# Enhancing Salp Swarm Algorithm Based on Elite Opposition based Learning and Cauchy Mutation Strategies

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## Abstract.

The significance of machine learning models for real life scenarios to design prediction model is outstanding. However, the nature of datasets available especially in biomedical domain calls for optimization strategies for effective and reliable solution. In view of this development, so many optimization algorithms are promising but not without limitations. For instance, the salp swarm algorithm (SSA), which is a higher level procedure algorithm, has demonstrated a lot of capacity to solve optimization challenges for prediction models. However, to solve an intricate optimization issues, the SSA is deficient with the dawdling convergence pace and a tendency of diminishing into sub-optimal results. Therefore, this research aims to enhance the algorithm using Cauchy mutation and elite opposition based learning strategies. The objective is achieved by fusing these strategies into the existing algorithm; thereby resulting to an enhanced SSA optimization algorithm christened *EOnCaSSA* in this paper. The search agents of 50, 100, and 150 were chosen for each bench functions and 300, 600 and 900 numbers of iterations were also chosen for each function. It is noteworthy that all the seven benchmark functions for unimodal functions have an optimum value of zero. The four evaluation metrics, which include the best, worst, average and standard deviation to determine and compare the performance of *EOnCaSSA* presents significant improvement over the tradition SSA. This implies that the enhanced algorithm can be employed to solve both simple and difficult optimization issues as it passes all the benchmark functions tests.

**Keywords:** Cauchy mutation strategy, elite opposition based learning strategy, EOnCaSSA, salp swarm algorithm, unimodal functions

## 1. Introduction

Presently, computer algorithmic strategies that learn patterns in data for predictive, diagnostic or analytics models have been constantly exploited by researchers across different real life scenarios; for example, in biomedical, bioinformatics and agriculture. Machine learning algorithms are such significant and promising examples that have been increasingly exploited to this effect. Consequently, an indispensable rate of success have been obtained but not without limitations (Malik, 2020; Zhang & Ling, 2018) While on one hand, the availability of raw datasets to be trained poses a serious challenge especially the biomedical data, on the other hand, the nature of the datasets in most cases naturally initiate some data engineering process (Saez, et al., 2021). This implies that for the learning algorithms to produce optimal results, some level of features engineering processes have to be initiated. Therefore, an effective and efficient machine learning based model is a function of how effective and reliable is the optimization strategies adopted or adapted (Faramarzi, et al., 2020). This fact forms the motivation of this research. There are several numbers of both existing machine learning and optimization algorithms.

Machine Learning (ML) algorithms as earlier noted have made an important contribution to different fields of research, such as disease prediction models. The algorithms predict disease based on the inputs or symptoms that are being fed into the models (Muthukumarasamy et al., 2021). For example, in order to measure the performance and the outcome of the Ebola disease fatality ratio, Forna *et al* (2021) focused on the scale and type of data omission by comparing different ML methods for estimating case fatality ratios. There are different types of machine learning algorithms which are; supervised learning, unsupervised learning, semi-supervised learning and reinforcement learning (Adamu & Awan, 2019). Naive Bayes, Linear Regression (LR), Support Vector Machine (SVM), Random Forest (RF), K-Nearest Neighbor (KNN) and Artificial Neural Network (ANN) are just few classification algorithms under supervised learning (Ray, 2019; Sharma & Mangat, 2016; Mallela et al., (2021). For instance the work of Soni *et al.* (2021) proposed an artificial intelligence approach for forecasting Ebola disease, so as to enhance disease detection via efficient data mining algorithms. However, the researchers admitted that the collection of more data on the disease is encouraged to further facilitate better results and improved accuracy. Consequently, owing to the natures, sizes, and formats of a given dataset, a better accuracy is always difficult to obtain; thus the need for features engineering processes.

