Volume 5, No. 6, July-August 2014
ISSN No. 0976-5697
International Journal of Advanced Research in Computer Science
REVIEW ARTICAL
Available Online at www.ijarcs.info

Review on Vehicle Routing Problem using Ant Colony Optimization

Charul Dhawan
Mtech (Research Scholar) Computer Science
SITM,Sonepat-131001(Haryana)

Prof.(Dr.)Vinay Kumar Nassa
Director Principal
SITM,Sonepat-131001(Haryana)

Ms.Maneela Bhugra
Asst.Professor(Computer Science)
SITM,Sonepat-131001(Haryana)

Abstract: Vehicle routing problem (VRP) concerns the transport of items from a depot to its number of customers using group of vehicles. VRP needs method to solve problem in terms of best route to service the customers. The solution must ensure that all the customers are served under the operational constraints and minimizing the overall cost. The solution can be obtained using one of the metaheuristic techniques Ant Colony Optimization (ACO). In Ant colony optimization a colony of artificial ants altogether find good solutions to difficult discrete optimization problems. It is not possible for each ant to find a solution to the problem under consideration which is probably a poor one, good-quality solutions can only emerge only if there is collective interaction among the ants. They act concurrently and independently and there, by their decision making process, finds the most efficient route. ACO helps in finding the best optimal path in vehicle routing as well. This paper presents a review on the application of ACO for solving VRP. The paper is mainly concerned with Capacitated VRP (CVRP) to explain the ACO optimization of VPR problem.

Keywords: VRP, ACO, Pheromone, metaheuristic, CVRP

I. INTRODUCTION

Vehicle routing problem is one of the main combinatorial optimization problems. Basic vehicle routing problem (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 at intended destination, and then return to the depot. Each vehicle can carry a limited weight and may also be restricted to the total distance to be travelled. Only one vehicle is allowed to visit each customer. The basic VRP is to route the vehicles, one route per vehicle, each starting and finishing at the depot, so that all customers are supplied with their demands and the total travelled cost is minimized. Moving a vehicle between the depot and the customers comes with a certain cost. A route is a sequence of visited customers by a certain vehicle, starting and ending at a depot. The goal of the Vehicle Routing Problem is to serve all customers, minimizing the total cost of the routes of all vehicles. An example is given in Figure 1.1.

The underlying structure of the VRP is a complete directed graph G(V,E) with cost matrix C:

a. $V = \{v_0, v_1, v_2 . . . v_n\}$ is a set of n+1 ($n \geq 1$) vertices. We distinguish the depot v0 and exactly n customers $\{v_1, v_2 . . . v_n\}$.
b. $E = \{(v_i, v_j) \mid 0 \leq i, j \leq n, i \neq j\}$ is the set of $|V| * (|V| - 1)$ (directed) edges (arcs) between the vertices, called the roads. If the distance between two vertices is identical in both directions, the restriction $i < j$ is added
c. $C = (c_{ij})$ is a matrix, where $c_{ij} \geq 0$ is the distance corresponding to edge (v_i, v_j); cii is always equal to 0. Also cij = $c(v_i, v_j)$. Depending on whether or not the VRP is symmetric, $c_{ij} = c_{ji}$. Also, the triangle inequality is generally assumed to hold here: $c_{ij} \leq c_{ik} + c_{kj}$ ($0 \leq i, j, k \leq n$).

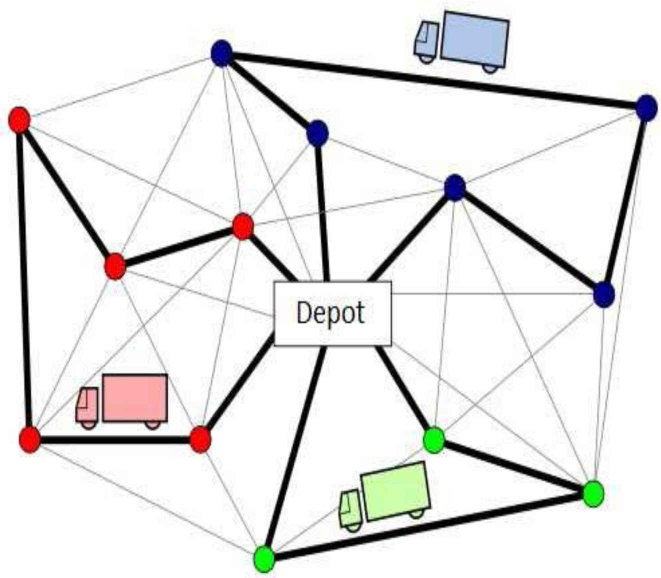

Figure 1: VRP with 13 customers and 3 vehicles.

