Modelling and Analysis of a Green Vehicle Routing Problem

ISBN: 978-81-924713-8-9

Jabir E
Vinay V. Panicker
R. Sridharan
National Institute of Technology
(e.jabir@gmail.com)
(vinay@nitc.ac.in)
(sreedhar@nitc.ac.in)

The classical vehicle routing problems are designed for distance or cost reduction. The routes generated by the model will be insensitive towards the environmental impact. In this work, a green vehicle routing problem is addressed. A meta-heuristic algorithm combining an Ant Colony Optimization algorithm with a Variable Neighbourhood Search algorithm is developed to solve the problem. The hybrid heuristic will search the solution space for the routing strategy, that minimizes the total supply chain cost which comprises of economic as well as emission cost. For consistency of solutions and solution convergence, the algorithm is tested on randomly generated problem instances.

1. Introduction

The backbone of the current industrial logistic networks is the fossil fuel based transportation sector. The distance or the time travelled by the vehicles account for the major component of the logistics cost. A minimization problem will design the routes with less time or distance variable. Greening the routes means implementing an environmental friendly vehicle route which will reduce the Green House Gas (GHG) emission. Among the greenhouse gases, CO_2 has the major share in a global basis. Methane and N_2O comes at the second and third with very less percentage contributions. The global emission scenario is shown in Figure 1.1. The inter-governmental panel on climate change is proposing a curb of 50%-80% GHG emissions by 2050 for avoiding serious and enduring climate change (4th assessment report of the inter-governmental panel on climate change). Figure 1.2 shows the global trend in CO_2 emissions through the last decade which shows a clear trend of increase. India emits more than 5% of global CO_2 emissions. In 2011, the transportation sector alone accounts for 22% of the global carbon emission (IEA STATISTICS, 2013).

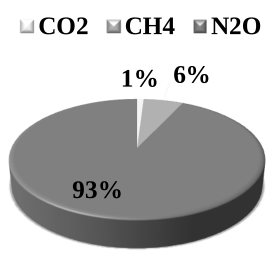

Figure 1.1 *Global GHG Emission*
Source: IEA statistics, (2013)

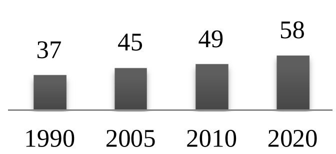

Figure 1.2 *Global GHG Emission*
Source: IEA statistics, (2013)

The classical vehicle routing problems aims at the possible economic cost reduction by proper assignment and demand allocation of potential clients towards a set of distribution centres. The general routing optimization problem will include the minimization of the distance travelled or time traversed for the customer service. The practical limitations of the business environment will impose the boundaries like maximum work hour constraints, maximum number and handling capacities of available transportation facilities and so on.

In this work, a multi-depot capacitated vehicle routing problem is analyzed. A supply chain cost reduction model is developed for the problem. Economic and environmental factors are considered in the supply chain cost structure. The economic factors considered in this study include route operating costs, fuel consumption costs and other operational costs. The environmental impact is measured in terms of cost of tons of CO_2 emission. Two algorithms namely, Ant Colony Optimisation (ACO) algorithm based heuristic and a hybrid algorithm combining ACO with Variable Neighbourhood Search (ACO-VNS) are proposed to solve the model. The algorithms are tested on problem instances randomly generated for a single product, two-echelon distribution-allocation supply chain.

In the literature, green-VRP can be broadly classified into three distinct problem scenarios, such as (i) Energy consumption based vehicle routing models (ii) Pollution and pollution reduction based models (iii) Waste management and reverse logistics related vehicle routing models. Lin et al. (2014) provides an outline of the research work in green logistics mainly confined from 2006 to 2012. Sbihi & Eglese (2007) has also reviewed the various scenarios coming under VRP and VRP variants such as, the green vehicle routing-scheduling problem and green logistics. Erdoäÿan & Miller-Hooks (2012), Yong and Xiaofeng (2009), Xiao et al. (2012) and Ćirović et al. (2014) considers energy consumption based routing models. Wygonik (2011), Huang et al. (2012), Lin et al. (2014), Demir et al. (2014), Kuo et al. (2014) and Jovanović et al. (2014) elucidates the pollution based routing scenarios.

The rest of the paper is structured as follows. Section 2 describes the problem considered in the work. Section 3 discusses the solution methodology adopted in the work. Section 4 reports the computational study, followed by results and discussion. Finally, the conclusions and suggestions for future research are given in Section 5.

