

Jaya with Experienced Learning

Prasenjit Baruah¹

UG-Student, Dept. of Production Engineering, N.I.T Tiruchirapalli, Tiruchirapalli, India

Abstract -Jaya Algorithm has emerged as a simple but the most effective approach in the field of engineering optimization and beyond. Unlike the conventional heuristic algorithms like PSO, GA, etc, it doesn't require any algorithm specific parameters. A modified version of the Jaya Algorithm has been proposed in this paper that can be used for solving constrained and unconstrained problems. Jaya tried to learn only from the 'best and the 'worst' of the candidate solutions. Such combination is expected to have biasness and may result local optimal. In order to avoid this, it is proposed in the modified Jaya to seek additional guidance from one each from the top and the bottom most 10% candidate solutions when endeavoring to look for improvement in subsequent iterations. The performance of the proposed algorithm is observed by implementing it on 5 test functions having different characteristics and the results obtained show much better results as compared to that from existing Jaya Algorithm.

Key Words: Optimisation, Jaya, Evolutionary Approaches, Endeavouring, Iterations.

1. INTRODUCTION

Optimization is basically seeking for the best or most effective use of a resource. In the field of Engineering, various optimization techniques have been employed to solve real life problems like cost reduction, scheduling, etc. The population based heuristic algorithms have two approaches: Evolutionary and Swarm Intelligence. As this paper deals with the modification of recently evolved random search algorithm 'Jaya', the concepts involved in the predecessors like TLBO, PSO, GA, etc have contributed greatly to understand the origin of the same.

PSO:- This Algorithm is based on the behavior of a flock of birds searching for food in a particular search space. These particles(i.e. candidates solutions) are moved around in the search space as per some formula. They are guided by their respective best solution in the search space(i.e. p_{best}) as well as the entire swarm's best known position(i.e. g_{best}). Thus it takes both its own solution and the leader's solution(i.e. most experienced) into account while searching for the optimal solution.

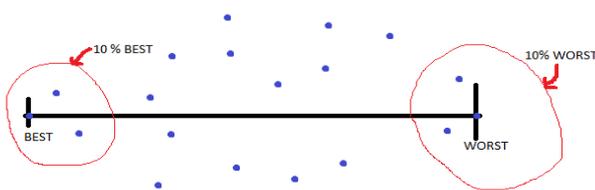
TLBO:- With the advent of TLBO, a parameter less optimization approach which gained great acceptance among the researchers, people started analyzing natural phenomenon to improve the random search and optimization techniques. TLBO replicates the events taking place inside a classroom. It consists of 2 phases - The Teacher Phase and The Learner's Phase. What happens in a classroom is the students(i.e. learners) gain knowledge in two ways! Either from what he has been taught by the teacher or by the mutual interaction with his fellow mates. Now the Teacher, being the most learned is considered as the 'best' solution. However, the learning capacity of every individual may be different. After gaining knowledge from the 'best', the students get themselves involve in group discussions where they interact with others and try to improve their knowledge.

JAYA:- It is a new random search optimization algorithm which is similar to TLBO in terms of consideration of parameters. But unlike TLBO, it has only one phase in which the solutions are moved towards the best by avoiding the worst. The success of this algorithm is due to the fact that it takes the worst solution into account while trying to improve each solution. Owing to its victorious nature, it has been named 'Jaya' which is a Sanskrit word meaning victory.

JAYA WITH EXPERIENCED LEARNING:- The proposed algorithm differs from the Jaya Algorithm in terms of the fact that it takes the neighbors of the Best and the Worst into consideration to make the search process more flexible and ultimately reach the optimum result. The immediate candidates to both the best and the worst act as an effective medium to transfer experience from the extremities(i.e. Best and Worst) to the rest. Unlike Jaya where the flow of information is discrete, here the very thing has been liquefied to ensure flow of more detailed information.

1.1 Model

Let's take the situation of occurrence of a natural calamity like Earthquake. The population near the epicenter would be the worst affected whereas the population far away from it would be safe and least affected(i.e. Best). However, the population in between these extremities will try to rush to an immediate safer place in reaction to the trembling .So, the concept of information flow must be continuous and versatile. It is beneficial to take guidance from both the individuals which are close to the Best and the Worst in addition to the two(i.e. Best & Worst).

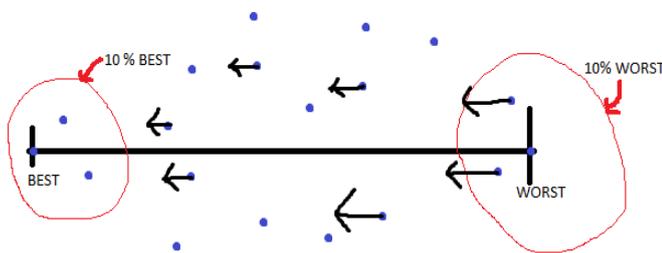


Blue Dots--No. of Candidates(say 20).

