp Swarm algorithm.

ISSN: 0971-1260
Vol-22-Issue-16-August-2019

4. PROPOSED HYBRID SSA-SA ALGORITHM

Salp Swam Algorithm is a new bio-inspired global search algorithm proposed by Seyedali in the year 2016, inspired by the simulation behavior of salps in oceans during foraging and navigating. Initially, it was tested on 19 benchmark problems and was used to solve 5 classical engineering design problems such as cantilever beam, welded beam, three-truss, I-beam, tension/compression designs problems and airfoil for aircrafts. Later on, it was used to find optimal solution for various engineering optimization problems such as short-term load forecasting [1], shop scheduling problems [2], tackle future selection problems [3], Extracting Parameters of PV-cell models [4], Pattern classification of neural networks [5], PID controllers for Doha distillation plant [6], formation of real and synthetic biomedical datasheet for a hospital [7], for solving engineering optimization problems [8], designing of fraction order PID controller for automatic generation control [9], solving economic load dispatch problem [10], predicting chemical component activities [11], parameter optimization of power system stabilizer [12], tuning the coefficients of PID controller , for reducing structural vibration [13], extracting parameters of PEM fuel cell [14], Fish image segmentation [15].

Apart from the above diverse applications of SSA, it has some drawbacks such as low convergence rate and local optima stagnation [16] . To overcome these drawbacks researchers have developed new variants of the said algorithm some of them are Binary Salp Swam algorithm [17], Hybrid Salp Swarm with Simulated Annealing for Feature Selection [18], Improved Salp Swam algorithm based on PSO for Future Selection [19], Chaotic Salp SSA for feature selection and global optimization [16], Improved Salp Swarm Algorithm for Feature Selection [20]. The Pseudo code of SSA algorithm is shown in Fig.1(a) and Pseudo code of SA algorithm is shown in Fig.1(b). The PSEUDO code of the proposed ameliorated algorithm is shown in Fig.2.

```
Initialize the salp population λ_i (i = 1, 2, … , n) considering ub and lb
while (end condition is not satisfied)
Calculate the fitness of each search agent (salp)
F=the best search agent
Update α by Eqn. (3.6)
    for each salp (λ_i)
        if (i==1)
          Update the position of the leading salp by Eqn. (3.5)
        else
          Update the position of the follower salp by Eqn. (3.8)
       end
   end
   Amend the salps based on the upper and lower bounds of variables
end while
```

Fig.1(a): PSEUDO code of Salp Swarm Algorithm

5. TEST BENCHMARK FUNCTIONS

The standard benchmark functions are the basic testing parameters for any new evolved algorithm as they set a perfect combination of simple and complex optimization problem which can test algorithms on ground level for finding the optimal of these functions and the results indicate the performance level of the newly developed algorithm. The benchmark functions are divided into three categories named as unimodal, multimodal and fixed dimension benchmark function, out of 23 benchmark functions seven are unimodal benchmark functions, six are multimodal and remaining ten are fixed dimension benchmark functions. The novelty of every algorithm is tested on these benchmark function and if the algorithm work well for these standard function then only it is applied for solution of other optimization problems.

ISSN: 0971-1260
Vol-22-Issue-16-August-2019

Assign $T_0 = 2 * |N|$ and % $|N|$ *is the number of attributes for each dataset*
Evaluate $BestSol \leftarrow S_i^{'}$
Evaluate $\delta(BestSol) \leftarrow \delta(S_i^{'})$ % δ indicate the quality of the solution
while $T \geq T_0$
Generate at random a new solution *TrialSol* in the neighbour of $S_i^{'}$
Calculate $\delta(TrialSol)$
if ($\delta(TrialSol) > \delta(BestSol)$)
do $S_i^{'} \leftarrow TrialSol$;
do $BestSol \leftarrow TrialSol$;
do $\delta(S_i^{'}) \leftarrow \delta(TrialSol)$;
$\delta(BestSol) \leftarrow \delta(TrialSol)$;
else if (($\delta(BestSol) \leftarrow \delta(TrialSol)$;)
Calculate $|TrialSol|$ and $|BestSol|$;
if($|TrialSol| < |BestSol|$)
$S_i^{'} \leftarrow TrialSol$;
$BestSol \leftarrow TrialSol$;
$\delta(S_i^{'}) \leftarrow \delta(TrialSol)$;
$\delta(BestSol) \leftarrow \delta(TrialSol)$;
end if
else
Calculate $\theta = \delta(TrialSol) - \delta(bestSol)$ % *accepting the solution*
Generate a random number, P= [0,1];
if ($P \leq e^{-\theta/T}$);
$S_i^{'} \leftarrow TrialSol; \delta(S_i^{'}) \leftarrow \delta(TrialSol)$;
end if
end if
T=0.93 * T; % *update Temperature*
end while

Fig.1(b): PSEUDO code of Simulated Annealing Algorithm

Initialize the salp population λ_i (i = 1, 2, … , n) considering ub and lb
while (end condition is not satisfied)
Calculate the fitness of each search agent (salp)
F=the best search agent
Update α by Eqn. (3.6)
for each salp (λ_i)
if (i==1)
Update the position of the leading salp by Eqn. (3.5)
else
Update the position of the follower salp by Eqn. (3.8)
end
further update the positions of salp using Simulated Annealing Algorithm *(Refer Fig.3.1)*
end
Amend the salps based on the upper and lower bounds of variables
end while

Fig. 2: PSEUDO code of ameliorated Salp Swarm Algorithm

ISSN: 0971-1260
Vol-22-Issue-16-August-2019

6. RESULTS AND DISCUSSION

In this work a common set of standard benchmark functions are taken into account in order to validate and compare the performance of the proposed optimization algorithm with other well-known algorithms. Here in this study 30 trail runs are taken into account in order to overcome the stochastic nature of proposed hybrid SSA-SA algorithm and each objective function has been evaluated for best, average, worst, standard deviation, median and p-values. In order to legitimize the exploitation phase of proposed SSA-SA algorithm, first seven unimodal benchmark function which include F-1, F-2, F-3, F-4, F-5, F-6 and F-7 are taken into consideration. The solution of unimodal benchmark function using SSA algorithm are shown in Table-1. the solution of multimodal benchmark functions which include F-8, F-9, F-10, F-11, F-12 and F-13 using SSA are shown in Table-2 and Table-3 shows the solution of Fixed-dimension benchmark function which include F-14, F-15, F-16, F-17, F-18, F-19, F-20, F-21, F-22 and F-23 using SSA algorithm.