2. Problem Description: Green MDVRP

In this work, a multi-depot capacitated vehicle routing problem (MDVRP) is considered. The problem is inspired from the two-echelon forward supply chain of a single product, distribution model. The supply chain network consists of *n* customers and *m* depots. The demand sharing between the vehicles and the depots are not allowed in the model. As an obvious consequence, the customers with demand quantity greater than the truck load or depot capacity itself is not considered in the problem scenario. In order to ensure continues flow of demand distribution, a customer will have an immediate successor and predecessor in a route. The optimization model has to allocate the customers to the depots by designing minimum cost routes. The total cost component includes two types of costs namely, economic cost and environmental cost. The economic cost includes the route dependent fixed cost, the route operating costs and the fuel consumption cost. The environmental costs are evaluated in monetary terms considering the CO_2 emissions. The assumptions imposed on the model are as follows:

- The demand of the customers is known.
- The capacities of depots and vehicles are known.
- The geographical location of the depots and the customers are known and mapped in to a Euclidean plane.
- Individual demand of each customer cannot exceed the capacity of a vehicle
- Each vehicle starts and ends the route at the same depot.
- Each depot and customer is visited by a vehicle exactly once i.e., the entire demand of the customer is met by a single vehicle.
- Homogeneous Vehicles are used. Capacity, speed and emission parameters are same.

2.1 Problem Formulation: Green MDVRP

The green MDVRP model is formulated as a variant of the canonical vehicle routing problem with capacitated routes and depots. The total supply chain cost of the model is a function of the distance travelled and the demand distribution pattern inside the route.

The notations used in the models are provided in Table 1.

Decision variables

$$x_{ijk} = \begin{cases} 1, \text{if vehicle } k \text{ is travelling from depot } i \text{ to customer } j, \forall i \in I, j \in J, k \in K \\ 0, \quad \text{otherwise} \ldots \end{cases}$$

$$f_{ij} = \begin{cases} 1, \text{ if customer } j \text{ is assigned to depot } i, \ \forall i \in I, j \in J \\ 0, \quad \text{otherwise} \end{cases}$$

Table 2.1 *Notations*

I	Set of depots ($i=1,2,\ldots,d$), where d being the upper bound on the number of depots
J	Set of customers ($j=1,2,\ldots,c$), where c being the upper bound on the number of customers
V	$I \cup J$
l_{ij}	Euclidian distance from node i *to* node j, for all $i \in V, j \in V$
C_v	Variable vehicle operating cost per unit distance
T	Fixed depot vehicle cost

C_{fuel}	Average fuel consumption cost per unit distance per unit vehicle weight
F_{CO2}	CO2 emission cost per unit weight of vehicle per unit distance
P_f	Diesel fuel price per unit volume
V_f	Volume of fuel consumption per unit distance per unit vehicle weight
Wp	Weight of each delivered product (the weight of recycled products is neglected)
W_{CO2}	Weight of CO2 emission per liter consumption of diesel
P_{CO2}	Average price per unit weight of CO2
k	Ratio of vehicle volume versus curb weight
W_{cargo}	Cargo weight when vehicle traverse a distance l_{ij}
Wv	Average gross weight per vehicle through travelling on each route
d_j	Demand of customer j, for all $j \in J$
Q_v	Capacity of the depot vehicle

Objective function
Minimize

$$Z = \sum_{k \in K} \sum_{i \in I} \sum_{j \in J} T \times x_{ijk} + \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} l_{ij} \times x_{ijk} \times v_f \left(P_f + P_{CO_2} \times W_{CO_2} \left(W_{\text{Cargo}} + \frac{W_{\text{Curb}}}{k} \right) \right) \quad (2.1)$$

Subject to

$$\sum_{j \in J} \sum_{i \in V} d_j \times x_{ijk} \le Q_v, \quad \forall k \in K \quad (2.2)$$

$$\sum_{j \in J} d_j f_{ij} \le W_i y_i, \quad \forall i \in I \quad (2.3)$$

$$\sum_{j \in J} \sum_{i \in V} x_{ijk} = 1, \quad \forall k \in K \quad (2.4)$$

$$\sum_{j \in V} x_{ijk} - \sum_{j \in V} x_{jik} = 0, \quad \forall i \in V, k \in K \quad (2.5)$$

$$\sum_{i \in I} \sum_{j \in J} x_{ijk} \le 1, \quad \forall k \in K \quad (2.6)$$

