COMPARATIVE STUDY ON NATURE INSPIRED ALGORITHMS FOR OPTIMIZATION PROBLEM

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Abstract— **Nature inspired algorithms are gaining popularity for optimizing complex problems. These algorithms have been classified into 2 general categories, namely Evolutionary and Swarm Intelligence, which have further been divided into a couple of algorithms. This paper presents a comparative study between Bat Algorithm, Genetic algorithm, Artificial Bee Colony Algorithm and Ant Colony Optimization Algorithm. These algorithms are compared on the basis of various factors such as Efficiency, Accuracy, Performance, Reliability and Computation Time. At the end, a table has been created which enables the reader to easily differentiate between them and realise which algorithm outperforms the others.**

Keywords— Artificial Bee Colony Algorithm (ABC), Ant Colony Optimization Algorithm (ACO), Bat Algorithm (BA), Genetic algorithm (GA), Facial Recognition, Travelling Salesman Problem (TSP)

I. INTRODUCTION

Nature is a habitat, an environment, and above all, a collection of various species. These species have different ways of living, different habits and different movements. The study of these movements and henceforth the transformation into algorithms is what we generally term as nature inspired algorithms. And the study of these nature inspired is what is the focus of this project. Nature inspired algorithms have been mainly classified into two categories, Evolutionary Algorithms and Swarm Intelligence Algorithms. While Evolutionary Algorithms are based on Darwin's theory of survival of the fittest, Swarm Intelligence Algorithms focus on collective behaviour of decentralised self-organised systems, both continuous and combinatorial. This project is a survey of the following 4 nature inspired algorithms- Bat, Genetic, Ant Colony Optimization and Artificial Bee colony. This survey has been carried out to compare these four algorithms and a table has also been created to demonstrate the factors in which the algorithm is better than the rest.

II. RELATED WORK

[1-4] discusses Bacterial Foraging Optimization Algorithm (BFO), Bat Algorithm (BA), Artificial Bee Colony, Cuckoo Search based on their characteristics. These papers also provide relationship between these and a comparative study is also presented. Talal, R and Alhanjouri in [5-7] compared Bat Algorithm with PSO algorithm for training at RBF networks and Genetic Algorithm and Ant Colony Optimization for the Travelling Salesman Problem respectively. In [8] the performance study and valuation of Genetic Algorithm and Ant Colony Optimization using accuracy as an important factor for facial feature extraction is discussed. Author in [9], [12] states that in this paper ACO, GA and SA were implemented and compared for solving TSP. These three algorithms provide optimal solution but it has been found that GA provides a better solution in comparison to ACO and SA. In [10-11] feature selection based on ABC & GA is discussed.

In [13-14] a comparative study between the performance of ABC algorithm with GA, DE, PSO, ES, ABS and AB algorithms on a large set of unconstrained test functions is stated. Maier in [15] worked on Water Distribution System optimization problems. Two case studies were considered. Their findings indicated the usage of ACOAs as an alternate to GAs. They concluded that ACOAs are better than GAs in terms of computational efficiency and ability to find near global optimal solutions. ACOAs were applied to traveling salesman and quadratic assignment problems and they have resulted in being better than other EAs, GAs included. In [16] it was concluded that ABC algorithm can be used efficiently for solving constrained optimization problems.

According to [17], ABC-AP is a powerful search and optimization technique for structural design. Bedi in [18] compared ABC and ACO and deduced that both have no centralized controller and self-organizing techniques. While ants in ACO back track route to food source using pheromones, bees in ABC use Path Integration and use direct path to come back to hive instead of back tracking their original route. In [19] it was concluded that ABC converges fast and is more efficient in performance than PSO. The work in [20] compares the performance of ABC algorithm with that of Differential Evolution (DE), Particle Swarm Optimization (PSO) and Evolutionary Algorithm (EA) for multi-dimensional numeric problems. They concluded that ABC can be efficiently employed to solve engineering problems with high dimensionality, and is better than the mentioned algorithms.

III. NATURE INSPIRED ALGORITHMS

A. BAT ALGORITHM

As the name suggests, this follows the movement of bats. It works on the principle of echolocation. The sound pulses are emitted 10-20 times per second and are converted to frequencies. These frequencies help us to determine the solution. Flowchart describing the working of bat algorithm has been demonstrated in Fig1.

