

Ant Colony Optimization Algorithm for Green Logistics using Android Devices

P Prathyash¹, Vinay V Panicker², and E Jabir³

¹M.Tech.Student

Dept. of Mechanical Engineering, NIT Calicut, India
prathyash007@gmail.com

²Assistant Professor

Dept. of Mechanical Engineering, NIT Calicut, India
vinay@nitc.ac.in

³ Research Scholar

Dept. of Mechanical Engineering, NIT Calicut, India
e.jabir@gmail.com

ABSTRACT— *In Logistics, excessive Green House Gas emission and high fuel consumption from vehicles has become not only an environmental problem but also an economic issue. Therefore, it is important to develop an economic and eco-friendly navigation system for logistics vehicles. The rise of smartphone applications within the transport sector has created new opportunities to solve such problems. In this paper, the objective is to minimize fuel consumption and carbon emission in transportation processes for single-source multi-destination shortest path problems (Similar to Traveling Salesman Problem). An Android application using a hybrid Ant Colony Optimization algorithm is proposed to solve this problem.*

Keywords— Green Logistics, Ant Colony Optimization, Traveling Salesman Problem, Android

1 INTRODUCTION

The Greenhouse gases (GHGs) are any gaseous compounds in the atmosphere that can absorb infrared radiation. By absorption the infrared radiation, the heat is trapped by it and this will cause increase of atmospheric temperature. This phenomenon is known as greenhouse effect and this ultimately leads to global warming. One of the most abundant GHG is carbon dioxide (CO₂) and the main contributor of this gas is burning fossil fuels for electricity, heat, and transportation. According to Environmental Protection Agency (EPA) report 2012, transportation sector is the second largest contributor to the Green House Gas. This is because of impulsive growth in number of vehicles used in both industrial as well as personal activities. Unlike personal vehicles, Logistics vehicles contributes high amount of GHG. Since GHG emission is directly related to the amount of fuel consumed, it can be treated as both environmental as well as economical issue. Therefore, it is important to develop a cost-efficient and eco-friendly system to solve such problems.

In this work, the impact of GHG emission in Vehicle routing problem without capacity constraint or in Traveling Salesman Problem (TSP) is considered. TSP is a proven NP-Hard problem in which a set of cities have to be visited from a source node such that every cities are visited exactly once and return back to the source node with minimum cost/distance. This is an example of a simple vehicle routing problem in which the vehicle capacity is higher than the total demand of the system.

Massive use of smartphone applications in transportation sector has created new opportunities to solve these types of problems. Android is the major Operating system used in smartphones. According to IDC-World-Wide Smartphone Shipments Survey (2014), 75% of total smartphone sales in 2013 were Android devices. The system proposed in this work is designed for Android devices.

2 PROBLEM FORMULATION

The objective of the problem is to minimize total cost, which includes total economic cost and emission cost, in the transportation activities from a single-source to multiple demand points in a network. This will result in minimization of total distance traveled, fuel consumption and GHG emission.

2.1 Formulation of total cost model

The total cost (TC) is considered as the sum of total economic cost ($TC_{economic}$) and total emission cost (TC_{GHG}) (equation 2.1). Total emission cost is the product of emission cost per litre of fuel (C_{GHG}) and the total volume of fuel consumed (V_f) (equation 2.2). Emission cost per litre of a fuel is calculated as in the equation 2.5, the product of carbon tax per kg of CO_2 and average weight of CO_2 emission per litre consumption of fuel. Total economic cost includes total cost on fuel consumed as well as total operational cost of the vehicle (equation 2.3). The equation 2.6 shows the variable mileage of the vehicle according to the load being carried.