$$x_{ijk} \in \{0, 1\}, \quad \forall\ i \in I, \forall j \in V, \forall\ k \in K \quad (2.7)$$

$$f_{ij} \in \{0, 1\}, \quad \forall\ i \in I, j \in V \quad (2.8)$$

The objective function (2.1) represents the total supply chain cost of the network. The economic side of the supply chain costs including the routing costs, travel costs and the fixed route building costs. The emission cost of the network is measured in monetary terms of the carbon emission. It depicts the environmental impact of the supply chain. Constraints (2.2) and (2.3) are the capacity constraints associated with the routes and the depots, respectively. Constraint (2.4) ensures that each customer belongs to exactly one route, and that each customer has only one predecessor in the route. Constraint (2.5) guarantees the continuity of each route, and that each route terminates at the depot where the route starts. . Constraint (2.6) ensures that a customer must be assigned to a depot if there is a route connecting them. Constraints (2.7) and (2.8) specify the binary variables.

3. Solution Methodology

The np hard MDVRP is solved using two algorithms namely, an ant colony optimization based heuristic and a hybrid meta-heuristic algorithm combining an Ant Colony Optimization (ACO) algorithm with a Variable Neighbourhood Search (ACO-VNS). The details of the solution methodology are provided in the following subsection. The solution representation is given in Figure 3.1. The numbers, $i=1, 2, \ldots, n$ are used for customers and $n+1$ to $n+m$ are used for representing depots. Zeros indicate the beginning or the end of a route. Every string must start by a depot element (i.e. *string (i=1)* $\ge n+1$) and should end at a zero.

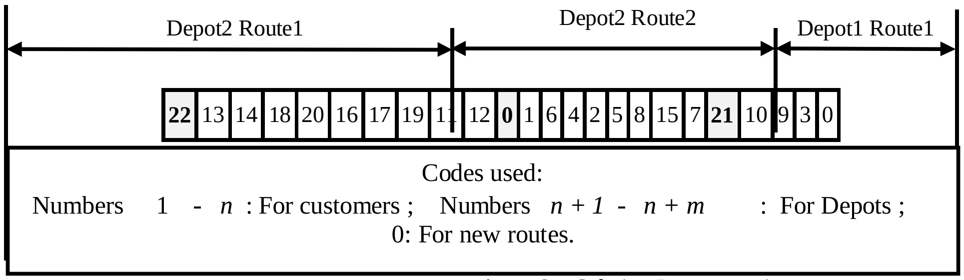

Figure 3.1 *Solution Representation*

3.1 Ant Colony Optimization (ACO) algorithm

An evolutionary Ant Colony Optimization (ACO) based algorithm is modeled as a constructive, route building heuristic to solve the green MDVRP. The ant behavior for searching the quality food is adapted for finding the routes that optimizes the total supply chain cost. Ants mimic the vehicles or trucks in the problem. Every ant makes a trail with a chemical substance called pheromone. Ants travel from a depot to a customer or from a customer to another customer. The best customer node selection is guided by the collective information stored as a presence of the chemical substance, known as ant pheromones. The probability of selecting a pair of nodes for the solution increases as more ants use the same link (depot-customer or customer-customer). The search is restricted by the problem boundary conditions for generating feasible solutions. The heuristic constructs a complete tour for the first ant prior to the second ant starting its tour.

The algorithmic parameters are (i) Magnitude of the pheromone intensity, α, (ii) Magnitude of visibility, β, (iii) Evaporation rate of pheromone, ρ, (iv) Pheromone increment amount, Q, (v) Number of ants and number of iterations. The pheromone content between two nodes is represented using two matrices (depot-customer and customer-customer). All the elements in the initial pheromone matrix are set to α value. Probability matrices between the depot to customer (P_{dc}) and customer to customer (P_{cc}) are calculated based on the initial values. The probability between the two nodes i and j is calculated using equation (3.1).

$$p_{ij}^{k} = \begin{cases} \dfrac{{\tau_{ij}}^{\alpha} {\eta_{ij}}^{\beta}}{\sum_{l \in N_i^k} {\tau_{il}}^{\alpha} {\eta_{il}}^{\beta}}, & if\ j \in N_i^k \\ 0 \quad , & other\ wise \end{cases} \tag{3.1}$$

where τ_{ij} is the pheromone intensity between the nodes i and j. The N_i^k represents the feasible neighborhood of ant k based on the problem boundary constraints. The visibility parameter between the edges i and j of the ACO (η_{ij}) is calculated using equation (3.2).

