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Review Article

Ant-Based System: Overviews, modifications, and applications from 1992 to 2022

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ABSTRACT

The complexity of real-world problems motivated the researchers to innovate efficient problem-solving techniques. Generally, natural-inspired, bio-inspired, metaheuristics-based evolutionary computation, and swarm intelligence algorithms have been frequently used for solving complex, real-world optimization and non-deterministic polynomial hard (NP-Hard) problems due to their ability to adjust to a variety of conditions. This paper shows an overview of swarm-based algorithms based on Ant behavior. The first algorithm that inspired Ant behavior in the search for food sources was developed in 1992 and tested in solving the TSP problem. Ant Colony Optimization (ACO) is a metaheuristic inspired by some Ant species' pheromone trail laying following behavior. Artificial Ant in ACO is a stochastic solution construction process that uses (artificial) pheromone information that is modified depending on the Ant's search experience which is possibly accessible in heuristic information to generate solutions for problems. Notable research has been gained since the proposal of the Ant system. These contribute to the creation of high-performance algorithmic variants of a generic algorithmic framework for ACO, its successful application to a wide range of computing difficult problems, and the theoretical understanding of its properties.

KEYWORDS
Ant Based System, Ant Colony Optimization, metaheuristic, optimization, swarm intelligence

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INTRODUCTION

Optimization has recently emerged as one of the most intriguing applications for real-world issues. Real-world problems can have single or multiple objectives; in general, the optimization technique attempts to minimize an objective function for any real-world problem. Swarm Intelligence (SI) includes several optimization techniques. Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and artificial bee colony (ABC) algorithms are the most well-known algorithms of Swarm intelligence that are widely used for solving various optimization problems (Almufti, 2015).

Ant Colony Optimization algorithm (ACO) is a swarm intelligence (SI) field method that was first represented in 1992 by Marco Dorigo (Dorigo, 1992) in his PhD thesis as a nature-inspired metaheuristic for solving hard combinatorial optimization (CO) problems. Later in 1997, Dorigo and Gambardella published a developed algorithm Ant Colony System (ACS) (Dorigo & Gambardella, 1997). One year later, in 1998, Dorigo presented Ant Colony Optimization algorithms (ACO) for the first time at a conference (Asaad & Abdulnabi, 2018). Ant system methods generally and specifically Ant colony optimization over 30 years ago from 1992 to 2022 have been adapted to solve many optimization problems in real-life situations (Blum, 2005). This paper is an attempt to review the ACO algorithm and its proposed applications which help the researcher in the future to apply it in other new and promising fields of application such as path planning and path following control of autonomous underwater vehicles.

Ant Colony Optimization (ACO)

Marco Dorigo and colleagues introduced the first ACO algorithms in 1992 (Almufti, 2015). The development of these algorithms was inspired by the observation of ant colonies. Ants are social insects. They live in colonies and their behavior is governed by the goal of colony survival rather than being focused on the survival of individuals (Dorigo, 1992). The behavior that inspired ACO is the ants' foraging behavior, and in particular, how ants can find the shortest paths between food sources and their nest. When searching for food, ants initially explore the area surrounding their nest randomly. While moving, ants leave a chemical pheromone trail on the ground. Ants can smell pheromones. When choosing their way, they tend to choose, in probability, paths marked by strong pheromone concentrations. As soon as an ant finds a food source, it evaluates the quantity and the quality of the food and carries some of it back to the nest. During the return trip, the number of pheromones that an ant leaves on the ground may depend on the quantity and quality of the food. The pheromone trails will guide other ants to the food source. It has been shown by (Almufti, Marqas, Othman, & Sallow, 2021) that the indirect communication between the ants via pheromone trails known as stigmergy enables them to find the shortest paths between their nest and food sources. This is explained in an idealized setting in Figure 1.

