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Comparative Study of Different Modified Artificial Bee Colony Algorithm with Proposed ABC Algorithm

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***Abstract** Swarm intelligence systems are typically made up of a population of simple agents or boids interacting locally with one another and with their environment. Artificial bee colony (ABC) algorithm, particle swarm optimization (PSO), ant colony optimization (ACO), differential evolution (DE) etc, are some example of swarm intelligence. In this work, an efficient modified version of ABC algorithm is proposed, where two additional operator crossover and mutation operator is used in the standard artificial bee colony algorithm. Here Crossover operator is used after the employed bee phase and mutation operator is used after scout bee phase of ABC algorithm and simulated results are compared with different modified version of artificial bee colony algorithms, like ABC with uniform mutation, ABC with crossover and mutation and Basic ABC algorithm. The simulated result showed that the proposed algorithm is better than all the modified version of ABC algorithm.*

***Keywords-** Artificial Bee Colony, ABC, crossover, Mutation, Genetic Algorithm, GA.*

I. INTRODUCTION

The problem of optimization is the most crucial problem in today's era and a great many work have been done to solve it. Previously a lot of work has been done on GA, ABC and hybridization of various evolutionary algorithms. There are few literatures available which compares their performance evaluation and suggests the best technique to be opted for specific problems.

Karaboga proposed the Artificial Bee Colony (ABC) algorithm based on a particular intelligent behavior of the honeybee swarms [1, 2, 3]. In this work, a particular intelligent behavior of a honey bee swarm, foraging behavior, is considered and a new artificial bee colony (ABC) algorithm simulating this behavior of real honey bees is described for solving multidimensional and multimodal optimization problems. A novel hybrid swarm intelligent approach is proposed by integrating both ABC and GA with introducing two information exchange processes between GA population and bee colony [4]. In [5], a crossover step is added to the standard PSO. The crossover is performed between each particle's individual best positions. After the crossover, the fitness of the individual best position is compared with that of the two offsprings, and the best one is taken as the new individual best position. In paper [6, 7], Many studies are available

in which PSO and crossover operators are applied. Genetic algorithms (GAs) are a family of computational models developed by Holland [8, 9, 10], which is based on the principles of natural biological evolution

The organization of the paper is as follows: section 2 gives different modified version of Artificial Bee Colony algorithm. Section 3 gives proposed methodology, Section 4 explains different benchmark functions and parameter setup for experiments. Section 5 describes the Experimental results and Section 7 gives Conclusion.

II. DIFFERENT MODIFIED VERSION OF ABC ALGORITHMS

1) Abc Algorithm With Uniform Mutation :

In this Work [11], one additional step, i.e. mutation operator, is added to standard artificial bee colony algorithm. Mutation operator is added after the employed bee phase of ABC algorithm. ABC algorithm has four phases: initialization phase, employed bees phase, onlooker bees phase and scout bees phase. Employed bee phase do the local search and mutation after the employed bee phase explore the search space and do the searching new area of solution space. Through mutation, on the one side, there is a chance of changing the local best position, and the algorithm may not be trapped into local optima.

On the other side, individual can make use of the others' advantage by sharing information mechanism. In this method, the mutation step is carried out on the probabilistic way in each food searching operation for each iteration during the life cycle of ABC optimization technique. Selection of food source is done in a random manner. Food Source is selected arbitrarily from the food size and mutation is performed. In mutation, generated offspring's replaces the older offspring's. The mutation operator used in this paper is uniform mutation. When performing mutation, we randomly select one food source and replace its one of the dimension value by random number generated in between lower and upper bound value of the food source.

2) ABC Algorithm With Crossover And Mutation :

In this work [12], two additional steps are added to standard Artificial Bee Colony Optimization, i.e., crossover and mutation operator of genetic algorithm.

Crossover operator is added after the employed bee phase and mutation operator is added after the scout bee phase of artificial bee colony algorithm. Crossover operator is applied to two randomly selected parents from current population. Two offspring generated from crossover and worst parent is replaced by best offspring, other parent remains same. Now mutation operator is applied after the scout bee phase.