$$\eta_{ij} = \frac{1}{\text{function value between node } i \text{ and } j} \tag{3.2}$$

The ant travel starts from a randomly chosen depot. When it comes to the customer selection, the customer with the highest value of probability from the P_{dc} matrix is served. The route construction from the chosen depot changes the pheromone content, the vehicle product stock and the depot total serving potential. As an ant moves from one node to another, the pheromone content is updated using equation (3.3). The increment in the pheromone value is indicated as $\Delta\tau_{ij}^{k}$. The increment in the pheromone trail is determined by equation (3.4).

$$\tau_{ij} = \tau_{ij} + \Delta{\tau_{ij}}^{k} \tag{3.3}$$

$$\Delta\tau_{ij}^{k} = \begin{cases} \dfrac{Q}{L_k}, & if\ ant\ k\ uses\ edge(i, j) \\ 0, & other\ wise \end{cases} \tag{3.4}$$

where, Q is the pheromone increment amount and L_k is the function value by the ant k on the edge (i, j). In this problem, L_k is the distance between the nodes for classical MDVRP.

The customer with the highest probability in the P_{cc} matrix with the already allocated customer is selected as the second customer. Then the pheromone trials between the selected nodes are updated. A route is constructed until the vehicle capacity constraint is met and the ant returns to the depot. If the depot has sufficient capacity to serve more customers, the second route is constructed. When a depot capacity constraint is met, next depot is selected randomly. The route building continued till all the customers are visited. When a solution is generated from an ant, the pheromone levels are updated by the evaporation process. The pheromone evaporation on edge (i, j) is updated using equation (3.5).

$$\tau_{ij} = (1 - \rho)\, \tau_{ij} \tag{3.5}$$

where, ρ is the parameter that controls the pheromone evaporation rate.

When all the customers are served, the total supply chain cost is calculated. The best solution is stored and updated as more ants pass by. This procedure continues till the predetermined number of ants constructs the route. When a predetermined number of ants complete the construction of routes, the iteration number is incremented. The procedure is repeated till the predetermined number of ants and iterations are completed.

3.2 ACO-VNS Based Heuristic

The neighborhood region of the ACO solutions is explored by combining the meta-heuristic with a Variable Neighborhood Search. The k^{th} neighborhood in the n^{th} iteration, N_n^k is generated by swapping the i^{th} element of the solution with j^{th} elements, where $j \neq i$. The flow chart for the proposed hybrid ACO-VNS based heuristic is shown in Figure 3.2.