The encircled region shown in figure corresponds to Top 10% near Best and Bottom 10% near Worst.10% of 20 is 2,there are 2 candidates each in addition to the Best and the Worst.

Now the remaining candidates between the two extremities will try to rush out to an immediate better place by taking guidance from anyone who are in the encircled region following the equations-

$$(\#)x' = x + \text{rand}(x_{\text{top}} - |x|) - \text{rand}(x_{\text{bottom}} - |x|) \dots \text{towards top 10\% and away from the bottom 10\%}$$



After taking guidance from the candidates within the marked regions , we seek guidance from the Best and the Worst as these are regarded as the most experienced to get finer results.

2. PROPOSED ALGORITHM

Let $f(x)$ is the objective function to be minimized(or maximized). At any iteration i , assume that there are n number of candidates (population size, i.e. (i.e. $k=1,2,3,\dots,n$)) and m number of design variables (i.e. $j=1,2,3,\dots,m$). Let the best candidate obtains the best value of objective function($f(x)_{\text{best}}$) and the worst candidate obtains the worst value of objective function($f(x)_{\text{worst}}$) in the entire candidate solution. Rank each candidate according to the objective function value. Obtain 10% of the population size and extract the values near the Best and the Worst solutions respectively. Select two random solutions each among the Top 10% and the Bottom 10% and modify each solution as per the following the equation:

$$x' = x + \text{rand}(x_{\text{top}} - |x|) - \text{rand}(x_{\text{bottom}} - |x|) \dots \text{towards top 10\% and away from the bottom 10\%}$$

where, x_{top} = randomly chosen number from top 10%, x_{bottom} = randomly chosen number from bottom 10%. x' is the new value of x and rand is a random number in the range[0 1]. The term " $\text{rand}(x_{\text{top}} - |x|)$ " sets the direction of the candidates' solutions towards the neighborhood of the Best. Whereas the term " $-\text{rand}(x_{\text{bottom}} - |x|)$ " sets the direction of the candidates' solutions away from the neighborhood of the Worst.

Ultimately, the candidates would seek guidance from the most experienced candidates that are the Best and the Worst. Therefore, the candidate solutions in the previous step are modified according to the Jaya equation which allows already oriented solutions to refine and gain the desired the result. The Jaya equation goes as follows :

$$x' = x + \text{rand}(x_{\text{best}} - |x|) - \text{rand}(x_{\text{worst}} - |x|)$$

Fig.1 shows the flowchart of the proposed algorithm. The algorithm always tries to get closer to success (i.e. reaching the best solution) and tries to avoid failure (i.e. moving away from the worst solution) gaining knowledge from the neighborhood. The algorithm strives to become successful by reaching the best solution in less number of iterations as compared to its parent algorithm(i.e. Jaya Algorithm) and hence it is modified. The proposed method is illustrated by means of an unconstrained benchmark function known as Sphere function in the next section.

2.1 Demonstration of working of the modified Jaya Algorithm

To demonstrate the working of Modified Jaya algorithm, an unconstrained benchmark function of Sphere is considered. The objective function is to find out the values of xi that minimize the value of the Sphere function.

$$\min f(x) = \sum x_i^2$$

subject to:

$$-100 < x_i < 100$$

Since the objective function is to be minimized, thus the minimum value of the given benchmark function is 0 for all xi values of 0. Now to demonstrate the modified Jaya algorithm, let us assume a population size of 20 (i.e. candidate solutions), two design variables x and y and two iterations as the termination criterion. The initial population is randomly generated within the ranges of the variables and the corresponding values of the objective function are shown in Table 1. As it is a minimization function, the lowest value of f(x) is considered as the best solution and the highest value of f(x) is considered as the worst solution.

Table -1: Initial Population

Candidate	X ₁	X ₂	f(x)	Rank
1)	-2	-8	68	13
2)	4	5	41	7
3)	-9	0	81	17
4)	-2	6	40	6
5)	8	-3	73	14
6)	6	-3	45	9
7)	0	7	49	11
8)	-4	5	41	7
9)	5	-7	74	15
10)	8	-6	100	19
11)	1	-8	65	12
12)	-1	-1	2	1
13)	8	5	89	18
14)	-4	-8	80	16
15)	-8	-9	145	20
16)	4	-1	17	3
17)	6	-3	45	9
18)	2	-1	5	2
19)	-6	0	36	4
20)	6	1	37	5

From Table 1, it can be seen that the Best solution is corresponding to Candidate 12 and the Worst solution is corresponding to Candidate 15. As we know 10% of 20 candidates in 2 thus we obtain two solutions each near the Best and near the Worst. Then we choose any random number from each two solutions to get rough direction.