Feature engineering processes entails data preprocessing, scaling, balancing and feature selection. In order to harp for a better model results, these processes are highly essential and inevitable. For instance, there are existing techniques or optimization algorithms that can be employed for feature selection. Salp swarm algorithm, particle swarm algorithm (PSO), bat algorithm, cuckoo search algorithm, grew wolf among others typical examples of algorithms used to optimally select attributes of a given dataset (Abualigah *et al.,* 2020; Ben-Chaabane et al., 2021; Hegazy *et al.,* 2020 more citations for others). Among all these algorithms, SSA, new efficacious meta-heuristic optimization algorithms is indeed promising for a robust predictive modeling especially in areas of biomedical and bioinformatics. It is used to select the best features in order to minimize redundancy of the given features, which in turn would reduce the complexity of the proposed network (Ben-Chaabane et al., 2021). However, SSA is limited by its susceptibility to fall into local optimal and slow convergence rate (Fan et al., 2020; there are other similar 2021 and even 2022 citations. put one or two more).

Therefore, considering these limitations, this research aims to enhance the SSA using the Cauchy Mutation and Elite Opposition Based Learning (EOBL) as framework to predict EBOV.

The remaining sections of this paper are organized as follows: section 2 accounts for the related works while, the proposed algorithmic methodology is presented by section 3. Section 4 acounts for the discussion of the framework based on the methodology; and section 5 presents the conclusion of the paper.

## 2. Related Work

This section presents the related literature to the main subject matter, which is the salp swarm algorithm. Nonetheless, other related algorithms for optimal selection of features for a given dataset are equally considered in this section. As earlier stated, a robust and reliable predictive model for any real life domain is always a function of how effective is the feature engineering mechanisms deployed. In recent times Salp Swarm algorithm has shown great value in feature selection task (Hegazy *et al.*, 2020). In their literature, the researchers aim to review the traditional SSA and ISSA (Improved SSA) for better accuracy, reliability and convergence speed. Consequently, the improved SSA performed better than the other optimizer in terms of speed and accuracy. They therefore recommended that more improvement can be done to bring much better accuracy.

Wu et al. (2019) conducted a research which aims to make equal the local and global exploration and to prevent early changes in stagnation and convergence. The result shows high level of performance and the ability to withstand local optimum when evaluated with the SSA algorithm. It is recommended that it should be further studied and practically carried out in solving optimization problem in engineering. Similarly, Abualigah *et al*. (2020) carried out an in depth study of SSA and how the scholars are motivated in several applications to implement it in computer science domain. The study classified the SSA into theoretical and application aspects. The outcome shows that when the algorithm is stuck in local optimal, mechanism should be engineered to reduce the exploitations process and convergence rate. Some important tools like the adaptive mechanisms can be used to minimize the convergence speed in relative to number of enhancement in iterating the best solution. SSA can be applied across different spheres of real life domains and researches.

Furthermore, Nautiyal et al. (2021) in their attempt to enable closed and informed search ability using Gaussian and Cauchy mutations brought large steps to improve the global search ability. The results show that by checking several mutations and selecting the best SSA, at least 23 benches are used to analyze the problems with dimension of 30 & 100. The improved SSA shows a better result which can be utilized to check for optimal machine learning models structured and weights. Also, the research of Ben-Chaabane et al. (2021) aims to enhance the performance of blind digital modulation detection approach in the aspect of multiple-antenna systems of the algorithm using the Feature weight and ML model. In comparing to other algorithms, the result shows that the rate of convergence of the proposed ISSA is high for a good number of the test functions based on speed and precision. For features selection, it is advised that more preprocessing techniques in ML ISSA can be used.