Table-1: Results of SSA algorithm for Unimodal test Benchmark functions

Fun.	Best Value	Avg. Value	Worst Value	SD	Med. Value	p-Value
F1	2.76989E-07	6.9471E-07	2.07365E-08	3.75094E-06	8.06518E-08	1.7344E-06
F2	1.927308693	1.338171895	0.253518212	5.290491681	1.542461489	1.7344E-06
F3	1869.485715	1745.505482	408.8851085	8721.962995	1296.354485	1.7344E-06
F4	11.26640767	3.492341149	5.95682381	18.75621619	10.57023671	1.7344E-06
F5	103.9427618	101.5914943	24.0664105	389.025386	51.54914113	1.7344E-06
F6	1.84673E-07	1.65872E-07	4.24597E-08	7.13191E-07	1.48234E-07	1.7344E-06
F7	0.167401194	0.084351711	0.063224184	0.483942742	0.148791623	1.7344E-06

Table-2: Results of SSA algorithm for Multimodal test Benchmark functions

Fun.	Best Value	Avg. Value	Worst Value	SD	Med. Value	p-Value
F8	-7458.42271	684.7136273	-8937.262932	-6043.076176	-7514.07054	1.7344E-06
F9	55.94975185	16.63377986	24.8739664	83.5763389	57.70752697	1.7344E-06
F10	2.492800163	0.771349745	8.10395E-05	3.934416859	2.537701189	1.7344E-06
F11	0.014845168	0.01114234	0.000881051	0.03926064	0.013862438	1.7344E-06
F12	7.196945613	4.349611096	2.668748697	23.54747263	6.413861835	1.7344E-06
F13	17.15524431	16.39549356	0.011902174	48.20238997	15.00415912	1.7344E-06

Table-3: Results of SSA algorithm for Fixed-Dimension test Benchmark functions

Fun.	Best Value	Avg. Value	Worst Value	SD	Med. Value	p-Value
F14	1.130277259	0.503382639	0.998003838	2.982105157	0.998003838	9.3327E-07
F15	0.00088407	0.000252903	0.000533799	0.00131089	0.000806811	1.7344E-06
F16	-1.03162845	2.53903E-14	-1.031628453	-1.031628453	-1.031628453	1.7268E-06
F17	**0**	**0**	**0**	**0**	**0**	1.7268E-06
F18	3	2.04899E-13	3	3	3	1.7333E-06
F19	-3.86278215	2.25201E-10	-3.862782148	-3.862782147	-3.862782148	1.7344E-06
F20	-3.20766967	0.047094302	-3.321995172	-3.161516164	-3.195859188	1.7344E-06
F21	-7.05301019	3.270911144	-10.15319968	-2.630471668	-7.62698591	1.7344E-06
F22	-8.77663034	3.044283223	-10.40294057	-2.751933564	-10.40294057	1.7344E-06
F23	-8.48484784	3.252925064	-10.53640982	-2.421734027	-10.53640982	1.7344E-06

Table-4 shows the results of unimodal benchmark function using hybrid SSA-SA algorithm, Table-5 shows the results of Multimodal benchmark function using hybrid SSA-SA algorithm and Table-6 shows the results of Fixed-dimension benchmark function using hybrid SSA-SA algorithm.

Table-4: Results of Hybrid SSA-SA algorithm for Unimodal test Benchmark functions

Fun.	Best Value	Avg. Value	Worst Value	SD	Med. Value	p-Value
F1	2.40422E-07	4.09679E-07	1.9721E-08	1.69971E-06	9.76753E-08	1.73E-06
F2	0.821882686	0.776056292	0.057459454	2.903841346	0.561789164	1.73E-06
F3	3.11056532	1.463603339	1.159250491	7.33429387	2.825010378	1.73E-06
F4	0.452291803	0.118681061	0.20322475	0.638914816	0.493175751	1.73E-06
F5	69.57841697	32.90238583	16.40345295	144.8127875	72.28648093	1.73E-06
F6	2.59187E-07	3.15091E-07	2.53125E-08	1.42395E-06	1.42729E-07	1.73E-06
F7	0.172597228	0.069187455	0.096976827	0.372588909	0.158184369	1.73E-06

Table-5: Results of Hybrid SSA-SA algorithm for multimodal benchmark functions

Fun.	Best Value	Avg. Value	Worst Value	SD	Median	p-Value
F8	-7220.39593	734.2271909	-8642.823971	-5795.0901	-7190.139507	1.73E-06
F9	2.654636403	0.542184805	1.989918134	3.979836268	2.984877197	1.73E-06
F10	1.129869424	0.120205209	0.931304943	1.340421343	1.155148565	1.73E-06
F11	0.000725946	0.000716752	2.39419E-05	0.002639097	0.000482085	1.73E-06
F12	0.116017646	0.087217502	0.003325055	0.263609047	0.103431485	1.73E-06
F13	0.017963968	0.022588141	7.48708E-05	0.104441447	0.012255433	1.73E-06