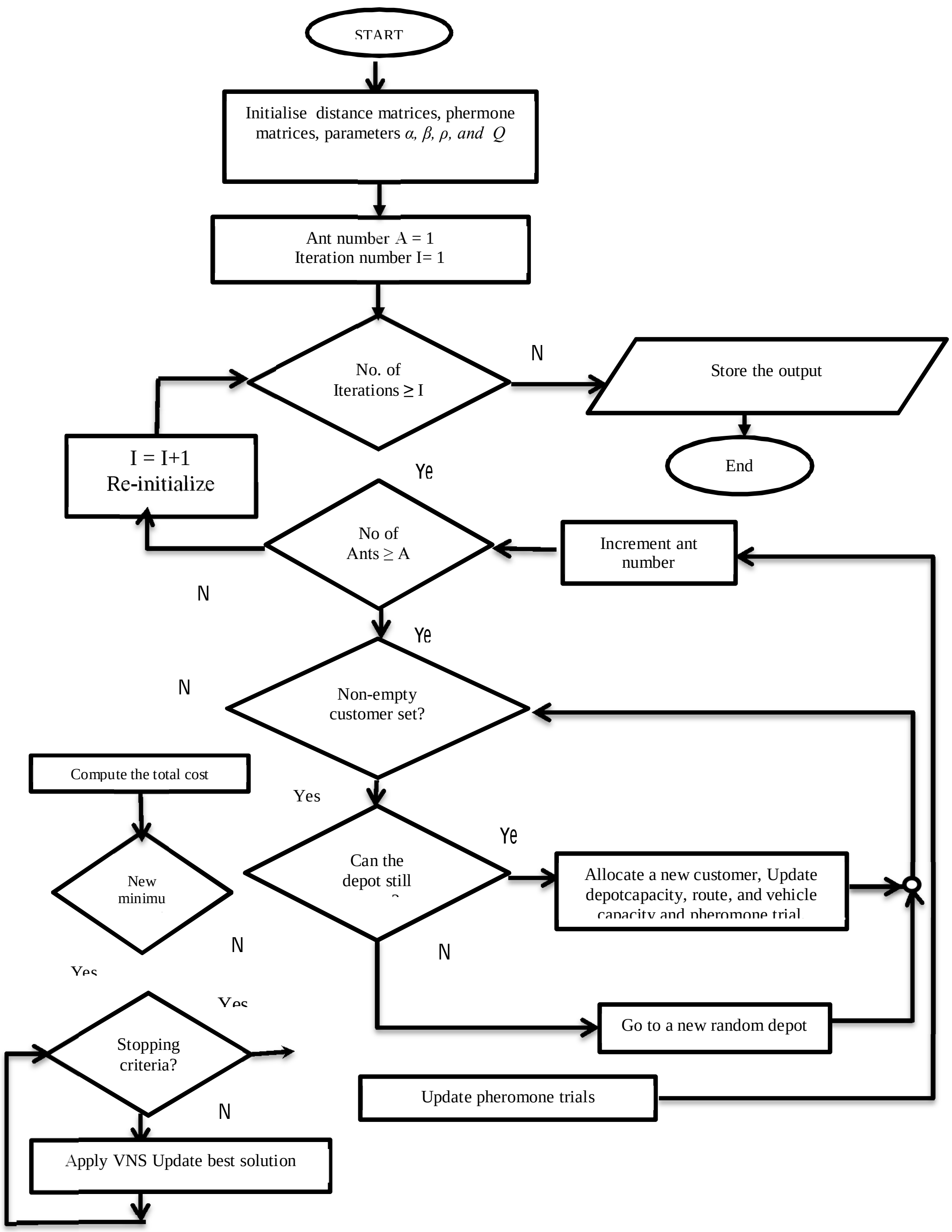

Figure 3.2 *Flowchart of the proposed hybrid ACO-VNS based heuristic*

The neighborhood generation from a parent string is represented in the Figures 3.3 (a-c). The VNS algorithm will stop the iterations once the algorithm reaches the local minima. Two separate counters are used to count the number of ants and number of iterations. Once the ant counter attained a maximum pre-determined value the algorithm will stop sending new ants to find the solution and the control will straight away go to the next iteration. The algorithm will terminate when the number of iterations exceeds a maximum pre-determined value.

1	2	3	4

Figure 3.3(a) *The Initial customer sequence of the VNS Algorithm.*

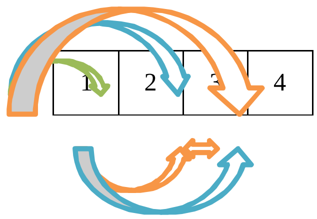

Figure 3.3 (b) *Neighborhood Generations: Exchange Rules*

2	1	3	4	3	2	1	4	4	2	3	1
1	3	2	4	1	4	3	2	1	2	4	3

Figure 3.3(c) *The New Neighbourhood Solutions*

4. Computational Experiments

The developed algorithms are coded in MATLAB and implemented on a Core *i*3 processor at 2.13 GHz PC with 3 GB RAM to solve the problem. The algorithms are tested on a set of randomly generated problem instances.

4.1 Problem Instances

The data for the MDVRP has been randomly generated. The problem instances are generated by varying different parameters such as the number of customers, n, number of depots m and vehicle capacity Q_v. There are two sets of problems for different parameter configurations. The number of depots considered is 2, 3, 5 and 10. The vehicle capacity considered is 70 or 150. The number of customers, n considered is $n \in \{10, 15, 20, 30, 50\}$. The other data (demands, depot capacities, fixed costs) are also integers. The problem instances are randomly generated with the following characteristics namely; (i) Demand follow a uniform distribution [20, 30]. (ii) Data pertaining to carbon emission and carbon costs are assumed based on Forbes (2009) and report of the Automotive Research Association of India (2008). The values for the various problem parameters are as follows.

C_{fuel}	\$1.0338
T	\$15/vehicle
P_{CO2}	\$20
W_{CO2}	0.027 Ton
W_{prod}	0.0189 Ton
V_f	0.01653 L/Ton/km
F_{CO_2}	\$0.89262/Ton/km
W_{curb}	16.2 Ton
K	5

4.2 Parameter Settings

The Taguchi method of experimental design is conducted on a randomly generated problem instance and is adopted for the study. The values for the algorithmic parameters are as follows.

