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Artificial Bee Colony Optimization—Population-Based Meta-Heuristic Swarm Intelligence Technique

Anand Nayyar, Vikram Puri and G. Suseendran

Abstract Swarm Agents are known for their cooperative and collective behavior and operate in decentralized manner which is regarded as Swarm Intelligence. Various techniques like Ant Optimization, Wasp, Bacterial Foraging, PSO, etc., are proposed and implemented in various real-time applications to provide solutions to various real-time problems especially in optimization. The aim of this paper to present ABC algorithm in a comprehensive manner. The ABC-based SI technique proposed has demonstrated that it has superior edge in solving all types of unconstrained optimization problems. Many researchers have fine-tuned the basic algorithm and proposed different ABC based algorithms. The result show that still lots of work is required mathematically and live implementation in order to enable ABC algorithm to be applied to constrained problems for effective solutions.

Keywords Swarm agents · Artificial bee colony optimization · Honey bees
Waggle dance · Optimization · Artificial bee · Swarm · Swarm intelligence

1 Introduction

The word "Swarm" [1] denotes animal aggregation like Birds, Fishes, Elephants, Bats as well as the colonies of insects like Ants, Bees, termites and Wasps performing collective behavior. Every agent in the swarm works without any sort of

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supervision and each of the agent has stochastic behavior because of its perception in the neighborhood. Swarm Intelligence (SI) is primarily concerned with collective behaviors that results from local interactions of swarm agents among each other along with their environment [2, 3]. Swarm Intelligence is basically regarded as discipline concerned with the study and research of collective behavior of swarm performed in nature like Building of nest, Foraging, sorting of items in colonies of insects, flocking, herding, schooling behaviors, etc. Considering the engineering view, it is regarded as bottom up design of distributed systems that demonstrates novel behavior at upper level due to results of varied actions of number of units interacting among each other along with their environment.

Swarm Intelligence [4] is regarded as one of the most important areas of research which is applied by different researchers for problem solving, computations and optimizing solutions. Swarm Intelligence as a discipline can be applied to a wide range of disciplines like Mathematics, Robotics, Telecommunications, Computer Science, Mechanical Engineering for performing combinatorial and continuous optimizations. Results show that Swarm Intelligence based techniques have given excellent results as compared to other techniques like Fuzzy Logic, Genetic Algorithm, Discrete Mathematics, etc.

The Algorithms in Swarm Intelligence are utilized to solve various real-time problems. The most classical algorithm in Swarm Intelligence is Genetic Algorithm (GA) [5, 6]. With the passage of time, various other swarm intelligence algorithms are proposed by various researchers like: Ant Colony Optimization (ACO) [7–10], PSO [11–13], Cat Swarm (CSO), Artificial Immune System, Elephant Swarm, Bat Swarm Optimization, Differential Evolution (DE) [14, 15] Wasp Optimization and many more.

Bees swarm around their hive and the behavior can be extended to other systems. Some other approaches based on Bee Colony Optimization are proposed to depict the same behavior of honey bees to solve various combinatorial problems [16].

In general, bee colony based algorithms [17] don't have any sort of unified foundation, and are based on different behavioral concepts. The algorithms can be distinguished on the basis of: Mating behavior of Honey bees; Foraging behavior of honey bees. In addition to this, recent research being conducted [18] and proposed algorithm suggested that selecting nest-site behavior of honey bees can be used in the real world for proposing optimization solutions.

Mating-Inspired Algorithms are inspired from bee colonies. Genetic Diversity is regarded as foundation stone which drives the mechanism of bee towards ecological success [19]. It is due to Young Queen polyandrous behavior during her flight.

Foraging behavior inspired algorithms of honey bees are regarded as decentralized process which works on decision making of individual bees. These algorithms inspire the bee colonies to maintain appropriate ratio of exploration and exploitation of food sources. This behavior is highly adaptive; means can be changed depending on the resources if required [20–22].