Table-6: Results of Hybrid SSA-SA Algorithm for Fixed-Dim. Benchmark functions

Fun.	Best Value	Avg. Value	Worst Value	SD	Med. Value	p-Value
F14	1.229679965	0.564079068	0.998003838	2.982105157	0.998003838	1.29E-06
F15	0.002082491	0.004975631	0.000309941	0.020363502	0.00071225	1.73E-06
F16	-1.03162845	3.60933E-14	-1.031628453	-1.031628453	-1.031628453	1.73E-06
F17	**0**	**0**	**0**	**0**	**0**	1.73E-06
F18	3	3.1233E-13	3	3	3	1.73E-06
F19	-3.86278215	4.74707E-10	-3.862782148	-3.862782145	-3.862782148	1.73E-06
F20	-3.22446596	0.060942762	-3.321995172	-3.158561841	-3.197406057	1.73E-06
F21	-5.05519773	7.69325E-12	-5.055197729	-5.055197729	-5.055197729	1.73E-06
F22	-5.26484745	0.970430863	-10.40294057	-5.087671825	-5.087671825	1.73E-06
F23	-5.48900939	1.372035571	-10.53640982	-5.128480787	-5.128480787	1.73E-06

The trail runs of SSA and proposed new technique i.e. SSA-SA which include unimodal, multimodal and fixed-dimensions are shown in Fig. 3 and 4(b). The convergence comparison curves of 23 standard benchmark functions using hybrid SSA-SA, which are divided into unimodal, multimodal and fixed-dimensions are show in Fig.4(a), 5 and 6. It is clear from the results that our algorithm is more accurate that the other already existing algorithms.

ISSN: 0971-1260
Vol-22-Issue-16-August-2019

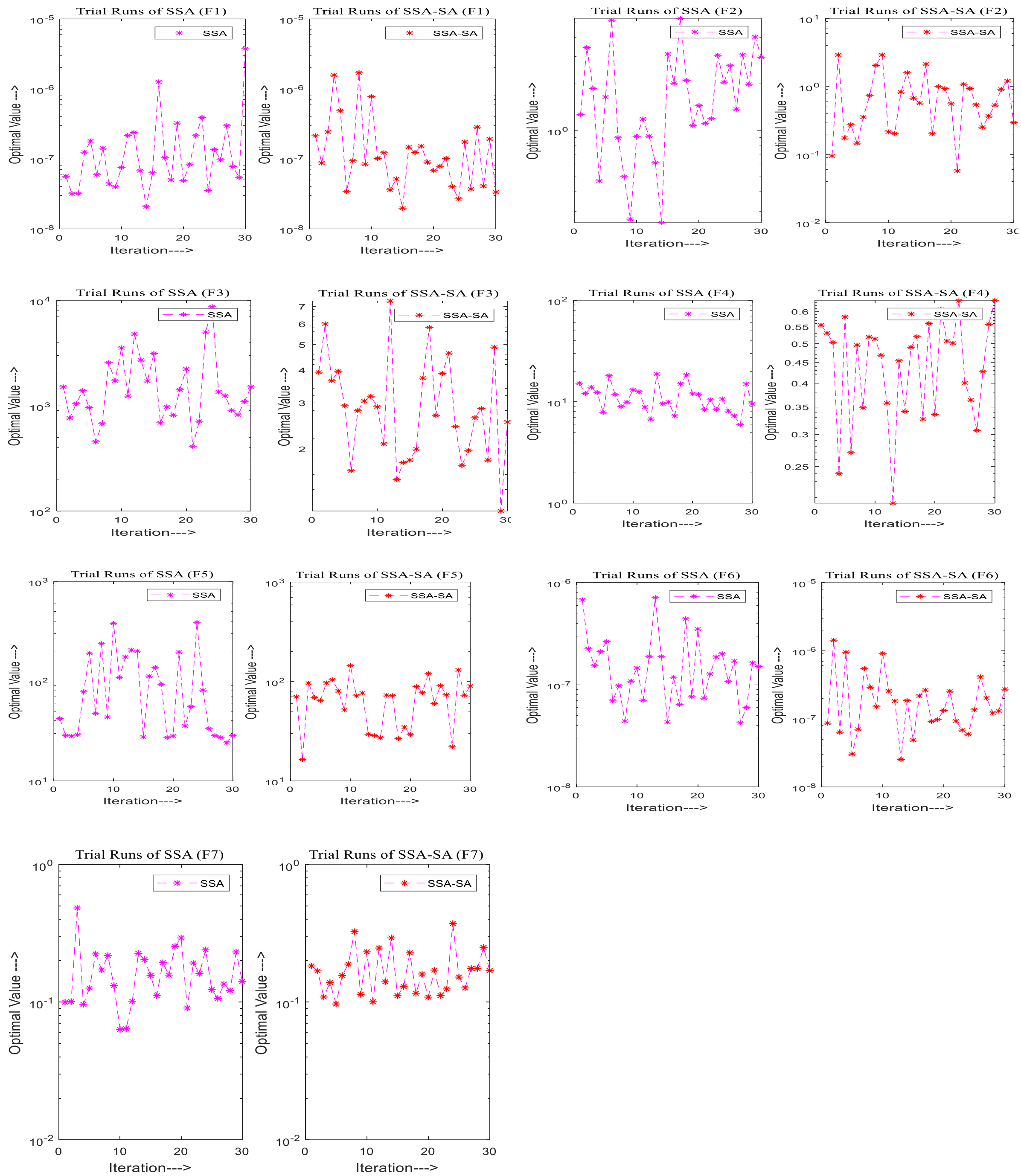
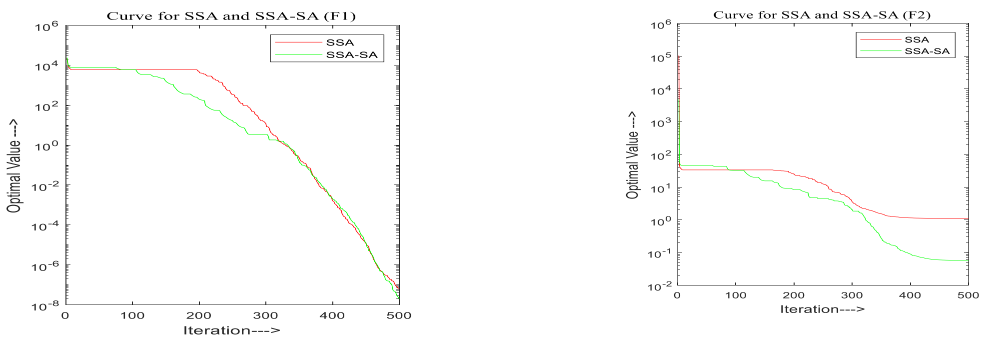