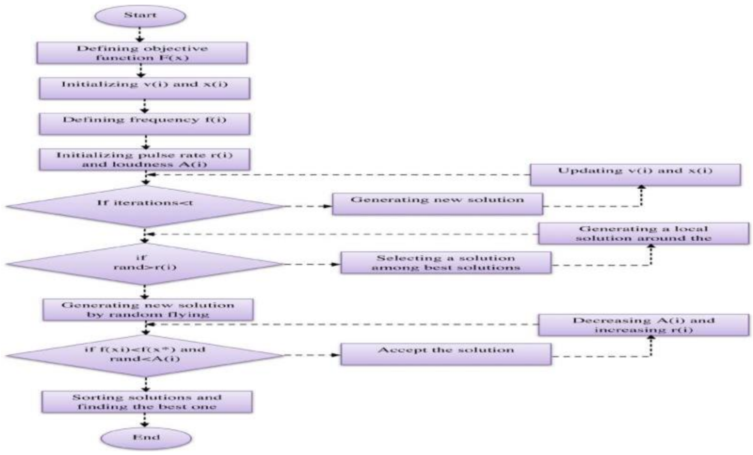

Fig 1: Diagram showing the working of Bat algorithm

B. GENETIC ALGORITHM

GA works on the Darwin's principle of survival of the fittest. It takes in mind the population size. The more the population, the greater will be the accuracy. Reason being, when the population size is large, the convergence velocity is less because it takes more time to reach the solution. On the other hand, if the population size is small, the convergence velocity will be more, which means we'll move towards the optimal solution fastly. As a result of which, the solution will be stuck in local minima or local maxima, from where it is difficult to recover. And we don't want such a situation to occur. Flowchart describing the working of genetic algorithm has been demonstrated in Fig2.

C. ANT COLONY OPTIMIZATION

ACO is a population-based high-level procedure that provides the inexact result to difficult optimization problems [21]. While using Ant Colony Optimization, a group of software agent known as ARTIFICIAL ANTS is assigned with a task to find a favorable solution to the given problem of optimization. The problem must be transmuted into a new problem of discovering the best path on a weighted graph. The ants incrementally construct the solution by operating on the graph. The process of solution construction is stochastic and is influenced by a pheromone model which means a set of graph components whose values altered at the runtime by the ants [21]. ACO algorithm is constructed on indirect communication within the colony, full of artificial ants and mediated by the pheromone trail. The pheromone trail in Ant Colony Optimization acts as a numerically distributed statistics which are used by ants to create a possible solution to the problem and is also adapted by the ants to exhibit their search experience [21]. Flowchart describing the working of ACO has been demonstrated in Fig3.

