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Ant Colony Optimization

Introduction

Ant colony optimization is a metaheuristic approach to solving complex optimization problems. Ant colony optimization is, as the name suggests, an algorithm based on the behaviour of ants. Due to their biological structure, ants use the pheromones they secrete to communicate within the colony. Inspired by this biological behaviour, ACO is based on the placement of artificial pheromone traces [1][2].

Dorigo introduced the Ant System as a solution to the Traveling Salesman Problem, which is an early version example of ACO [3][4][5]. Although the Ant system was a different and original work put forward at that time, it was not good enough to compete with the Traveling salesman problem algorithms. However, it was still a promising work and this resulted in many studies and developments on this subject [6].

ACO has a wide range of work areas. Some of those; scheduling [9], packet-switched routing [13], protein-ligand docking [10], assembly line balancing [11], DNA sequencing [8], sequential ordering [12], and 2D-HP protein folding [14], vehicle routing.

The appearance of the first version of ACO in 1991 attracted the attention of many researchers. Many new versions and improvements have been put forward. As a result, ACO is today considered as a highly advanced meta-heuristic.

Natural Ant Behaviours

When the ant colonies are examined, it is seen that the ants called random travelers to roam around the nest in search of a food source. These ants leave the pheromone traces they secrete on the paths they pass, both in order to be able to return to their nests and to give information about the food source to other ants [16].

Other ants reach the food source by following the pheromone on the path to the source. At this point, there are sources of food found by many random travelers. But some of them are far from the nest and some are close. Ants prefer the path that has the strongest pheromone among these pathways with various amounts of pheromones. Since more pheromones will be secreted per unit time on the shorter path than the long one, the ants actually instinctively choose the shortest path to reach the source. Since the selected path will be used by the ants in the colony, the amount of pheromone on the path will increase continuously over time.

Deneubourg et al. [7] created an experimental environment to observe how ants choose their path with pheromones to reach their food source. In the experiment, they used a double bridge connecting the ants' food source and their nest. For the first experiment, they adjusted both bridge lengths equally, as shown in Figure 1. In the second experiment, they used two separate bridges of different lengths, as in Figure 1b.

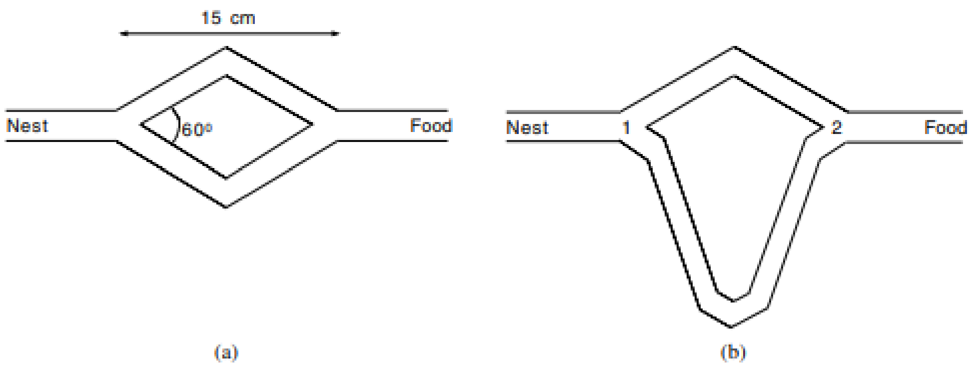

Figure 1. Double bridge experiment [7].

Since the amount of pheromones is not sufficient to make a selection at the beginning, the ants randomly choose one of the bridges, indiscriminately, in search of resources. While the amount of pheromone was insufficient, when looking at the ants' choice of bridges, the probability of choosing one of the two bridges for almost every ant was 50%. However, in both experiments, ants identify only one main path over time and use this path. For the second experiment, this is an expected result as the length of the bridges and the number of pheromones deposited in the bridges are different.