Fig.3: Trial runs of SSA and Hybrid SSA-SA for Unimodal test Benchmark functions



ISSN: 0971-1260
Vol-22-Issue-16-August-2019

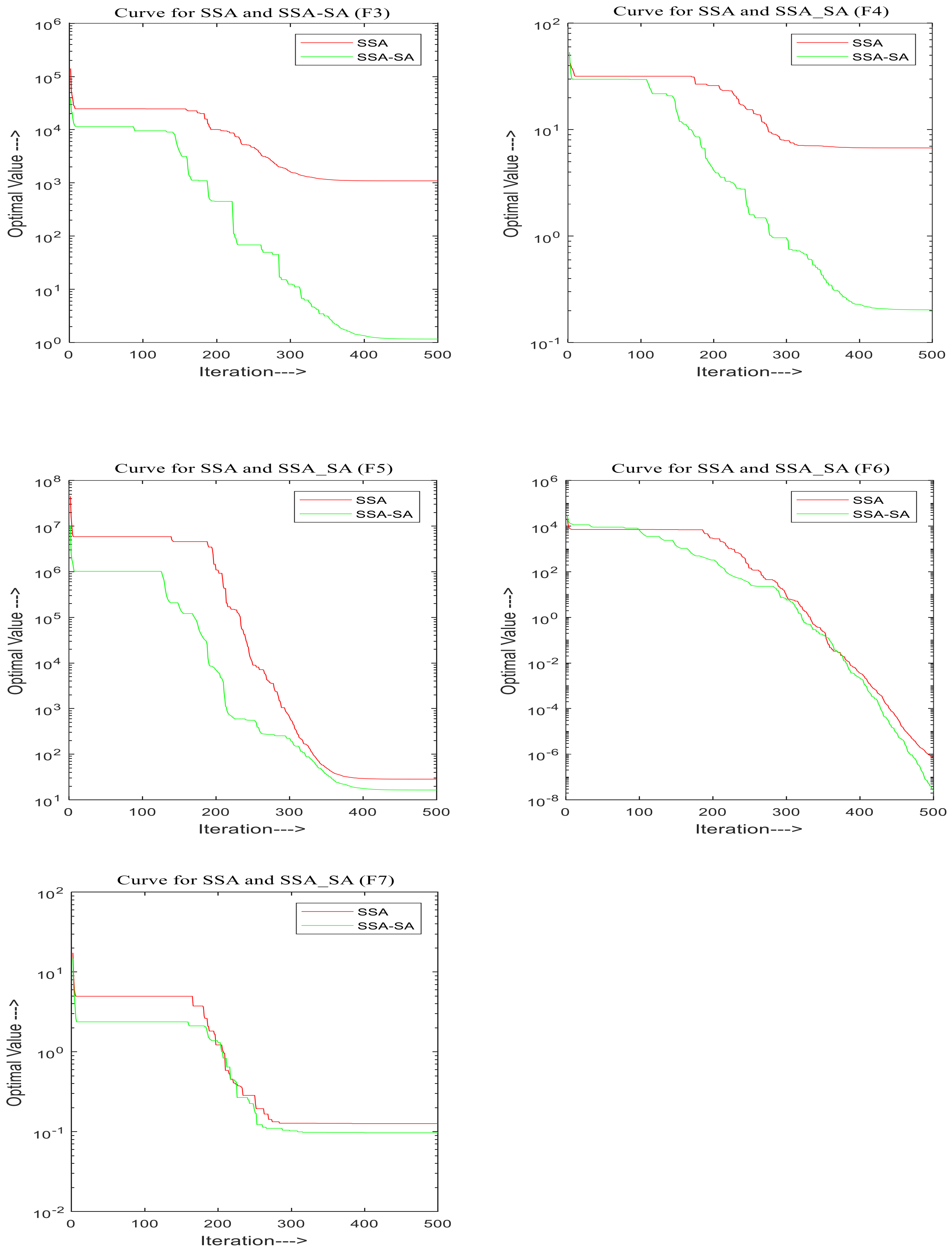


Fig. 4(a): Convergence curves of Hybrid SSA-SA for Unimodal Benchmark functions