It is evident that several attempts are constantly in place to improve the SSA by equally considering other similar algorithms. In view of this development, the research of Gurses et al. (2021) exploited several strategies of these algorithms that leverage on populations; they are but not limited to hybrid-slime mold algorithm and simulated annealing algorithm. By comparison of the results, it was reported in the literature that the probabilistic approaches outperforms the regular optimization algorithms used. In furtherance to improve the SSA, Tubishat et al. (2020) used opposition based learning development with local search algorithm of SSA to enhance its exploitation. In order to find solution to selection challenges and choose the overall features compactments of wrapper mode. It was deduced that on the overall 18 dataset used, the ISSA algorithm out performs the traditional SSA algorithm. Also, considering to choose few numbers of features, the level of originality shown by ISSA is premised on using LSA and OBL approach. However, the process of choosing additional features more than the other optimization algorithms is a major shortcoming in the proposed ISSA. The researchers therefore suggested that further check using real world challenges and dataset is highly recommended with classifiers.

More so, Soni et al. (2021) claimed to proposed a more robust hybrid predictive model for ebola virus in order to enhance the disease detection and increase the result accuracy of the system. Various accuracies were obtained from the various classifiers include the hybrid techniques after training the given dataset. The researchers therefore submitted that for a more improved results to be obtained, more dataset is consequently required; also encouraged interested researchers to hybridize the techniques used in their work.

In an effort to improve the SSA, the research of Fan et al., (2020) attempted to ameliorate the challenge of real time activity and precision of the traditional SSA, a new hybrid algorithm known as perturbation weight SSA was introduced. From the results it can be deduced that the hybrid algorithm is faster than the regular SSA. Similarly, Ibrahim et al., (2019) proposed the hybridization of Salp Swarm algorithm and Particle Swarm Optimization (SSAPSO) so as to verify which of the best features can be used in different UCI datasets. Based on the accuracy measures, the ratio of the chosen features to the processor's time and other metrics used in checking the fitness performance of SSAPSO outperforms several other algorithms. It is recommended that the algorithm is applied in several other fields like signal processing and image processing.

## 3. The Proposed Methodology of the enhancing SSA

This research proposes the hybrid adoption of both elite opposition based learning and Cauchy mutation strategies as method to enhance the tradition SSA. The Elite opposition-based learning and Cauchy mutation algorithms are employed to produce arbitrary preliminary results for every iteration to enhance the multiplicity during the discovery process; and enhance the global search ability of the traditional SSA.

As stated earlier, Salp Swarm Algorithm is a recent higher level heuristic algorithm in which the development is inspired by the attributes of swarming salps. It's commonly described by a search method, which is easy and posses some sort of handling parameters. Conversely, to solve difficult optimization challenges, the SSA may be deficient with dawdling convergence pace and a tendency of resulting into sub-optimal outputs. To solve these problems, the Cauchy mutation would be applied to produce huge numbers of mutation to boost the global search potential. On the other hand, the elite opposition-based learning would be employed to create arbitrary preliminary solutions; each iteration is expected to increase the diversity during the process to discover optimal results.

The Salp chains are mathematically modelled by segmenting the Salp population as leader and followers. The leader guides the swarm during foraging while the follower follows (Mirjalili, *et al.,* 2017). In comparison to other swarm-based mechanisms, the location of Salp is described in an n-dimensional search space and n is defined as the given number of variables for the problem to consider.

The location of the leader is updated using the equation 1, which is defined as follows (Mirjalili, *et al.,* 2017):

$$x_j^1 = \begin{cases} F_j + c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 \geq 0 \\ F_j - c_1\left((ub_j - lb_j)c_2 + lb_j\right) & c_3 < 0 \end{cases} \tag{1}$$

where,
$F_j$ is the spot of the source of food in the $jth$ dimension,
$ub_j$ shows the major hop (upper bound) of $jth$ dimension
$lb_j$ presents the minor hop (lower bound) of $jth$ dimension
$c_1$, $c_2$ and $c_3$ are arbitrary values between 0 and 1.

The coefficient $c_1$as defined by equation 2, is the most significant factor in SSA in that it stabilizes the process of search space (Mirjalili, *et al.,* 2017).

$$c_1 = 2e^{-\left(\frac{4l}{L}\right)^2} \tag{2}$$

where,
$l$ stands for present iteration
$L$ denotes numbers of highest iterations

The position of the followers is equally revised using eq. 3, which is defined as (Mirjalili, *et al.,* 2017):

$$x_j^i = \frac{1}{2}(x_j^i + x_j^{i-1}) \tag{3}$$

Therefore, based on these strategies, Algorithm 1 presents the enhancement based on the existing algorithm.

