A New Ant Colony Algorithm for Traveling Salesman Problem with Negative Weight Edges

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Article Info
Page Number: 1560-1565
Publication Issue:
Vol. 72 No. 1 (2023)

Article History
Article Received: *15 October 2022*
Revised: *24 November 2022*
Accepted: *18 December 2022*

Abstract

We propose a new Ant Colony Algorithm (ACO) which is a Hybrid combination of ACO with Simulated Annealing (SA). We call this algorithm the ACOSA algorithm. This new algorithm has been used to solve the Traveling Salesman Problem with some Negative Weight Edges (TSPne).

We compare the original ACO on TSPne with ACOSA and report their performance. It is observed that the new ACOSA algorithm gives more optimal results as compared to ACO on TSPne.

Keywords: Nature Inspired Optimization, Ant Colony Algorithms, Traveling Salesman Problem, Simulated Annealing.

1. Introduction

One of the fundamental concepts in Computer Science are that some problems are unsolvable through algorithms and computers. These problems are called uncomputable or undecidable Problems. Another fundamental concept is that some problems have no efficient algorithms to solve them. These problems are called as intractable problems. Some optimization problems are NP-Hard (Intractable) and that cannot be solved efficiently through algorithms.

Thus, Computer Scientists took inspiration from Nature. Nature was discovered to be a source of many tricks. These tricks could be used to find sub-optimal solutions for NP-Hard optimization problems. Many nature inspired algorithms have been proposed in past decades. Ant Colony Optimization is one example. One of the original tricks to be discovered by computer scientists was that ants leaving pheromone trails to reinforce good solutions [5,7,8,9].

Ant Colony Optimization (ACO) was the earliest metaheuristic proposed in 1991 by Marco Dorigo [5] derived from observing the foraging behavior of real ants found in nature. Dorigo published his groundbreaking work on Ant Colonies in 1999 [7], 2004 [8], and 2006 [9]. ACO was inspired by observing the foraging behavior of real ants. The ants reinforce good solutions through making strong pheromone trails. ACO is used to solve many NP-Hard Optimization problems such as Traveling Salesman Problem (TSP).

Traveling Salesman Problem (TSP) is a classic problem in Mathematics and Computer Science; originally formulated in 1800s by W R Hamilton who was an Irish Mathematician. In the era between 1940s and 1960s many mathematicians and computer scientists worked seriously on this problem and produced results [1].

Number of papers have been presented to solve TSP by using ACO [1, 2, 3, 4, 6, 10, 11, 12, 14, 15, 16, 18, 19, 20, 21, 22, 23, 24]. Recently authors have used ACO to solve Multimodal optimization (MMO) TSP problem [10] and Dynamic TSP problem [15,19]. In [15] Yang has given improved ACO for TSP using modified updating strategy for Pheromone. Some authors use Simulated Annealing based ACO to solve Traveling Salesman Problem, see [13, 17]. In [16] author has used Ant Colony System to solve generalized Traveling Salesman Problem with Non-Negative Edges with new correction rules. In our knowledge no paper has been presented for negative edges in TSP particularly. Here we deal with Traveling Salesman Problem with Negative Weights. It is worth remembering that some algorithms do not work on Graphs with Negative Weights, such as Dijkstra's Algorithm.

In this paper, we create a new variation of ACO by using concept of Simulated Annealing algorithm. In ACO-Simulated Annealing algorithm the ant goes in the wrong direction with some non-zero probability. This concept has been used in our new proposed variant of ACO, called ACOSA, where ants favor the worse paths which is decided by the value of a random variable crossing a threshold.

After creating this new variant ACOSA, codes for ACO and ACOSA have been run on TSP problem in which the graph had some negative weight edges. Experiments have been conducted with 9% edges as negative weights in the graph.

A real-life scenario of TSP with negative weights that can be used to justify its utility is to imagine a vehicle which travels on road. For some routes it might earn profit by selling goods. For other routes if goods are not sold; thus, instead of profit the vehicle incurs a loss due to fuel consumption (the loss is indicated by the negative weight of that edge). This kind of example can be seen in the situations e.g. recently due to Covid lockdown air flights could not travel to many destinations and showed huge revenue loss. If the loss is negative that can be interpreted as profits. Therefore, the minimum TSP path minimizes loss and thereby maximizes profit. Though since TSP is a minimization problem, we can represent profits by negative edges and losses by positive edges.

Through experimental results we observed that our ACOSA algorithm works more optimally than original ACO on TSPne. The whole paper is divided into four sections. The First section is Introduction. Second section gives the Problem Statement and the Methodology to be used. In the Third section the Experimental Results have been shown. The Fourth section is Conclusion and Future Directions.

2. Problem Statement and Methodology

In this section, we explain the methodology which has been used for ACOSA on TSPne.

2.1 Ant Colony Optimization

Ant Colony Optimization is a probabilistic technique for solving computational problems which is done through finding good paths in graphs. The inspiration is derived from ants which lay down pheromone trails to reinforce good solutions.

The first step in Methodology is to program Ant Colony Optimization. Given below is the block diagram for ACO (Fig. (1)).

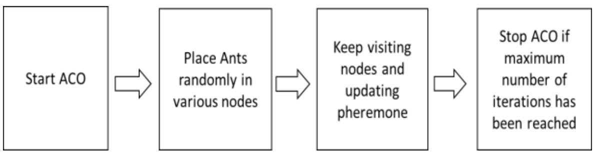

Figure 1. Block Diagram of ACO

All the equations in ACO were coded and implemented as a computer program. The following equation exhibits the Pheromone Equation:

$$p_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha}.[\eta_{ij}]^{\beta}}{\sum_{l\in j_{i}^{k}}[\tau_{il}(t)]^{\alpha}.[\eta_{il}]^{\beta}} \tag{1}$$

where τ_ij represents the pheromone trail and η_ij represents the visibility between the two nodes, while α and β are the parameters that can be adjusted to control the relative weight of the trail intensity and the trail visibility.