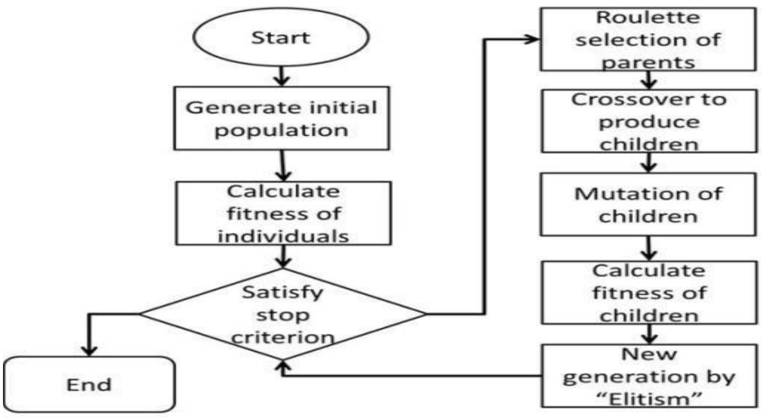

Fig 2: Diagram showing the working of Genetic Algorithm

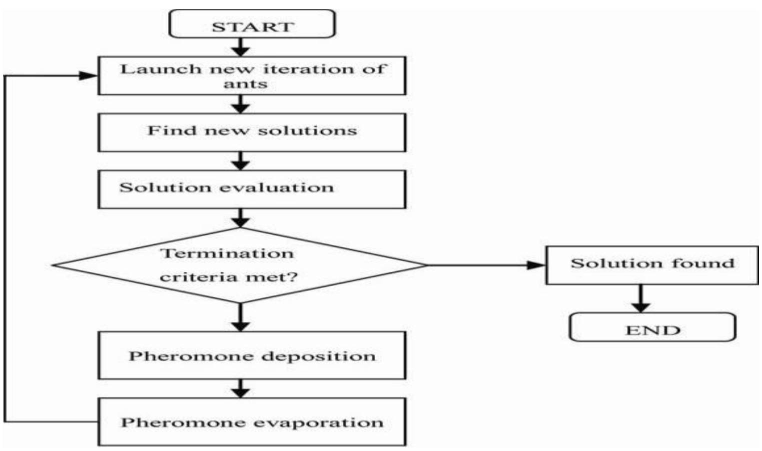

Fig 3: Diagram showing the working of ACO algorithm

D. ARTIFICIAL BEE COLONY ALGORITHM

Karaboga introduced ABC algorithm in 2005. It is a swarm-based, population-based algorithm, inspired by the intelligent foraging behaviour of honey bees and is based on the model proposed by Tereshko and Loengarov. ABC algorithm consists of three elemental components: employed foraging bees, unemployed foraging bees and food source [22]. The first two components, employed and unemployed bees search for rich food sources close to the hive. To implement ABC, the given problem is first converted to the problem of finding the best parameter vector which minimizes an objective function. Then, the artificial bees randomly discover a population of initial solution vectors and then iteratively improve them by employing the strategies: moving towards better solutions by means of a neighbour search mechanism while abandoning poor solutions [22]. Flowchart describing the working of ABC has been demonstrated in Fig4.

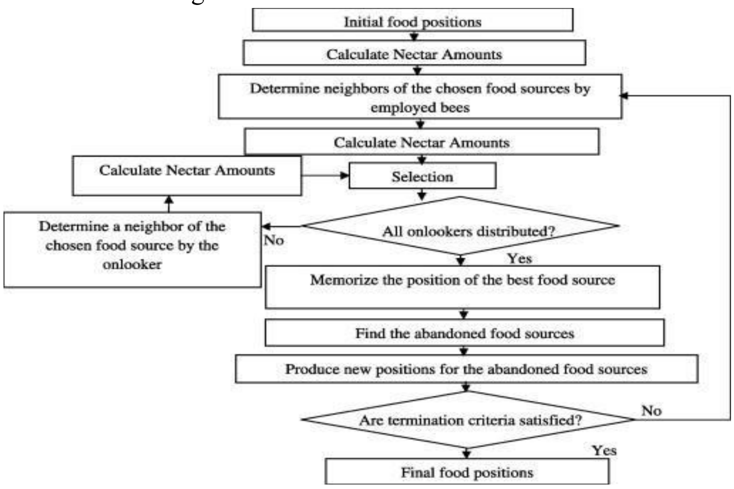

Fig 4: Diagram showing the working of ABC

IV. OBSERVATIONS

This section discusses the comparative analysis observed on the above mentioned nature inspired algorithms.

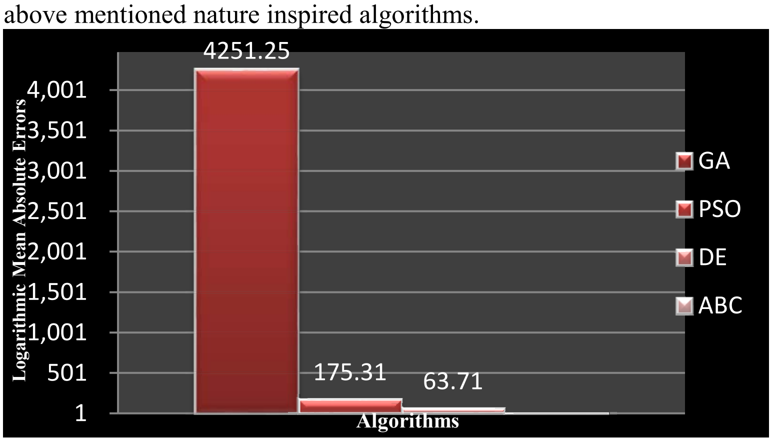

Fig 5: Mean absolute errors of Algorithms

S. No.	Towns	Parameters	ACO	GA
1	3	Total Distance	6	6.07
		Simulation Time	3.0078	16.71
2	6	Total Distance	21	20.57
		Simulation Time	6.19	18.21
3	9	Total Distance	45	29.62
		Simulation Time	5.42	18.1
4	15	Total Distance	120	92.54
		Simulation Time	13.08	22.45
5	20	Total Distance	210	351.83
		Simulation Time	23.63	24.1
6	25	Total Distance	325	397
		Simulation Time	34.43	27.56
7	30	Total Distance	465	508.79
		Simulation Time	41.45	28.41
8	32	Total Distance	528	435.67
		Simulation Time	44.18	29.57
9	35	Total Distance	630	449.29
		Simulation Time	55.19	36.12
10	40	Total Distance	820	508.17
		Simulation Time	73.41	35.31

