Optimize One Max Problem by PSO and CSA

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Abstract. The optimal solution in mathematical concepts, computer science, and finance is to find the best solution out of all possible solutions. The type of optimization problem is determined by whether the variables are continuous or discrete. The One Max problem is proposed to be improved in this paper, and because the concept of optimization is moving towards the idea of the optimal method. Based on the time dimension difference, the CSA and PSO algorithms have been proposed as more effective in optimization. Since the PSO algorithm is the oldest in the optimization field and CSA is modern. Nevertheless, despite being newly configured, the CSA algorithm has proven its effectiveness. Both algorithms must use values that are generated at random. Each cycle has a predetermined range of values for 100, 500, and 1000 cycles, and the values are calculated using the Sigmoid function. They go through 30 cycles with a number of function evaluations of 100,000. The Sigmoid function, which raises values above 0.5 to 1, is used to display the results for each range of 30 values. The results showed that the CSA algorithm outperformed PSO by 20% in terms of improvement values for each cycle (100, 500, and 1000). The CSA algorithm was selected as the preferred method for improving the One Max problem because of its efficiency and speed. Moreover, it has less dispersion than the PSO algorithm.

Keywords: Optimizations, One Max Problem, Sigmoid, CSA, PSO.

1 Introduction

Marketing investigators are interested in achieving peak performance, which it necessarily involves personal well-being, self-determination, and efficiency. The working principle for optimum results is challenging, resulting in an out-of-the-ordinary state of effectiveness. The optimization problem in mathematics, computer science, and economics is to discover the optimal answer from all potential solutions. Optimization problems are classified into two types based on whether the variables are continuous or discrete.

This study covers One Max Problem Optimization that maximizes the number of ones in a feasible solution, the problem itself is quite simple and widely used in the evolutionary computational community. The instructions lead to solving the One Max Problem using Particle Swarm Optimization (PSO) and Crow Search Algorithm (CSA).

Each program runs 30 times with the number of function evaluations = 100,000. Take Upper Bound= 1 and Lower Bound = -1. The problem is solved for three different dimensions which are D = 100, D = 500, D= 1000. The two algorithms were compared using the following metrics:

Best, Mean, Median, Worst, and Standard Deviation. Also, make statistical analysis using Wilcoxon etc.

Particle Swarm Optimization and Crow Search Algorithm were presented for solving continuous optimization problems. On the other hand, the One Max Problem is a binary optimization problem so the solution space must be adapted from the continuous domain to the binary domain. It can be used Sigmoid Function for this purpose.

Simple Steps in the Algorithms:

Firstly, generate a random number between the lower bound and upper bound. Suppose it is -0.3232 Calculate $Sigmoid$ (-0.3232) = 0.419. So, if it is less than 0.5 it becomes 0. The objective value is 0[1].

After that PSO and CSA generate a new solution using the existing solution (0.3252). Suppose it is -0. 5131. Calculate $Sigmoid$ (-0.5131) = 0. 374. Again it is less than 0.5, it becomes 0. The objective value is 0. After that, the two algorithms generate a new solution using the existing solution (-0.5131). Suppose it is 0. 0856. Calculate $Sigmoid$ (0.0856) = 0.521, now it is greater than 0.5 so it becomes 1. The objective value is 1.

The following sections represent this paper: Section 1: Introduction; Section 2: Literature Review; Section 3: Methodology; Section 4: Experimental Outcomes; Section 5: Discussion; and Section 6: Conclusion.

2 Related Work

Business researchers are concerned with optimal performance, which necessitates personal well-being, independence, and optimization. The operating mechanism for optimum performance is complicated, which results in an unusual state of performance. Any system's performance status can advance from one level to another, increasing output, effectiveness, and delivery time[2]. The level of optimal performance affects why performance is at its best. Understanding the complexities of optimal functioning, such as how someone achieves optimal cognitive functioning, is novel, especially in terms of educational and social implementation methods, and it advances our understanding of the relationship between optimization and optimal performance[3].

The CSA algorithm has been used by researchers to address a wide range of issues in numerous fields[4]. In order to address integer optimization and minimax problems, this study suggests a new cuckoo search algorithm that combines the cuckoo search algorithm with the hill-climbing approach. Calling itself Cuckoo and Hill Climbing Hybrid Search, the suggested method (CSAHC). The hill climb algorithm is used by CSAHC as an intensification process to speed up the search and overcome the slow convergence of the conventional cuckoo search algorithm after the standard cuckoo search is applied to the number of iterations. By using 13 criteria, performance validation is determined. According to the results of an experimental simulation, CSAHC works better than regular CSA[5]. Our contribution to this study is to suggest other optimization algorithms like PSO to solve the One Max problem and compare them among other criteria.