For the first experiment, this result can be explained as follows; There is no pheromone on the bridges when the experiment begins, so the ants will not have any preference. They will randomly pick one of the 2 bridges. However, due to random fluctuations, after a while, more pheromones will form on one bridge than another, which will make that path more attractive to ants. In other words, as a result of an autocatalytic process, the path to the source will be reduced to one. Ants that take the long way and the short way perform the same process and secrete pheromones. But on the short path, the amount of pheromone will be more than the long path over time. For example, the ant that goes the long way may not reach the source yet, while the ant that takes the short route may be on its way back to the home. This indicates that more pheromones are released in the short distance per unit time [8]

In the second experiment, the starting phase will be the same as in the first experiment. The ants that are explored will make random choices since there were no pheromones on bridges before. At this stage, there will be probabilistic fluctuations like in the first experiment. However, these fluctuations will lose their importance over time because the lengths of the bridges are different from each other. The unit length pheromone trace will be greater over time for the short path. For example, an ant that chooses the shortest path will reach the source and return to the nest while the ant that chooses the long way will not yet reach the source. This example is shown step by step in Figure 2. In other words, more pheromones are secreted per unit time for the shortcut. In the next step, the stronger the pheromone on the short path will be feedback for other colony members. And over time, only the short path will be used by almost all ants as the path to the source.

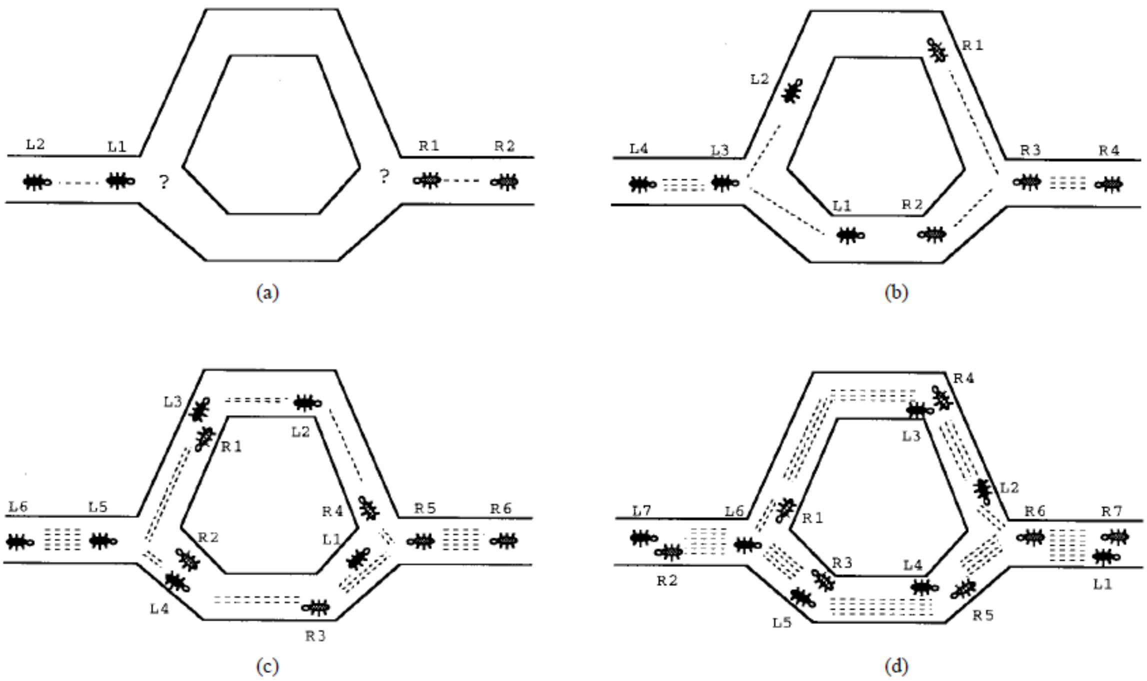

Figure 2. Pheromone traces on the paths [9].

Bajpai et al. Mentioned another experiment supporting the double bridge experiment in their 1990 study [10]. After a while, an obstacle is placed between the nest and the source as in Figure 3. There are two separate ways to overcome the obstacle, one of them is shorter than the other. Thus, an experiment environment similar to the double bridge experiment is obtained. When this experimental environment is observed in certain intervals, it is observed that the short path is preferred as the main route over time, as in the double bridge experiment.