Table 1: Simulation Results by [23]

ABC has a lower mean absolute error which makes it better in performance than the other algorithms like GA [19]. ACO and GA have been studied for the TSP. Their simulation produced the results as depicted in Table 1. This resulted in a conclusion that for smaller towns, ACO performs better than GA because ants cover larger distance in small time. On the other hand, GA favours larger towns or larger population [23].

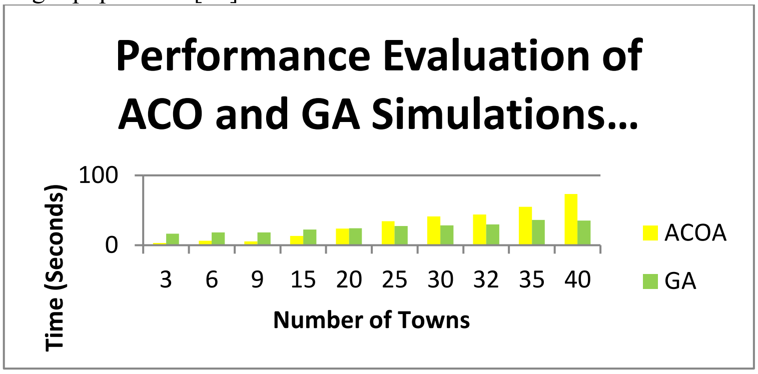

Fig 6: Performance Evaluation of ACO and GA Simulations based on Timing [23]

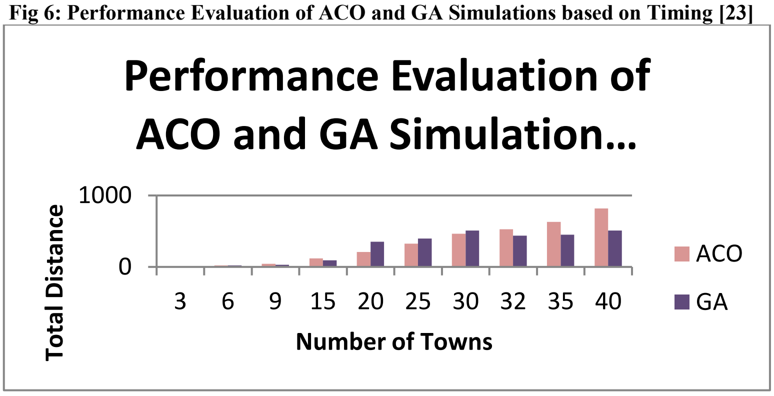

Fig. 7: Performance Evaluation of ACO and GA Simulation based on Distance [23]

Since the problem focused on by [23] was TSP, we need shortest distance to reach the solution. And we know that in TSP, we need to cover each and every town on our way to the destination. In Fig. 6, it is described that GA reduces the distance to the minimum. This is because in GAs, the chromosomes are paired which in turn reduces the redundancy. On the other hand, ACO keeps on increasing its distance.

TSP Files	Number of Cities	ACO		
		Best	Worst	Average
city10	10	128.34	135.47	127.95
city15	15	175	181.5	177.62
city29	29	8914.85	9970.25	9437.44
city30	30	524.96	555.4	543.31
city35	35	378	391.3	385.65
att48	48	3426.8	3793.15	3611.97
eil51	51	428	451.35	436.84
city51	51	502.72	556.34	526.45
eil75	75	542.3	551.03	548.56

Table 2: Performance of ACO for TSP [9]

TSP Files	Number of Cities	GA		
		Best	Worst	Average
city10	10	111.96	117.1	112.35
city15	15	138.3	145	143.72
city29	29	8019.05	8154.2	8089.56
city30	30	463	491.5	475.9
city35	35	285.76	297.46	294.13
att48	48	2818.24	3008.3	2910.95
eil51	51	420.2	443.28	433.43
city51	51	414	427.14	419.05
eil75	75	533.6	537.81	534.75

Table 3: Performance of GA for TSP [9]

Table 2 and Table 3, as depicted by [9] show the best, the worst and the average of ACO and GA for 20 runs. They concluded that when we have fewer cities, the results of ACO and GA are close. But the solution GA gave was better than that of ACO [9].