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Through mutation, on the one side, there is a chance of changing the local best position, and the algorithm may not be trapped into local optima. When performing mutation, randomly one food source is selected and replace its one of the dimension value by random number generated in between lower and upper bound value of the food source.

3) ARTIFICIAL BEE COLONY ALGORITHM:

In the ABC algorithm, the colony of artificial bees contains three groups of bees: employed bees, onlookers and scouts. A bee waiting on the dance area for making decision to choose a food source is called an onlooker and a bee going to the food source visited by itself previously is named an employed bee. A bee carrying out random search is called a scout. In the ABC algorithm, first half of the colony consists of employed artificial bees and the second half constitutes the onlookers. For every food source, there is only one employed bee. In other words, the number of employed bees is equal to the number of food sources around the hive. The employed bee whose food source is exhausted by the employed and onlooker bees becomes a scout. The main steps of the algorithm are given below:

Initialize.

Repeat

1) Place the employed bees on the food sources in the memory;
2) Place the onlooker bees on the food sources in the memory;
3) Send the scouts to the search area for discovering new food sources.

UNTIL (requirements are met).

II. PROPOSED METHODOLOGY:

In this proposed method, two additional steps are added to standard Artificial Bee Colony Optimization is of crossover and mutation operator. The first step of the ABC algorithm is to generate the population. Initial populations generated by ABC are used by employed bees. After this phase, crossover operators are applied.If crossover criteria or probability satisfies than two random parents are selected to perform crossover operation on them .After crossover operation new off springs are generated. Replacement of worst parent is done with best generated offspring if it is better than the worst parent in terms of fitness. Here crossover operator is applied to two randomly selected parents from current population.

Two offspring generated from crossover and worst parent is replaced by best offspring, other parent remains same. Now mutation operator is applied after the scout bee phase. Through mutation, on the one side, there is a chance of changing the local best position, and the algorithm may not be trapped into local optima. On the other side, particle can make use of the others' advantage by sharing information mechanism. In this method, the mutation step is carried out on the probabilistic way in each food searching operation for each iteration during the life cycle of ABC optimization technique. Selection of food source is done in a random manner. Food Source is selected arbitrarily from the food size and mutation is performed. In mutation, generated offspring's replaces the older offspring's. The mutation operator used in this paper is uniform mutation. When performing mutation, we randomly select one food source and replace its one of the dimension value by random number generated in between lower and upper bound value of the food source. The proposed algorithm is discussed below -

Algorithm 1: ABC with Crossover and Mutation Operator [*Initialsation Phase*]

for i=0 to max number of Food source NF
    do for d=0 to dimension size **do**
    Randomly initialize food source positions Xij **end for d**
  Compute fitness of each food source **end for i**

Repeat

[*Employed Bee Phase*]

for i=0 to max no of employed bee
    do for d= 0 to dimension **do**
        produce new candidate solution
    end for d
    Compute fitness of individual
    if fitness of new candidate solution is better **than** the existing solution replace the older solution.
end for i
for i = 0 to max number of food source NF **do**
    Calculate the probability for each food source.
end for i

[Crossover phase]

If crossover criteria satisfies
  For i=0 to maximum no. of food source
    Select two random individuals from the current population for crossover operation.
    Apply crossover operation
    New offspring generated from parents as a result of crossover. Replace the worst parent with the best new offspring if it is better.
  end of i

[Onlooker Bee Phase]

for i=0 to max no of onlooker bee **do**
    choose food source on the basis of probability Pi **for d= 0** to dimension **do**
        produce new candidate solution for food source position Xij
    end for d
    compute fitness of individual food source
    if fitness of new candidate solution is better **than** the existing solution replace the older solution.
end for i

[Scout Bee Phase]

If any food source exhausted **than**
replace it by new random position generated by scout bee.

[Mutation Phase]

If mutation criteria is met **then**

Select random particle from current population for mutation operator.

