

# Jaya with Experienced Learning

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**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.

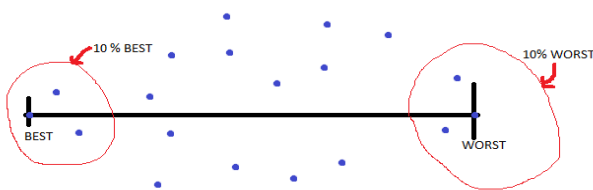
TLBO:- With the advent of TLBO, a parameter less optimization approach which gained great acceptance among the researchers, people started analyzing natural phenomenon to improve the random search and optimization techniques. TLBO replicates the events taking place inside a classroom. It consists of 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).

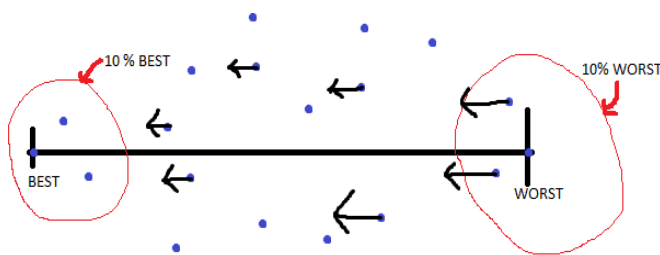


Blue Dots--No. of Candidates(say 20).

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,  $x_{\text{top}}$  = randomly chosen number from top 10%,  $x_{\text{bottom}}$  = randomly chosen number from bottom 10%.  $x'$  is the new value of  $x$  and  $\text{rand}$  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 :

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

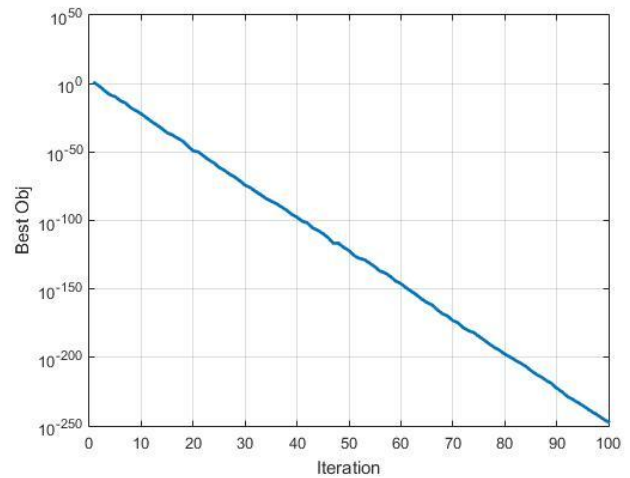
Fig.1 shows the flowchart of the proposed algorithm. The algorithm always tries to get closer to success (i.e. reaching the best solution) and tries to avoid failure (i.e. moving away from the worst solution) gaining knowledge from the neighborhood. The algorithm strives to become successful by reaching 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.



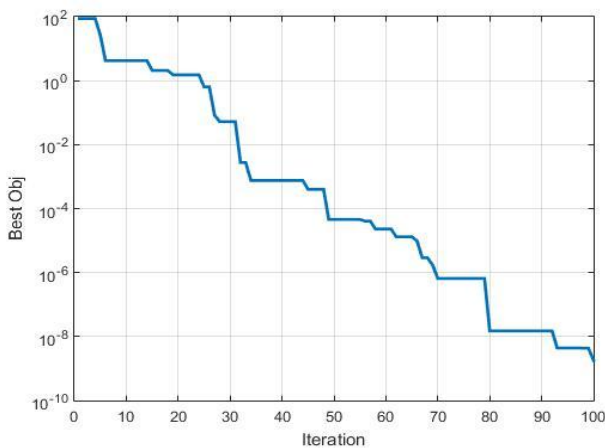


considered along with the normal Jaya, the results converge towards the optimum in lesser iterations(Fig(3) illustrates the Best Objective function value at 100th iteration).Now in the 4th case, we combine both Top 10% and the Bottom 10% along with normal Jaya Algorithm(Refer Fig(4)). Even though the 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).

