Ambulance Routing with Ant Colony Optimization

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Abstract. The Vehicle Routing Problem (VRP) is a generic name given to a whole class of problems in which a set of routes for a fleet of vehicles based on one or several depots must be determined for a number of geographically dispersed customers. Ant Colony Optimization (ACO) studies artificial systems that take inspiration from the behavior of real ant colonies and is used to solve discrete optimization problems. This paper attempts to solve ambulance routing as a VRP with ACO i.e. route ambulance so that injured people can be accommodated in hospitals as soon as possible (at least time). This traveling time depends on length of the traveled route and capacity of the hospitals. The implementation is done in MATLAB environment. Preliminary results showed that ACO can conveniently be used for routing problem.

Keywords: ambulance routing, ant colony optimization, ant system, vehicle routing problem

1. Introduction

Ant Colony Optimization (ACO) is an approach for solving combinatorial optimization problems. ACO is the result of research on computational intelligence approaches to combinatorial optimization originally conducted by Dr. Marco Dorigo, in collaboration with Alberto Colorni and Vittorio Maniezzo [3]. It is inspired by the foraging behavior of ants and their inherent ability to find the shortest path from a food source to their nest [7].

The Vehicle Routing Problem (VRP) is a generic name given to a whole class of problems in which a set of routes for a fleet of vehicles based at one or several depots must be determined for a number of geographically dispersed cities or customers [8].

This paper aims at ambulance routing as a VRP with ACO. In this problem the assumptions made are: a) The number and the location of injured people are known; b), the locations of ambulances as well as hospitals are known; and c) the capacity of the ambulances as well as hospitals are predefined. Ambulances are to transport injured people to the hospitals. The object is to route ambulance so that injured people can be accommodated in hospitals with minimum cost (at least time). This traveling time depends on the length of the traveled route and the capacity of the hospitals .

Section 2 of this paper presents a brief description of ant colony optimization and its algorithms. First the natural behavior of ants is discussed and an algorithm of ACO is shown. In section 3, there is a brief introduction to the Vehicle Routing Problem (VRP) and its variants. First VRP is discussed and its formulation is shown. Then the VRP solutions are listed. In chapter 4, there is a brief introduction to our case study, its solution and results.

2. Ant Colony Optimization

Insects like ants are social. It means that they live in colonies and their behavior is directed to the survival of the colony as a whole. Most species of ants are blind. However, while each ant is walking, it deposits on the ground a chemical substance called pheromone. Ants can smell pheromone and when choosing their way, they tend to choose, in probability, paths with high pheromone density. The ants using the pheromone trail have the ability to find their way back to the food source. The pheromone evaporates over time. It has been shown experimentally that the pheromone trail following behavior can affect the detection of shortest paths. This cooperative work of the colony determines the insects' intelligent behavior and has captured the attention of many scientists and the branch of artificial intelligence called swarm intelligence [2].

2.1. Ant Colony Optimization

Ant Colony Optimization (ACO) studies artificial systems that take inspiration from the behavior of real ant colonies. It is used to solve discrete optimization problems [4].

The first ACO system was introduced by Marco Dorigo and was called Ant System (AS) [3]. AS was initially applied to the travelling salesman problem [4].

Dorigo, Gambardella and Stützle have been working on various extended versions of the AS paradigm. Dorigo and Gambardella have proposed Ant Colony System (ACS) [4], while Stützle and Hoos have proposed MAX-MIN Ant System (MMAS) [6]. They have both have been applied to the symmetric and asymmetric travelling salesman problem, with excellent results.

2.2. Ant System

In AS, the probability of moving from node i to node j is given as

$$p_{ij}^{k}(t) = \begin{cases} \dfrac{\tau_{ij}^{\alpha}(t)\eta_{ij}^{\beta}(t)}{\sum_{u\in\mathcal{N}_i^k(t)}\tau_{iu}^{\alpha}(t)\eta_{iu}^{\beta}(t)} & \text{if } j \in \mathcal{N}_i^k(t) \\ 0 & \text{if } j \notin \mathcal{N}_i^k(t) \end{cases} \quad (1)$$

where τ_{ij} represents the a posteriori effectiveness of the move from node i to node j, as expressed in the pheromone intensity of the corresponding link, (i, j); η_{ij} represents the a priori effectiveness of the move from i to j (i.e. the attractiveness, or desirability, of the move), computed using some heuristic. The pheromone concentrations, τ_{ij} , indicate how profitable it has been in the past to make a move from i to j, serving as a memory of previous best moves.

Pheromone evaporation is implemented as given in equation (2). After completion of a path by each ant, the pheromone on each link is updated as

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \Delta\tau_{ij}(t) \quad (2)$$

With

$$\Delta\tau_{ij}(t) = \sum_{k=1}^{n_k} \Delta\tau_{ij}^{k}(t) \quad (3)$$

Where $\Delta\tau^{k}_{ij}(t)$ is the amount of pheromone deposited by ant k on link (i, j) and k at time step t.