Apply mutation operation to generate new individuals new offspring generated from the result of mutation.

New set of sequence is generated for offspring Compute the cost for that offspring Compute the fitness of updated individual Memorize the best food source so far

Until (Stopping criteria met).

III. BENCHMARK FUNCTIONS AND PARAMETER SETUP

From the standard set of benchmark problems available in the literature, four important functions are considered to test the efficiency of the proposed method. All the problems are composed of continuous variables and have different degree of complexity and multi-modality. The set of test functions include unimodal and multimodal functions which are scalable (the problem size can be varied as per the user's choice). In our experiments, problem size for all problems is set to 30. These are minimization problems having a minimum at 0. The problems are listed in Table 2.

The first control Parameter is Maximum cycle number and the value of this parameter we have taken in our experiment as 2500. The next parameter in our experiment is maximum number of food source and we have taken its value to be 30. Another control parameter is number of runs and we have taken its value in our experiment as 30. It must be noted that each run contains maximum cycle number, which is 2500 in our experiment. The fourth control parameter is Dimension and its value is taken as 30. The control parameter for mutation operator is Probability. Therefore we need to find the value of this parameter also. The value of mutation probability is 0.2.

IV. EXPERIMENTAL RESULTS

In this section we analyze the result obtained by our algorithm. To test the efficiency of our algorithm results of ABC with Mutation and crossover is compared with different modified version of ABC algorithm results. Table 1 shows the comparison of proposed algorithm with different modified version of ABC algorithm. Results show the mean fitness values calculated by ABC and ABC with mutation operator, ABC with crossover and mutation operator, Basic ABC algorithm for four benchmark function sphere, rosenbrock, griewank and rastrigin. From the result table 1 it is clear that our proposed algorithm outperforms the original ABC algorithm. Our proposed algorithm performs better than the ABC algorithm and there is no fixed value for the mutation probability for which algorithm performs good for all function. We have used mutation probability 0.2 in our experiment.

V. CONCLUSION

In this paper, real coded crossover and mutation operator is applied after the employed bee phase and scout bee phase of ABC algorithm. With the help of crossover operator, new off springs are generated from initial population and replace the worst parent with best offspring and with mutation operator, randomly select one food source and replace its one of the dimension value by random number generated in between lower and upper bound value of the food source. The experiments are performed on four standard benchmark functions available in the literature and obtained results are compared with different version of modified ABC algorithms. As future work to apply other types of mutation operators and crossover operator in the ABC algorithm.

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Table -1 shows the comparison of proposed algorithm with different modified version of ABC algorithm.

Benchmark Functions	Basic ABC Algorithm	ABC With Mutation	ABC with Mutation and Crossover	Proposed ABC algorithm
Sphere	1.1402e-15	1.1251e-15	1.1158e-15	1.0945e-15
Rosenbrock	1.2651e	1.3612e	1.2839e	1.2587e
Griewank	1.1102e-15	1.0695e-15	1.0348e-15	1.0019e-15
Rastrigin	1.5889e-3	1.346e-5	1.228e-5	1.191e-5

Table 2 shows standard benchmark functions

Function Name	Function	Search Space
Sphere	$Min\ f(x) = \sum_{i=1}^{n} x_i^2$	$-5.12 \le x_i \le 5.12$
Griewank	$Min\ f(x) = \sum_{i=1}^{n} \frac{x_i^2}{4000} - \prod_{i=1}^{n} \cos\left(\frac{x_i}{\sqrt{i}}\right) + 1$	$-600 \le x_i \le 600$
Rosenbrock	$Min\ f(x) = \sum_{i=1}^{n-1} 100(x_{i+1} - x_i^2)^2 + (x_i^2 - 1)^2$	$-30 \le x_i \le 30$
Rastrigin	$Min\ f(x) = 10n + \sum_{i=1}^{n} (x_i^2 - 10\cos(2\pi x_i))$	$-5.12 \le x_i \le 5.12$

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