ISSN: 0971-1260
Vol-22-Issue-16-August-2019

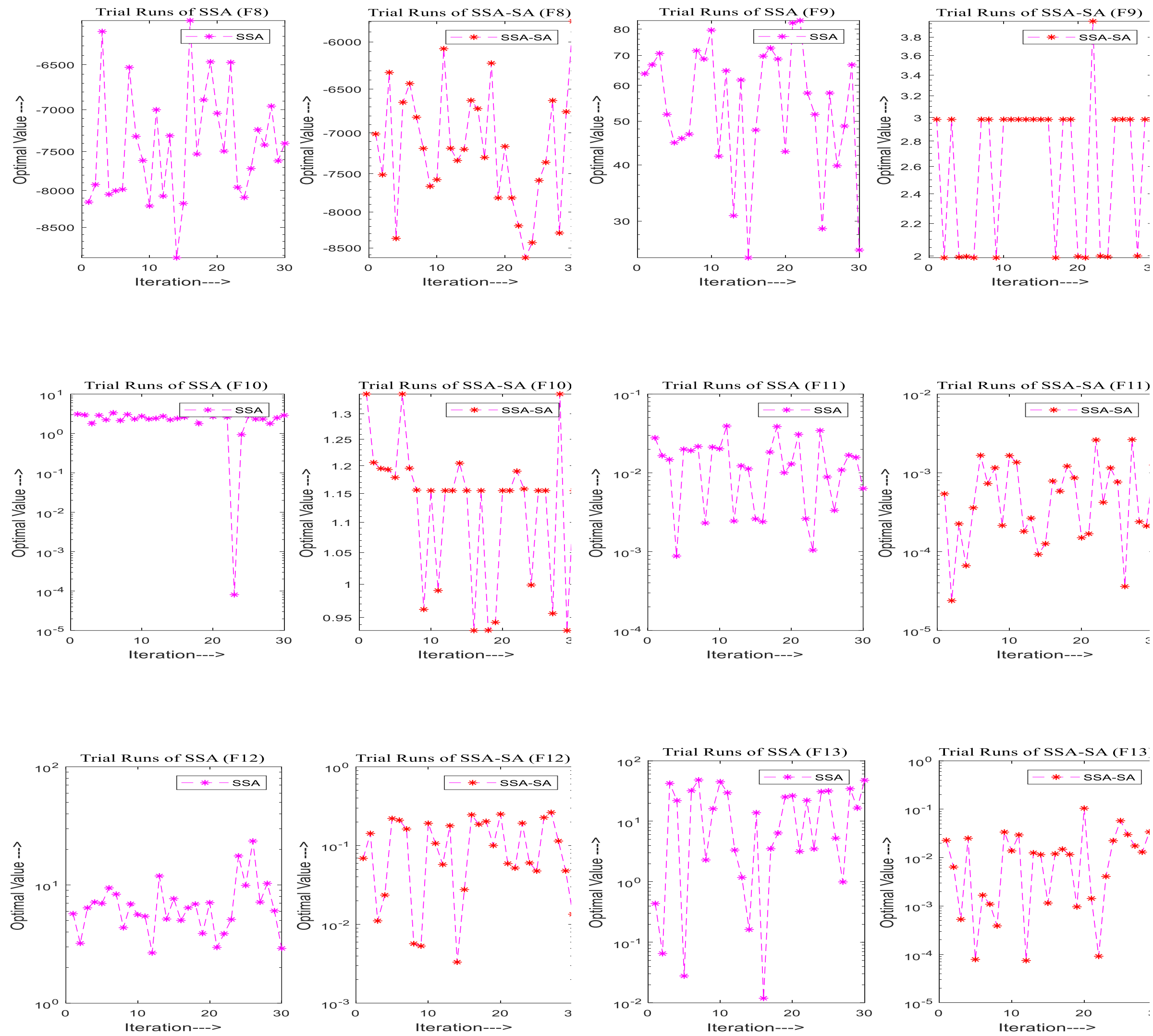
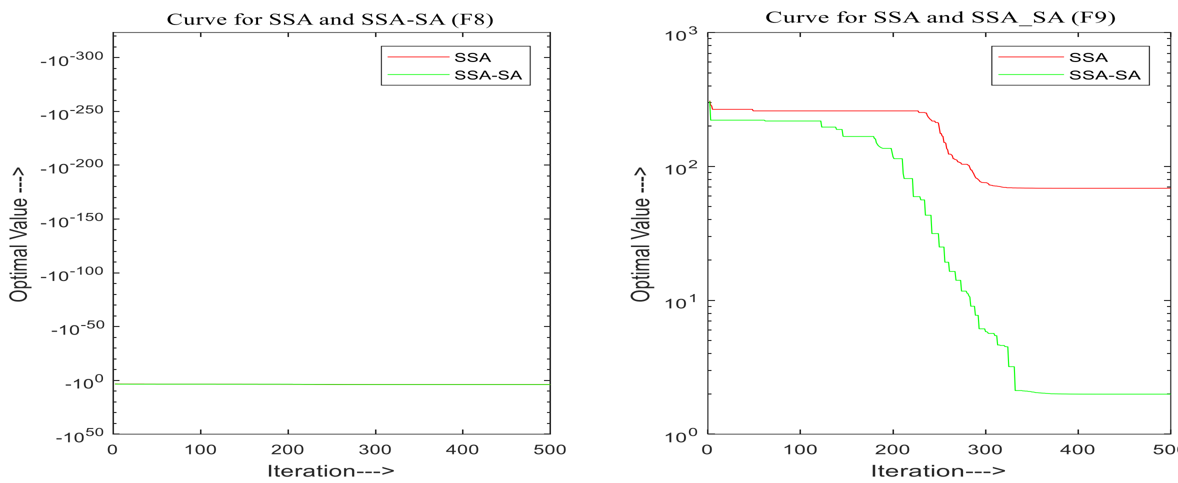


Fig. 4 (b): Trial runs of SSA and Hybrid SSA-SA for Multimodal test Benchmark functions