The following equation describes the pheromone updated rule

$$\Delta\tau_{ij}(t+n) = \rho\tau_{ij}(t) + \Delta\tau_{ij} \tag{2}$$

ρ, $0 \leq \rho \leq 1$ is the evaporation constant, which determines how fast the pheromone will evaporate. Next equation defines the sum on all m ants of the pheromone deposited by each ant on edge (ij)

$$\tau_{ij} = \sum_{k=1}^{m} \Delta\, \tau_{ij}^{k} \tag{3}$$

The amount of trail $\Delta\tau_{ij}^{k}$ can be calculated by using the formula

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{Q}{L_k},\ if\ k^{th}\ ant\ use\ edge(i,j) \\ \qquad in\ its\ tour \\ 0, \qquad otherwise \end{cases} \tag{4}$$

Above equation describes the update of pheromone where Q is a constant and L is the length of tour. Thereby the update is inversely proportional to the length of the tour followed by kth ant.

2.2 TSP

The equations of ACO have been used to find optimal solution of travelling salesman problem with negative edges

$$Min\ D = \sum_{i=1}^{n-1} d(i,(i+1) + d(n,1) \tag{5}$$

where D represents the sum of the TSP tour which is a total of the individual $d(i,j)$ that denotes the distance from i^{th} – to j^{th} vertex.

2.3 Simulated Annealing

Simulated Annealing is basically a probabilistic search technique which is inspired by the analogy of metals freezing and cooling into a minimum energy state. It is used in many optimization techniques for combinatorial optimization [13]. One of the aims achieved by SA is to escape from local optima and out-turn to delay convergence.

2.4 ACOSA

In this section of methodology, we describe how Ant Colony Optimization can be combined with Simulated Annealing to create a new variant.

In Simulated Annealing the ball rolls in the wrong direction with a non-zero probability. This concept has been applied to Ant Colony Optimization by adding if condition to the pheromone equation code which depends on a random variable.

By modifying the code, we are able to create a new version of ACO called ACOSA (Fig. 2) where the ant goes in the wrong direction with some non-zero probability.

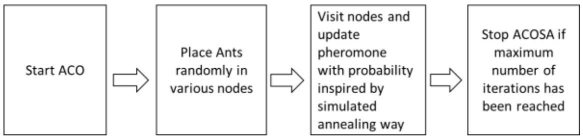

Figure 2. Block diagram of ACOSA

In order to verify ACO and ACOSA on traveling salesman problem with negative weights, we did experiment with random symmetric graphs with number of vertices ranging from 7 to 12. The results of these experiments are reported in the experimental results section below.

3. Experimental Results

The new ACOSA algorithm is a hybrid of ACO with SA and directs the ants to choose the wrong direction with finite probability. This section presents a comparison between proposed modified ACO (called ACOSA) and the original ACO on graphs.

We performed the original ACO algorithm on TSP graphs with 9% of edges randomly being assigned negative weights. The graphs in the experiments contain 7 to 12 vertices. We then executed ACOSA algorithm on the same data and recorded the performances. The results are summarized in table below.

Table 1. Comparison of the optimal cost of TSP route computed by ACO, ACOSA with SA rate 0.2 and ACOSA with SA rate 0.9.

n	ACO(S=0.09)	ACOSA(SA rate =0.2)	ACOSA(SA rate =0.9)
7	-61.51	-247.72	-155.13
8	-205.54	-373.29	-258.05
9	-242.66	-299.68	-248.23
10	-23.399	-286.76	-218.02
11	-124.47	-212.48	-99.924
12	28.835	-133.88	-36.86

In the above table n represents the number of vertices in the graph. 9% of the edges in the graph have been chosen negative. The entries in the second column shows the results for the ACO on graphs with respective vertices. In third and fourth columns ACOSA with SA rate of 0.2 and SA rate of 0.9 has been computed. These entries give the optimal cost of TSPne path. We can see the best performance is when the SA rate is 0.2, in ACOSA. Table 1 shows that ACOSA performs better than ACO on these graphs.

Table 2. Comparison of running times of ACO, and ACOSA with SA rate 0.2 and ACOSA with SA rate 0.9. (with 9% negative edges)

N	ACO(S=0.09)	ACOSA(SA rate =0.2)	ACOSA(SA rate =0.9)
7	17.7234	18.8088	19.5211
8	20.153	21.0364	20.908
9	23.1622	24.3539	24.1088
10	24.304	26.3935	26.3731
11	27.2074	33.8354	30.3371
12	29.7759	31.7999	31.7999

Table 2 displays the time complexities of the original ACO and ACOSA. It is observed that time taken by our new algorithm is very close to the time taken by the original ACO.

4. Conclusion

In this paper we proposed a new algorithm ACOSA which is a hybrid of Ant Colony with Simulated Annealing. The results on experiment shows that ACOSA has a better cost complexity than ACO when run on TSP graphs with negative edges.

As per experimental results shown in Table 1 and Table 2 we conclude that our new algorithm performs better in terms to find optimal path. Though it is observed that the time complexities of ACOSA is almost similar and slightly on the higher side to the ACO.

The proposed work can be extended to other Nature Inspired Techniques, such as Swarm Intelligence, Artificial Immune System, Artificial Neural Computation, & Evolutionary Computation, which can be made hybrid in a similar manner with Simulated Annealing. By the experimental results it might be observed whether the time complexity is an improvement on the ACO and ACOSA with an improvement on cost complexities as well.

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