- Magnitude of pheromone intensity (α) = 0.4
- Magnitude of visibility (β) = 2
- Evaporation rate of pheromone (ρ) = 0.2
- Pheromone increment amount (Q) = 4
- Number of ants = 100
- Number of iterations = 40

5. Results and Discussion

The developed algorithms are tested on a number of randomly generated instances. The generated problem instances are characterized by the following criteria (i) The number of depots (*m*), (ii) The number of customers (*n*) (iii) The vehicle capacity (Q_V).

The solutions obtained for the problem instances using the proposed algorithms ACO and ACO-VNS are tabulated in Table 5.1. $Cost_{max}$, $Cost_{min}$ and $Cost_{average}$ are the worst, best and average solutions obtained using the two heuristic algorithms in the computational study. The algorithms are tested for consistency by computing the deviation of the average solution from the best solution with respect to the average solution. The percentage deviation is calculated using the equation 5.1.

$$\%\ deviation = \frac{\text{Cost}_{average} - \text{Cost}_{min}}{\text{Cost}_{average}} \times 100 \qquad (5.1)$$

The percentage deviation of the ACO based heuristic varies from 0 % to 4.6774 % with a median value of 0.0244%. The ACO-VNS based heuristic also shows consistent performance with deviation ranging from 0 % to 1.5374 % with a median value of 0.0785%.

Table 5.1 *Computational Results of Proposed Heuristics*

PI	*n*	*m*	Q	ACO				ACO-VNS			
				$Cost_{max}$	$Cost_{min}$	$Cost_{average}$	% deviation	$Cost_{max}$	$Cost_{min}$	$Cost_{average}$	% deviation
1	10	2	70	4431.40	4431.4	4431.4	0.0000	4422.6	4422.6	4422.6	0.0000
2	10	2	70	5378.20	5378.2	5378.2	0.0000	5366.9	5366.9	5366.9	0.0000
3	15	2	70	7739.30	7738.6	7739.0	0.0052	7736.2	7734.8	7735.5	0.0090
4	15	2	70	6575.00	6575.0	6575.0	0.0000	6569.2	6567.7	6568.2	0.0076
5	20	3	70	10538.00	10538.0	10538.0	0.0000	10539.0	10537.0	10538.0	0.0095
6	20	3	70	5478.90	5476.6	5478.1	0.0274	4463.2	4448.1	4454.6	0.1459
7	20	3	150	9743.40	9686.3	9719.3	0.3395	96821.0	9670.8	9678.2	0.0765
8	20	3	150	5608.80	5608.8	5608.8	0.0000	4576.1	4576.1	4576.1	0.0000
9	30	3	70	13906.00	13873.0	13895.0	0.1583	13904.0	13870.0	13892.0	0.1584
10	30	3	70	7640.00	7640.0	7640.0	0.0000	6655.8	6594.0	6625.7	0.4784
11	30	3	150	16236.00	15769.0	15924.0	0.9734	14214.0	14130.0	14186.5	0.3983
12	30	3	150	7848.40	6841.3	7177.0	4.6774	5797.3	5797.3	5797.3	0.0000
13	50	5	70	26285.00	25457.0	25871.0	1.6002	26218.0	25425.0	25822.0	1.5374
14	50	5	70	13082.00	13041.0	13062.0	0.1608	9862.0	9728.9	9795.5	0.6799
15	50	5	150	28007.00	27995.0	28001.0	0.0214	24862.0	24821.0	24841.0	0.0805
16	50	5	150	13436.00	13426.0	13431.0	0.0372	10202.0	10079.0	10140.0	0.6016

PI – Problem Instance; N-Number of Customers; M - Number of Depots; Q- Vehicle Capacity

Table 5.2 provides the cost improvement obtained using the hybrid meta-heuristic over the ACO based algorithm. The solution diversification by introducing a variable neighborhood search is showing a clear improvement in the search results. The results show that there is an improvement on an average of 8.56 %, 6.85 % and 8.48 % in the economic cost, the emission cost and the total supply chain cost respectively. The percentage gain or loss in costs is also provided in Table 5.2. Figure 5.1 shows the comparison between the performances of the two heuristics.