ISSN: 0971-1260
Vol-22-Issue-16-August-2019

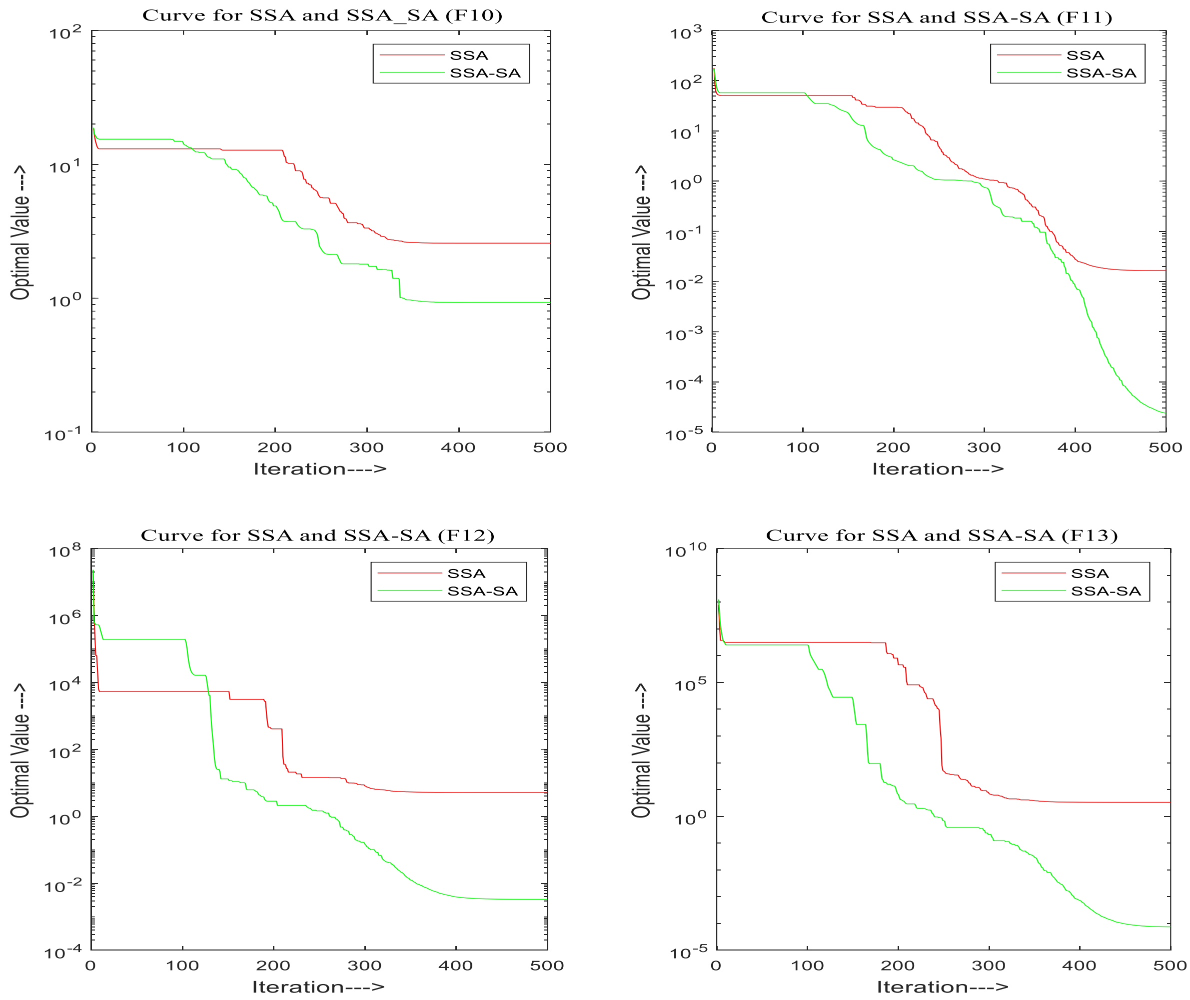
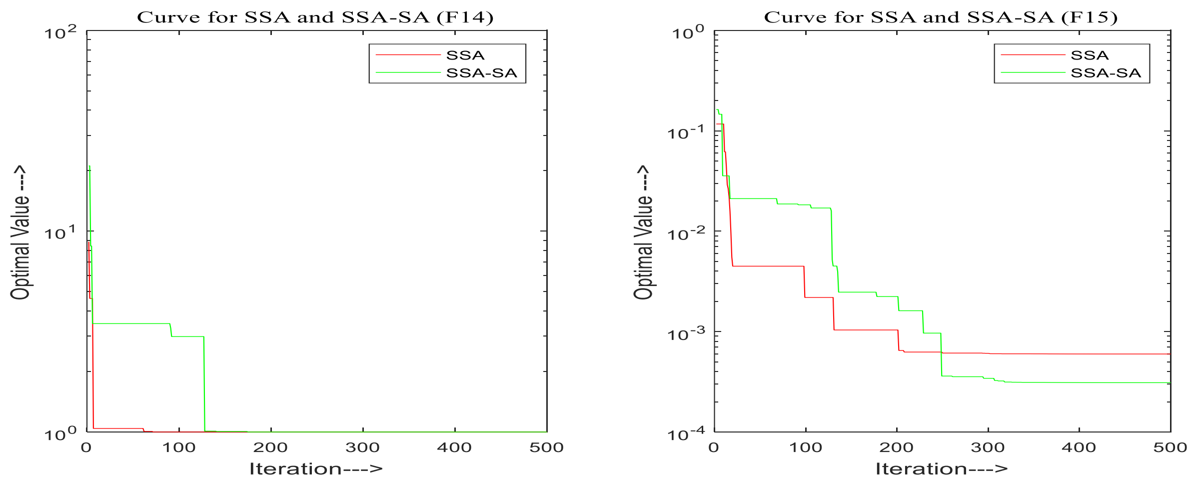
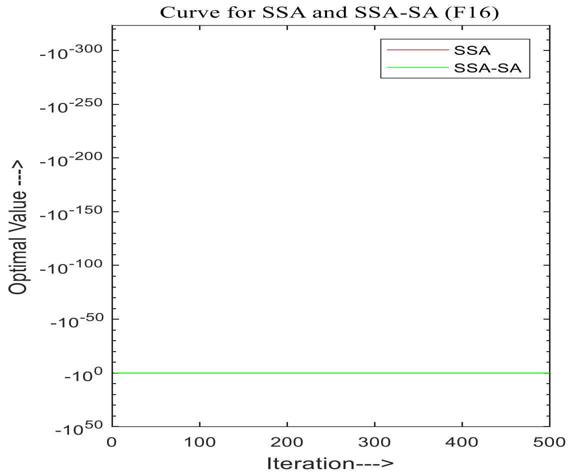
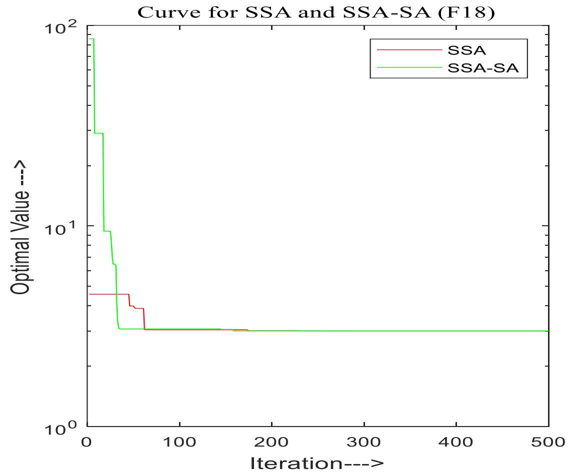


