



ACO for Capacitated Vehicle Routing Problem

Charul Dhawan*, Maneela Bhugra

Department of Computer Science & DCRUST
India

Parul Dhawan

Department of IT & MDU
India

Abstract— *Ant Colony Optimization (ACO) is a paradigm for designing metaheuristic algorithms for combinatorial optimization problems. In this paper we will use ACO for solving Vehicle Routing Problem (VRP). The core objective is to minimize the number of vans to do the task and find out the best optimal route using ACO. In this paper, we will also discuss about the various variants of VRP. Finally, computational results are shown and compared with the results before applying the approach.*

Keywords— *VRP, ACO, metaheuristic, pheromone, CVRP.*

I. INTRODUCTION

A typical vehicle routing problem (VRP) aims to find a set of tours for a number of vehicles starting from a depot serving a lot of customers and return to the depot without exceeding the capacity constraints of each vehicle at minimum cost. Since the customer combination is not restricted to the selection of vehicle routes, VRP is considered as a combinatorial optimization problem where the number of feasible solutions for the problem increases exponentially with the number of customers increasing [1]. Heuristic algorithms such as simulated annealing (SA), genetic algorithms (GAs), neural network system and ant colony optimization are widely used for solving the VRP. Among these heuristic algorithms, ant colony optimizations (ACO) are new optimization methods [2] which simulate the food-seeking behaviors of ant colonies in nature. The flexibility of the ACO metaheuristic allowed its application to many vehicle routing problems where fleet of vehicles with the limitations on customer accessibility, time windows, and the order imposed by pick-ups and deliveries complicate the problem formulation. The objective of this paper is to describe how the ant colony optimization can be used to solve the capacitated vehicle routing problem.

The paper is structured as follows: first we outline the VRP with its variants; then we introduce ACO, providing an overview of the ACO and its biological analogy, followed by our proposed system for solving cvrp. Finally, we will apply our algorithm to a real world problem and will compare the results. For more information on paper guidelines, please contact the journal publications committee as indicated on the journal website. Information about final paper submission is available from the conference website.

II. VRP AND ITS VARIANTS

The vehicle routing problem is one of the main combinatorial optimization problems that many heuristics are compositing to solve it. The basic vehicle routing problem [3] (VRP) consists of a number of customers, each requiring a specified weight of goods to be delivered. Vehicles dispatched from a single depot must deliver the goods required, and then return to the depot. Each vehicle can carry a limited weight and may also be restricted in the total distance it can travel. Only one vehicle is allowed to visit each customer. The problem is to find a set of delivery routes satisfying these requirements and giving minimal total cost. In practice, this is often taken to be equivalent to minimizing the total distance travelled, or to minimizing the number of vehicles used and then minimizing total distance for this number of vehicles.

The variants of VRP include: Capacitated VRP (CVRP), VRP with Time Windows (VRPTW), Dynamic VRP (DVRP), Open VRP (OVRP) and so on with different constraints [3,4].

A. Capacitated VRP:

The Capacitated Vehicle Routing Problem (CVRP) [4] is the basic version of the VRP. The name derives from the constraint of having vehicles with limited capacity. In the classic version of the CVRP, customer demands are deterministic and known in advance. Deliveries cannot be split, that is, an order cannot be served using two or more vehicles. The vehicle fleet is homogeneous and there is only one depot.

B. VRP with Time Windows:

In a Vehicle Routing Problem with Time Windows (VRPTW) the capacity constraint still holds and each customer i is associated with a time interval called the time window, and with time duration, the service time. Time windows can be set to any width, from days to minutes, but their width is often empirically bound to the width of the planning horizon. The presence of time windows imposes a series of precedence on visits, which make the problem asymmetric, even if the distance and time matrices were originally symmetric.

C. VRP with Pick-up and Delivery :

In VRP with pick-up and delivery [5] (VRPPD) a vehicle fleet must satisfy a set of transportation requests. The transport items are not originally concentrated in the depots, but they are distributed over the nodes of the road network.

A transportation request consists in transferring the demand from the pick-up point to the delivery point. These problems always include time windows for pick-up and/or delivery and also constraints that express the user inconvenience of waiting too long at the pick-up point and impose a limit on riding time.