The problem is to find a set of delivery routes satisfying these requirements and giving minimal total cost.

VRP is categorized on the basis of constraints as Capacitated VRP (CVRP), VRP with Time Windows (VRPTW), VRP with Pick-up and Delivery(VRPPD), Split Delivery Vehicle Routing Problem (SDVRP),Dynamic VRP (DVRP), Site-Dependent Vehicle Routing Problem (SDVRP) and Multi Depot Vehicle Routing Problem(MDVRP).

II. LITERATURE REVIEW

The Capacitated Vehicle Routing Problem (CVRP) is a well-known combinatorial optimization problem which is concerned with the distribution of goods between the depot and customers.

Meta-heuristics have become prominent approaches in tackling complex and multi-objective problems [3]. Recent examples include a bus driver scheduling problem and a resource constrained project scheduling problem [13]. What are known as metaheuristic techniques are tabu search, simulated annealing, genetic algorithm, evolutionary algorithm and Ant Colony Optimization.

This literature survey is based on analyzing ant colony optimization for solving capacitated vehicle routing problem. With the intension of finding the best optimal path in terms of distance and the total cost the research work is analyzed. This review shows brief working of the research works that are being carried out by various authors. Here are discussed some of the papers published related to the ACO approach and solving vehicle routing problem using ACO approach.

Bhanu Pratap Singh, Sohan Garg (2013) presented a characteristic study on Ant Colony optimization Algorithms for Routing Problems. This approach tried to maximize network lifetime by routing through paths, which used the least amount of energy relative to each node. In this research paper, ant based optimized routing algorithms such as ant net algorithm, mobile ant algorithm, adaptive swarm based routing algorithm to solve routing problems were also discussed.[1]

Majid Yousefikhoshbakht, Farzad Didehvar and Farhad Rahmati (2013) proposed a new modified version of the ant colony optimization (ACO) mixed with insert, swap and 2-opt algorithm called NMACO for solving the multiple traveling salesman problem (MTSP) . The MTSP is one of the most important combinatorial optimization problems in which the objective is to minimize the distance traveled by several salesmen for servicing a set of nodes. Since this problem belongs to NP-hard Problems, some metaheuristic approaches have been used to solve it in recent years. Furthermore, a new state transition rule and an efficient candidate list was also used in order to assess the efficiency of the proposed algorithm..[2]

Tan W. F, L.S.Lee ,and Z.A Majid (2012) proposed a heuristic approach for capacitated vehicle routing problem The proposed ACO approach utilized a pheromone evaporation procedure of standard ant algorithm in order to introduce an evaporation rate that depends on the solutions found by the artificial ants .By using this approach, the results obtained from the proposed algorithms showed that the application of combination of two different heuristics in the ACO had the capability to improve the ants' solutions better than ACO embedded with only one heuristic. ACO with swap and 3-opt heuristic has the capability to tackle the CVRP with satisfactory solution quality and run time.[3]

Y. Zare Mehrjrdi (2012) reviewed the literature on the topic of deterministic vehicle routing problem (VRP) and gave a review on the exact and approximate solution techniques. The heuristic methods were categorized into four groups: tour building heuristics, tour improvement methods, two-phase methods and Lagrangian relaxation heuristic approaches.[4]

Yu Bin and Zhang Hong proposed an improved ant colony optimization (IACO), which possesses a new strategy to update the increased pheromone, called ant-weight strategy, and a mutation operation, to solve VRP. The idea of the mutation operation is to randomly mutate the tour and hence produce a new solution that is not very far from the original one. In this paper, the mutation operator is designed to conduct customer exchanges in a random fashion. Initially, an Ant System solves the master problem for a given number of iterations. Given the best found solution so far the algorithm determines for each route of this solution the centre of gravity. Then it clusters these route centers and solves each of the resulting clusters independently by applying SbAS. After all sub problems have been solved it re-assembles the global solution and updates the global pheromone information [5]