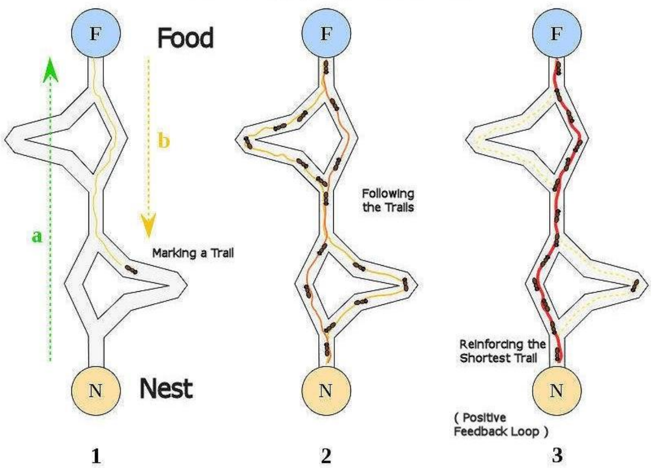

Figure 1. Ant searching behavior

The traveling salesman problem (TSP) is an important factor in testing and improving the Ant System (AS) algorithms and algorithms that are based on the behavior of Ant (Almufti, 2015). The first appearance of the Ant System by Marco Dorigo in 1992 was tested on the traveling salesman problem (Dorigo, 1992).

Traveling Salesman Problem (TSP)

TSP is an NP-hard problem in combinatorial optimization (Almufti, Marqas, Othman, & Sallow, 2021). Given a set of cities in which every city must be visited once only and return to the starting city for completing a tour such that the length of the tour is the shortest among all possible tours (Blum, 2005). In general, there are two different kinds of TSP, Symmetric TSP (STSP) and Asymmetric TSP (ATSP). The number of tours in the ATSP is (n-1), Whereas it is (n-1)!/2 in STSP for n cities. Formally, the TSP is a complete weighted graph G (N, A) where N is the set of cities that must be visited, and A (i, j) is the set of arcs connecting the cities (Almufti, 2015). The length between the city Ai and Aj can be represented as dij. Thus the optimal (minimum length) tour to the TSP can be found as shown below in Eq.1.

$$Btour = \left(\sum_{i=1}^{n-1} d_{p(i)\,p(i+1)}\right) + d_{p(n)\,p(1)} \qquad (1)$$

Where p is a probability list of cities with minimum distance between the city (pi and pi+1) (Almufti S. M., 2015)

ACO algorithm

ACO algorithm uses TSP an agent (Artificial ant) which is equal to the number of cities of TSP (M ==N, M number of an ant for N city), each ant makes a solution tour, initially, all ants locate at a city randomly, then every ant chose the next city upon a probability-based function to depend on both pheromone trail accumulated on edge and heuristic value, the formula used for choosing next city called random proportional rule (2), shows the probability of ant (k) that locate at the city (i) to visit the city (j).

$$P_{ij}^{k} = \frac{[\tau_{ij}]^{\alpha}.[\eta_{ij}]^{\beta}}{\sum_{1\in\mathcal{N}_i^k}[\tau_{ij}]^{\alpha}.[\eta_{ij}]^{\beta}} \quad , \text{if } j \in \mathcal{N}_i^k \qquad (2)$$

Where (α and β) are variables that determine the influence of pheromone trail and heuristic information, where α is a parameter to regulate the influence of τ_{ij} and β is a parameter to regulate the influence of η_{ij}, (α and β) have effect in the process of choosing next city as shown below.

- $\alpha < \beta$ The closet city is more likely to be chosen.
- $\alpha > \beta$ The arcs that have more pheromone intensity are more likely to be use.
- $\alpha = 0$, heuristic value uses for the choosing without pheromone.
- $\beta = 0$, pheromone uses for the choosing without heuristic value, which may cause poor result.

$$\eta_{ij} = 1/d_{ij} \qquad (3)$$

(η_{ij}) is a priori available heuristic value, (dij) is the distance between cities (i and j), (τ_{ij}) is the pheromone trail matrix, and ($\mathcal{N}_i^k$) is the set of the neighborhood that ant (k) haven't visit them yet. The probability that ant (k) choose arc (i, j) increase with the value pheromone trail (τ_{ij}) and heuristic value (η_{ij}).