Table 5.2 *Comparative study of ACO and ACO-VNS results*

PI	*n*	*m*	Q	ACO			ACO-VNS			%change in economic cost	%change in emission cost	%change in total cost
				Economic cost	Emission cost	Total cost	Economic cost	Emission cost	Total cost			
1	10	2	70	4192.0	239.4	4431.4	4189.0	237.6	4422.6	0.0716	0.7735	0.1986
2	10	2	70	5167.0	211.2	5378.2	5167.0	211.2	5366.9	0.0000	0.0000	0.2101
3	15	2	70	7326.0	412.6	7738.6	7323.0	411.8	7734.8	0.0410	0.1913	0.0490
4	15	2	70	6256.0	319.0	6575.0	6252.0	315.7	6567.7	0.0639	1.0135	0.1100
5	20	3	70	10240.0	297.8	10537.8	10238.0	298.9	10536.9	0.0195	**-0.3857**	0.0081
6	20	3	70	5223.0	253.6	5476.6	4213.0	235.1	4448.1	19.3375	7.2950	18.7798

7	20	3	150	9304.0	382.3	9686.3	9297.0	373.8	9670.8	0.0752	2.2413	0.1607
8	20	3	150	5284.0	324.8	5608.8	4280.0	296.1	4576.1	19.0008	8.8503	18.4130
9	30	3	70	13393.0	479.9	13872.9	13391.0	478.9	13869.9	0.0149	0.2181	0.0220
10	30	3	70	7312.0	328.0	7640.0	6294.0	300.0	6594.0	13.9223	8.5131	13.6901
11	30	3	150	14519.0	657.5	15176.5	13498.0	632.3	14130.3	7.0322	3.8211	6.8931
12	30	3	150	6407.0	434.3	6841.3	5389.0	408.3	5797.3	15.8889	5.9822	15.2600
13	50	5	70	24651.0	806.1	25457.1	24636.0	788.9	25424.9	0.0608	2.1307	0.1264
14	50	5	70	12502.0	538.9	13040.9	9362.0	366.9	9728.9	25.1160	31.9103	25.3967
15	50	5	150	26875.0	1132.1	28007.1	23802.0	1018.7	24820.7	11.4344	10.0168	11.3771
16	50	5	150	12677.0	749.4	13426.4	9532.0	547.2	10079.2	24.8087	26.9802	24.9299

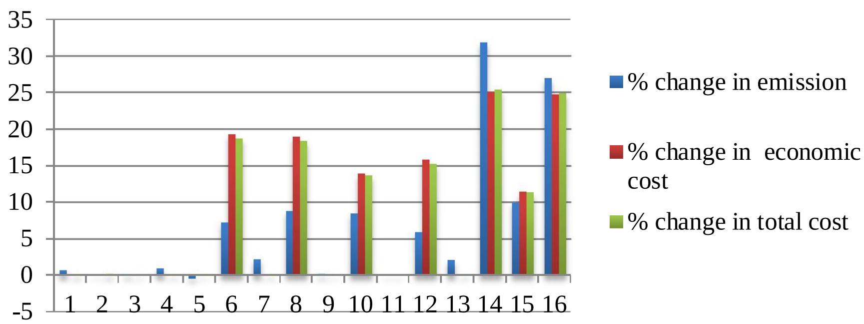

Figure 5.1 *comparative studies of ACO and ACO-VNS Resuslt*

Interestingly, for some solutions with a better economic cost as well as the total cost, the corresponding emission cost is worst. Overall, it is understood that the emission costs are much less compared to the economic cost. Hence, it can be inferred that the route selection decision is mainly dominated by the economic costs. Lin et al. (2014) also provides a similar observation while discussing the environmental analysis of a pickup and delivery problem. This optimization model is able to provide a direction to the routes of the classical vehicle routing problem based on the emission level.

6. Conclusion

In this work, a green-MDVRP problem is formulated. The carbon emission of the logistic network is added as a cost function to the routing costs for accounting the environmental impact of the supply chain. Two soft computing search procedures are developed to solve the discrete optimisation problem. An ACO based heuristic and a hybrid heuristic combining ACO and VNS are used to solve the problem near optimally. The algorithms are tested on randomly generated problem instances. The hybridisation provides significant improvement in the solutions. Based on the computational study, the results are found to be consistent over the test data. The computational results in this work provide guidelines for environmentally conscious and responsible route selection decisions.

In the current work, the study is limited to the carbon emissions. Future work can be conducted by considering other GHG emissions, noise levels and so on. The multi-objective scenarios where the decision maker wants a portfolio of solutions will be an interesting extension to the current study. Furthermore, the work can be extended for measuring carbon footprint of the supply chain network, life cycle assessment for supply chains, designing emission restricted routes, environment governance decisions and environmental tax calculations.