In Honey bee colonies, Scout bees efficiently search for food and back to hive and tell the source of food via waggle-dance. Waggle-dance also specifies the

distance of food from source, direction as well as quality. On the basis of waggle-dance, the bees distribute themselves in terms of profitability.

In ABC Algorithm, bees are classified into two groups—Employed Bees (EB) and Onlooker Bees (OB). Employed Bees perform the task of finding and maintaining promising solutions; Onlooker bees perform the task of local search. The task of exploration and exploitation is done by Employed bees. If the solution of EB's does not improvise over a series of steps, it will be abandoned and then a new random solution will be used. EBs' are known as 'Scouts' when choosing a new random solution.

In this research paper, the comprehensive review of Artificial Bee Colony Optimization (ABC) is presented which was proposed by Karaboga [22].

2 Artificial Bee Colony

2.1 Features of Intelligent Swarms

The world consists of many different kinds of swarms, but considering every swarm as intelligent is not right, as every swarm has its own intelligence. The important characteristic which results in the collective behavior by means of local interactions among simple agents is "Self-Organization". The following are the four types of characteristics given by Bonabeau et al. [1]:

1. Positive Feedback: It is basically defined as the development of best structures. Trail laying, recruitment and reinforcement in ants forming Ant Colony Optimization are examples of positive feedback.
2. Negative Feedback: Counterbalancing positive feedback and stabilizing collective pattern. Negative feedback is utmost necessary in order to avoid saturation.
3. Fluctuations: Random walk, task switching, errors among individual swarm agents are termed as fluctuations which are highly important for creativity.
4. Multiple Interactions: One individual agent in complete swarm makes use of information coming from other agents and spread throughout the network for work completion.

Apart from the above four characteristics, tasks are performed simultaneously by specialized agents called "Division of Labor" which is equally important as Self-Organization to complete intelligence in swarm agents [23].

2.2 Real Honey Bees—Foraging Behavior

A model depicting the foraging behavior of honey bee colony based on reaction-diffusion equations [24–26] was proposed by Tereshko. The emergence of collective intelligence of honey bees comprises of three main components:

a. Sources of Food
b. Foragers—Employed
c. Foragers—Unemployed

Food Sources: In order to determine the effective food source, a forager bee has to determine various characteristics with regard to food sources like, distance between food source and hive, taste of nectar, energy richness, easiness in extracting the energy from nectar. Considering simplicity, the "Profitability" of food source can be represented with single quantity.

Employed Foragers: It is primarily designated at specific food source which is currently being exploited. The bee carries the information about the food source back to hive and share with other bee agents in the hive. The information being shared is all about: distance, direction as well as profitability of food source.

Unemployed Foragers: They perform the task of only searching the food source to exploit. Under bee colonies, there are two types of Unemployed foragers: Scouts and Onlookers. Scouts—search the food in the nearby environment surroundings; Onlookers: wait in hive for information by scouts to exploit the food source. The average number of scouts is near to 5–10% as compared to other bees in bee colonies or in hive.

Information exchange among honey bees is regarded as the most important event which occurs. While examining the entire hive, it is possible to distinguish between some parts that commonly exist in all hives. The most important aspect of hive is to exchange the information regarding food source via Waggle-Dance. As the information about different food sources is available to onlooker bees on the dance floor, onlooker bees watches various dances and then decides which is the most profitable food source to exploit. The most profitable source has the highest probability to be chosen as compared to other food sources.

Considering honey bees, the following characteristics can be defined on which the principle of Self-Organization is based:

- Positive Feedback: With the increase in the amount of food sources, more onlooker bees visits the food sources.
- Negative Feedback: Food source exploitation is stopped by bees.
- Fluctuations: The scouts perform search in environment to locate food source in random fashion.
- Multiple Interactions: The information of food sources is shared by employed bees with onlooker bees on the dance floor to exploit and extract food (Fig. 1).
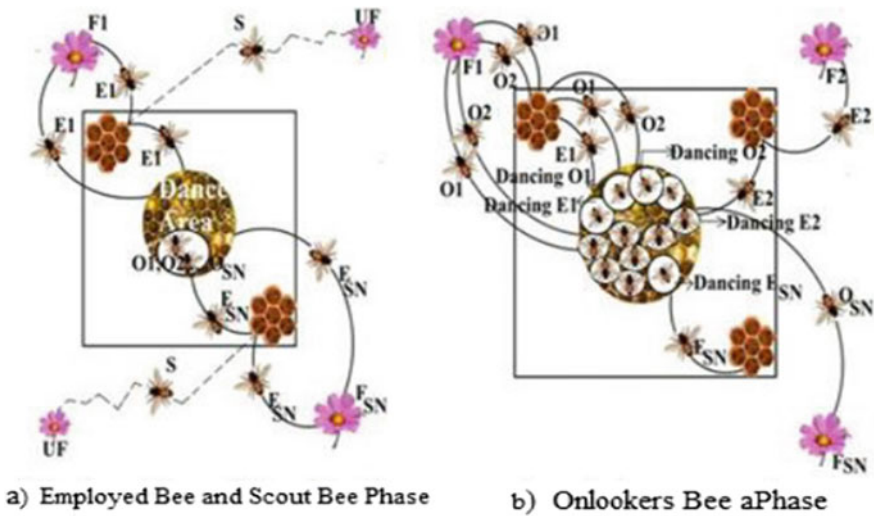
Fig. 1 **a** Phases of working of employed bee and scout bee **b** onlooker bee phase [37]

2.3 Artificial Bee Colony Optimization (ABC) Algorithm

2.3.1 Theoretical Foundation of ABC Algorithm

Artificial Bee Colonies can be categorized into three types of bee groups: Employed Bees; Onlooker Bees and Scout Bees.

Employed Bees are designated at specific food sources and comes back to hive and perform the waggle dance to aware the onlooker bees regarding food source. Onlooker bees watch the waggle-dance of employed bees to choose the most profitable food source among all waggle-dances. Scout bees search for food source randomly. Onlooker and Scout Bees are also termed as "Unemployed Bees".

All the food sources are discovered by scout bees in the initial phase. After that, the food sources nectar level is exploited by employed bees and onlooker bees, and this process remains continuous unless the bees become exhausted. Then, the employed bee which was exploiting the exhausted food source becomes a scout bee in search of further food source once again. In other words, the employed bees whose food sources are exhausted transforms itself to scout bee. In ABC Algorithm, the position of food source is regarded as a possible solution to the problem and the nectar amount in food determines the quality (fitness) of the problem. The number of employed bee is equal to a number of food sources (solutions) as every single employed bee is associated with only one food source.

Algorithm Structure—General Approach

Initialization Phase
REPEAT
      Employed Bees Phase
      Onlooker Bees Phase
      Scouts Bees Phase
      Memorize the best solution attained till now
UNTIL (Cycle = Maximum Cycle Number or a Maximum CPU Time)
ABC Algorithm- Pseudocode.

2.3.2 Phases of ABC Algorithm

Initialization Phase: In the first step of ABC Algorithm, generation of randomly distributed initial population of sn/2, where sn = size of population. Each solution x_i (I = 1, 2, sn/2) is regarded as D Dimensional vector. It is regarded as time consuming process and sometimes become impossible to estimate feasible solution in random fashion. In this phase, random values between the lower and upper limits of parameters are assigned to solution parameters. Failure i is regarded as non-improvement number of solution x_i.

The following Algorithm demonstrates Initialization phase of ABC Algorithm

for $i = 1$ to $sn/2$ **do**
   for $j = 1$ to D **do**
      Generate $\bar{x}_i$ solution
   $x_i^j = x_{min}^j + rand(0, 1)(x_{max}^j - x_{min}^j)$
      where x_{min}^j and x_{max}^j are lower and upper bound of the
parameter j, respectively.
   end for
   $failure_i = 0$
end for

After the phase of initialization, the evaluation of population is done with respect to the search iterations being performed by employed bees, onlooker bees and scout bees.