***Algorithm 1: An Enhanced SSA***

***Parameters:*** *The initial population of the Salp ($x_i$); food source (fs); salp population's upper and lower bound (ub, lb) the elite opposition members ($s_s$); Elite Opposition Based Learning function $E_{fxn}(e_i)$; Cauchy_Mutation (CauM) function $C_{fxn}$ ($c_i$); random draw function ($Rand_{fxn}$)*

***Input:*** $x_i$

***Output***: *fitness function ($F_f$)*

**Procedure:**

1. Initialize $x_i$ (i = 1, 2, ..., n) considering ub and lb; $s_s$
2. (**if** old fs > new fs; update new fs else keep old fs )
3.     Compute $F_f$ of each $x_i$
4.     $F_f$ = the best search agent
5.     Update $c_1$ by Eq. (2)
6.         **forEach** $x_i$
7.             **if** (i==1) **then**
8.                 Update the position of the leading salp by Eq. (1)
9.               **else**
10.                 Update the position of the follower salp by Eq. (3)
11.             **end**
12.             $Rand_{fxn}$ ($x_i$) // the starting point of enhancement
13.             **if** $F_f$ ($E_{fxn}$ ($e_i$)) $\leq$ $F_f$ ($x_i$) then
14.               EOBL($e_i$) //replace the salp with elite member
15.             **end**
16.             **if** $F_f$ $C_{fxn}$ ($c_i$) < $F_f$ ($x_i$) then
17.               CauM ($c_i$) // replace the Salp with the mutant agent
18.             **end**
19.         **end**
20.         update $x_i$ // amend the salps based on the bounds
21. **end**
22. return F

From the algorithm, parameters which include variables and functions such as salp population, random draw and Cauchy mutation functions are defined.

Steps 1 to 2 initialize the salp population by putting into consideration the major and minor hops so as to identify the food source for the salp. Elite members are equally initialized. If the condition is satisfied that is, identify the newly found food source. If the old food source is better than the new food source, update the new food source else keep the old food source. Then the algorithm proceed to compute the fitness function of the entire search space agents (the salp, elite members and the mutant agent) as indicate by steps 3 and 4. Consequently, the coefficient $c_i$, which is the most significant factor of SSA is progressively updated as presented by Eq. 2.

For each salp, from steps 6 to 11 as long as the salp position is at index 1, the algorithm keeps updating the location of the leader using eq. 1; else update the location of the follower using Eq. 3.

The main ingredients of the enhancement starts from steps 12 to 17 by initializing the salp agents using the user defined random draw function $Rand_{fxn}$ ($x_i$). If the fitness function of the elite member is better than the fitness function of the ordinal Sap, then replace the Salp with the elite member. Similarly, if the fitness function of the mutant agent is better than the fitness function of the ordinal Salp then replace the Salp with the mutant agent. Finally, the salp agent is mended based on the upper and lower bounds of variable; and return the best salp agent via the fitness function as indicated by step 22.

More so, for simple illustration and understanding, Figure 1 presents the flowchart of the proposed algorithm's enhancement. The initial population of the Salp and the elite opposition members are initialized, and food source is equally identified. Then, the mutant agents are also initialized after generated by Cauchy method.