NajmeZehraNaqvi, Harmeen Kaur Matheru and Komal Chaddha(2011) , in their paper, presented a review report on ant colony optimization for evaluating the chronological order and solving the vehicle routing prolem. The pACS+1-shift algorithm was used o obtain a significant improvement in the solution cost .Estimation based ACO was also discussed in this paper.[6]

Zhi-Gang Ren proposed a new approach to solve the Set covering problem. The main differences between it and the existing ACO-based approaches lie in three aspects. First, it adopts a novel method, called single-row-oriented method, to construct solutions. When choosing a new column, it first randomly selects an uncovered row and only considers the columns covering this row, rather than all the unselected columns as candidate solution components. Second, a kind of dynamic heuristic information is used in this approach.. Finally, a simple local search procedure is developed to improve solutions constructed by ants while keeping their feasibility. The proposed algorithm was tested on a number of benchmark instances. Computational results show that it is able to produce competitive solutions in comparison with other metaheuristics.[7]

John E. Bell (2008) presented a meta-heuristic method of ant colony optimization (ACO) to an established set of vehicle routing problems (VRP). The procedure simulates the decision-making processes of ant colonies as they forage for food and is similar to other adaptive learning and artificial intelligence techniques such as Tabu Search, Simulated Annealing and Genetic Algorithms. Modifications are made to the ACO algorithm used to solve the traditional travelling salesman problem in order to allow the search of the multiple routes of the VRP. Experimentation shows that the algorithm is successful in finding solutions within 1% of known optimal solutions and the use of multiple ant colonies is found to provide a comparatively competitive solution technique especially for larger problems.[8]

To apply the ACO for solving the CVRP, Voss (1999) first developed an ACO algorithm which is called Ant System (AS) for the problem and then presented an improved AS in Bullnheimer et al. (1999).Since then, many researchers have proposed new methods to improve the original ACO especially by applying other algorithms into the ACO to tackle the large-scaled CVRP. Riemann et al. (2004) proposed an approach called D-Ants which is competitive with the best Tabu Search (TS) algorithm in terms of solution quality and computation time[9] which was improved over the hybrid approach proposed by Doerner et al. (2002) for solving the CVRP by combining the AS with the savings algorithm. [10]

Marco Dorigo et al.(1999) described two paradigm applications of ACO algorithms to travelling salesman problem and packet switched networks. The work followed three directions- the study of formal properties of the ant system, development of ant net for quality of applications and development of further applications to combinatorial optimization problems.[13]. The detailed description of routing applications of ACO algorithms can be found in (Dorigo et al 1998)[14]

Taillard et al.(1993) suggested decomposing the problem and proposes two distinct methods for partitioning a problem instance. For uniform problems, a partition into sectors was suggested, while for non-uniform problems. Taillard used a partitioning method based on trees and associated shortest path. In this partitioning method, the decomposition of the arborescence consists in deleting arcs in such a way that the sub problems successively created involve a quantity of goods as close to the capacity of the specified number of vehicles and as far from the root as possible.[15]

Megnanti et al.(1985)introduced the extent and nature of the vehicle routing problem complexities and drew contrasts with other applications of combinatorial optimization. It also summarized a number of successful uses of optimization for vehicle fleet planning . [16]

Billy E. Gillett et al.(1974) illustrated an efficient algorithm, called the sweep algorithm, for solving medium- as well as large-scale vehicle-dispatch problems with load and distance constraints for each vehicle. The locations that were used to make up each route are determined according to the polar-coordinate angle for each location. An iterative procedure was then used to improve the total distance traveled over all routes. The algorithm had the feature that the amount of computation required increases linearly with the number of locations if the average number of locations for each route remains relatively constant. For example, if the average number of locations per route is 7.5, the algorithm takes approximately 75 seconds to solve a 75-location problem. In contrast, the time to solve a problem with a fixed number of locations increased quadratically with the average number of locations per route.[17]

