International Journal of Scientific and Technical Advancements

ISSN: 2454-1532

A Review on Ant Colony Optimization and Its Applications

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Abstract— A strong robustness and good calculative methodology for addressing dynamic problem in various areas has always been in search. Ant Colony Optimization (ACO) in array of algorithm is one such tool and is first successful computational model of Swarm Intelligence (SI). It takes inspiration from foraging behavior of some ant species. This paper provides an overview on ant colony optimization and its applications.

Keywords— Algorithms; Ant Colony Optimization; Artificial Ants; Meta-heuristic; Pheromones; Stigmergy; Swarm Intelligence; Travel Salesman Problem (TSP).

I. Introduction

ACO was proposed by Marco Dorigo in 1992 in his PhD Thesis. ANTS'2018 was the latest event held based on ACO which was about the behavioural models of social insects, swarm intelligence, its application and swarm robotics systems. ACO algorithm is a colony of artificial ants or cooperative agents, designed to solve a particular problem. It has been inspired by Double Bridge experiments run by Goss [1] using real ants. Ants use volatile chemical substances known as pheromones, whose intensity and direction can be perceived with their long, mobile antennae to communicate. Ants that happened to pick the shortest route to food will return to the nest early, and will reinforce this shortest route by depositing food trail pheromone on their way back to the nest. This route will gradually attract other ants to follow, and as more ants follow the route, it becomes more attractive to other ants. This is autocatalytic or positive feedback process. When the food source is finished, no new food pheromone trails are marked by returning ants and the volatile pheromone scent slowly evaporates. This negative feedback help ants to deal with environment changes. This trail-laying, trail-following behavior is called stigmergy [2]. This behaviour of ants inspire ACO which is used to solve practical combinatorial optimization problem such as travel salesman problem (TSP), dynamic travelling salesman problem (DTSP), quadratic assignment problem (QAP), assembly line balancing[3], sequential ordering[4], protein–ligand docking[5] and many more.

II. Double Bridge Experiment

The experiment was done using a double bridge connecting a nest of ants and a food source. Goss, Deneubourg and colleagues in the late 1980s[6] considered differ two versions over multiple experiment runs. In one version, the longer branch was twice as long as the short one and both branches are presented from the beginning of the experiment as shown in Fig. 1(a). It was observed that most ant traffic (80-100%) was eventually concentrated on the short branch in more than 90% of the experiment runs as shown in Fig. 1(b) where r is the ratio between the two branches.

(a)

Fig. 1(a). Both branches present from beginning.

(b)

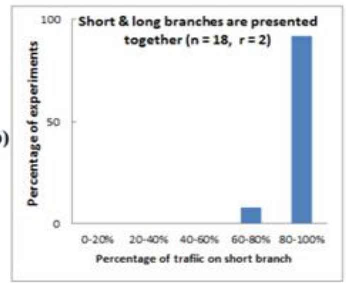


Fig. 1(b). Distribution of the percentage of ants that selected the shorter branch over n experiments

(a)

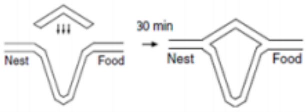
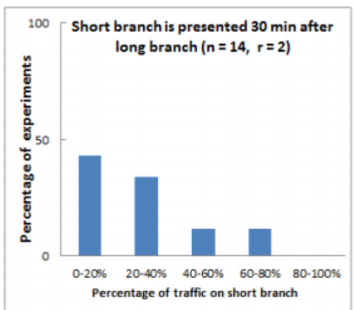


Fig. 2(a).Only longer branch was present in the starting.

(b)



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ISSN: 2454-1532

In another version, initially only the long branch was presented, and then when a stable pheromone trail has formed on that long branch, the short branch was offered after 30 minutes, as shown in Fig. 2(a). Short branch was half of the long one as in previous version of this experiment. This version was deigned to examine what happens when the ant colony is offered, after convergence, a new better (i.e., shorter) path between the nest and the food. It was observed that the short branch was not frequently selected (e.g., only 0-20% of ant traffic took the newly-offered short branch in almost 50% of the experiment runs), and thus the colony largely remained trapped on the initially only-offered long branch as shown in Fig. 2(b).