Rank 3- Candidate 16

Rank 18- Candidate 13

Now each value of x1 and x2 are modified so as to move towards the Top 10%(neighborhood of Best) and away from the Bottom 10%(neighborhood of Worst) according to the equation

$$x' = x + \text{rand}*(x(\text{top}) - |x|) - \text{rand}*(x(\text{bottom}) - |x|)$$

Table 2:- Intermediate Values of x & y

Candidate	X ₁	X ₂	f(x)
1)	-1.13032	-11.0012	122.304
2)	1.6754	3.2095	13.107
3)	-10.6589	-1.7176	116.562
4)	-5.0974	1.098	27.189
5)	4.5655	-5.8762	55.373
6)	5.0714	-6.7306	71.020
7)	-0.41	0.4715	0.390
8)	-5.1839	4.5263	47.360
9)	2.6381	-9.8639	104.256
10)	5.1398	-10.5914	138.595
11)	-2.7599	-14.6612	222.567
12)	1.2258	-1.5318	3.848
13)	7.5609	0.4371	57.358
14)	-5.0043	-9.9355	123.757
15)	-11.0092	-16.3155	387.195
16)	3.1478	-4.9816	34.724
17)	3.3089	-5.7573	44.095
18)	-0.4448	-4.7152	22.430
19)	-8.6951	-5.2508	103.175
20)	5.4819	-2.5033	36.317

Table 3:- New values of the variables and the objective function during first iteration by applying Jaya equation

Candidate	X ₁	X ₂	f(x)
1)	-3.1368	-5.7610	43.028
2)	8.6872	12.1429	222.917
3)	-13.7594	3.3264	200.386
4)	-1.9240	19.9074	400.006
5)	4.4683	-0.6958	20.449
6)	6.2774	-1.3923	41.344
7)	1.8268	14.2776	207.187
8)	0.3468	12.3851	153.510
9)	11.4634	-10.1755	234.950
10)	13.9739	-4.2168	213.051
11)	-0.7326	-6.6909	45.304
12)	3.8758	2.8432	23.105
13)	8.1448	13.4868	248.231
14)	-6.5320	0.3247	42.772
15)	-9.0659	-2.7507	89.756
16)	13.8833	6.4337	234.138
17)	8.9978	5.5559	111.828
18)	0.4113	1.7064	3.080
19)	2.4192	4.8777	29.644
20)	9.4932	4.0549	106.563

13)	7.5609	0.4371	57.358	16
14)	-6.5320	0.3247	42.772	12
15)	-9.0659	-2.7507	89.756	19
16)	4	-1	17	5
17)	3.3089	-5.7573	44.095	14
18)	0.4113	1.7064	3.080	3
19)	2.4192	4.8777	29.644	8
20)	5.4819	-2.5033	36.317	9

Table 4 has been updated based on the fitness of the Objective function by comparing the values among Table 1,2 &3. Thus, the Updated table has values from all the 3 tables depending on the goal(i.e. minimization or maximization). It validates the fact that the candidates are acquiring information from the neighborhood of the Best and the worst too. In this way, it approaches the optimum result by executing the required number of iterations.

2.2 Approach

The working of the proposed algorithm has been found out by comparing the results of the following four cases:

- (1) Jaya Algorithm
- (2) Jaya Algorithm + Top 10%(near the BestSol)
- (3) Jaya Algorithm + Bottom 10%(near the WorstSol)
- (4) Jaya Algorithm + Top 10% + Bottom 10%.

All the above mentioned algorithms have been coded in Matlab and the outcomes are compared on the basis of convergence rate and better results. For this purpose the objective function is taken as the Sphere function and the other parameters like range of design variables, max iterations, etc are kept constant.