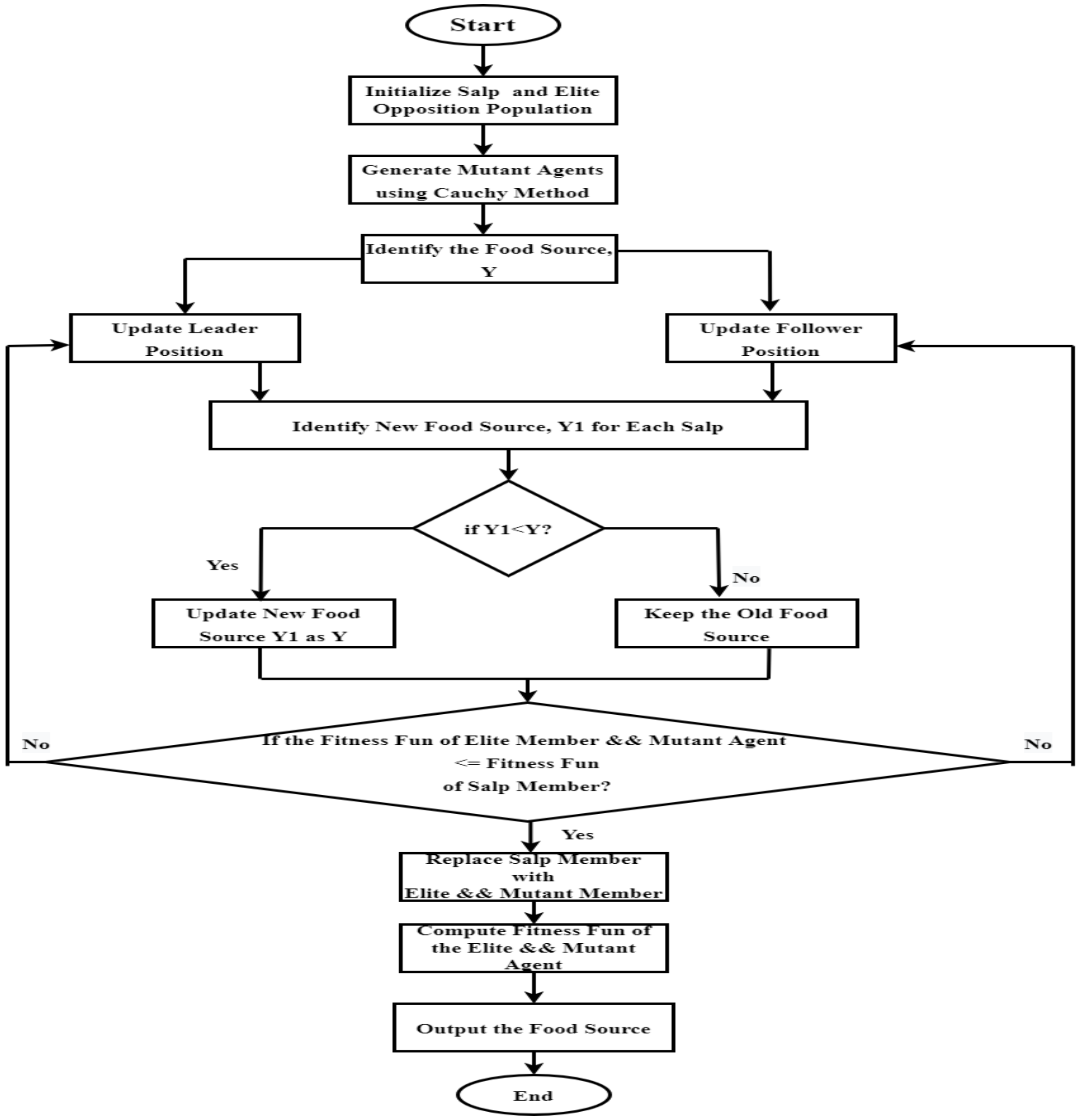


*Figure 1: Flowchart of the Improved Salp Swarm Optimization Algorithm*

The salp populations are categorized into the leader and followers. The leader and the follower's positions are initialized and then updated to their new positions. A new food source named *Y1* is found for the updated leader and followers. Furthermore, fitness functions are computed, updated for the new food source and compared with the fitness function of the old food source.

