An Ant Colony and Simulated Annealing Algorithm with Excess Load VRP in a FMCG Company

Srinivas Rao T
Department of Mechanical Engineering, Amrita School of Engineering, Bengaluru, Amrita Vishwa Vidyapeetham, India

t_srinivas@blr.amrita.edu

Abstract Fast moving consumer goods pose a major research problem as the objective is to reach the customers in an efficient manner. The delivery of goods to consumers must reach quickly without any hurdles. We assume that the FMCG companies have multiple number of warehouse hubs to reach its vast majority of consumers. Sometimes a single vehicle may not be enough to complete the tour, hence we may require another small vehicle to reach the small set of customers. The above problem has been modelled as a supply chain vehicle routing model. In our paper we have used ant colony and simulated annealing algorithm to discuss the above problem and compare their efficiencies.

1. Introduction

In ant colony optimization, the shortest distance to reach the tour is mimicked by observing the behavior of ants. The behavior of ants to reach the food destinations is similar to our vehicle routing system where the salesperson is required to cover the destinations in minimum time with shortest distance. How the ants reach the food destination is that ants lay a chemical substance called pheromone while in search of food destination. The deposition of these pheromones is strong if the destination is reached, thereby giving signal to the successive ants to follow. This phenomenon of ant behavior can lead to a constrained solution space.

The Simulated annealing is a probabilistic algorithm which aims to find the global optimum in a large finite search space. It's a good algorithm compared to brute force and gradient descent algorithms. The solutions reached thru simulated annealing are tentatively near approximate if not exact.

Annealing is a heat treatment process in which the defects of the materials are reduced by controlled heating and cooling of materials. Hence Simulated annealing is derived from annealing. In simulated annealing the worst solutions are rejected as a result of the probability of cooling.
2. Literature Review

Dantzig and Ramser [1] were the first to introduce the Vehicle Routing Problem (VRP). The non-polynomial problems are hard to solve and VRP is one them; There are many improvements which have been done over the years on this vehicle routing problems. An improved version of the vehicle routing problem is Capacitated Vehicle Routing Problem (CVRP). It involves design of optimal delivery routes reaching out to different customers located at different locations, the constraint being the vehicle capacity [2].

There is a lot of research going on in the field of Hybrid Meta Heuristics but they are very complex to solve. Constructive heuristics are less in complexity, and they have less computational time with medium accuracy. They are very useful in meeting the delivery requirements of FMCG company [3]. For problems with large customer depots or routes some exact algorithms have been proposed but they are not adequate to solve [4]. Famous constructive heuristics are Clarke and Wright Savings algorithm [5], Sweep Algorithm [6] and the Cluster First and Route Second Fisher and Jaikumar [7] algorithm, Holmes and Parker algorithm [8] and a popular local improvement heuristic is K-Opt Exchange method [9].

3. SA Based Algorithm

Process 1 We define the process of SA by starting with $\gamma(0), \delta$ is represented as ending point. K has been assigned a high value which represents temperature, n is represented as count of iterations performed at a particular temperature, and set $k=0$.

Process 2 $\gamma(k+1) = N(\gamma(k))$ is represented as the neighborhood

Process 3 $\Delta\phi = (\Delta\phi(\tau^k((k+1)) - \phi(\tau^k((k)))) < 0, set k = k + 1$;  
Otherwise set random number $r$ in the range $(0,1)$. If Otherwise proceed to step2.

Process 4 If $|\tau^k((k+1)) - \tau^k((k))| < \propto$ and as $K$ becomes small, Terminate the solution; otherwise if $(k \mod n)=0$ then reduce $K$ according to a cooling schedule go to step 2;

4. ANT Colony Based Algorithm

The above problems of vehicle routing, job scheduling, stochastic problems can be solved by combinatorial algorithms but all are np hard. Therefore problems like VRP, TSP and Job scheduling can best be solved by non-traditional algorithms like ant colony and simulated annealing which may not provide the exact solutions but we can reach the near global optimum conditions. The ACO can be adopted in real time situations in which the graph changes dynamically. In computer science engineering often there will be Network routing problems which can be best solved by ACO.

There will be several software agents called as artificial ants which are used extensively in ant colony algorithms. The movement of these ants is regulated by adoption of certain rules in the algorithm. The rules of ACO are as follows,

1) Lateral movements of ants to each destination only once.
2] No far destination is chosen; 
3]The pheromone deposition of the ants is based on probability, which guides the ant to choose their next destination 
4] There will be more deposition of pheromone along the edges as the ant meets its target the food destination i.e reaching the shortest route in the vehicle routing problem. A weak rout leads to evaporation of pheromone.

The rule for an ant to reach next destination is guided by the probability formulae by Dorrigo which was adapter from 1997 paper. All the artificial ants are scattered in the selected cities of the tour. They then reach their next destination based on the formulae.

The stochastic formulae to move the ant from destination x to destination y is given by the following equation

\[
\partial_{xy}^k = \begin{cases} 
\frac{\alpha x y}{\alpha x z \times \gamma_{xz}} \\
\frac{\beta x y}{\beta x z \times \gamma_{xz}} \\
\sum z \in allowed x \\
0
\end{cases}
\]

(1)

where:

\(\partial_{xy}^k\) denotes the stochastic variable of kth ant that will visit destination x from y.

\(z \in allowed x\) is the set of destinations not visited by k ant to city x.

\(\alpha\) represents the pheromone trails relative importance.

\(\beta\) represents distances relative importance .