7 benchmark functions, as depicted in Table 4 were used to compare ABC and BA. On the basis of these 7 benchmark functions, Table 5 shows that ABC is better than BA [24].

No.	Name	D	C	S	Function	f_{min}
f_1	Sphere	30	U	$[-5.12,5.12]^D$	$f_1(x)=\sum_{i=1}^{D} x_i^2$	0
f_2	Step	30	U	$[-100,100]^D$	$f_2(x)=\sum_{i=1}^{d}([x_i+0.5]^2)$	0
f_3	Rosenbrock	30	U	$[-15,15]^D$	$f_3(x)=\sum_{i=1}^{d-1}[100(x_{i+i}-x_i^2)^2+(x_i-1)^2]$	0
f_4	Quartic	30	U	$[-1.28,1.28]^D$	$f_4(x)=\sum_{i=1}^{n} i x_i^4$	0
f_5	Griewank	30	M	$[-600,600]^D$	$f_5(x)=\frac{1}{4000}\sum_{i=1}^{d} x_i^2-\prod_{i=1}^{d}\cos\frac{x_i}{\sqrt{i}}+1$	0
f_6	Rastrigin	30	M	$[-15,15]^D$	$f_6(x)=\sum_{i=1}^{d}[x_i^2-10\cos(2\pi x_i)+10]$	0
f_7	Ackley	30	M	$[-32,32]^D$	$f_7(x)= -20\exp\left(-0.2\sqrt{\frac{1}{d}\sum_{i=1}^{d} x_i^2}\right)-\exp\left(\frac{1}{n}\sum_{i=1}^{n}\cos 2\pi x_i\right)+20+e$	0

Table 4: Benchmark functions used in the experimental studies [36]

No.	f_{min}	ABC		BAT		Better Performance by
		Mean	Std. Dev.	Mean	Std. Dev.	
f_1	0.0	6.38e−10	8.30e−11	2.38E+01	6.85E+00	ABC
f_2	0.0	0	0	1.08E+04	3.63E+03	ABC
f_3	0.0	3.11e+00	1.30e+00	4.29E+05	3.14E+05	ABC
f_4	0.0	9.01e−11	2.66e−11	1.29E+01	2.22E+01	ABC
f_5	0.0	9.84e−10	4.57e−10	9.09E+01	2.46E+01	ABC
f_6	0.0	6.12e−16	9.30e−17	4.64E+02	7.87E+01	ABC
f_7	0.0	1.22e−11	7.10e−12	1.52E+01	1.13E+00	ABC

Table 5: Performance comparison of ABC and BA on the benchmark functions [36]

V. RESULT AND DISCUSSION

BETTER	BA	GA	ACO	ABC
BA		Accuracy, Efficiency, Performance		Accuracy, Efficiency
GA			Accuracy, Computational Time, False Acceptance Rate and False Rejection Rate	
ACO	Performance	Efficiency, Reliability		Reliability
ABC	Performance	Performance	Performance, Efficiency, Computation Time	

Table 6: Comparative Analysis of Bat, Genetic, Ant Colony and Artificial Bee Colony algorithms

Through this comparative study it was observed that each and every algorithm has their advantages over each other. As shown in Table 6 the comparative analysis, BA has advantage over GA in terms of Accuracy, Efficiency and Performance. BA also has advantage over ABC algorithm in term of Accuracy and Efficiency. Therefore, BA should be preferred for the applications where Accuracy is an important factor. GA shows its advantages over ACO algorithm in terms of Facial Recognition for TCP protocols. ACO is better in Performance as compared to BA. In terms of Efficiency and Reliability, it shows good results than GA and is much more reliable than ABC optimization. ABC optimization is good in terms of Performance as compared to BA, GA and ACO.

VI. CONCLUSION

Through this paper a comparative study was conducted on nature inspired algorithms namely BA, GA, ACO Algorithm and ABC Algorithm. These algorithms were analysed based on the parameters like Accuracy, Performance, Efficiency, Reliability and Computation Time.

Based on the results of analysis it was concluded that the performance of these algorithms varies and depends upon the type of parameter. These parameters determine which algorithm outperforms others.

These comparisons will be helpful in eradicating the short comings of any of the four algorithms.

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