In the same vain, the fitness function of the elite members and the mutant agents are also computed and compared with the fitness function of the optimal food source of the salp that are not elite or mutant agents. If the elite members and mutant agents are better, the salp will be replaced with the elite member and mutant agent. This would enhance exploration and exploitation process of the SSA. Then, a new fitness function is computed, and the best search agent finds an optimal new food source.

## 4. Discussion

This section discusses the performances of Salp swarm algorithm, its improved version herein dubbed as Elite Opposition, and Cauchy based SSA (EOnCaSSA). More so, the results of the benchmark functions for unimodal functions are also discussed.

The performance of the enhanced SSA (EOnCaSSA) is proposed for fourteen benchmark functions however, only seven is able to be presented in this paper as the work is still in progress. Standard performance metrics such as the best, worst, standard deviation, and average were used to effectively compute the performance of the enhanced algorithm. The search agents of 50, 100, and 150 were chosen for each bench functions and 300, 600 and 900 numbers of iterations were also chosen for each function. It is important to mention that all the seven benchmark functions have an optimum value of zero. Therefore, performances are measured based on the closeness of the obtained values to zero.
It is observed from Table 2 that as the numbers of search agents and iterations progresses or increases, the performances of the algorithms increase. This implies that as the numbers of search agents' increases, more random, initial solutions are generated resulting from the application of the elite opposition-based algorithm to SSA. Furthermore, the application of the Cauchy mutation technique to the traditional SSA increases the searching and operation's ability of the existing SSA. Cauchy mutation generates a good number of mutations to optimize the global search strength of the existing SSA. Table 2 shows the results of the improved algorithm of unimodal test functions. These results were computed after thirty individual runs. All the performance metrics, including the worst, best, average, and standard deviation of EOnCaSSA, show significant improvement over the standard SSA. The worst, best, standard deviation, and average of the EOnCaSSA for all the benchmark functions exhibit lower values as compared to SSA. This implies that the improved algorithm can be employed to solve simple and difficult optimization issues as it passes all the benchmark functions tests.