In this thesis we uses ($\alpha = 1$ and $\beta = 2$), the initial value of pheromone matrix usually set to a small value which is greater than zero.

$$\textbf{for all } (i,j) \Leftrightarrow \tau_{ij} = \tau_0 \text{ , } \textbf{where } \tau_0 > 0 \qquad (4)$$

Ants chose the city which contain larger amount of pheromone on the connecting edges between the current city and next one. Each ant after adding new city to its tour makes a local pheromone update (5), by adding the $\Delta\tau_{ij}$ to the old τ_{ij}

$$\tau_{ij}new = \tau_{ij}old + \Delta\tau_{ij} \qquad (5)$$

Where the value of $\Delta\tau_{ij}$ can be found as shown in (6), $\Delta\tau_{ij}$ changes according to the length (L_k) tour (7)

$$\Delta\tau_{ij} = \sum_{k=1}^{m} \Delta\tau_{ij}^{k} \qquad (6)$$

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{L_k}, & \text{if ant } k \text{ uses arc (ij)} \\ 0 & \text{otherwise} \end{cases} \qquad (7)$$

Where τ_{ij} is the pheromone trail on the arc (ij), m is the number of ants, and $\Delta\tau_{ij}$ is the summation of change in the $\Delta\tau_{ij}^{k}$, which is equal to a constant value (Q) over the current length of the tour constructed by ant (k), in this thesis we use value (Q=1). The process of pheromone trail update continues until all ant complete their tour by visiting all cities and returning to the start city, after all, ants terminate the construction of the tour followed by pheromone evaporation (8) and a global pheromone update (4) for the shortest tour. The shortest tour will have the greatest amount of pheromone. Pheromone evaporation reduces the amount of pheromone in an arc which makes ants follow one path.

$$\tau_{ij}new = (1 - \psi).\, \tau_{ij}old \qquad (8)$$

Whereas $(0 < \psi < 1)$ is a constant quantity used for reducing pheromone trail, here we used ($\psi = 0.5$) that decrease τ_{ij} value by 0.5 which iteratively lead to disappear pheromone trail in unused arc. Figure 2 shows ACO Pseudo-code and Figure 3 shows ACO flowchart.

```
Initialize
Loop
      Each ant is positioned on a starting node
      Loop
            Each ant applies a state transition   rule to incrementally
            build a solution and a local pheromone updating rule
      Until all ants have built a complete solution
      A global pheromone updating rule is applied
Until end condition
```