D. Dynamic VRP:

When the service requests are not completely known before the start of service, but they arrive during the distribution process. This variant is called Dynamic Vehicle Routing Problem (DVRP) [5,6]. Since new orders arrive dynamically, the routes have to be replanned at run time in order to include them. Every driver has, at each time step, a partial knowledge about the remainder of his/her tour. Among possible applications of DVRP we find feeder systems, which typically are local dial-a-ride systems aimed at feeding another, wider area, transportation system at a particular transfer location.

E. Multi-Depot VRP:

The MDVRP extends the CVRP by allowing multiple depots. The SDVRP is another generalization of the CVRP in which one can specify that certain customers only can be served by a subset of the vehicles.

III. ANT COLONY OPTIMIZATION

All Ant colony optimization is a metaheuristic in which a colony of artificial ants cooperate in finding good solutions to difficult discrete optimization problems. ants use *pheromone trails* to communicate information regarding shortest paths to food. A moving ant lays some pheromone (in varying quantities) on the ground, thus marking a path with a trail of this substance. An isolated ant moves mostly randomly and when it detects a previously laid pheromone trail it can decide, with high probability, to follow it, thus reinforcing the trail with its own pheromone. The collective behavior that results is a form of autocatalytic behavior where the more ants follow a trail, the more attractive for other ants it becomes. The process is thus characterized by a positive feedback loop, where the probability with which an ant chooses a path increases with the number of ants that previously chose the same path.[7], The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph representing the problem to solve.

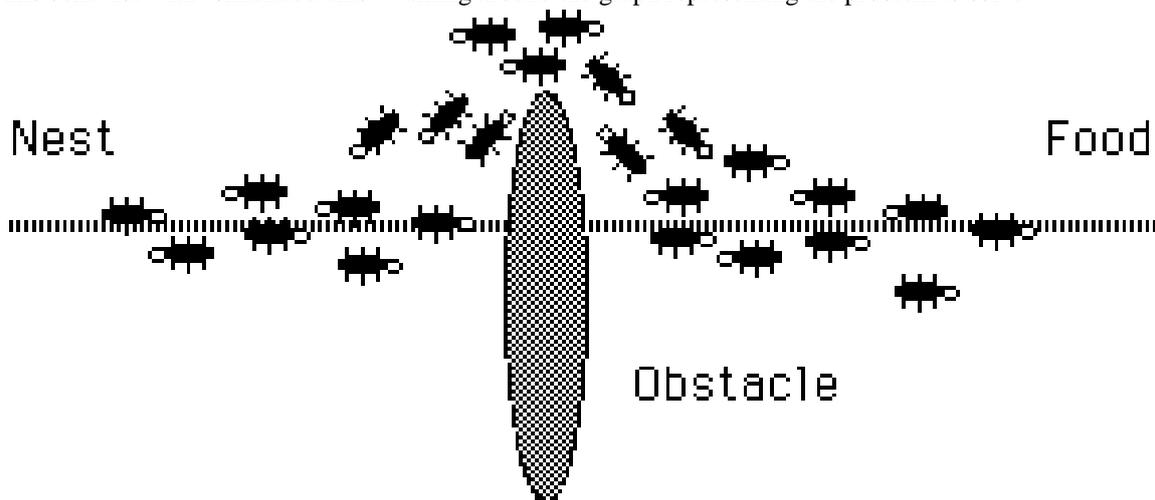


Fig1 Biological analogy of Ant colony optimization

When an ant completes a solution, during the construction phase, the ant evaluates the solution and modifies the trail value on the components used in its solution. This pheromone information will direct the search of the future ants.