No. of Candidates: 20

Design Variables: 2

Max Iterations: 100

Lower Bound: -100

Upper Bound: 100

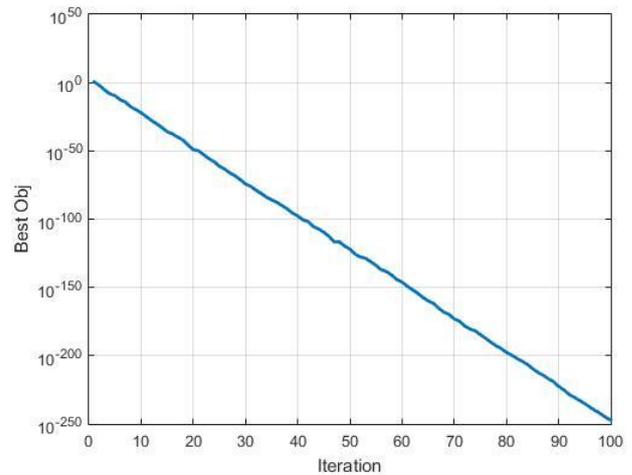
It is observed that the results of the first two cases are almost similar(Fig(1) & Fig(2)). However, when a random candidate solution from the neighborhood of the Worst is

Table 4:- Updated values of the variables and the objective function based on fitness comparison at the end of first iteration

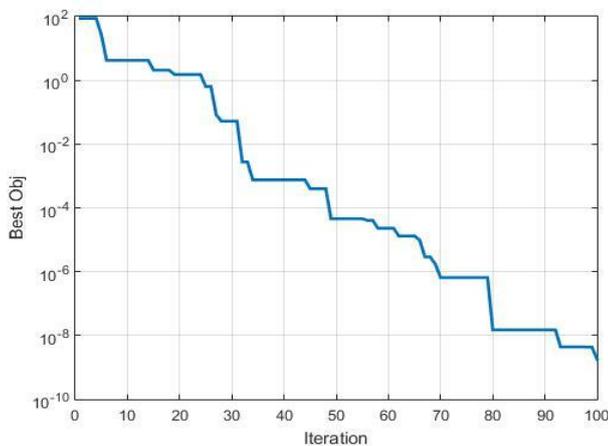
Candidate	X ₁	X ₂	f(x)	Rank
1)	-3.1368	-5.7610	43.028	13
2)	1.6754	3.2095	13.107	4
3)	-9	0	81	18
4)	-5.0974	1.098	27.189	7
5)	4.4683	-0.6958	20.449	6
6)	6.2774	-1.3923	41.344	11
7)	-0.41	0.4715	0.390	1
8)	-4	5	41	10
9)	5	-7	74	17
10)	8	-6	100	20
11)	-0.7326	-6.6909	45.304	15
12)	-1	-1	2	2

considered along with the normal Jaya, the results converge towards the optimum in lesser iterations(Fig(3) illustrates the Best Objective function value at 100th iteration).Now in the 4th case, we combine both Top 10% and the Bottom 10% along with normal Jaya Algorithm(Refer Fig(4)). Even though the results of the 3rd and 4th cases are almost comparable, it is always better to seek information from both the side(i.e. the top & the bottom).

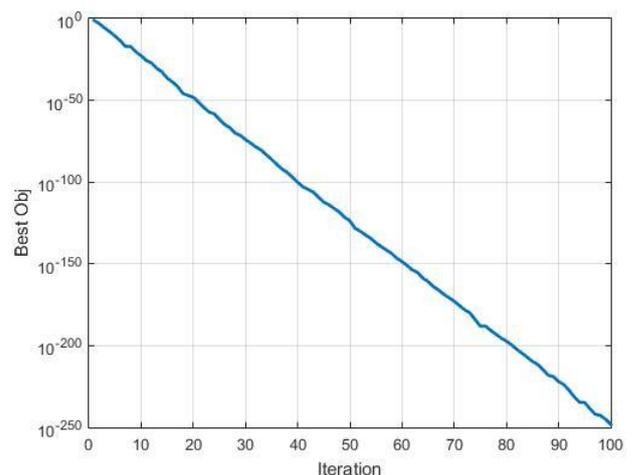
Thus, the 4th case is retained for further study. The very Algorithm is implemented on various unconstrained test functions like Sphere, Matyas, Booth, etc and constrained Himmelblau function.



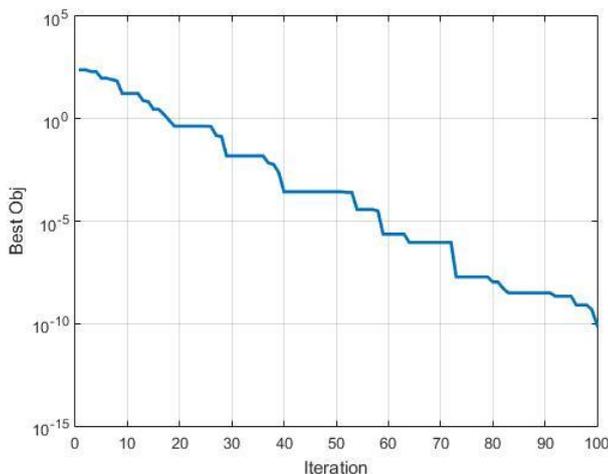
Fig(3)-Jaya Algorithm + Bottom 10%:- Iteration 100: Best Obj = 7.6219e-248