3. Vehicle Routing Problem

VRP considers the problems concerning the distribution of goods between depots and final users (customers).The objective of the VRP is to deliver a set of customers with known demands on minimum-cost vehicle routes originating and terminating at a depot. In the two figures below we can see a picture of a typical input for a VRP problem and one of its possible outputs [8]:

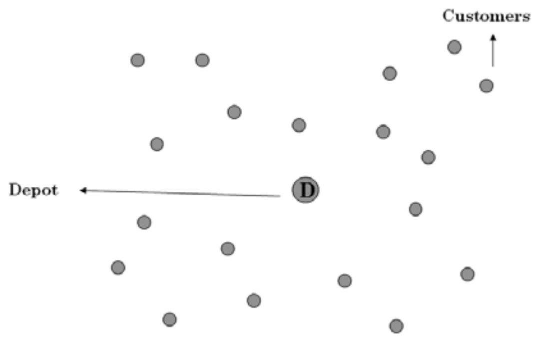

Figure 1. Typical input for a Vehicle Routing Problem

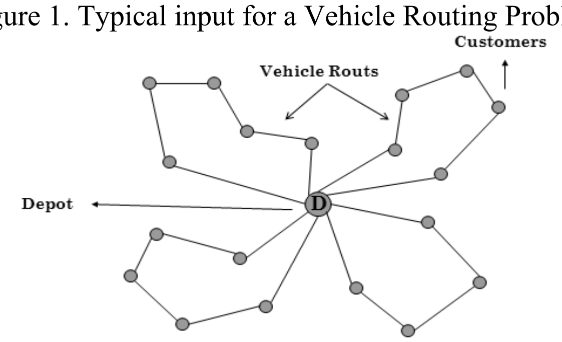

Figure 2. An output for the instance above

The VRP is a problem which falls into the category of NP Hard problems, meaning that the computational effort required solving this problem increase exponentially with the problem size [8]. For such problems it is often desirable to obtain approximate solutions, so they can be found fast enough and are sufficiently accurate for the purpose. Usually this task is accomplished by using various heuristic methods, which rely on some insight into the problem nature [8].

The VRP arises naturally as a central problem in the fields of transportation, distribution and logistics. In some market sectors, transportation means a high percentage of the value added to goods. Therefore, the utilization of computerized methods for transportation often results in significant savings ranging from 5% to 20% in the total costs. Usually, in real world VRPs, many side constraints appear. Some of the most important restrictions are [8]:

- Every vehicle has a limited capacitate (Capacitated VRP - CVRP)
- Every customer has to be supplied within a certain time window (VRP with time windows - VRPTW)
- The vendor uses many depots to supply the customers (Multiple Depot VRP - MDVRP)
- Customers may return some goods to the depot (VRP with Pick-Up and Delivering - VRPPD)
- The customers may be served by different vehicles (Split Delivery VRP - SDVRP)
- Some values (like number of customers, theirs demands, serve time or travel time) are random (Stochastic VRP - SVRP)
- The deliveries may be done in some days (Periodic VRP - PVRP)

3.1. Vehicle Routing Problem's Formulation

The VRP is a combinatorial problem whose ground set is the edges of a graph $G(V,E)$. The notation used for this problem is as follows:

- $V = \{v_0, v_1, \ldots, v_n\}$ is a vertex set, where:
  - Consider a depot to be located at v_0.
  - Let $V' = V \setminus \{v_0\}$ be used as the set of n cities.
- $A = \{(v_i, v_j) | v_i, v_j \in V;\ i \neq j\}$ is an arc set.

- C is a matrix of non-negative *costs* or *distances* cij between customers v_i and v_j.
- d is a vector of the customer demands.
- Ri is the route for vehicle i.
- m is the number or vehicles (all identical). One route is assigned to each vehicle.

When $c_{ij} = c_{ji}$ for all $(v_i, v_j) \in A$ the problem is said to be symmetric and it is then common to replace A with the edge set $E = \{(v_i, v_j) | v_i, v_j \in V; i < j\}$.

With each vertex vi in V' is associated a quantity qi of some goods to be delivered by a vehicle. The VRP thus consists of determining a set of m vehicle routes of minimal total cost, starting and ending at a depot, such that every vertex in V' is visited exactly once by one vehicle.

3.2. Solution Techniques for VRP

Here, the most commonly used techniques for solving Vehicle Routing Problems are listed. Near all of them are heuristics and metaheuristics because no exact algorithm can be guaranteed to find optimal tours within reasonable computing time when the number of cities is large. This is due to the NP-Hardness of the problem. Next we can find a classification of the solution techniques we have considered:

- **Exact Approaches**: As the name suggests, this approach proposes to compute every possible solution until one of the bests is reached.
- **Heuristics**: Heuristic methods perform a relatively limited exploration of the search space and typically produce good quality solutions within modest computing times
- **Meta-Heuristics**: In metaheuristics, the emphasis is on performing a deep exploration of the most promising regions of the solution space. The quality of solutions produced by these methods is much higher than that obtained by classical heuristics like Ant Algorithms [1].