Dantzig and Ramser et al (1959) first introduced the vehicle routing problem and proposed a linear programming based heuristic for its solution. In their paper, the authors described a real-world application (concerning the delivery of gasoline to gas stations) and proposed the first Mathematical programming formulation and algorithmic approach for the solution of the problem. [18]

III. PROBLEM IDENTIFICATION

The Capacitated Vehicle Routing Problem (CVRP)[6]concerns the design of a set of minimum cost routes, starting and ending at a single depot, for a fleet of vehicles to service a number of customers with known demands. Mathematically, it can be represented by a weighted graph G = (V, A) with V = {0,1, 2,…, n} as the vertex set and A = {(i, j) | i, j Є V} as the edge set. The depot is denoted as vertex 0 and the total of n cities or customers to be served are represented by the other vertices. For each edge (i,j), i¹j, there is a nonnegative distance dij each measured using Euclidean computations. Each customer i, i=1, 2… n, is associated with a nonnegative demand qi and a service time di which have to be satisfied. The demand at the depot is set to qo= 0 and its service time is set to do = 0. the objective of the CVRP is to find a set of minimum cost routes to serve all the customers by satisfying the following constraints which are listed in Voss (1999):

a. Each customer is visited exactly once by exactly one vehicle,
b. All vehicle routes start and end at the depot,
c. For each vehicle route, the total demand does not exceed the vehicle capacity Q and
d. For each vehicle route, the total route length (including service times) does not exceed a given bound L.

IV. ANT COLONY OPTIMIZATION

A Metaheuristic is a heuristic method for solving a very general class of computational problems. It attempts to provide an efficient framework which combines user given black-box procedures. Such procedures are usually application specific heuristics. Metaheuristics are generally applied to problems for which there is no satisfactory problem specific algorithm or heuristic; or when it is not practical to implement such a method. Most commonly used metaheuristic are targeted to combinatorial optimization problems. It is interesting to notice that the best performing metaheuristic are almost inspired by nature. a series of metaheuristic methods have been devised and successfully applied to a wide range of applications.

The Ant Colony Metaheuristic [11] is a relatively new addition to the family of nature inspired algorithms for solving N P-hard combinatory problems. Also known as Ant Colony Optimization (ACO) or Ant System (AS) algorithm. Ant Colony Optimization (ACO) is a recently proposed metaheuristic approach for solving hard combinatorial optimization problems. The inspiring source of ACO is the pheromone trail laying and following behavior of real ants which use pheromones as a communication medium. It is a population based approach where a collection of agents cooperate together to explore the search space In analogy to the biological example, ACO is based on the indirect communication of a colony of simple agents, called (artificial) ants, mediated by (artificial) pheromone trails. The pheromone trails in ACO serve as a distributed, numerical information which the ants use to probabilistically construct solutions to the problem being solved and which the ants adapt during the algorithm's execution to reflect their search experience.The algorithm can be characterized by the following steps:

a. The optimization problem is formulated as a search problem on a graph;
b. A certain number of ants are released onto the graph. Each individual ant traverses the search space to create its solution based on the distributed pheromone trails and local heuristics;
c. The pheromone trails are updated based on the solutions found by the ants;
d. If predefined stopping conditions are not met, then repeat the first two steps; Otherwise, report the best solution found.

A. Biological analogy of ACO:

The ants,who lack sophisticated vision, could manage to establish the optimal path[6] between their colony and the food source within a very short period of time. This is done by an indirect communication known as stigmergy via the chemical substance, or pheromone, left by the ants on the paths. Though any single ant moves essentially at random, it will make a decision on its direction biased on the "strength" of the pheromone trails that lie before it, where a higher amount of pheromone hints a better path.

As an ant traverses a path, it reinforces that path with its own pheromone. A collective autocatalytic behavior emerges as more ants will choose the shortest trails, which in turn creates an even larger amount of pheromone on those short trails, which makes those short trails more likely to be chosen by future ants.

Over time, however, the pheromone trail starts to evaporate, thus reducing its attractive strength. The more time it takes for an ant to travel down the path and back again, the more time the pheromones have to evaporate. A short path, by comparison, gets marched over more frequently, and thus the pheromone density becomes higher on shorter paths than longer ones. Pheromone evaporation also has the advantage of avoiding the convergence to a locally optimal solution. If there were no evaporation at all, the paths chosen by the first ants would tend to be excessively attractive to the following ones. In that case, the exploration of the solution space would be constrained.