IV. PROBLEM FORMULATION

We now present a mathematical formulation of the Capacitated Vehicle Routing Problem (CVRP) which is the most general version of the VRP. The CVRP is defined on a complete undirected network $G=(V, E)$ with a node set and an arc set E . Node 0 is a depot with m identical vehicles of capacity Q , m can be fixed a priori or left as a decision variable. Each other node $i > 0$ represents a customer with a non-negative demand q_i and each arc (i, j) has a non-negative travel distance $d_{ij}=d_{ji}$. [8]

V. PROPOSED WORK

The algorithm mainly consists of the iteration of these steps:

- Random deployment
- Reconnaissance
- Route Building
- Route Optimization

Step1: Random Deployment: In this step, firstly a virtual environment is created and the nodes are deployed. Information about deployed units like identification number and position will be kept in memory in form of list, so that can be accessed later on for further operations.

Step2:Reconnaissance: Reconnaissance phase will serve for collecting geographical data about deployed units in our world. We assume availability of scouting units / agents/ ants / bots. Process of find out pheromone Strength/ how Pheromone Strength is calculated Scouting unit will deploy H-units of probing matter at source position before leaving. This can be related to Hormones/Scent that is left by ant in actual world.Following steps are carried out:

- 1) H-units of probing matter are deployed at source node.
- 2) Scouting unit travels to destination node in a straight line.
- 3) And returns to source node in straight line without any delay or waiting time.
- 4) The amount of probing matter lost/ the no of units lost will provide scouting-unit information about distance between source and destination nodes.
- 5) This distance information is stored in list form for future references

Pheromone Strength = (units left initially – units found on arrival) / 2 (two - way journey)

Step3: Initial Route Building. : Approach focuses on covering all nodes with minimum agents and using an agent to its full capacity.

Algorithm:-

- While all nodes are not covered and agents are available for route building.
- Choose a free agent and start a new route. Select university as start point.
- While agent capacity is not full
- Choose node at minimum distance from current position and add to route. Set node as current position.
- When agent capacity is full add university as destination node and close route.

Step4: - Level 1 Route optimization – reordering nodes within a route to minimize total length of route.

A route consists of various nodes to be travelled in a specific order and hence total length of route can be determined. Greedy approach used for building route ensures the best node is chosen as next but the overall order in not controlled and may not be best.

Process of route - distance probing / distance calculation for a route.

- 1) H-units of probing matter are deployed at university node.
- 2) Agent unit will follow route and travel to nodes in given order.
- 3) And returns to university node without any delay or waiting time.
- 4) The amount of probing matter lost/ the no of units lost will provide Agent-unit information about total distance of current route with nodes in specific order.
- 5) This distance information is stored in list form for future references.

Now for optimization purpose the agent unit shuffle the order of nodes in the route and will re-probe the total distance of shuffled route, if the new distance is lesser than current order than shuffled route is saved into memory with its distance value else the shuffled route is discarded.

Algorithm for internal route optimization

- Load current order of nodes and total route distance.
- Shuffle order of nodes.
- Re-probe total route distance.
- If new distance is lesser, update memory with new order of nodes
- Else discard the shuffled route.

VI. RESULTS AND ANALYSIS

We are considering an example of a pizza corner where a number of customers are to be served and then the delivery boy has to return to the corner.

Firstly the nodes(customers) are deployed in a virtual environment.

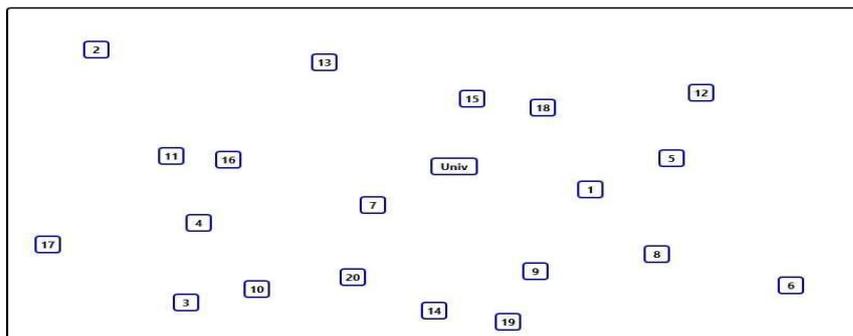


Fig2.Nodes deployed randomly

Initial Routes are calculated and marked with different colors. Following Routes are calculated