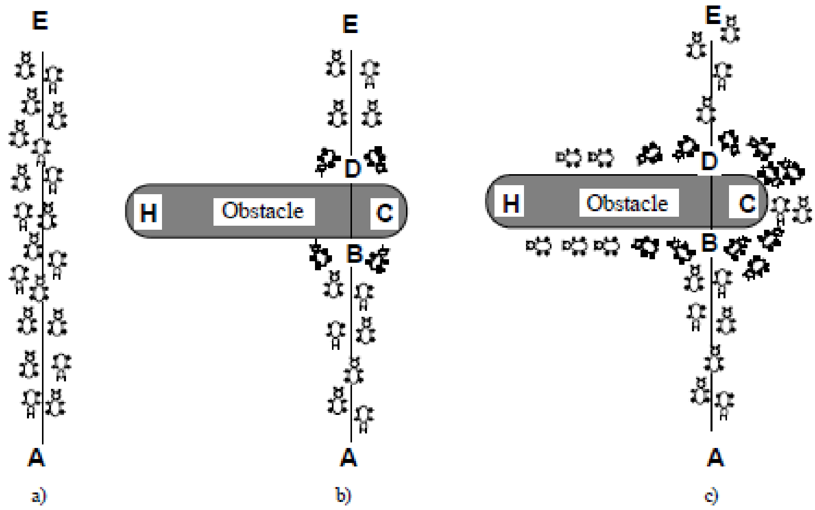

Figure 3. An obstacle is placed between the nest and the source [10].

A model that explains the dynamics of the double bridge experiment is developed by Ayşe et al. According to this model, the length of the short path ls is represented by the length of the long path. It crosses both roads at a constant speed of k ants v km / s per second and leaves a pheromone on its path. In this case, the ant that takes the shortcut will finish the road in ts = ls / v, while the ant that takes the long path (r * ts) (r = ll / ls) will be on its way.
Also, there is another concept called evaporation. The pheromone is not permanent. It will evaporate over time. In this way, the possibility of ants going to resources that are depleted or that are further away will be reduced. In Eq 1, the pheromone update equations can be seen.

$$T_{xy} \leftarrow (1-p)T_{xy} + \sum_{k}^{m} \Delta T_{xy}^{k} \qquad (1)$$

In Eq 1, while T_{xy} represents trail level, p represents evaporation constant. Hence, the next pheromone amount is calculated using the previous amount and the evaporation constant.

Artificial Ants

Artificial ants are representations of real ants in the virtual world. Therefore, they differ on some points. First of all, real ants are nearly wild creatures. Some even underground species are completely blind. However, artificial ants are not exactly blind. Due to the design of the algorithm, artificial ants are initialized with a random but appropriate point. Thus, they do not set off on a blind course like real ants.

Besides, artificial ants have a certain amount of memory. In situations where there is no evaporation or the shortest path is not found for some reason, real ants can go into a cycle. Due to their instincts, they will get rid of this loop after a while, but there will be a delay in the feed collection time. By giving tabu lists to artificial ants, the routes that may cause the above situation is blocked. The mentioned memory unit is a simple data structure, such as a list.
Lastly, although the method is inspired by ant colonies, it developed is to manage a large number of individuals with regional interaction. This means that there is no single ant behavior but the behavior of the whole of individual ants.

Algorithm

The first proposed algorithm by Dorigo [5] consists of four main stages:

i. Initialization: Like real ants, artificial ants can secrete pheromone. However, it is a fixed value for all ants. In this stage, the pheromone variable is set. Also, there some other parameters such as starting point, the function, etc. are determined in this stage. Note here: there are several pheromone variables for each ant in more recent studies.
ii. Constructing Ant Solutions: After initialization, a set of ants build a solution to the problem being solved using pheromones values and other information.
iii. Local Search: The function to be analyzed can have more than one minimum point. In this case, a group of ants can get stuck at a local minimum point. To solve this problem, a comparison is made between local minimums found by other ants, and all ants are allowed to move to the more appropriate point.
iv. Global Pheromone Update: This is the last stage, and it includes an update in pheromone variables based on search experience reflected by ants.

The basic ACO algorithm can be seen in Algorithm 1.