The following algorithm demonstrates the procedure deployed by Employed Bees to search the food in a random manner in an environment.

- Feasible Solution is: violation$_i$ $\leq$ 0 is best as compared to infeasible solution, i.e., violation$_j$ $\geq$ 0.
- The solution which is having best objective function value is selected between violation$_i$ $\leq$ 0 or violation$_j$ $\leq$ 0.
- The one having smaller constrained violation is preferred, i.e., violation$_i$ $\geq$ 0 and violation$_j$ $\geq$ 0.

When all employed bees complete the process of food search, they return to hive and share the information via Waggle-dance with onlooker bees on the basis of probability values.

The following Algorithm shows the Onlooker Bees—Probability calculation phase.

for $i = 1$ to $sn/2$ **do**
Calculate the probability values p_i for the solutions using fitness and/or violation of the solutions by

$$p_i = \begin{cases} 0.5 + \left(\dfrac{fitness_i}{\sum\limits_{j=1}^{sn} fitness_j} \right) \times 0.5 & \text{if solution is feasible} \\[4ex] \left(1 - \dfrac{violation_i}{\sum\limits_{j=1}^{sn} violation_j} \right) \times 0.5 & \text{if solution is infeasible} \end{cases}$$

where $violation_i$ is the penalty value of the solution $\tilde{x}_i$ and $fitness_i$ is the fitness value of the solution $\tilde{x}_i$ which is proportional to the nectar amount of that food source. The fitness is determined by

$$fitness_i = \begin{cases} 1/(1+f_i) & \text{if } f_i \geq 0 \\ 1 + abs(f_i) & \text{if } f_i < 0 \end{cases}$$

where f_i is the cost value of the solution $\tilde{x}_i$.
end for

ABC Algorithm—Onlooker Bees Phase-Probability Calculation

Onlooker bees compute the feasible solution on basis of employed bee's information and choose which food source has the highest amount of nectar.

for $i = 1$ to $sn/2$ **do**
　for $j = 1$ to D **do**
　　Produce a new food source $\tilde{v}_i$ for the employed bee of the food source $\tilde{x}_i$ by using

$$v_{ij} = \begin{cases} x_{ij} + \phi_{ij}(x_{ij} - x_{kj}), & \text{if } R_j < MR \\ x_{ij}, & \text{otherwise} \end{cases}$$

　　where $k \in \{1, 2, \ldots, sn\}$ is randomly chosen index that has to be different from i and ϕ_{ij} is uniformly distributed random real number in the range of $[-1,1]$. R_j is uniformly distributed random real number in the range of $[0,1]$ and MR is a control parameter of ABC algorithm in the range of $[0,1]$ which controls the number of parameters to be modi?ed.
　end for
　If no parameter is changed, change one random parameter of the solution $\tilde{x}_i$ by

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj})$$

　　where j is uniformly distributed random integer number in the range $[1, D]$.
　　Evaluate the quality of $\tilde{v}_i$
　　Apply the selection process between $\tilde{v}_i$ and $\tilde{x}_i$ based on Deb's method
　　If solution $\tilde{x}_i$ does not improve $failure_i = failure_i + 1$, otherwise
$failure_i = 0$
end for

After giving a food source, ABC Algorithm [17] makes a selection among various food sources to select the best one. Another modification of ABC Algorithm is to solve constrained optimization problem using DEB's rule rather than using Greedy Algorithm [27].

By applying DEB's rule, the bee is able to memorize the new position by overwriting the old food position. Deb's method makes use of tournament selection operator, where two solutions are compared with the following conditions:

- Feasible Solution is: $violation_i \leq 0$ is best as compared to infeasible solution, i.e., $violation_j \geq 0$.

- The solution which is having best objective function value is selected between $violation_i \leq 0$ or $violation_j \leq 0$.
- The one having smaller constrained violation is preferred, i.e., $violation_i \geq 0$ and $violation_j \geq 0$.