- Route 1 (Aqua) \Rightarrow U-7-20-14-19-U \Rightarrow (66+97+68+47+209=487)
- Route 2 (Purple) \Rightarrow U-15-18-1-5-U \Rightarrow (92+43+111+66+171=483)
- Route 3 (Brown) \Rightarrow U-9-8-6-12-U \Rightarrow (147+92+110+265+222=836)
- Route 4 (Cadet Blue) \Rightarrow U-13-16-11-4-U \Rightarrow (165+146+29+90+220=650)
- Route 5 (Light Green) \Rightarrow U-10-3-17-2-U \Rightarrow (224+45+131+262+342=1004)

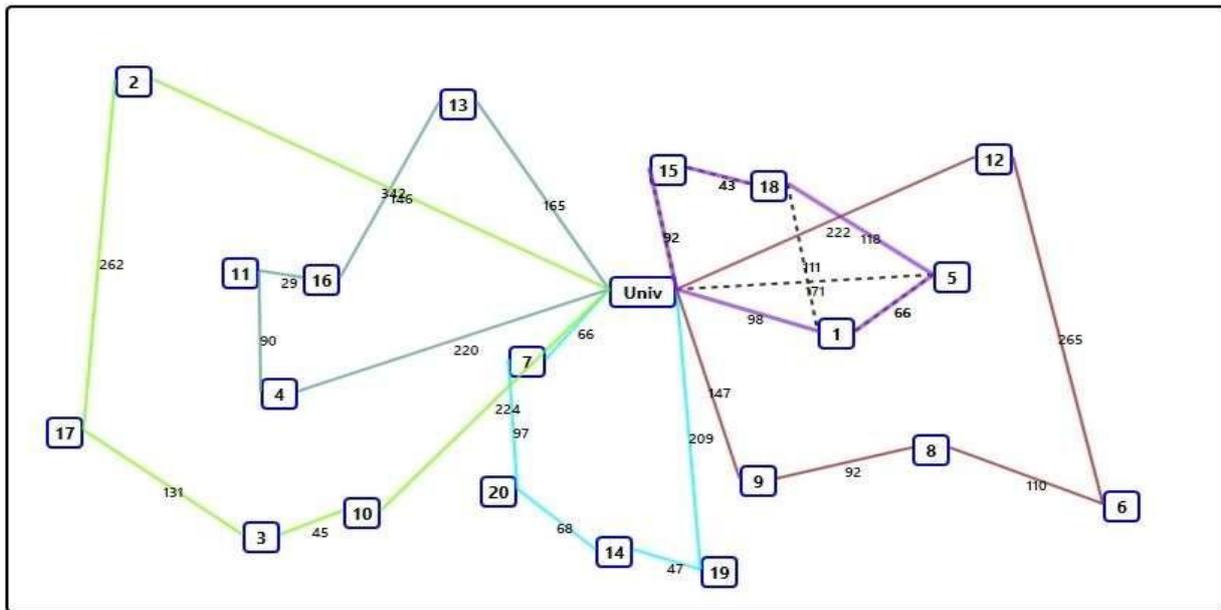


Fig3 Example 1 route calculation.

In the next step, we find shortest path with minimum agents to its full capacity.