Figure 2. ACO Pseudo-code

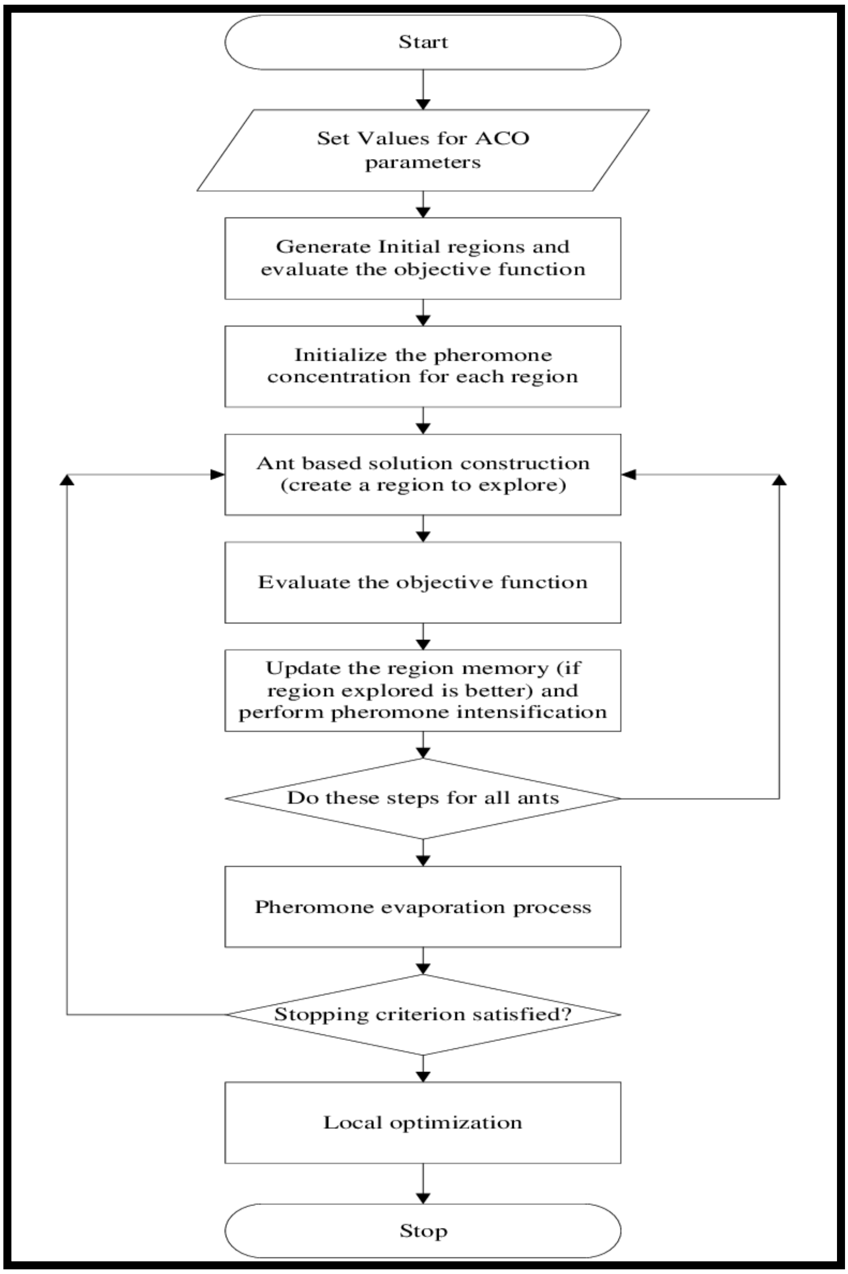

Figure 3. ACO flowchart

Modifications of Ant based optimization algorithm

Generally, all the metaheuristics algorithms after their first appearance undergo many modifications and improvements so that they can be used to solve various problems (Almufti, 2019). 30 years from the first appearance of Ant based optimization algorithm in 1992. To meet the demands of real-world problems many modifications have been applied to the original ACO to improve the performance of the proposed algorithm. In this section, some of the modifications and improvements of the ACO algorithm are listed and arranged according to the development year, as shown in Table 1.

Table 1. Ant based optimization algorithm modifications

Year	Scientist Name	Modification
1992	M. Dorigo	Proposed the ant system in his doctoral thesis (which was published in 1992). A technical report extracted from the thesis and co-authored by V. Maniezzo and A. Colorni was published five years later.
1995	Gambardella and Dorigo	Proposed ant-q, the preliminary version of ant colony system as first extension of ant system.
1996	Gambardella and Dorigo	Proposed ant colony system.
1997	Dorigo and Gambardella	Proposed ant colony system hybridized with local search.
1997	Schoonderwoerd and his colleagues	Published an improved application to telecommunication networks.
1998	Dorigo	Dorigo launches first conference dedicated to the ACO algorithms.
1998	Stützle	Proposes initial parallel implementations.
1999	Gambardella, Taillard and Agazzi	Proposed macs-vrptw, first multi ant colony system applied to vehicle routing problems with time windows.
1999	Bonabeau, Dorigo and Theraulaz	Publish a book dealing mainly with artificial ants.
2000	M. Dorigo , G. Di Caro et T. Stützle,	Special issue of the Future Generation Computer Systems journal on ant algorithms.
2000	Hoos and Stützle	Invent the max-min ant system.
2000	Gutjahr	Provides the first evidence of convergence for an algorithm of ant colonies.
2001	Iredi and his colleagues	Published the first multi-objective algorithm.
2002	Bianchi and her colleagues	Suggested the first algorithm for stochastic problem.
2004	Dorigo and Stützle	Publish the Ant Colony Optimization book with MIT Press.
2004	Zlochin and Dorigo	Show that some algorithms are equivalent to the stochastic gradient descent, the cross-entropy method and algorithms to estimate distribution.