When all employed bees complete the process of food search, they return to hive and share the information via Waggle-dance with onlooker bees on the basis of probability values.

for $i = 1$ to $sn/2$**do**
    Calculate the probability values p_i for the solutions using fitness
    and/or violation of the solutions by

$$p_i = \begin{cases} \left(0.5 + \left(\dfrac{fitness_i}{\sum\limits_{j=1}^{sn} fitness_j}\right) \times 0.5\right) & \text{if solution is feasible} \\[4ex] \left(\left(1 - \dfrac{violation_i}{\sum\limits_{j=1}^{sn} violation_j}\right) \times 0.5\right) & \text{if solution is infeasible} \end{cases}$$

where $violation_i$ is the penalty value of the solution $\bar{x}_i$ and $fitness_i$ is the fitness value of the solution $\bar{x}_i$ which is proportional to the nectar amount of that food source. The fitness is determined by

$$fitness_i = \begin{cases} 1/(1+f_i) & \text{if } f_i \geq 0 \\ 1 + abs(f_i) & \text{if } f_i < 0 \end{cases}$$

where f_i is the cost value of the solution $\bar{x}_i$.
end for

ABC Algorithm—Onlooker Bees Phase-Probability Calculation

Onlooker bees compute the feasible solution on the basis of employed bee's information and choose which food source has the highest amount of nectar.

```
t = 0, i = 1
repeat
   if random < p_i then
      t = t + 1
      for j = 1 to Ddo
         Produce a new food source v̄_t for the onlooker bee of the food
source x̄_i by using
      end for
      Apply the selection process between v̄_t and x̄_i based on Deb's
method
         If solution x̄_i does not improve failure_i = failure_i + 1, otherwise
failure_i = 0
   end if
   i = i + 1
   i = i mod ((sn/2) + 1)
until t = sn/2
```

Onlooker Bee Phase—ABC Algorithm

After the distribution of all onlooker bees, food sources which are not rich in nectar are not exploited and left abandoned. The food sources which are left abandoned by bees is replaced by new food sources discovered by scouts. Different ABC Algorithms [28] proposed for constrained and unconstrained problems is the production of artificial scouts at a predetermined period of cycles for discovering food sources randomly. This time period id called Scout Production Period.

```
if cycle mod SPP = 0 then
  if max(failure_i) > limit then
    Replace x̄_i with a new randomly produced solution by
  end if
end if
```

SCOUT Bees Phase ABC Algorithm

```
place each employed bee on a random position in the search space
while  stop criterion not met  do
  for all employed bees do
    if # steps on same position = 1 then
      choose random position in search space
    else
      try to find better position
      if better position found then
        move from current position to found position
      end if
    end if
  end for
  for all onlooker bees do
    choose an employed bee and move to its position
    try improve position
  end for
end while
```

Complete ABC Algorithm

2.4   ABC Algorithm Under Constrained & Unconstrained Optimization Problems [29]

ABC Algorithm in Constrained Optimization Problems
Step 1: Initialize the Population of Solutions.
Step 2: Population Evaluation
Step 3: cycle =1
Step 4: Repeat
Step 5: Produce new solutions for the employed bees and evaluate the bees.
Step 6: Apply Greedy Selection process
Step 7: Calculate the Probability values for the solutions.
Step 8: Produce the new solutions for the onlookers from the solutions selected
         depending on conditions and evaluation of solutions.
Step 9: Apply Greedy Selection Process
Step 10: Determine the abandoned solution for the Scout. If exists, and replace with
          new randomly produced solution.
Step 11: Memorize the best solution attained so far
Step 12: Cycle= cycle +1
Step 13: until cycle = MCN

