# Study of Ant Colony Optimization and Artificial Bee Colony Optimization Techniques

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***Abstract :*** In computer science, evolutionary computation algorithms are bio-inspired algorithms based on the biological evolution which is used for optimization. Ant Colony Optimization (ACO) is a probabilistic evolutionary technique in computer science which can be used to solve computational problems like finding best paths in graphs. Artificial Bee Colony (ABC) algorithm is an evolutionary optimization technique which can be used for optimization of numerical problems. This paper discusses the evolution and variants of Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) algorithms and their applications.

***Keywords* - Ant Colony Optimization, Artificial Bee Colony Optimization, Hyperparameter Optimization.**

## 1. INTRODUCTION

Evolutionary Computation techniques are famous in computer science for problem solving as they can produce highly optimized solutions in a wide range of areas. Ant Colony Optimization and Artificial Bee Colony optimization techniques are used to find the optimized solutions for shortest routes and achieving the communication goals by giving the information about the food source to other ants and bees.

In general ants are fond of finding the food source using the shortest path from their source (colony) to the destination (food source). Ant Colony Optimization (ACO) algorithm is a technique which is inspired by the phenomenon followed by ants to find the best or shortest path of food source is developed by Macro Dorigo in 1992.

The Artificial Bee Colony (ABC) algorithm is a bio-inspired, swarm-based, meta heuristic technique which was developed based on the foraging behavior of bee colonies. This algorithm was proposed by Dervis Karaboga in 2005.

Hyperparameter optimization or tuning is a process of selecting optimal hyperparameters for a learning algorithm. The parameter whose value is used to learn other parameter values is known as hyperparameter. Hyperparameters are used to control the learning process. Hyperparameter optimization generates a set of hyperparameters which are used to generate optimal model which minimizes the loss function on the given independent data. Grid search, random search, Bayesian optimization, Gradient-based optimization, evolutionary optimization, population-based are different approaches in hyperparameter optimization.

The main objective of this paper is to present a summary of developments and variants with applications of ACO and ABC algorithms.

## 2. ANT COLONY OPTIMIZATION

### 2.1 Basic Ant Colony Optimization Phenomenon

In real world ants find the best shortest routes or paths between food (destination) and their colony (source). Ants are almost blind. They lay Pheromone trails (chemicals left on the ground), which is used as a signal to the remaining ants. The process of laying pheromone on the ground is called STIGMERGY. If the other ant decides, to follow the Pheromone trail, it also lays more Pheromone, thus reinforcing the trail. If a greater number of ants follow the trail, i.e., more Pheromone trail in the same path, the more likely ants are to follow it. Over time the strength of the Pheromone starts decaying. Pheromone which was built on shorter path faster will be followed by the remaining ants because the Pheromone doesn't have much time as it starts decaying overtime. Fig.1 depicts the behavior of ants in finding the shortest path between their colonies and the food sources.

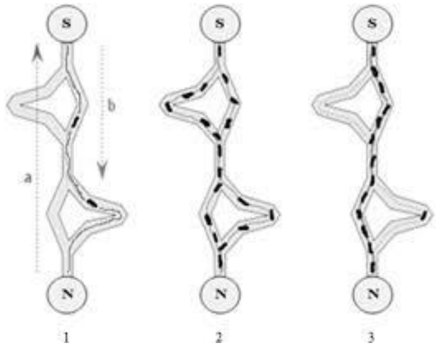


Fig.1: Ants behavior in finding the shortest path between the nest and the food source

### 2.2 Improved Ant Colony Optimization for Communication Network Routing Problem

Adaptability is the main goal in the communication network routing. The traffic in the network is unpredictable. The structure of the network is also not fixed, i.e., new nodes can be added and the old nodes also can be removed. This makes the process of routing tedious because the parameters are not constant. The routing should be dynamic. A new Improved Ant Colony Optimization algorithm was proposed by Dongming Zhao et al. [1] in which all the ants evaluate its pheromone for the quality of the route. Ant-weight strategy is used for updating the pheromone increment. The results have proved that the cost of the communication is reduced with higher packet delivery.