Fig(1)- Jaya Algorithm :- Iteration 100: Best Obj = 1.7865e-09



Fig(4)-Jaya Algorithm + Top 10% + Bottom 10%:- Iteration 100: Best Obj = 6.0578e-249



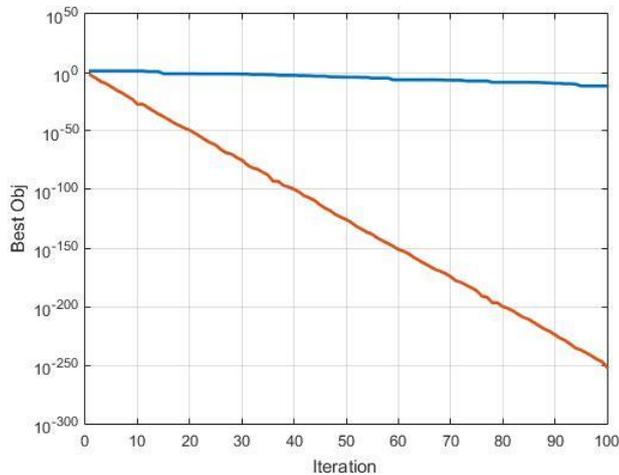
Fig(2)-Jaya Algorithm + Top 10%:- Iteration 100: Best Obj = 8.1968e-11

3. CONCLUSIONS

This paper highlights the flexibility in information flow by disregarding the biased culture(i.e. considering only the best & the worst) which is being followed in the Jaya Algorithm. However, by including random solutions from the surrounding of the Best and the Worst, the number of solutions generated in each iteration gets increased. But there is a significant difference in the results obtained by the modified Jaya(Refer Fig(5)). While the Jaya Algorithm converges to around 10^{-10} , the modified one converges to around 10^{-249} for 100 iterations.

The proposed algorithm is implemented on 5 constrained and 1 unconstrained functions . The results obtained by

the proposed algorithm are compared with the Jaya Algorithm and it has shown satisfactory results for the proposed algorithm.



Fig(5)- Jaya V/S Proposed algorithm.

The following table shows the results obtained by implementing Jaya Algorithm on the below mentioned 5 test functions taking 100 iterations for every case.

	JAYA			PROPOSED		
Func	X ₁	X ₂	Optim um	X ₁	X ₂	Opti mum
Sphere	9.53 06e- 06	- 1.58 73e- 05	3.427 8e-10	5.90 09e- 124	- 9.71 16e- 125	3.576 4e- 247
Booth	1.02 41	2.98 52	0.001 1	1.00 06	2.99 96	5.996 3e-07
Matyas	- 0.00 36	- 0.00 32	4.972 6e-07	- 2.82 78e- 62	- 3.27 82e- 62	4.235 5e- 125
Three hump camel function	3.86 74e- 05	1.38 54e- 04	2.754 3e-08	4.25 28e- 125	- 4.27 85e- 124	1.684 7e- 247
Himmelblau	3.59 35	- 1.86 81	0.008 9645	3.00 00	2.00 00	8.646 3e-08

ACKNOWLEDGEMENT

I would like to extend my heartfelt gratitude to Professor Anil Kumar Agrawal, Mechanical Engineering Department, Indian Institute of Technology (IIT-BHU) who expertly guided me through my research work as a part of Summer Internship, 2017. His generous behavior and constant guidance helped me to enjoy learning during the work.

My humble appreciation also goes to my friends who stand by me and support me in every small step I take towards trying something new.

At last but not the least, I would love to mention my family who unconditionally support me and let me build my dreams come true.

REFERENCES

[1] Rao, R., 2015. Jaya: A simple and new optimization algorithm for solving constrained and unconstrained optimization problems. International Journal of Industrial Engineering Computations, 7(1), pp.19-34.

[2] Rao, R.V., Savsani, V.J. and Vakharia, D.P., 2012. Teaching-learning-based optimization: an optimization method for continuous non-linear large scale problems. Information Sciences, 183(1), pp.1-15.

[3] Rao, R.V., Savsani, V.J. and Vakharia, D.P., 2011. Teaching-learning-based optimization: a novel method for constrained mechanical design optimization problems. Computer-Aided Design, 43(3), pp.303-315.

[4] Atul B. Patil M.Tech Student Department of Computer Science and Engineering, 2016, Bus driver scheduling problem using Jaya Algorithm and Teaching Learning Based Optimisation (TLBO) Techniques.