Table 2.1 Notations used in formulation

Notations	Formula	...	Equation
TC	$TC_{economic} + TC_{GHG}$...	(2.1)
TC_{GHG}	$C_{GHG} \times V_f$...	(2.2)
$TC_{Economic}$	$C_{fuel} \times V_f + C_{op}$...	(2.3)
V_f	$\sum_{i \in C_0} \sum_{j \in C_0} \frac{d_{ij} \times x_{ij}}{M_{ij}}$...	(2.4)
C_{GHG}	$P_{CO_2} \times W_{CO_2}$...	(2.5)
M_{ij}	$M_v \left[1 - \rho \left(\frac{w_{ij}}{W_v} \right) \right]$...	(2.6)

2.2 Formulation of Green Travelling Salesman problem (GTSP)

The proposed TSP formulation considers the minimization of total cost. This includes total economic as well as emission cost. Here the total emission varies with the load of the truck.

$$\min TC \quad \dots \quad (2.7)$$

Subjected to

$$\sum_{i \in C_0} x_{ij} = 1 \quad \forall j \in C_0 \quad \dots \quad (2.8)$$

$$\sum_{i \in C_0} x_{is} = \sum_{j \in C_0} x_{sj} \quad \forall s \in C_0 \quad \dots \quad (2.9)$$

$$x_{ij} = \begin{cases} 1 & \text{If there is a path between } i \text{ and } j \\ 0 & \text{Otherwise} \end{cases} \quad \forall i, j \in C \quad \dots \quad (2.10)$$

The decision variable x_{ij} is binary integer which takes the value 1 if there exists a connection between node i and j and 0 otherwise. All nodes must be visited by the truck that is considered with the constraint 2.8. The constraint 2.9 ensures that all incoming trucks will be going out. That means the truck will not end its tour until it reaches the Source/ Depot.

3 FACTORS AFFECTING GREEN VRP

Factors affecting green vehicle routing problem can be broadly classified into Uncontrollable and Controllable factors. Uncontrollable factors includes Road angle, Nature of road, Environmental conditions, Engine efficiency, Traffic conditions etc. and Controllable factors are Distance travelled, Load carried, Speed of travel etc. In this work, traffic conditions are considered for suggesting alternate routes. For optimization, distance travelled and Load carried are considered.

4 SOLUTION APPROACHES

Since the traditional TSP has been shown to be NP-hard, using an exact algorithm will be time consuming. This high time consumption can be reduced by introducing a heuristic or a meta-heuristic algorithm or a combination of both. In this work, a combination of meta-heuristic (Ant Colony Optimization Algorithm) and a local heuristic has been proposed.

4.1 Ant Colony Optimization Algorithm (ACO)

ACO is a discrete optimization technique which imitates the foraging behavior of ants in an ant colony. The algorithm works with natural behavior of ants in finding the shortest path to reach its food source and back to their nest. For example, consider the experimental setting shown in Figure 4.1.

Suppose ants established a stable path from point A to E (Figure. 4.1.a). If an obstacle H-C is introduced in that

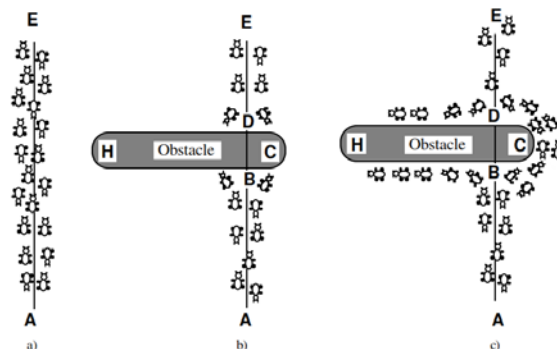


Figure 4.1 Real ant behavior (Dorigo et al [3])

path which cuts off the path (Figure. 4.1.b), ants will move towards C and H with equal probability due to equal pheromone level in both directions. Since ants moving towards point C completes the path before the ants moving towards H (Figure. 4.1.c) pheromone level increases in that path, more ants will follow the completed path and pheromone deposit increases in that path. After some time the shortest path will have higher pheromone level and majority of ants will follow that path.

4.2 Proposed ACO Algorithm

After the initialization of parameters and input of problem data, every ACO algorithm consists of ant solutions construction, daemon actions (optional), and pheromone information update. The explanations of these three components are as follows:

Solution Construction: A set of m artificial ants construct solutions from elements of a finite set of available solution components. A solution construction starts with a set of random initial solutions. Then, at each construction step, the current solution set is improved by adding a feasible solution component from the set of available solution components. The choice of a solution component is selected probabilistically at each construction step.