Based on the deposition of pheromone trail which is calculated by the dorigo’s formulae the ant will choose the next city. By tactically changing the \(\alpha\) and \(\beta\) parameters we can determine larger weights.

5. Pheromone Update

When the solution is completed, the pheromones are updated by the following formulae

\[
\phi_{xy} \leftarrow (1 - \rho)\phi_{xy} + \sum \Delta \phi_{xy}^{k}
\]

(2)
Where $\phi_{xy}$ is the amount of pheromone deposited for the movements of ant from city $x$ to $y$. The pheromone evaporation coefficient is represented by $\alpha$. $\Delta\phi_{xy}^k$ represents the pheromone deposition by the $K$th ant.

6. Implementation of Results

The data from the FMCG company has been extensively tested using the ant colony and simulated annealing algorithm by using MATLAB Version 2016. The latitude and longitude of the locations have been shown in table 1.

Table 1: Coordinates for the various customers and depot

| Customer No. | X-Co-ordinate | Y-Co-ordinate |
|--------------|---------------|--------------|
| Depot        | 40            | 50           |
| 1            | 45            | 68           |
| 2            | 45            | 70           |
| 3            | 42            | 66           |
| 4            | 42            | 68           |
| 5            | 42            | 65           |
| 6            | 40            | 69           |
| 7            | 40            | 66           |
| 8            | 38            | 68           |
| 9            | 38            | 70           |
| 10           | 35            | 66           |
FIGURE 1 Results of SA Based Algorithm
FIGURE 2 Results of Ant Colony Algorithm
7. Conclusions

The Ant Colony algorithm performs better than SA as noted from the above table. However, for small loads we have solved using SA algorithm the total distance covered is 135.87 units which is the same as using ant colony algorithm. From above we conclude that when the loads exceed the total truck load,
a small load truck can be used covering the locations where excess load is there, in our problem we have noticed that there seven destinations which showed excess loads and the same can be facilitated using small load trucks.

References

[1] Mohamed M.S. Abdulkader, Yuvraj Gajpal, Tarek Y. ElMekkawy .2015 Hybridized ant colony algorithm for the Multi Compartment Vehicle Routing Problem, In Applied Soft Computing, 37, 196-203

[2] Christofides, N., 1976. The vehicle routing problem. RAIRO Operations Research 10 (2), 55-70.

[3] Thibaut Vidal, Teodor Gabriel Crainic, Michel Gendreau, Christian Prins 2013. Heuristics for multi-attribute vehicle routing problems: A survey and synthesis. European Journal of Operational Research 231, 1-21.

[4] Gilbert Laporte 1991. The vehicle routing problem: An overview of exact and approximate algorithms. European Journal of Operational Research 59, 345-358.

[5] Clarke, G., Wright, J.W., 1964. Scheduling of vehicles from a central depot to a number of delivery points. Operations Research 12 (4), 568-581.

[6] Gillett, B., Miller, L., 1974. A heuristic algorithm for the vehicle-dispatch problem. Operations Research 22 (2), 340-349.

[7] Fisher ML and Jaikumar R 1981. A generalized assignment heuristic for vehicle routing. Networks 11: 109-124.

[8] R. Holmes and R. Parker, 1976. A vehicle scheduling procedure based upon savings and a solution perturbation scheme. Operations Research 27, 83-92.

[9] Taillard, E., Badeau, P., Gendreau, M., Guertin, F., Potvin, J.-Y., 1997. A tabu search heuristic for the vehicle routing problem with soft time windows. Transportation Science 31 (2), 170-186.

[10] Solomon, M., 1987. Algorithms for the vehicle routing and scheduling problems with time window constraints. Operations Research 35 (2), 254-265.

[11] Xin MA, 2010. Vehicle Routing Problem with Time Windows Based on Improved Ant Colony Algorithm. International Conference on Information Technology and Computer Science.

[12] Wang Xu-ping, XU Chuan-lei, HU Xiang-pei, Genetic Algorithm for Vehicle Routing Problem with Time Windows and a Limited Number of Vehicles. 2008 International Conference on Management Science & Engineering (15th), September 10-12, 2008

[13] C.Y. Lee, S.W. Lin, K.C. Ying, M.R. Yang. An Advanced Approach for Vehicle Routing Problem with Time Windows. Department of Industrial Engineering and Management, National Taipei University of Technology, Taipei, Taiwan
[14] Gillett, B. and Miller, 1974. A heuristic algorithm for the vehicle dispatch problem. Operations Research, vol.22, pp. 340-349.
[15] J-F Cordeau, M Gendreau, G Laporte, J-Y Potvin and F Semet, 2002. A guide to vehicle routing heuristics. Journal of the Operational Research Society 53, 512-522.
[16] Michael Schneider, Bastian Sand , Andreas Stenger. 2013. A note on the time travel approach for handling time windows in vehicle routing problems. Computers & Operations Research 40, 2564-2568
[17] T Srinivas Rao. A Comparative Evaluation of GA and SA TSP in a Supply Chain Network. Materials Today: Proceedings 4 (2017) 2263-2268
[18] Darshan Hegde, Samta Phulli, Deepak Ravi, Srinivas Rao T, Prakash Marimuthu K, “A Simulated Annealing Approach to Solve a Vehicle Routing Problem in a FMCG Company “International Journal of Mechanical Engineering and Technology (IJMET) Volume 8, Issue 11, November 2017, pp. 958-963, Article ID: IJMET_08_11_097
[19] T Srinivas Rao,” Ant Colony TSP to evaluate the performance of Supply Chain Network “ published in Materials Today Proceedings.Materials Today: Proceedings Volume 5 (2018)