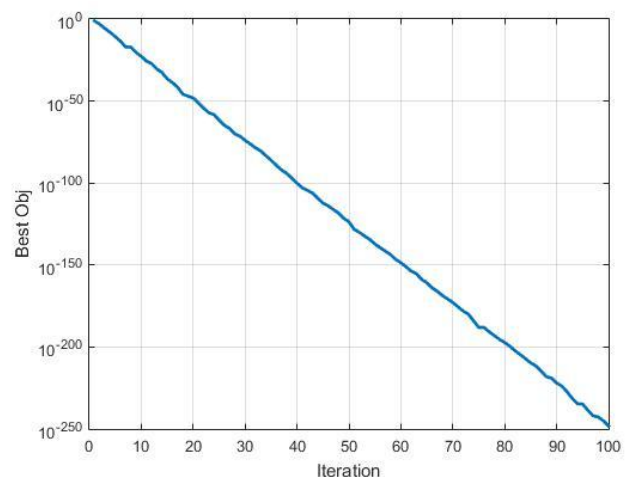
Thus, the 4th case is retained for further study. The very Algorithm is implemented on various unconstrained test functions like Sphere, Matyas, Booth, etc and constrained Himmelblau function.



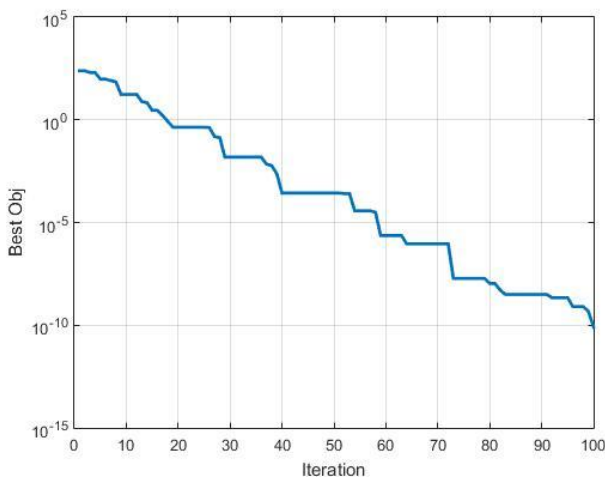
Fig(3)-Jaya Algorithm + Bottom 10%:- Iteration 100: Best Obj = 7.6219e-248



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



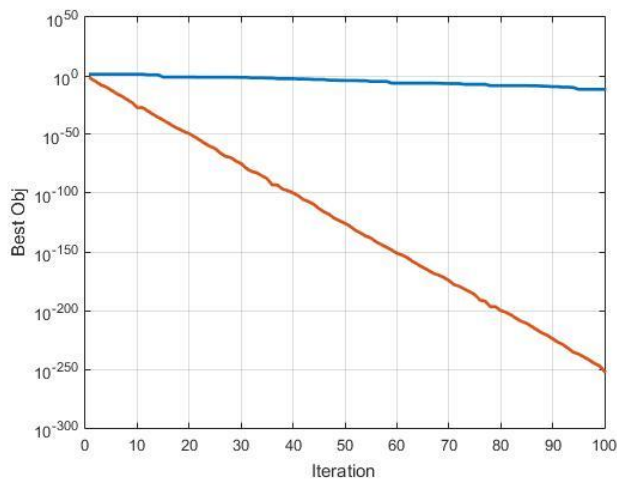
Fig(2)-Jaya Algorithm + Top 10%:- Iteration 100: Best Obj = 8.1968e-11

### 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 <sub>1</sub>	X <sub>2</sub>	Optimum	X <sub>1</sub>	X <sub>2</sub>	Optimum
Sphere	9.5306e-06	-1.5873e-05	3.4278e-10	5.9009e-124	-9.7116e-125	3.5764e-247
Booth	1.0241	2.9852	0.0011	1.0006	2.9996	5.9963e-07
Matyas	-0.0036	-0.0032	4.9726e-07	-2.8278e-62	-3.2782e-62	4.2355e-125
Three hump camel function	3.8674e-05	1.3854e-04	2.7543e-08	4.2528e-125	-4.2785e-124	1.6847e-247
Himmelblau	3.5935	-1.8681	0.0089645	3.0000	2.0000	8.6463e-08

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