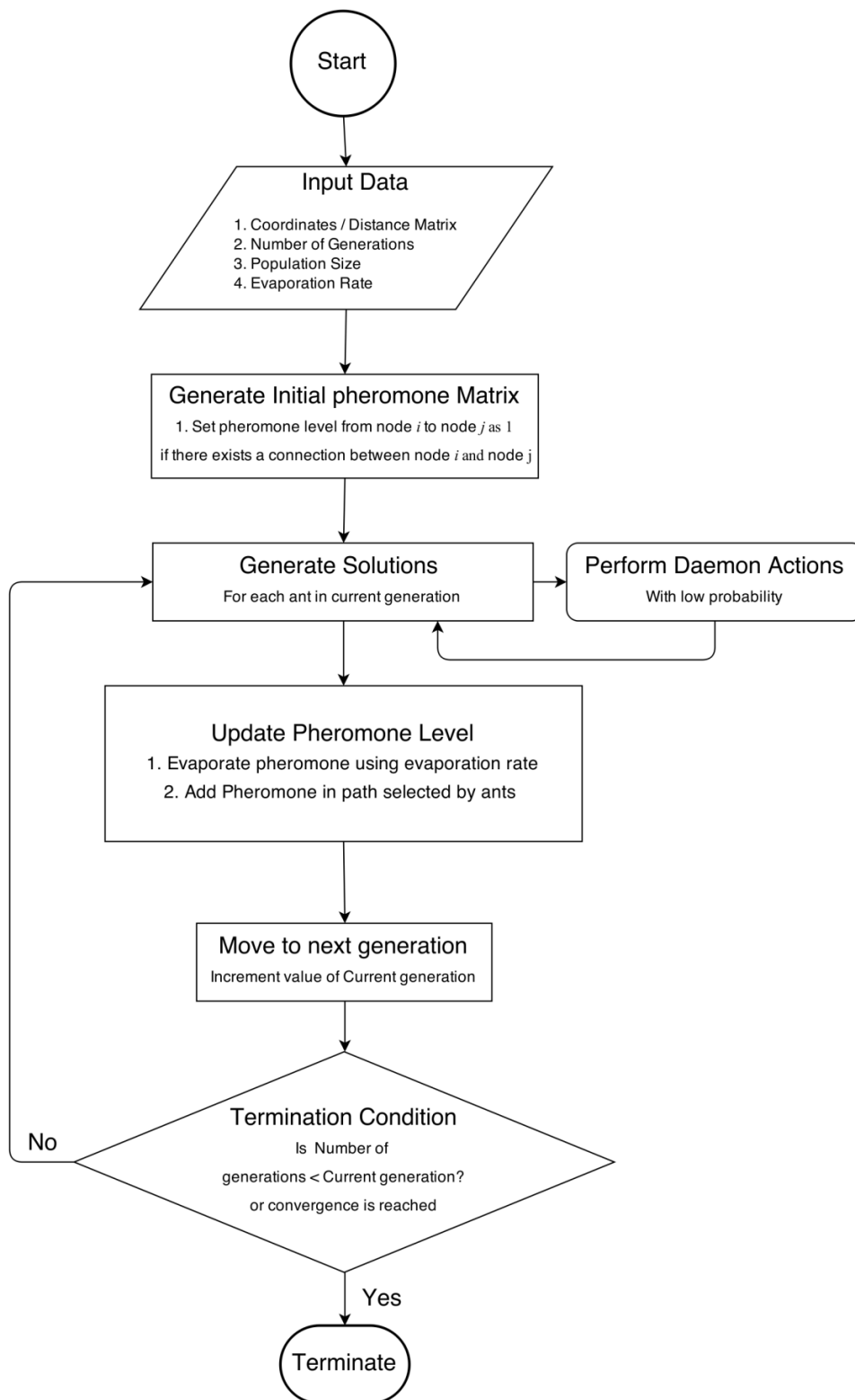


Figure 4.2 Flowchart of proposed Ant Colony Optimization Algorithm

Daemon Action: A daemon actions phase could be implemented once solutions have been constructed by all ants in iteration. In general, daemon actions could be used to implement a problem specific and/or a centralized action, which intends to improve the solutions obtained by the ants. (Example: Local Search Procedures)