Thus, when one ant finds a good (i.e., short) path from the colony to a food source, other ants are more likely to follow that path, and it eventually leads all the ants following a single path. The idea of the ant colony algorithm is to mimic this behavior with "simulated ants" walking around the graph representing the problem to solve.

Fig. 2 depicts the biology analogy of ants. In fig A, Real ants follow a path between the nest and a food source; In B, An obstacle appears on the path and the Ants choose whether to turn left or right with equal probability; (C) Pheromone is deposited more quickly on the shorter path is shown in fig C . Finally , all ants chose the shorter path.(fig D).

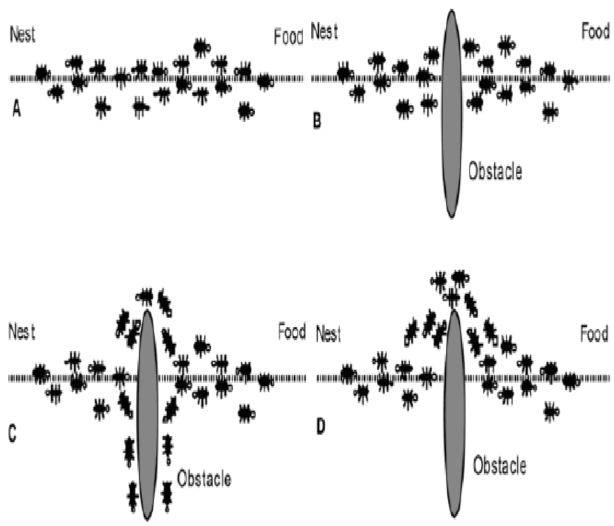

Figure 2 Biological analogy of Ant colony optimization

The original idea comes from observing the exploitation of food resources among ants, in which ants' individually limited cognitive abilities have collectively been able to find the shortest path between a food source and the nest [12].

Ants use the environment as a medium of communication. They exchange information indirectly by depositing pheromones; all detailing the status of their "work". The information exchanged has a local scope, only an ant located where the pheromones were left has a notion of them. This system occurs in many social animal societies (it has been studied in the case of the construction of pillars in the nests of termites). The mechanism to solve a problem too complex to be addressed by single ants is a good example of a self-organized system. This system is based on positive feedback (the deposit of pheromone attracts other ants that will strengthen it themselves) and negative (dissipation of the route by evaporation prevents the system from thrashing). Theoretically, if the quantity of pheromone remained the same over time on all edges, no route would be chosen. However, because of feedback, a slight variation on an edge will be amplified and thus allow the choice of an edge. The algorithm will move from an unstable state in which no edge is stronger than another, to a stable state where the route is composed of the strongest edges.

The basic philosophy of the algorithm involves the movement of a colony of ants through the different states of the problem influenced by two local decision policies, viz., trails and attractiveness. Thereby, each such ant incrementally constructs a solution to the problem.

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.

Furthermore, the algorithm also includes two more mechanisms, viz., trail evaporation and daemon actions. Trail evaporation reduces all trail values over time thereby avoiding any possibilities of getting stuck in local optima. The daemon actions are used to bias the search process from a non-local perspective. [10,18].

The probability that the foraging ants move from point i to j is as follows.

$$p_{ij} = \begin{cases} \dfrac{[\tau_{ij}]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{h\in\Omega}[\tau_{ih}]^{\alpha}[\eta_{ih}]^{\beta}}, & \text{if } j \in \Omega, \\ 0, & \text{otherwise,} \end{cases} \tag{1}$$

The formula (1) combines the diversity and the feedback of the foraging ants, and $\tau ij(t)$, $\eta ij(t)$ are respectively the pheromone function and heuristic function. α, β are the heuristic factor, Ω is the set of nodes which can be visited starting from i and the diversity and feedback are shown by the different α, β. The pheromone updating rules are as follows when the ants forage at t and t+n time.

$$\tau_{ij}(t+n) = (1-\rho)\times\tau_{ij}(t) + \sum_{k=1}^{m}\Delta\tau^{k}{}_{ij}(t)$$

$$\Delta\tau^{k}{}_{ij}(t) = \begin{cases} Q & \textit{if the ant pass}(i,j) \\ 0 & \textit{otherwise} \end{cases} \tag{2}$$

ρ is a volatile coefficient and 1- ρ is the residual coefficient $\Delta\tau kij(t)$ is the increasing amount of pheromone between I and J.