4. Solving Ambulance Routing as a VRP with ACO

Suppose there are some injured people in determinate locations, some ambulances in those locations and some hospitals with determinate capacity. Ambulances want to transport injured people to the hospitals.

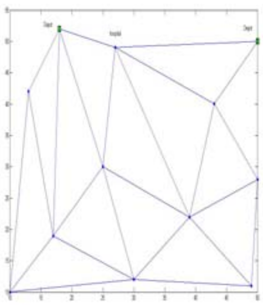

Figure 3. The input graph

In this problem the correspondence to VRP can be considered as below:

- Depots: location of injured people
- Goods: injured people
- Vehicle: Ambulance
- Customer: hospital

We want route ambulance so that injured people be accommodated in hospitals as soon as possible (at least time). This traveling time depends on length of the traveled route and capacity of the hospitals.

The inputs are:

- Adjacency matrix that represents a graph showing location of injured people, hospitals and routes between them.
- Capacity of hospitals and ambulances.
- The number of injured people in each depot.

The output is:

- a route for each ambulance that satisfy objective function

To solve the problem, Ant System algorithm is used. Each individual ant simulates an ambulance. Route is constructed by incrementally selecting hospitals by ambulances until all injured people delivered to given hospitals.

Ants return and transport other injured people until all injured accommodate in hospitals

The parameters which are used, are as follow:

- Number of Locations that have injured people (depots number): i
- Number of Ambulance in every location: m(i)
- Number of injured person in every depot: Q(i)
- Capacity of every Ambulance: QA
- Capacity of Hospital : QH
- Number of iteration: N // Stopping Condition

The pseudo code is as follow:

```
Set parameters
For i=1:N //Stopping Condition
  Place ambulance in injured person locations
  while all injured people do not accommodate in hospitals
        for j=1:sum(m)
              get injured person on ambulance
              reduce injured person number in depot
              while capacity of ambulance is not zero //construct rout
                    select next node probability
                    if node is hospital
                          reduce capacity of hospital
                          increase capacity of ambulance
                    else if node is another depot
                          get injured person on ambulance
                          reduce injured person number in depot
                          reduce capacity of ambulance
              end
              Pheromone Evaporation
              Pheromone Update
        end
  end
end
```

5. Results and Conclusions

The implementation is done in MATLAB environment. The inputs are adjacency matrix that represents a graph showing location of injured people, hospitals and routes between them; capacity of hospitals and ambulances and the number of injured people in each depot. The output is also a route for each ambulance that satisfies objective function. This route is represented in a weighted, red colored line in following figures. Figures 4 and 5 show the optimum routes of ambulances in node 11 i.e. depot 1 and node 12 i.e. depot 2 respectively.

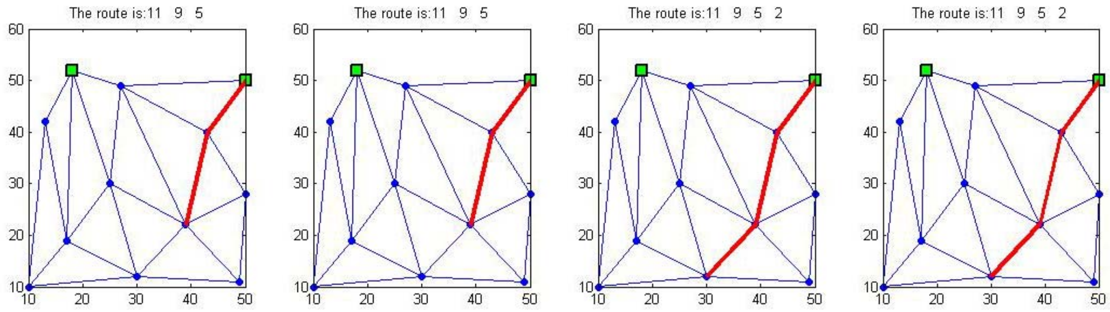

Figure 4. optimum routes of ambulances in depot 1

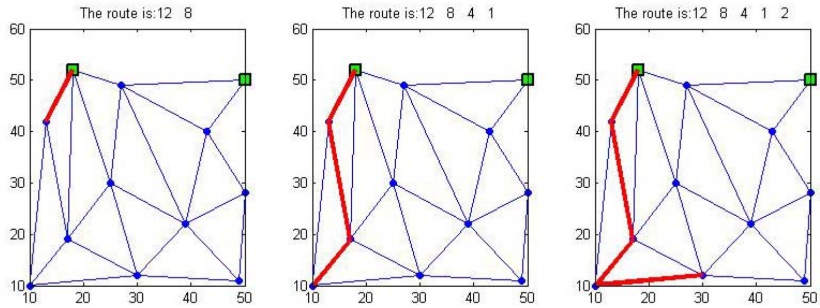

Figure 5. optimum routes of ambulances in depot 2

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