Pheromone Updating: The main objective of pheromone updating is to avoid premature search convergence, and to bias the ants' search into a solution search space that contains good or promising solutions. Usually, each ant performs pheromone updating by (i) decreasing all the pheromone values through pheromone evaporation, and (ii) increasing the pheromone values associated with a chosen set of good solution(s). The proposed algorithm starts with a set of input data which includes coordinate/distance matrix, number of the colonies of ant or number of iterations, Population size of the colony and pheromone evaporation rate. Using input data, initial solutions are constructed by considering pheromone values of all paths are equal. Some solutions after daemon action (2-opt) are also included with low probability. After generating a set of solutions, the pheromone level is updated. This will continue until termination condition is satisfied. The flowchart of the algorithm is shown in Figure 4.3. Since the problem considered in this literature is operational level decision making problem, it must be solved as quickly as possible, but when we restrict execution time, quality of the solution decreases. And also there is no mechanism for checking neighborhood solutions of the final solution for further improvement. As a solution of all these issues, we can introduce a few iterations of Local Search at the end of the algorithm.

4.3 Local Search Procedures

Local search algorithms can be combined to the proposed algorithm to improve its performance. The problem considered in this work requires solution in minimum execution time if possible. Implementation of local search can reduce execution time without affecting the quality of the solution. These types of algorithms can also be used to search the possibility of better solution in the neighborhood of the solution provided by ant colony optimization algorithm. Different local search algorithms are being used in the literature out of which four most commonly used local search algorithms are combined with the proposed algorithm.

Local search algorithms used:

A. 2-Opt

This heuristic is performed by exchanging connection between two edges in a graph in order to get a neighboring solution. We can repeat the process up to either a fixed number of iteration or a desired level of improvement.

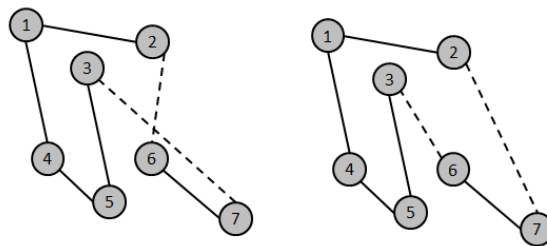


Figure 4.3 2-Opt

B. 2-Exchange & 3-Exchange

This method interchanges position of certain number of nodes to search improvement. In 2-Exchange, two random nodes swaps their positions to obtain a neighboring. Whereas in 3-Exchange is performed by interchanging position 3 nodes in solution sequence.

C. Random Search

This heuristic generates a set of random solutions and accepts solutions that are better than current best solution.

D. Pairwise Exchange

In this method, a pair of nodes in the solution sequence is exchanged with another pair to obtain a new solution.

5 SYSTEM ARCHITECTURE

The proposed software package includes two components namely, a web based software package and an Android application. The web based software, which is hosted by a web server, is used by two types of users – Administrator

and Customers. The Android application part is for a third type of user – Driver of the vehicle. The Ant Colony Optimization Algorithm will run in server which is controlled by the Administrator. The near optimal route, i.e., the solution for the problem will be send to Android App whenever there is a change in existing route.

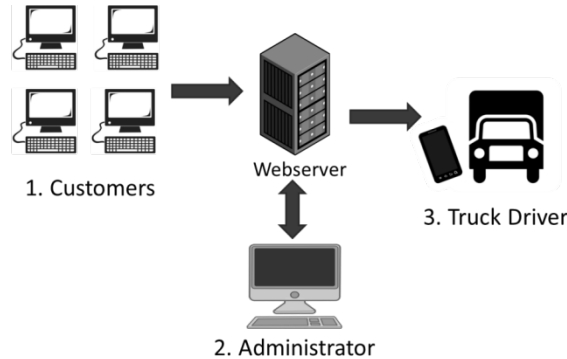


Figure 5.1 Software user types

The registered customers can place order of available products. After verification of available orders, administrator can run the optimization algorithm and obtain a good solution. The System Architecture is shown in Figure 5.2.