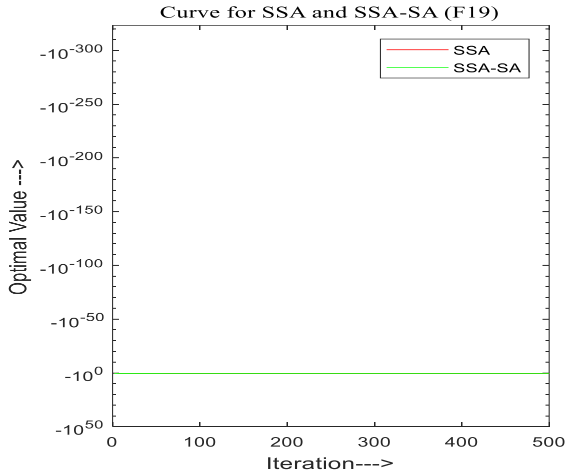
Fig.5: Convergence curves of Hybrid SSA-SA for Multi-modal Benchmark functions

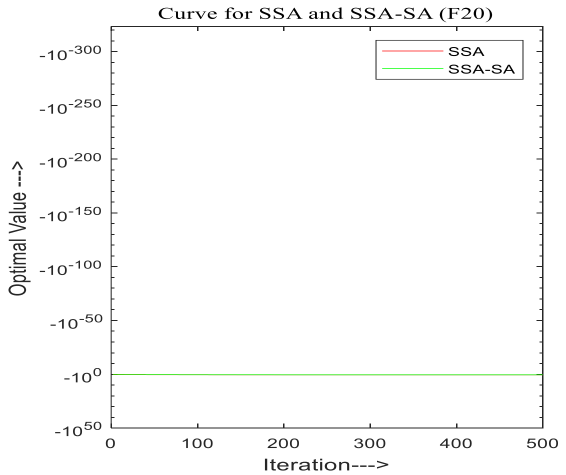


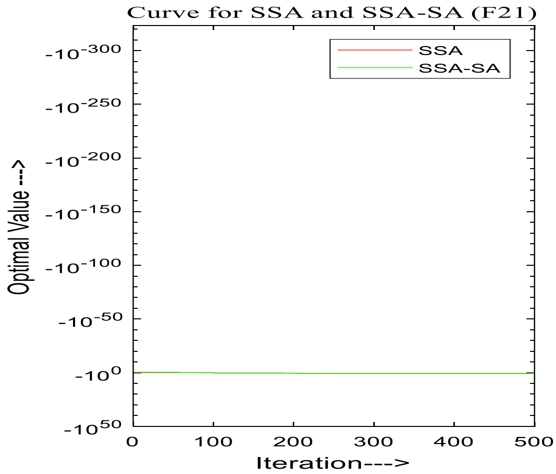
ISSN: 0971-1260
Vol-22-Issue-16-August-2019