### 2.3 Improved Ant Colony Optimization for Generalized Traveling Salesman Problem

Generalized Traveling Salesman Problem (GSTP) consists of set of nodes which are divided into clusters and the goal is to identify the minimum cost tour passing through only one node from each cluster. Kan Jun-man et al. [2] proposed a new variant of Ant Colony Optimization algorithm which is used to solve GSTP. This algorithm consists of two approaches. In the first approach, the ant which finds the shortest route first travels all the cities, meanwhile the other ants stops till this ant finishes the traveling. In the second approach, all the ants will have different routing strategies and adjust to other ant route, if it is better then enhance the pheromone of the better route. The results have proved that the new version of Ant Colony Optimization has improved the performance and speed of convergence for GSTP.

### 2.4 Ant Colony Optimization for Variable Selection

Research is the process of developing reliable models from different sources of experimental data. The quality of the model always depends on the selection of appropriate variables. Ant Colony Optimization algorithm is used for the variable selection process. C. M. Pessoa et al. [3] identified many versions of Ant Colony Optimization techniques which help in the selection of appropriate variables to develop the models.

### 2.5 Ant Colony Algorithm for Online Resource scheduling

Load balancing is a methodology which is used to distribute the dynamic workload across all the nodes evenly. This is used to improve the overall performance of the system. The load balancer accepts all the incoming tasks from various locations and distributes to the respective data centers for proper distribution of tasks locally. V. Manickavasagan et al. [4] proposed Ant Colony based Load balancer algorithm which is used to distribute the tasks more efficiently. This load balancer consists of request monitoring, file accessing and also keep track of virtual machine status.

### 2.6 Improved Ant Volony Optimization (IMVPACO) Algorithm

Stagnation of the pheromone is the basic drawback of ACO algorithm. The change of the pheromone is a part of the evolutionary process. The path which contains more pheromone will be considered as the best path. But some better solutions or paths might be forgotten in the initial stages due to less passage of the ants. This can influence the final outputs. To overcome this problem Ping Duan et al. [5] proposed an improved version of ACO algorithm called IMVPACO. In this algorithm, updating the rules and strategy of adjusting the pheromones adaptively will generate a better quality solution based on the increment of the pheromone.

### 2.7 Hyperparameter Optimization using Ant Colony Optimization

Victor O. Costa et al. [10], proposed Hierarchical Ant Colony Model Builder ($HACO_{MB}$) which is used to deal with the hierarchical space of the auto machine learning problem to perform the classification. This method selects the Support Vector Machine (SVM) kernels and optimize the hyperparameters.

XiaoLi Zhang et al. [11], proposed a grid-based Ant Colony Optimization algorithm to select hyperparameters for the support of SVMs when there is a confused problem in order to select the parameters to improve the general performance.

Hiba Basin Alwan et al.[12], proposed Continuous Ant Colony Optimization to select the parameters for SVMs. The performance of SVM depends on the process of tuning the parameters which is a difficult process. This methodology improves the performance of SVMs.

## 3. ARTIFICIAL BEE COLONY OPTIMIZATION

### 3.1 Basic Artificial Bee Colony Optimization Phenomenon

The honeybees use a communication language of extreme precision, based on dances. The explorer bee also known as “Scout” will perform this dance. If any food source is found by the Scout, after returning to the hive, the Scout gives the information to the remaining bees about the food like the distance, quality and quantity of the food found. With the olfactory, visual and tactile perception, the remaining bees understand the information that was transmitted by the Scout bee. The information is transmitted using two types of dances. (i) The first type is round dance. This dance is used when the food source is very close to the hive and this dance form indicates only the direction of the food source. (ii) The second type is waggle dance. This dance contains eight schemes which indicate the distance and direction of the food source from the hive. The speed of the dance indicates the distance of the food source from the hive. If the dance is faster, then the food source is closer to the hive. The inclination of the dance from the vertical indicates the direction of the food source with reference to the angle between the food source and the sun relative to the hive. The type of the food is informed by the odor of the bee when it is rubbed. The quantity of the food is specified by the wriggling of the bee. If the wriggling is more, it means that the quantity of food is more. Fig.2 depicts the waggle dance of the honeybee.