2005	M. Zlochin, M. Birattari, N. Meuleau, et M. Dorigo	First applications to protein folding problems.
2012	Prabhakar and colleagues	Publish research relating to the operation of individual ants communicating in tandem without pheromones, mirroring the principles of computer network organization. The communication model has been compared to the Transmission Control Protocol.
2015	Saman M. Almufti	Proposed U-TACO powered by GDA and 2-OPT for solving TSP.
2016	Zaidman, Daniel; Wolfson, Haim J	First application to peptide sequence design.
2017	Mladineo, Marko; Veza, Ivica; Gjeldum, Nikola	Successful integration of the multi-criteria decision-making method PROMETHEE into the ACO algorithm (HUMANT algorithm).
2022	Saman M. Almufti	Combined ACO with Canny for detecting image edges.

Ant-based algorithms applications

Ant system methods generally and specifically Ant colony optimization over years ago has been adapted to solve many optimization problems in real-life situations such as Mobile and Wireless Sensor Networks (WSNs), vehicle routing problem, Network Security, Computer Architecture, Data Mining, and many other problems (Stutzle, Lopez-Ibznez, & Dorigo, 2011), (table 2-1) shows some applications of ant system in general and ACO in various field.

Table 2. Summarize GWO applications in a different field

Problem/Application	Algorithm Name	Authors
Traveling salesman	AS	Dorigo, Maniezzo & Colomi
	Ant-Q	Gambardella & Dorigo
	ACS & ACS-3-opt	Dorigo & Gambardella
	MMAS	Sttitzle & Hoos
	ASrank	Bullnheimer, Hartl & Strauss
	BWAS	Cordon, et al.
	U-TACO	Saman M. Almufti
Quadratic assignment	AS-QAP	Maniezzo, Colomi & Dorigo
	HAS-QAPa	Gambardella, Taillard & Dorigo
	MM AS-QAP	Sttitzle & Hoos
	ANTS-QAP	Maniezzo

	AS-QAPb	Maniezzo & Colomi
Scheduling problems	AS-JSP	Colomi, Dorigo & Maniezzo
	AS-FSP	Sttitzle
	AC S-SMTTP	Bauer et at
	AC S-SMTWTP	den Besten, Stlitzle & Dorigo
	ACO-RCPS	Merkle, Middendorf & Schmeck
Vehicle routing	AS-VRP	Bullnheimer. Hartl & Strauss
	HAS-VRP	Gambardella, Taillard & Agazzi
Connection-oriented network routing	ABC	Schoonderwoerd et at
	ASGA	White, Pagurek & Oppacher
	AntNet-FS	Di Caro & Dorigo
	ABC-smart ants	Bonabeau et at
Connection-less network routing	AntNet & AntNet-FA	Di Caro & Dorigo
	Regular ants	Subramanian, Druschel & Chen
	CAF	Heusse et at
	ABC-backward	van der Put & Rothkrantz
Sequential ordering	HAS-SOP	Gambardella & Dorigo
Graph coloring	ANTCOL	Costa & Hertz
Shortest Common supersequence	AS-SCS	Michel & Middendorf
Frequency assignment	ANTS-FAP	Maniezzo & Carbonaro
Generalized assignment	MMAS-GAP	Ramalhinho Lourenco & Serra
Multiple knapsack	AS-MKP	Leguizamon & Michalewicz
Optical networks routing	ACO-VWP	Navarro Varela & Sinclair
Redundancy allocation	ACO-RAP	Liang & Smith
Constraint satisfaction	Ant-P-solver	Solnon
Image Edge Detection	ACO-Canny	Saman M. Almufti

CONCLUSION

Ant system methods belong to the swarm-based metaheuristic algorithm the first algorithm that used ant behavior was proposed in 1992 by Marco Dorigo et al. (Almufti, 2022). After its appearance, many modifications have been proposed for it and it has been adept to solve various problems in different fields. This paper firstly addressed this overviewed the Ant-based algorithm and then presented some of its modifications were presented in detail, finally some of its applications considering parameter tuning, different approaches for feature selection and classification, and then hybridized forms were discussed. The applications in different fields were discussed including engineering medical, power dispatch, reliability optimization, etc.

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