Alg. 1 The basic ACO

```
procedure ACO
        initialization;
        while (Iterate until end criteria is reached) do
                BuildAntSolutions;
                LocalSearchMethod ;
                PheromonesGlobalUpdate;
        end
end ACO
```

Usage areas and some studies in these areas

Considering the literature studies, it is seen that ant colony optimization algorithms are applied to the solution of many different problem types. These types of problems and some of the techniques developed for these types of problems can be listed as follows:

- **Vehicle routing problem**

In 2008, Donati et al. [11] proposed multiple ant colony systems. This model may be counted as the first multiple ant colony models. With the help of this system, they solve the time-dependent vehicle routing problem. After that, Gajpal and Abad [12] improved the same approach to solving the vehicle routing problem in 2009. In addition, in 2006, Chen and Ting [13] proposed that ACO can solve the time-windowed vehicle routing problem. In 2007, Fuellerer et al. [14] worked on a different version of the vehicle routing problem called the two-dimensional loaded vehicle routing problem. Mazzeo and Loiseau [15] dealt with the Capacitated Vehicle Routing Problem in 2004 using ACO. Moreover, Zhang et al. [16] and Gajpal and Abad [17] use simultaneous distribution and vehicle routing.

- **Quadratic assignment problem**

Ant colony optimization is one of the best algorithms for the Quadratic Assignment Problem (QAP). For the first time, Maniezzo et al. Tried to offer a solution to QAP using the Ant system in 1994 [18]. Later, Maniezzo and Colorni published an improved version of their first study in 1999 [19]. Gamberdella et al. Proposed the ant system-based HYBRID ANT SYSTEM FOR THE QAP algorithm. In 2008, Saremi et al. [20] Combined ACO with a quadratic assignment problem approach to improving the structure of websites. Also, Demirel and Toksarı are the researchers who used ACO for the optimization of the quadratic assignment problem in [21]. Apart from these, many studies have been published trying to provide better solutions to QAP from different angles [22] [23] [24].

- **The scheduling problem**

Silva et al. [25] hybridized a genetic algorithm and ACO for reprogramming of logistics processes in 2002. They also their method for scheduling problems in 2006 [26]. Huang and Liao [27] are other researchers who combined ACO with another approach. They hybridized ACO with tabu search to solve the job scheduling problem. Tseng and Chen [28], researchers working on another hybrid algorithm, developed a combination of ACO and genetic algorithm to solve the resource-constrained project scheduling problem by developing an algorithm called ANGEL. Seçkiner and Kurt [29] worked on the job rotation scheduling problem while Heinonen and Pettersson [30] applied ant colony optimization and visibility studies together to the job scheduling problem. Rossi and Dini [31] updated ACO for the problem of flexible work scheduling with routing flexibility and separable set times. Liao and Juan [32] also used ant colony optimization for single-machine delay scheduling problems in sequence-dependent adjustments, while Cheng et al. [33] proposed a hybrid structure based on ant colony for single-machine total delay problems. Yağmahan and Yenisey [34] and Lin et al. [35] solved multipurpose flow type scheduling problems by ACO and improved ACO, respectively. Gajpal and Rajendran [36] also suggested the ant colony optimization algorithm for minimizing the completion-time variances of the work in the flow.

- **The traveling salesman problem**

The roaming vendor problem (TSP) can be expressed simply: A vendor spends its time visiting cities (or nodes) cyclically. Visits each city only once per tour and ends where it started. TSP takes care of determining the transition order of nodes to minimize the total distance traveled. Many advanced ACO algorithms have been proposed for TSP. One of them is Ant System (ASrank) [37], which has an elitist strategy and ranking proposed by Bullnheimer et al. Dorigo and Gambardella Ant Colony System (ACS) [9] and Shuttle and Hoos's MAX-MIN Ant System (MMAS) [23] studied for TSP. Besides, Garcia-Martinez et al. [38] published a work that classifies and analyses ACO algorithms for TSP. On the other hand, Cheng and Mao [39] solved TSP with time windows by modifying ACO. In the study of Bajpai and Yadav, a divide and conquer-based approach was used in order to provide better solutions to the TSP (divide the nodes into sub-nodes). And a better performance has been achieved compared to the traditional ant colony algorithm.

- **Resource assignment problem**

Researchers also worked on resource assignment problem. While Chaharsooghi and Kermani [40] solved the multi-purpose resource assignment problem, while Yin and Wang [41] solved the nonlinear resource assignment problem using ACO.

- **Graph painting problem**

In 1997, Costa and Hertz [42] created a new version of ACO named ANTCOL for painting graphs. Also, Dowsland and Thompson [43] modified ANTCOL to solve the same problem. In addition, Bui et al. [44] proposed an ant-based algorithm.

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