The fact that the majority of ants continued to choose the long branch can be explained by two reasons: The high pheromone concentration and the slow evaporation of pheromone. Firstly, the high-level pheromone concentration on the long branch (compared to the zero-level pheromone-trail concentration on the short branch) led to an autocatalytic behaviour that continued to reinforce the long branch, even after a shorter one was offered. Secondly, the very slow rate of pheromone evaporation did not allow the ant colony to forget the suboptimal path which they initially chose, preventing the new and shorter path to be discovered and learned [7]. In fact, the pheromone trails of most ant species were observed to be persistent for a long time-scale, ranging from at least several hours up to several months (depending on the colony size, weather conditions, the ant species, etc.). Thus, the pheromone evaporation rate is a key parameter in the process, because it controls the trade-off between path-exploration of new (and hopefully better) paths and path exploitation of the already established path. So, while making artificial ant colony optimization techniques, it is a common practice to set the pheromone evaporation to a sufficiently short time-scale. This helps artificial ants to forget errors and allow a continuous improvement [1].Also, helps in being trapped on suboptimal path or solution.

III. REAL ANT VS. ARTIFICIAL ANTS

The following table gives the difference between the artificial ants and the real ants which helps in understanding a natural phenomenon and designing natural inspired algorithm.

Criteria	**Real Ants**	**Artificial Ants**
Pheromone Depositing Behaviour	Pheromone is deposited both ways while ants are moving (i.e. on their forward and return ways).	Pheromone is often deposited only on the return way after a candidate solution is constructed and evaluated.
Pheromone Updating Amount	The pheromone trail on a path is updated, in some ant species, with a pheromone amount that depends on the quantity and quality of the food [7].	Once an ant has constructed a path, the pheromone trail of that path is updated on its return way with an amount that is inversely proportional to the path length stored in its memory
Memory Capabilities	Real ants have no memory capabilities.	Artificial ants store the paths they walked onto in their memory to be used in retracing the return path. They also use its length in determining the quantity of pheromone to deposit on their return way.
Return Path Mechanism	Real ants use the pheromone deposited on their forward path to retrace their return way when they head back to their nest	Since no pheromone is deposited on the forward path, artificial ants use the stored paths from their memory to retrace their return way
Pheromone Evaporation Behaviour	Pheromone evaporates too slowly making it less significant for the convergence.	Pheromone evaporates exponentially making it more significant for the convergence.
Ecological Constraint	Exist, such as predation or competition with other colonies and the colony's level of protection	Ecological constraints do not exist in the artificial/virtual world.
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TABLE I. Difference between real and artificial ants [2]

IV. ANT COLONY OPTIMIZATION METAHEURISTIC

A very easy ant-based algorithmic rule is given to explain the basic behavior of the ACO meta-heuristic. The main idea is to model problem to be solved as search for optimal path in a weighted graph, called construction graph and use artificial ants to do so. The artificial ant follows the steps discussed in

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IJSTA

International Journal of Scientific and Technical Advancements

ISSN: 2454-1532

the algorithm to find best solution and the flowchart [9] is also shown below. During this the goal of artificial is to select the nodes on construction graph that minimize the overall cost of solution path.

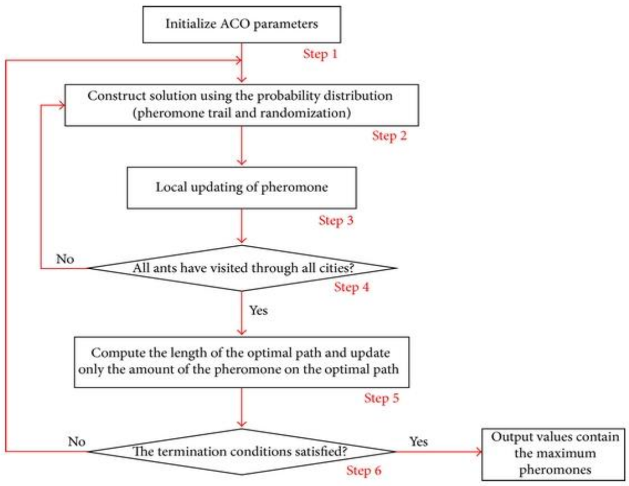

Fig. 3. Flowchart of ant colony optimization

Algorithm 1: Basic flow of ACO

1. First represent the solution space by a construction graph and then set ACO parameters and initialize pheromone trails
2. And the thirds and imp step to generate ant solutions from each ant‘s walk on the construction graph mediated by pheromone trails.
3. Then update pheromone intensities.
4. Go to step 2, until all ants have visited all cities.
5. Update the pheromone intensities on the optimal path.
6. Go to step 2, and repeat until convergence or termination conditions are met.

ACO‘s second step is to construct ant solutions. A probability rule drives an ant to sequentially choose the solution components that make use of pheromone trail intensities and heuristic information. This step is done as explained below.