PSO, a strategy for optimization that was inspired by social animals' group behavior, was one of the techniques the researchers covered. In-depth swarm optimization (PSO). A swarm of particles may flow across the parameter space that specifies the courses pushed by them as their best performers and those of their neighbors, and this is how the set of potential solutions to an optimization problem is established. The ability of particle swarm optimization to resolve various optimization issues in chemical measurements is demonstrated in this work. Through the offered succinct literature survey as well as many other fields of chemical measurement, optimization can be used. It has been demonstrated to be helpful for signal alignment as a result of its capacity to find the ideal orientation in space according to the projection index or for variable selection[6]. It can use PSO for solving the One Max problem for its high ability to spread and determine values in different places.

Researchers have first introduced the Automatic Propulsion Particle Swarm Optimization (CSA-PSO) technology, which serves both electric companies and their customers in terms of economic and environmental benefits. In this study, the allocation, size, and number of urban planning clusters were optimized based on the goals of minimizing overall costs and energy loss[7]. To calculate the decrease in overall costs and total energy losses, a new reduction ratio formula is applied. It is demonstrated that the CSA-PSO method is superior at resolving the optimal power flow problem with RDGs. Compared to recent metaheuristic innovations[8]. It can be said that the contribution that PSO and CSA make in the field of improvement and problem solving is the best in all areas.

3 Methodology

This research study provides a more thorough comparison between the PSO and CSA algorithms in order to look into the various optimization approaches for the One Max Problem. Without going against restrictions, optimization works towards (the best or most efficient use) of a particular set of parameters. Cost reduction and maximizing productivity and efficiency are the most typical objectives. One of the primary quantitative methods used in industrial decision-making is optimization. Each algorithm is executed 30 times with job evaluation count = 100000. The upper bound = 1 and the lower bound = -1. The solution to the problem has three different dimensions which are D = 100, D = 500, and D = 1000. The following criteria were used to compare and evaluate the performance of the two algorithms; Best, Mean, Median, Worst, and Standard Deviation. Also, we have statistical analysis using Wilcoxon. The way it works is; generate a random number between the lower bound and the upper bound. According to the sigmoid function, if the value is less than 0.5, the objective value becomes 0. If it is greater than 0.5, it becomes 1. For execution 30 values will be collected for each of the three dimensions (100, 500, and 1000) of the two algorithms, and a comparison will be made between their output values according to the criteria mentioned above.

3.1 PSO (Particle Swarm Optimization) Algorithm

A stochastic optimization algorithm, introduced in 1995, is a population-based that is driven by the intelligent collective behavior of some animals such as flocks of birds or flocks of fish and ants, also it has undergone many improvements. It’s a technique for computing that enhances an issue by iteratively attempting to raise the quality of a possible solution[9]. By moving a set of potential solutions—here referred to as particles—in the search space in accordance with a straightforward mathematical formula over the particle's position and velocity, it solves problems. Each particle moves toward the best-known positions in the search space, which is updated when other particles find better positions. This movement is governed by each particle's local most well-known position. It is anticipated that this swarm would promote better solutions[10].

These are the definitions of the corresponding update formulas for PSO[11]:

$$vij(k + 1) = w \cdot vij(k) + c1r1(pbestij(k) - xij(k)) + c2r2(gbestj(k) - xij(k)) \quad (1)$$

$$xij(k + 1) = xij(k) + vij(k + 1), j = 1, 2, . . . , D \quad (2)$$

the current position is xij(k) for the j-th dimension of the i-th particle in the k-th iteration and vij(k) is the velocity for the i-th particle in the j-th dimension in the k-th iteration; pbesti=(pbesti1, pbesti2,..., pbestiD) is the best position for the i-th particle that has ever been searched. W is the inertia weight, which influences how much the particle maintains its initial velocity, determining the tendency to be optimized globally or locally. gbest = (gbest1, gbest2..., gbestD) is the best place for which all particles have ever been searched. This model's purpose is to mimic bird behavior, and it is: Each unique bird is represented as a random point in the Cartesian coordinate system with an initial velocity and position. Run the program again, this time using the "nearest proximity velocity match rule," and set each individual's speed to equal that of its closest neighbor. If the iteration is repeated, all of the points will quickly have the same velocity. Because this model is overly naive and divorced from actual settings, an additional random variable is added to the speed component. In other words, in addition to satisfying "the nearest proximity velocity match," each speed will also have a random variable added to it at each iteration, making the overall simulation resemble the real scenario, as shown in the pseudocode below[12, 13].

```
For each particle
        Set position and velocity at random.
End

t=1
Do
       For each particle
            Determine the fitness function
```

```
            If fitness value > pBest Then
                  Set current fitness value as pBest
      End
      Update particle with best fitness value as gBest
      For each particle
            Calculate new velocity using equation (18)
            Update position using equation (19)
      End
t=t+1
While (t < maximum iterations)

Post process the result.
```