*Table 1: Results of the Algorithm on Unimodal Test Functions*

| | | | Original SSA | | | | Modified SSA with Cauchy and EOBL | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Function | Search-Agent | Iteration | Best | Worst | Average | STD | Best | Worst | Average | STD |
| | 50 | 300 | 1.05E-02 | -0.03679 | 0.018979 | -0.00084 | 6.34E-130 | -1.75E-66 | -9.18E-67 | 5.06E-67 |
| F1 | 100 | 600 | 9.38E-10 | -1.05E-05 | 3.99E-07 | 5.67E-06 | 1.57E-244 | 1.87E-125 | 9.13E-125 | 4.34E-125 |
| | 150 | 900 | 2.02E-10 | -4.00E-06 | -4.92E-07 | 2.59E-06 | 0 | -2.11E-166 | -1.09E-166 | 0 |
| | 50 | 300 | 0.040627 | -0.04063 | -0.0040624 | 0.012847 | 1.50E-65 | -3.65E-67 | -1.69E-67 | 9.52E-68 |
| F2 | 100 | 600 | 2.48E-06 | -1.31E-06 | -6.77E-08 | 4.67E-07 | 5.90E-127 | 1.40E-129 | 4.20E-129 | 1.75E-129 |
| | 150 | 900 | 6.51E-07 | -9.87E-08 | 2.53E-08 | 1.18E-07 | 9.26E-183 | -1.00E-184 | -7.01E-185 | 0.00E+00 |
| | 50 | 300 | 1.76E-06 | -0.00109 | 2.97E-05 | 0.000847 | 2.87E-135 | 1.65E-71 | 1.21E-70 | 7.54E-71 |
| F3 | 100 | 600 | 2.38E-11 | -2.87E-06 | 4.41E-08 | 2.10E-06 | 5.98E-240 | 9.46E-124 | 5.28E-122 | 4.51E-122 |
| | 150 | 900 | 1.17E-11 | -1.70E-06 | -5.49E-08 | 1.30E-06 | 0.00E+00 | 3.23E-167 | 8.22E-166 | 0.00E+00 |
| | 50 | 300 | 8.36E-06 | -8.36E-06 | 2.50E-06 | 5.44E-06 | 1.44E-68 | 1.41E-70 | 1.88E-69 | 1.25E-69 |
| F4 | 100 | 600 | 3.23E-06 | -3.23E-06 | 1.73E-07 | 2.21E-06 | 9.49E-122 | 1.96E-125 | 2.71E-124 | 1.95E-124 |
| | 150 | 900 | 8.63E-07 | -8.63E-07 | 5.74E-08 | 4.81E-07 | 1.00E-179 | 1.84E-181 | 9.25E-181 | 0.00E+00 |
| | 50 | 300 | 125.0459 | -0.92443 | 0.73592 | 1.4781 | 9.00E+00 | 1.06E-42 | 1.21E-41 | 6.02E-42 |
| F5 | 100 | 600 | 7.0475 | 0.000527 | 0.13097 | 0.21975 | 9.00E+00 | 2.11E-92 | 9.36E-91 | 6.66E-91 |
| | 150 | 900 | 74.9216 | -0.54364 | 0.83469 | 1.0029 | 9.00E+00 | 3.39E-134 | 7.78E-133 | 7.52E-133 |
| | 50 | 300 | 5.68E-11 | -0.5 | -0.5 | 2.40E-06 | 2.50E+00 | -7.14E-46 | -3.49E-46 | 2.42E-46 |
| F6 | 100 | 600 | 8.58E-12 | -0.5 | -0.5 | 9.73E-07 | 2.50E+00 | 7.77E-94 | 2.48E-93 | 1.17E-93 |
| | 150 | 900 | 6.51E-12 | -0.5 | -0.5 | 6.68E-07 | 2.50E+00 | -2.21E-113 | -9.17E-114 | 6.15E-114 |
| | 50 | 300 | 0.0055919 | -0.12042 | -0.010465 | 0.08655 | 0.0006431 | -6.88E-60 | -3.88E-60 | 2.61E-60 |
| F7 | 100 | 600 | 0.0033586 | -0.12238 | 0.014447 | 0.082234 | 0.0025307 | -2.48E-104 | -1.51E-104 | 8.56E-105 |
| | 150 | 900 | 0.0027178 | -0.10754 | -0.0091155 | 0.083963 | 0.0015741 | 1.53E-141 | 1.45E-140 | 8.62E-141 |

However, the experiment is still work in progress as more cases beyond seven for multimodal test functions are currently considered. Figures 2 and 3 represent the parameter spaces and the convergence curves for functions 2 and 5 respectively as samples for unimodal test functions.