ABC Algorithm in Unconstrained Optimization Problems [29]
Step 1: Initialize the Population of Solutions.
Step 2: Population Evaluation
Step 3: cycle =1
Step 4: Repeat
Step 5: Produce new solutions for the employed bees and evaluate the bees.
Step 6: Apply selection process based on Deb's Method.
Step 7: Calculate the Probability values for the solutions.
Step 8: Produce the new solutions for the onlookers from the solutions selected
         depending on conditions and evaluation of solutions.
Step 9: Apply selection process based on DEB's method.
Step 10: Determine the abandoned solution for the Scout. If exists, and replace with
          new randomly produced solution.
Step 11: Memorize the best solution attained so far
Step 12: Cycle= cycle +1
Step 13: until cycle = MCN

3   Bee Colony Optimization

Bee Colony Optimization [30–36] was developed by Lucic and Teodorovic and is primarily based on the principle of collective bee intelligence. Artificial Bees are regarded as individual agents, and work collaboratively to solve complex combinatorial optimization problems. Every bee in the colony proposes a novel solution for each problem.

Bee Colony Optimization comprises of two phases: Forward Pass and Backward Pass. In forward pass, every artificial bee explores the area. It performs some predefined set of movements which either give a new solution or proposes improvements to existing solutions. After getting new results, the bees move back

to the next and proceed to the next phase called backward phase. In backward phase, the bees share the information regarding their solution.

Applying Bee Colony Optimization to Travelling Salesman problem, the problem of TSP is decomposed into stages. In every stage, a bee selects a new node to be included in the partial Travelling salesman tour visited so far.

Considering mother nature, bees perform a waggle-dance which acts as an information base for other bees regarding quantity, quality and distance of the food. In BCO search algorithm, the artificial bees propose solution quantity, i.e., Objective function value. During the stage of backward pass, every bee decides which food source to consider whether to search again or go to some other food source or abandon the existing food source. Every bee, choose a new solution from recruiters by roulette wheel.

In second forward pass, bees expand the partial solutions created, with a pre-defined number of nodes, and after that perform backward pass and return to hive. On returning to the hive, bees again decide whether to choose, make a decision or perform third pass.

The two phases in BCO, i.e., Forward and Backward and performed until the best solution is determined.

Consider stages as st = {st1, st2, st$n$} which are regarded as a finite number of pre-selected stages, m is the number of stages. B stands for number of bees participating in the search process and I will be regarded as number of iterations to be performed.

Partial solutions at stage st$_j$ can be denoted as S_j (j = 1, 2, ….m).

(1) *Initialization*. Determine the number of bees B, and the number of iterations I. Select the set of stages $ST = \{st_1, st_2 ,..., st_m\}$. Find any feasible solution x of the problem. This solution is the *initial best solution*.
(2) Set $i: = 1$. Until $i = I$, repeat the following steps:
(3) Set $j = 1$. Until $j = m$, repeat the following steps:
Forward pass: Allow bees to fly from the hive and to choose B partial solutions from the set of partial solutions S_j at stage st_j.
Backward pass: Send all bees back to the hive. Allow bees to exchange information about quality of the partial solutions created and to decide whether to abandon the created partial solution and become again uncommitted follower, continue to expand the same partial solution without recruiting the nestmates, or dance and thus recruit the nestmates before returning to the created partial solution. Set, $j: = j + 1$.
(4) If the best solution x_i obtained during the i-th iteration is better than the best-known solution, update the best known solution ($x: = x_i$).
(5) Set, $i: = i + 1$.

Bee Colony Optimization Algorithm

4 Conclusion and Future Scope

Artificial Bee Colony Optimization is regarded as one of the most modern techniques discovered in the area of Swarm Intelligence. It is derived from honeybees foraging behavior. The paper presents the comprehensive concept of Artificial Bee Colony Optimization. Considering all the works performed and algorithms been proposed by several researchers, most of the work is performed theoretically and lots of work need to be updated and modified to fine tune the performance for better

implementation in real-world applications. It is used for solving combinatorial optimization problems. In order to improvise the overall performance of Bee Colony Based Algorithms, new production mechanisms need to be worked out and proposed.

Future Scope

Considering future work, the prime focus would be on improvising the methodology and work structure of ABC Algorithm and implementation of ABC-based Routing Protocol for MANETS, WSN and other wireless communication networks.

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