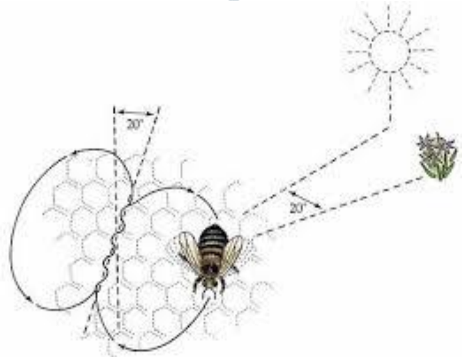


Fig.2: Waggle Dance of the bee

### 3.2 Artificial Bee Colony algorithm for Constrained problems

The ABC algorithm was initially proposed for the unconstrained problems to generate optimal solutions. Later Dervis Karaboga et al. [6] proposed that ABC algorithm can be used to solve constrained problems also. Constrained problems can be encountered in VLSI design, structural optimization, economics and so on. Constrained problem is used to minimize the value of a variable.

### 3.3 Artificial Bee Colony algorithm for Fuzzy Clustering

The main goal of clustering is to divide the data objects into groups based on the similarities. But in general the real application doesn't have any sharp boundaries in which the data can belong to one or more clusters which is not accepted. Fuzzy clustering allows the data points to belong to more number of clusters instead of bounding to a single cluster. A membership value is assigned to each data object in the cluster which ranges between zero and one. The value of the membership of a data object depends on how close it is to the center of the cluster. Dervis Karaboga et al. [7] proposed that the ABC algorithm can be used for fuzzy clustering to classify the data. The results indicated that ABC algorithm is successful with fuzzy clustering.

### 3.4 New Artificial Bee Colony (NABC) algorithm

The main drawback with the ABC algorithm is that it shows less convergence speed during the search process. To overcome this drawback Yunfeng Xu et al. [8] proposed a new Artificial Bee Colony (NABC) algorithm. This algorithm modifies the search pattern of both scout and onlooker bees. This approach is simpler and easy to implement.

### 3.5 Quick Artificial Bee Colony (qABC) algorithm for optimization problems

Dervis Karaboga et al. [9] proposed a new algorithm called Quick Artificial Bee Colony (qABC) algorithm which is used to model the foragers behavior in ABC algorithm more accurately. This algorithm improves the local search ability performance. The qABC algorithm has better convergence than ABC algorithm and can be used for all types of optimization problems.

### 3.6 Hyperparameter Optimization using Artificial Bee Colony Optimization

Intrusion Detection System (IDS) is a complicated problem due to the traffic in the network and the data streams will be irrelevant and redundant. Jun Wang et al. [13] proposed Artificial Bee Colony-Support Vector machine (ABC-SVM) algorithm for selecting the hyperparameters of the SVM and to build novel IDSs.

Zuriani Mustaff et al.[14], proposed an Enhanced Artificial Bee Colony algorithm which is used for tuning the hyperparameters of Least Square Support Vector Machine (LSSVM). This method assured the parameter selection accuracy.

Wenbo Zhu et al.[15], proposed a neuro-evolution framework with ABC to evolve the hyperparameters of Convolutional Neural Networks (CNN) automatically.

## 4. CONCLUSION

Ant Colony Optimization (ACO) and Artificial Bee Colony (ABC) algorithms are bio-inspired algorithms which are based on evolutionary process and are used to generate optimized solutions for many real time applications. Many variants of ACO and ABC were proposed for different areas based on the problem. These techniques are used to perform the classification of data objects along with the classification algorithms known as ACO miners and ABC miners.

It has also been observed that hyperparameter optimization is mostly done with the support vector machines using ACO and ABC algorithms. It can also be extended to the deep learning approaches. The combination of ACO and ABC techniques can be used to generate better optimal solutions.

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