7. References

1. Cowlinga., P.I. and Keuthenb, R., (2005), ‘Embedded local search approaches for routing optimization’ , Computers & Operations Research, Vol. 32, 465–490.
2. Ćirović., G., Pamuc, D. and Bozˇanic, D., (2014), ‘ Green logistic vehicle routing problem: Routing light delivery vehicles in urban areas using a neuro-fuzzy model’**,** Expert Systems with Applications, Vol. 41, 4245–4258.
3. Demir, E., Bektas, T. and Laporte, G., (2014), ‘ The bi-objective Pollution-Routing Problem’, European Journal of Operational Research, Vol. 232, 464–478.
4. ErdoÄŸan, S., and Miller-Hooks, E., (2012), ‘ A grepagesen vehicle routing problem’, Transportation Research Part E: Logistics and Transportation Review, Vol. 48(1),100–114.
5. OECD/ITF, ‘Greenhouse gas reduction strategies in transportation sector: Preliminary report’, (2008).
6. Hansen, E. and Mladenovir, N., (1997), ‘Variable neighborhood search’, Computer and Operations Research Vol. 24(11), 1097-1100.

7. Hansen, E. and Mladenovir, N. (2011), 'Variable neighborhood search: principles and applications', European Journal of Operation Research, Vol.130, 449-467.
8. http://www.forbes.com/2009/06/03/cap-and-trade-intelligent-investing-carbon.html Accessed on 08/07/2014.
9. 'IEA Statistics', (2013), http://www.iea.org/publications/freepublications/publication Accessed on 08/07/2014.
10. Huang, Y., Shi., C., Zhao, L. and Woensel., T.V., (2012), 'A Study on Carbon Reduction in the Vehicle Routing Problem with Simultaneous Pickups and Deliveries', IEEE 978-1-4673-2401-4112.
11. 'Key world energy statistics', (2013). http://www.iea.org/publications/freepublications/publication/ KeyWorld2013.pdf Accessed on 08/07/2014.
12. 'The Emissions Gap Report', (2012). http://www.unep.org/publications/ebooks/emissionsgap2012. Accessed on 08/07/2014.
13. Kuo, T.C., Chen, G. Y-H., Wang, M.L. and Ho, M. W., (2014), 'Carbon footprint inventory route planning and selection of hot spot suppliers', International Journal of Production Economics, Vol.150, 125–139.
14. Park, J. and Kim, B., (2010) 'The school bus routing problem: A review', European Journal of Operational Research, Vol.202, 311–319.
15. Lin., C. Choy, K.L., Ho., G.T.S and Ng, T.W., (2014), ' A genetic algorithm-based optimization model for supporting green transportation operations', Expert systems with applications, Vol. 41, 3284-3296.
16. Lin, C., Choy, K.L., Ho, G.T.S., Chung, S.H. and Lam, H.Y., (2014), 'Survey of Green Vehicle Routing Problem: Past and future trends', Expert Systems with Applications, Vol. 41, 1118–1138.
17. Sbihi, A. and Eglese, R.W., (2010), ' Combinatorial optimization and green logistics', Annals of Operational Research, Vol. 175, 159–175.
18. Sbihi, A. and Eglese, R. W., (2007), 'The relationship between vehicle routing and scheduling and green logistics – a literature survey', Working paper, Department of Management Science, Lancaster University Management School, LA14YX
19. 'Report on Emission Factor development for Indian Vehicles', (2008), Automotive Research Association of India.
20. Soysal., M., Bloemhof-Ruwaard, J.M. and Vander Vorst., J.G.A.J, (2014), ' Modelling food logistics networks with emission considerations: The case of an international beef supply chain', International Journal Production Economics, Vol. 152, 57–70.
21. Wygonik, Erica. and Goodchild, Anne., (2011), 'Evaluating CO2 emissions, cost, and service quality trade-offs in an urban delivery system case study', IATSS Research, Vol. 35,7–15.
22. Xiao, Y., Zhao, Q., Kaku, I. and Xu, Y., (2012), 'Development of a fuel consumption optimization model for the capacitated vehicle routing problem', Computers & Operations Research, Vol. 39, 1419-1431.
23. Yong., P. and Xiaofeng, W., (2009), 'Research on a Vehicle Routing Schedule to Reduce Fuel Consumption', International Conference on Measuring Technology and Mechatronics Automation. IEEE 978-0-7695-3583-8/09.