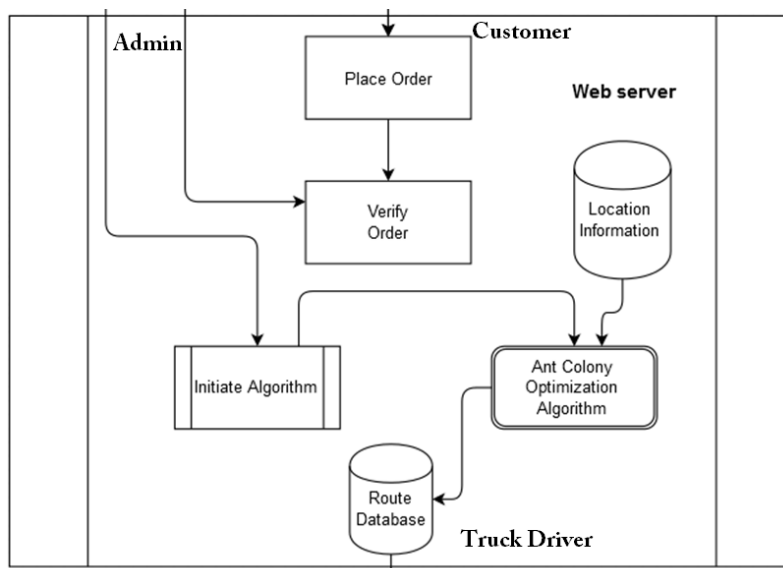


Figure 5.2 System Architecture

6 RESULTS AND ANALYSIS

The proposed algorithm was tested by evaluating different benchmark problems available in different TSP libraries (distance optimization models) and their result are shown in the Table 6.1. Total of 20 different benchmark problems with problem size varying from 14 to 127 cities were considered. From the results, it is found that as problem size increases, the chance of getting optimum solution decreases when the time of execution is restricted. Maximum of 7.2% error is obtained when large sized problem is considered within a computational time of 60 seconds. Still the proposed algorithm is able to give good enough solutions in less computational time.

Table 6.1: Computational Results (Distance Minimization Model)

Sl no.	Instances	Cities	BKS	Error %	Best	Average
1	<i>burma14</i>	14	30.879	0	30.8785	31.54513
2	<i>p01</i>	15	291	0	291	291
3	<i>ulysses16</i>	16	74	0	73.99983	74.60614
4	<i>gr17</i>	17	2085	0	2085	2085
5	<i>br17</i>	17	39	0	39	39
6	<i>ulysses22</i>	22	75.31	0	75.3097	76.11625
7	<i>bays29</i>	29	2020	0	2020	2086.85
8	<i>wi29</i>	29	27603	0	27603	28678
9	<i>DJ38</i>	38	6656	0.05	6659.4	6969.231
10	<i>swiss42</i>	42	1273	0	1273	1361.4
11	<i>att48</i>	48	33523	1.7	34119.83	34983.28
12	<i>eil51</i>	51	426	0.04	426.2	440.6402
13	<i>berlin52</i>	52	7542	1.8	7685.014	8215.951
14	<i>st70</i>	70	678.6	2	692.3246	732.1989
15	<i>eil76</i>	76	538	3.8	566.3017	592.9051
16	<i>pr76</i>	76	108159	3	111437.3	117784.2
17	<i>Rat99</i>	99	1219.2	7.1	1306.332	1374.564
18	<i>kroA100</i>	100	21282	6.1	22583.06	5865.323
19	<i>lin105</i>	105	14379	7.2	15414.09	17172.22
20	<i>bier127</i>	127	118282	7	126562.5	19475.73

7 FUTURE ENHANCEMENT

In this study, a single-source multiple-destination routing problem similar to Traveling Salesman Problem is considered for solving. The problem can be expanded for other transportation problems by introducing constraints like time window and capacity constraints. Or it is also possible to include more factors affecting Green Vehicle Routing Problem which are not considered in this work.

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