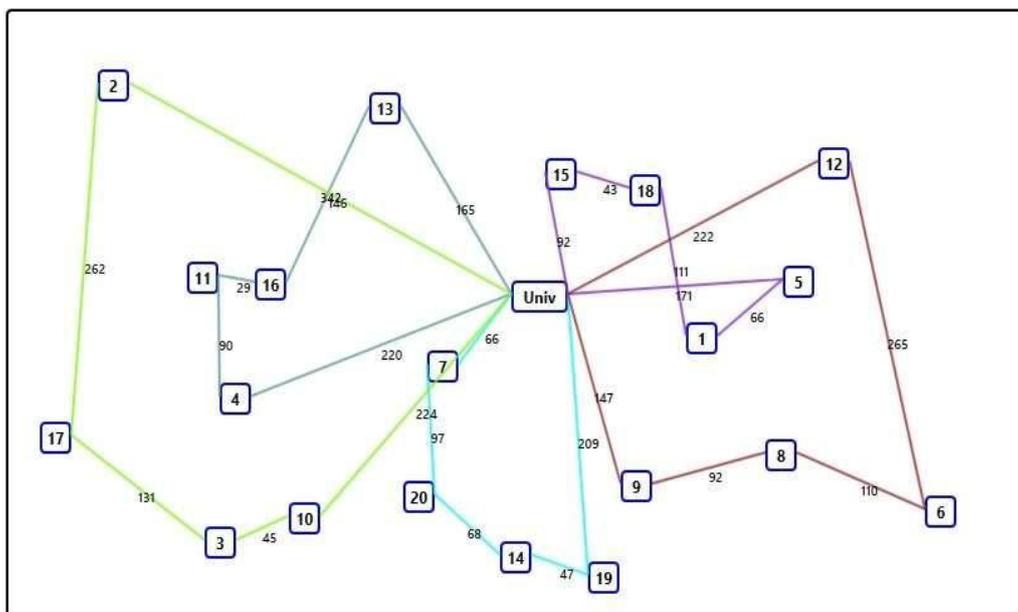


Fig 4. Example 1 step 4 Optimization

Level 1 Optimization is applied on all routes and improvement are noticed in route 2
 Before optimization (actual order)
 U-15-18-1-5-U \Rightarrow (92+43+111+66+171=483)
 After optimization (optimized order)

Paths 5-U (171) & 18-1 (111) are removed, while Paths 1-U (98) & 18-5(118) are added.

U-15-18-5-1-U => (92+43+118+66+98 = 417)

It is noticeable that a gain of (483-417=66) units has been made.

Thus the Route 2 will be updated to new order of U-15-18-5-1-U

Routes 1,3,4,5 remain unchanged.

Analysis: From the above results, we saw the our approach could successfully produced the desired results. Among the three proposed scenarios and their possible optimizations, the implemented optimization of Level 1 has produced noticeable results and can be marked as a successful optimization. Comparatively small amount of memory can is used for marking, allocation and calculations. And as per our objective, the optimal result was found at the minimum cost with minimum number of vehicles required.

VII. CONCLUSION

We concluded form the proposed work that the optimal route can be found using ACO metaheuristic. We discussed the variants of VRP. ACO is viable approach in dynamic scenarios and thus the best for finding optimal route in CVRP at minimum cost. We have also shown that the method we proposed is able to achieve good results on real problems as well.

REFERENCES

- [1] Bell, J.E., McMullen, P.R., 2004. Ant colony optimization techniques for the vehicle routing problem. *Advanced Engineering Informatics* 1 (8), 41–48.
- [2] Dorigo, M., Maniezzo, V., Colorni, A., 1996. Ant system: optimization by a colony of cooperating agents. *IEEE Transactions on Systems, Mans, and Cybernetics* 1 (26), 29–41
- [3] P. Toth “The Vehicle Routing Problem, chapter An Overview of Vehicle Routing Problems” SIAM, Society for Industrial and Applied Mathematics, Philadelphia, USA, 2000.
- [4] Tan, W.F., “Ant Colony Optimization for Capacitated Vehicle Routing Problem” *Journal of Computer Science* 8 (6): 846-852, 2012 ISSN 1549-3636.
- [5] NajmeZehraNaqvi et.al. “Review Of Ant Colony Optimization Algorithms On Vehicle Routing Problems And Introduction To Estimation-Based ACO” 2011 International Conference on Environment Science and Engineering IPCBEE vol.8 (2011) © (2011) IACSIT Press, Singapore.
- [6] Bell, J.E. and P.R. McMullen, 2004. Ant colony optimization techniques for the vehicle routing problem. *Adv. Eng. Inform.*, 18: 41-48. DOI: 10.1016/j.aei.2004.07.001
- [7] A.E. Rizzoli, · R. Montemanni, E. Lucibello ,L.M. Gambardella” Ant colony optimization for real-world vehicle routing problems From theory to applications” © Springer Science + Business Media, LLC 2007
- [8] Aziz Ezzatneshan” A algorithm for the Vehicle Problem” *International Journal of Advanced Robotic Systems, Vol. 7, No. 2 (2010)*