V. CONCLUSION

The VRP has been one of the important problem in the field of distribution and logistics. It allows selection of combination of customers in determining delivery routes for each vehicle. Since there is no known polynomial algorithm that can find the optimal solution in every instance, the VRP is considered NP- hard. For such problems, the use of heuristics is considered reasonable approach in finding solutions. This paper presents ACO metaheuristic for solving Vehicle Routing Problem.

VI. REFERENCES

[1] Bhanu Pratap Singh, Sohan Garg “A Characteristics Study of Ant Colony Optimization Algorithms for Routing Problems”IJARCSSE Volume 3, Issue 3, March 2013

[2] Majid Yousefikhoshbakht, Farzad Didehvar and Farhad Rahmati “Modification of the Ant Colony Optimization for Solving the Multiple Traveling Salesman Problem” Romanian Journal of Information Science And Technology Volume 16, Number 1, 2013, 65–80

[3] Tan, W.F., “Ant Colony Optimization for Capacitated Vehicle Routing Problem” Journal of Computer Science 8 (6): 846-852, 2012

[4] Y. Zare Mehrjerdi “Vehicle Routing Problem: Meta-heuristic Approaches” International Journal of Applied Operational Research Vol. 2, No. 3, pp. 55-68, Autumn 2012.

[5] Yu Bin , Yang Zhong-Zhen “An improved ant colony optimization for vehicle routing problem” European Journal of Operational Research ,Science Direct ,2012

[6] NajmeZehraNaqvi et.al. “Review Of Ant Colony Optimization Algorithms OnVehicle Routing Problems And Introduction ToEstimation-Based ACO” 2011 International Conference on Environment Science and Engineering IPCBEE vol.8 (2011) © (2011) IACSIT Press, Singapore.

[7] Zhi-Gang Ren, Zu-Ren Feng, Liang-Jun Ke, Zhao-Jun Zhang” New ideas for applying ant colony optimization to the set covering problem” Computers & Industrial Engineering 58 (2010) 774–784

[8] M. Reimann, M. Laumanns, “Savings based ant colony optimization for the capacitated minimum spanning tree problem”, Computers & Operations Research 33 (2006) 1794–1822

[9] M. Reimann , K. Doerner , R.F. Hartl . “D-ants: savings based ants divide and conquer the vehicle routing problem”. Computers&Operations Research 2004; 31:563–91.

[10] Jones, D. F., Mirrazavi, S. K., Tamiz, M., “Multi-objective meta-heuristics: An overview of the current state-of-the-art. European Journal of Operational Research, 137, 1–9, 2002.

[11] D.A. Alexandrov and Y.A. Kochetov “The behavior of the ant colony algorithm for the set covering problem” Operations Research Proceedings 1999, pages 255–260. Springer Verlag, 2000.

[12] Marco Dorigo, Gianni Di Caro “Ant Colony Optimization: A New Meta-Heuristic” IEEE, 1999

[13] Marco Dorigo, Gianni Di Caro “Ant Colony Optimization: A New Meta-Heuristic” IEEE, 1999

[14] G. Di Caro, M. Dorigo. “AntNet: Distributed stigmergetic control for communications networks”. Journal of AI Research, 9:317–365, 1998.

[15] R. E. Taillard, “Parallel iterative search methods for vehicle routing problems. Networks” 1993;23:661–73

[16] Magnanti “Combinatorial Optimization and Vehicle Fleet Planning: Prospective and Prospects”. Network, 7, 179-213, 1981

[17] Gillet, B. E.et. al. “A Heuristic Algorithm for the Vehicle Dispatch Problem. Operations Research, 22, 340-349.1974

[18] G.B. Dantzig and J.H. Ramser. “The truck dispatching problem”. Management Science, 6:80, 1959