3.2 Crow Search Algorithm (CSA)

It's a new metaheuristic optimization method that mimics the cognitive behavior of crow swarms. Askarzadeh introduced this technique in (2016), and preliminary results have shown its capacity to solve numerous complex engineering optimization issues. It works by simulating birds storing and collecting surplus food as needed using a newly developed swarm intelligence algorithm[14]. In optimization theory, the crow is the researcher, the surrounding environment is the search space, and randomly storing the position of the food is a possible option. The location with the most food is regarded as the universal optimum solution among all food locations, with the quantity of food as the aim function. It works by duplicating the intelligent behavior file of crows, which has gotten a lot of interest because of advantages like simple implementation, a minimal number of parameters, adaptability, and so on[15].

The definitions of the corresponding formulas for CSA are[16]:

$$x_i^{iter+1} = x_i^{iter} + r_i \cdot fl_i^{iter} (m_j^{iter}\, x_i^{iter}) \longrightarrow x_i^{iter+1} = \text{a random position.} \tag{3}$$

$$x_i^{iter+1} = \begin{cases} x_i^{iter} + r_i \cdot fl_i^{iter} (m_j^{iter}\, x_i^{iter}) & ri \geq AP^{iter} \\ \text{, a random position} & \end{cases} \tag{4}$$

ri is an integer number between 0 and 1, and $fl_i^{\ iter}$ denotes the flight length of crow i at iteration iter,where $AP_i^{\ iter}$ signifies the awareness probability of crow j at iteration iter[17].

3.3 One Max Problem

One Max problem is a simple optimization problem. The aim of the problem is maximizing the number of ones in a feasible solution x. x can be either 0 or 1[18]. The formula of the problem is given below.

$$\max f(x) \sum_{i=1}^{D} xi \tag{5}$$

where D is the dimension of the problem. One Max Problem is a binary optimization problem so that the solution space must be adapted from continuous domain to binary domain. we can use the Sigmoid Function for this purpose. The Sigmoid Function[19]: If $Sigmoid\ (x) \geq 0.5$ then it becomes 1, otherwise 0.

$$Sigmoid\ (x) = \frac{1}{1 + e\text{^}{-x}} \tag{6}$$

4 Experimental Results

The results of the values for the PSO and CSA algorithms were collected, the collection of values was based on implementation thirty times in three different dimensions (100, 500, and 1000). In each execution cycle, random numbers were generated depending on the mentioned dimension range. The resulting value is confined between the lower bound, which is -1, and the upper bound, which is 1. Depending on the Sigmoid function, the output value is made either 1 or zero, and the values confined within the range are summed for each cycle, as in Table 1.

Table 1. Methodological Results for PSO and CSA Algorithm.

Run Number	D=100		D=500		D=1000	
	PSO	**CSA**	**PSO**	**CSA**	**PSO**	**CSA**
1.	54	80	241	313	520	601
2.	48	81	241	320	557	594
3.	50	75	266	314	496	587
4.	48	82	255	304	488	595
5.	53	80	250	323	511	598
6.	60	80	252	324	473	602
7.	49	76	239	312	488	594
8.	52	81	266	307	482	594
9.	49	75	240	311	515	592
10.	43	79	268	324	501	596
11.	49	83	224	308	496	601
12.	56	75	243	310	471	594
13.	56	78	244	317	492	594
14.	50	75	259	309	490	594
15.	48	84	262	304	496	586
16.	37	82	237	309	524	585
17.	50	75	248	321	485	583
18.	51	75	254	311	503	588
19.	60	78	250	308	507	586
20.	53	79	252	316	472	595

21.	44	76	252	321	501	599
22.	54	73	263	322	472	590
23.	50	76	258	309	486	577
24.	55	80	257	316	496	602
25.	53	73	254	312	454	596
26.	52	78	259	317	492	604
27.	47	78	243	316	529	596
28.	60	76	239	312	502	593
29.	47	80	245	317	495	587
30.	53	76	260	316	495	596

Comparing the results of the two algorithms in the iteration of 100000, it was found that the CSA has higher and more accurate values than the PSO algorithm for the three dimensions. We can say that optimization using the CSA algorithm has better results. But it remains only to measure the results on the evaluation criteria mentioned to confirm the conclusions that have been found.