Let $G = (N, E)$ be a construction graph on which artificial ants iteratively deposit pheromone trails to help choose the graph nodes of quality paths that correspond to solution components, Ni is the set of one-step neighbors of node *i* . One-step neighbor of node *i* is the node which is connected with node *i* with an edge. When an ant k build a solution, ant k applies a probabilistic action choice rule, called random proportional rule. A random proportional rule is used as the decision rule using a heuristic value and a pheromone value. The probability with which ant k, currently at node *i*, chooses to go to node *j* is given by (1) equation [2].

$$P_{ij}^k(t) = \begin{cases} \dfrac{[\tau_{ij}(t)]^\alpha * [\eta_{ij}]^\beta}{\sum_{l \in N_i^k} [\tau_{il}(t)]^\alpha * [\eta_{il}]^\beta}, & j \in N_i^k \\ 0, & j \notin N_i^k \end{cases} \qquad (1)$$

Where η_{ij} is a heuristic value and τ_{ij} is a pheromone value. Parameters α and β are two parameters which determine the relative influence of the pheromone trail and the heuristic information. N_i^k is the feasible neighborhood of ant *k* which ant *k* in node *i* possibly moves to. By this probabilistic rule, the probability of choosing a particular move from node *i* to node *j* increase with the value of the associated pheromone trail τ_{ij} and of the heuristic information value η_{ij}.

ACO‘s third step is to update pheromone trails. At the beginning, the pheromone trails of all arcs on the construction graph are initialized to a small constant value (τ_o). After a solution path is constructed in fifth step, the pheromone trails are updated in two ways, as shown in [2] equations 2 and 3.

$$\tau_{ij}(t+1) \leftarrow (1-\rho) * \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^k(t), \quad \forall\, i,j \in A,\ 0 \le \rho < 1 \qquad (2)$$

$$\Delta\tau_{ij}^k(t) = \begin{cases} Q/C^k(t) & , if\ arc(i,j) \in T^k(t) \\ 0 & , otherwise \end{cases} \qquad (3)$$

Where *Q* is an application-specific constant, *m* is the number of ants, ρ is evaporation rate, A represents all arcs of the problem‘s construction graph, $C^k(t)$ is the overall cost function of tour $T^k(t)$ constructed by the k^{th} ant at the t^{th} iteration, and $T^k(t)$ is the set of all arcs visited by ant k at the iteration t.

V. APPLICATIONS

Ant colony optimization has been applied to solve various problems varying from quadratic assignment to fold protein or routing vehicles and a lot of methods derived from this has been applied to dynamic problems in stochastic problems, real variables, multi-targets parallel implementations and multi-targets [10]. It has also been used to produce near-optimal. The following is the list of few applications of ACO.

i. The travelling salesman problem
ii. NP-hard combinatorial optimization problems
iii. Routing in telecommunication networks
iv. Scheduling problems
v. Vehicle routing problem
vi. Data mining
vii. Job scheduling in aluminum foundry
viii. Bioreactors optimization
ix. Pickup and delivery problems
x. Space–planning
xi. Flow manufacturing

These were the few applications of ACO which can be guide to understand ACO better and apply it in different areas.

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VI. TRAVEL SALESMAN PROBLEM EXPLAINED

When apply ACO to the TSP, consider the construction graph defined by the set of cities which are the set of vertices of the graph. In the TSP movement from any given city to any other city is possible; the construction graph is fully connected so the number of vertices is equal to the number of cities. The lengths of the edges between the vertices are set proportional to the distances between the cities represented by these vertices and pheromone values and heuristic values are associated with the edges of the graph. Pheromone values are modified at runtime and represent the entire experience of the ant colony on the other hand heuristic values are problem dependent values that, in TSP these are set to be the inverse of the lengths of the edges [11].

Then the solution is constructed by the ant as follows. Each ant starts from a randomly selected city represented by vertex of the construction graph. Then, it moves along the edges of the graph at each construction step. Memory of its path is stored by ant, and in subsequent steps it chooses among the edges that do not lead to vertices that it has already visited. Once ant has visited all the vertices of the graph it has constructed the solution. Edges are chose probabilistically by ant to follow among those that lead to yet unvisited vertices. The probabilistic rule is biased by pheromone values and heuristic information. The pheromone and the heuristic value associated to an edge are directly proportional to the probability an ant will choose that particular edge. The pheromone on the edges is updated, once all the ants have completed their tour. Each pheromone values is initially decreased by a certain percentage. An amount of additional pheromone proportional to the quality of the solutions to which it belongs (there is one solution per ant)is received by each edge.

Until a termination criterion is satisfied this procedure is repeatedly applied.

VII. CONCLUSION

It is clear that ACO is a powerful algorithm for solving complex combinatorial problems and can be used in future problems also and few modifications in it can help in solving even more complex problems. This model has been stepping stone for understanding and formulation of other models in swarm intelligence and its applications.

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