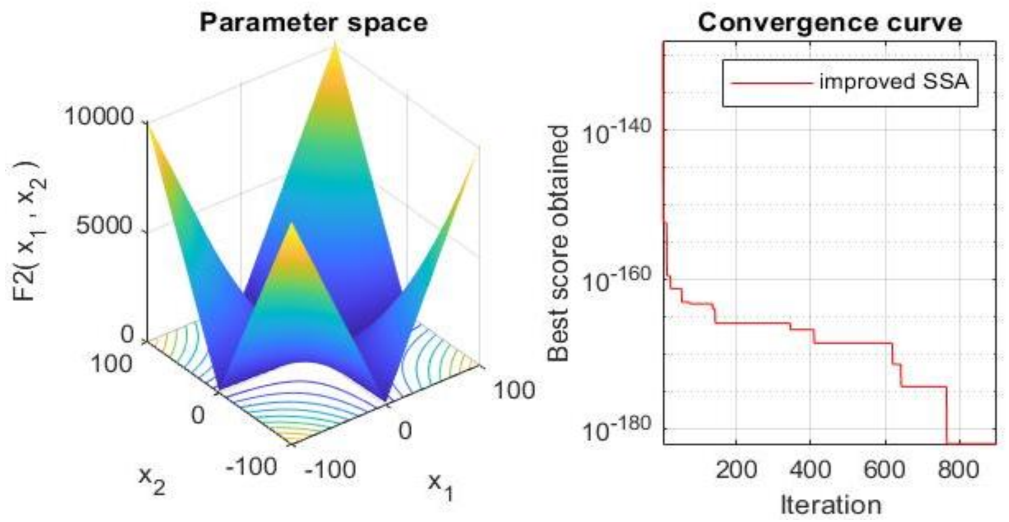


*Figure 2: Convergence Curve and Parameter space plot of F2 at 900 iterations*

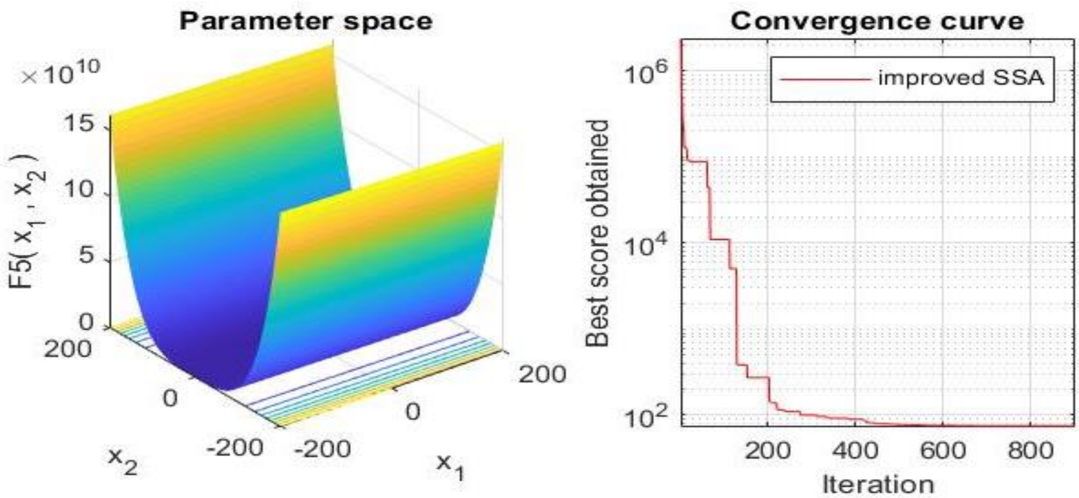


*Figure 3: Convergence Curve and Parameter space plot of F5 at 900 iterations*

## 5. Conclusion

SSA, a higher level heuristic algorithm is indeed promising in solving optimization problems for prediction or classification models. However, to solve difficult optimization challenges, the SSA lacks the capacity of fast convergence time and equally posses the tendency of declining into sub-optimal outputs. To solve the problems, this research aims to improve the algorithm using Cauchy mutation and elite opposition based learning strategies. This was achieved by embedding these strategies into the existing algorithm; consequently, yielding out an extended SSA optimization algorithm. The Cauchy mutation was used to create large numbers of mutations to amplify the global search strength, while elite opposition-based learning was applied to generate random initial solutions. Thus, the generated solutions for iteration improve the diversity during the exploration process. Search agents of 50, 100, and 150 were chosen for each bench functions and 300, 600 and 900 numbers of iterations were also chosen for each function. In the end, the results of the enhanced algorithm (EOnCaSSA) outperforms the traditional SSA across the four standard metrics for evaluation, which include best, worst, standard deviation, and average. This is because the seven benchmark functions for unimodal test functions have an optimum value of zero. It has established that performances are measured based on the closeness of the obtained values to zero.

As earlier stated, the experiment for the proposed EOnCaSSA is still in progress because more test functions of 8 to 14 would be carried out to create room for multimodal test functions. In that way, the robustness of EOnCaSSA would have been ascertained and affirmed. Similarly, in the nearest future the researchers hope to further use the algorithm to optimise a given set of Ebola virus's dataset for a more accurate prediction model.

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