Table 2. Evaluation Criteria.

Evaluation Criteria	**D=100**		**D=500**		**D=1000**	
	PSO	**CSA**	**PSO**	**CSA**	**PSO**	**CSA**
1. Best	60	84	268	324	557	604
2. Mean	51	78	250	314	498	593
3. Median	50	78	225	313	496	594
4. Worst	37	73	224	304	454	583
5. Standard Deviation	5.01	2.97	10.32	5.76	22.55	6.28
6. Wilcoxon	statistic=0.0, pvalue=1.695481551569235 2e-06	statistic=0.0, pvalue=2.429705533046 2724e-06	statistic=0.0, pvalue=1.722428282743073 3e-06	statistic=0.0, pvalue=1.705141514598868e-06	statistic=0.0, pvalue=1.7180929312456739e-06	statistic=0.0, pvalue=1.6805458207281375e-06

It is clear from the evaluation criteria table that the CSA algorithm outperforms PSO in the (Best, Mean, Median, Worst, Wilcoxon) value and also the standard deviation of the dispersion of values. The lower the standard deviation of a data set, the closer the data is to the mean and the less scattered[20]. If the standard deviation is a large number, this indicates that the dispersion of the data is high. So, the standard deviation is a number to indicate the degree of dispersal of the members of the data set[21]. It has been concluded that the values of the algorithm CSA are less scattered than the algorithm PSO.

5 Discussion

CSA and PSO produced very different results in optimizing the One Max Problem in terms of (Best, Mean, Median, Worst, Wilcoxon values and standard deviation). As well as the values of the two algorithms in the three dimensions (100,500,1000). It was discovered that the CSA algorithm has better and more precise values for the three dimensions than the PSO algorithm. We can say that using the CSA algorithm for One Max problem optimization produces superior outcomes. Additionally, because the values of the CSA algorithm are more uniform than those of the PSO method, the CSA algorithm's evaluation criteria table is superior than the PSO algorithm.

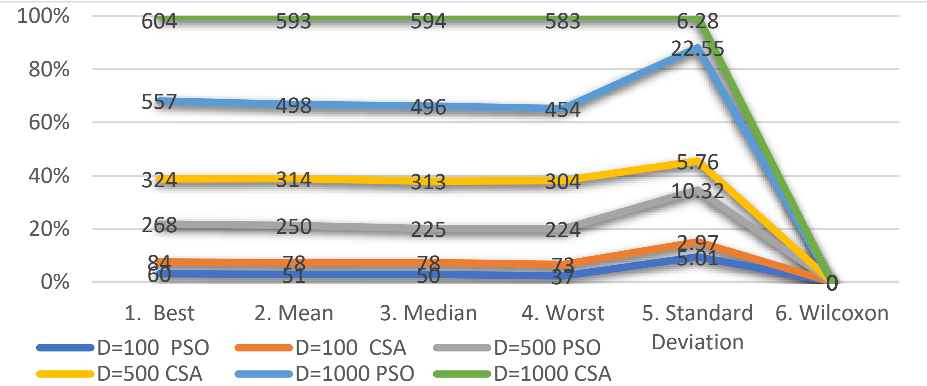

Fig. 1. Evaluation Criteria for PSO and CSA

6 Conclusion

It was found that CSA has higher and more accurate values than the PSO algorithm for the three dimensions. We can say that optimization with CSA algorithm has better results. In addition, the evaluation criteria table of CSA algorithm is superior to PSO as the values of CSA algorithm are less dispersed than PSO algorithm.The CSA and PSO algorithm were proposed to improve the One Max problem and the results proved that the CSA algorithm outperformed the PSO in the improvement values by 20% for each cycle (100, 500 and 1000). We conclude from Table No.1 that, the values collected by default in the CSA algorithm were more effective and higher accuracy of PSO values, many of which have been neglected because they are weak values in the Sigmoid function. As for the criteria table, it was concluded that all the values in the CSA algorithm were close to the mean values, and this indicates the balance of the algorithm values, as well as the low value of the standard deviation coefficient, from which it was concluded that the amount of dispersion in it is small, unlike the PSO algorithm. Therefore, it is recommended to use the CSA algorithm to improve One Max Problem.

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