ISSN: 0971-1260
Vol-22-Issue-16-August-2019

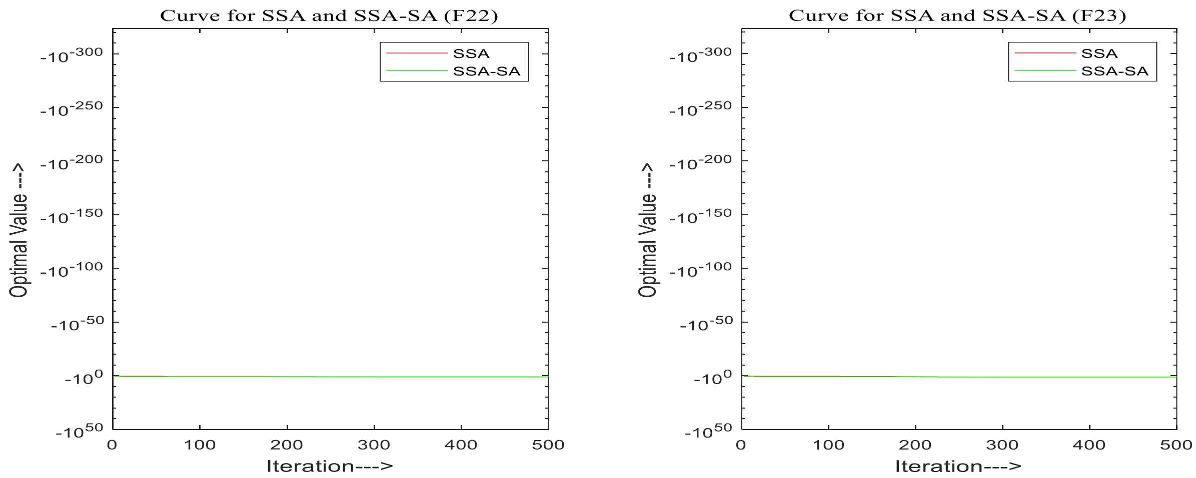


Fig.6: Convergence curves of Hybrid SSA-SA for Fixed-Dimension Benchmark functions

CONCLUSION

In the proposed research author has developed the ameliorated variant of the Salp swarm optimizer and tested the performance of the proposed optimizer for scalar objective numerical optimization problems and experimentally observed that the proposed ameliorated Salp swarm optimizer performs much better than classical Salp Swarm optimizer and such a powerful optimizer can be adopted to solve various engineering optimization problems and other real life problems.

REFERENCES

[1] J. Wang and Y. Gao, "on Modified Lower Upper Bound Estimation in Combination with Multi-Objective Salp Swarm Algorithm for Short-Term Load Forecasting," 2018.

[2] Z. Sun, R. Hu, B. Qian, B. Liu, and G. Che, *Salp Swarm Algorithm Based on Blocks on Critical Path for Reentrant Job Shop Scheduling Problems*, vol. 1. Springer International Publishing, 2018.

[3] I. Aljarah, M. Mafarja, A. A. Heidari, H. Faris, Y. Zhang, and S. Mirjalili, "Ac ce p te d cr t," *Appl. Soft Comput.*, 2018.

[4] R. Abbassi, A. Abbassi, A. Asghar, and S. Mirjalili, "An efficient salp swarm-inspired algorithm for parameters identification of photovoltaic cell models," *Energy Convers. Manag.*, vol. 179, no. August 2018, pp. 362–372, 2019.

[5] A. A. Abusnaina and S. Ahmad, "Training Neural Networks Using Salp Swarm Algorithm for Patter Classification," no. June, 2018.

[6] A. Mathematics, "ijpam.eu," vol. 119, no. 12, pp. 12707–12720, 2018.

[7] H. T. Ibrahim, W. J. Mazher, O. N. Ucan, and O. Bayat, "Feature Selection using Salp Swarm Algorithm for Real Biomedical Datasets Feature Selection using Salp Swarm Algorithm for Real Biomedical Datasets," no. March, 2018.

[8] D. Wang, Y. Zhou, and S. Jiang, *A Simplex Method-Based Salp Swarm Algorithm for Numerical and Engineering Optimization*, vol. 2. Springer International Publishing, 2018.

[9] T. K. Mohapatra and B. K. Sahu, "Design and implementation of SSA based fractional order PID controller for automatic generation control of a multi-area, multi-source interconnected power system," *2018 Technol. Smart-City Energy Secur. Power*, pp. 1–6.

ISSN: 0971-1260
Vol-22-Issue-16-August-2019

[10] Y. V. K. Reddy and M. D. Reddy, "Solving Economic Load Dispatch problem with Multiple Fuels using Teaching Learning based Optimization and Salp Swarm Algorithm," vol. 1, no. May, pp. 5–15, 2018.

[11] A. G. Hussien, A. E. Hassanien, and E. H. Houssein, "Swarming behaviour of salps algorithm for predicting chemical compound activities," no. Icicis, pp. 315–320, 2017.

[12] S. Ekinci, "Parameter Optimization of Power System Stabilizer via Salp Swarm Algorithm," *2018 5th Int. Conf. Electr. Electron. Eng.*, pp. 143–147, 2018.

[13] S. Mahdi, H. Baygi, and A. Karsaz, "A hybrid optimal PID-Fuzzy control design for seismic exited structural system against earthquake : A salp swarm algorithm," pp. 220–225, 2018.

[14] A. A. El-fergany, "Extracting optimal parameters of PEM fuel cells using Salp Swarm Optimizer," *Renew. Energy*, vol. 119, pp. 641–648, 2018.

[15] A. Ibrahim, A. Ahmed, S. Hussein, and A. E. Hassanien, "Fish Image Segmentation Using Salp Swarm Algorithm," vol. 4, pp. 42–51, 2018.

[16] G. I. Sayed, G. Khoriba, and M. H. Haggag, "A novel chaotic salp swarm algorithm for global optimization and feature selection," 2018.

[17] R. M. Rizk-allah, A. E. Hassanien, and M. Elhoseny, "A new binary salp swarm algorithm : development and application for optimization tasks," *Neural Comput. Appl.*, vol. 0123456789, 2018.

[18] M. Khamees and A. Albakry, *Multi-objective Feature Selection : Hybrid of Salp Swarm and Simulated Annealing Approach*, vol. 1. Springer International Publishing.

[19] R. Ali, I. Ahmed, D. Oliva, M. Abd, and E. Songfeng, "Improved salp swarm algorithm based on particle swarm optimization for feature selection," *J. Ambient Intell. Humaniz. Comput.*, vol. 0, no. 0, p. 0, 2018.

[20] A. M. Al-zoubi, S. Mirjalili, and H. Fujita, "PT US CR," *Knowledge-Based Syst.*, 2018.