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$_2$O 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).

![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 CO₂ 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. Erdoğan & 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 CO₂ 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.

<table>
<thead>
<tr>
<th>Decision variables</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_{ijk} \begin{cases} 1, \text{ if vehicle } k \text{ is travelling from depot } i \text{ to customer } j, \forall i \in I, j \in J, k \in K \ 0, \text{ otherwise} \end{cases}$</td>
</tr>
<tr>
<td>$f_{ij} \begin{cases} 1, \text{ if customer } j \text{ is assigned to depot } i, \forall i \in I, j \in J \ 0, \text{ otherwise} \end{cases}$</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Notations</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I$ Set of depots $(i=1,2,\ldots,d)$, where $d$ being the upper bound on the number of depots</td>
</tr>
<tr>
<td>$J$ Set of customers $(j=1,2,\ldots,c)$, where $c$ being the upper bound on the number of customers</td>
</tr>
<tr>
<td>$V$ $I \cup J$</td>
</tr>
<tr>
<td>$l_{ij}$ Euclidian distance from node $i$ to node $j$, for all $i \in V, j \in V$</td>
</tr>
<tr>
<td>$C_v$ Variable vehicle operating cost per unit distance</td>
</tr>
<tr>
<td>$T$ Fixed depot vehicle cost</td>
</tr>
</tbody>
</table>
Objective function
Minimize

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

Subject to

\[ \sum_{j \in J} d_j f_{ij} \leq W_i y_i, \quad \forall i \in I \] \quad (2.2)

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

\[ \sum_{j \in V} x_{ijk} = 1, \quad \forall k \in K \] \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)

\[ \sum_{i \in I} \sum_{j \in J} x_{ijk} \leq 1, \quad \forall k \in K \] \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, \( i=1, 2, ..., n \) 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 \( (i=1) \geq n+1 \)) and should end at a zero.
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, $\alpha$, (ii) Magnitude of visibility, $\beta$, (iii) Evaporation rate of pheromone, $\rho$, (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 $\alpha$ 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).

$$P_{ij}^k = \begin{cases} \frac{\tau_{ij}^a \eta_{ij}^b}{\sum_{i \in N_i^k} \tau_{il}^a \eta_{il}^b}, & \text{if } j \in N_i^k \\ 0, & \text{other wise} \end{cases}$$

(3.1)

where $\tau_{ij}$ 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 ($\eta_{ij}$) is calculated using equation (3.2).

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

(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).

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

(3.3)

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

(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).

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

(3.5)

where, $\rho$ 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.
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.

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

Figure 3.3 (b) Neighborhood Generations: Exchange Rules

Figure 3.3(c) The New Neighbourhood Solutions

4. Computational Experiments
The developed algorithms are coded in MATLAB and implemented on a Core i3 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.

\[
\begin{align*}
C_{\text{fuel}} & = 1.0338 \\
T & = 15/\text{vehicle} \\
P_{\text{CO2}} & = 20 \\
W_{\text{CO2}} & = 0.027 \text{ Ton} \\
W_{\text{prod}} & = 0.0189 \text{ Ton} \\
V_f & = 0.01653 \text{ L/Ton/km} \\
F_{\text{CO2}} & = 0.89262/\text{Ton/km} \\
W_{\text{curb}} & = 16.2 \text{ Ton} \\
K & = 5
\end{align*}
\]

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 (\( \alpha \)) = 0.4
- Magnitude of visibility (\( \beta \)) = 2
- Evaporation rate of pheromone (\( \rho \)) = 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. \(Cost_{\text{max}}, Cost_{\text{avg}}, \text{and } Cost_{\text{avg}}\) 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.

\[
\text{% deviation} = \frac{\text{Cost}_{\text{average}} - \text{Cost}_{\text{min}}}{\text{Cost}_{\text{average}}} \times 100
\] (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**

<table>
<thead>
<tr>
<th>PI</th>
<th>(n)</th>
<th>(m)</th>
<th>Cost(_{\text{max}})</th>
<th>Cost(_{\text{min}})</th>
<th>Cost(_{\text{avg}})</th>
<th>% deviation</th>
<th>Cost(_{\text{max}})</th>
<th>Cost(_{\text{min}})</th>
<th>Cost(_{\text{avg}})</th>
<th>% deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>10</td>
<td>2</td>
<td>70</td>
<td>4431.40</td>
<td>4431.4</td>
<td>4431.4</td>
<td>0.0000</td>
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</tr>
<tr>
<td>2</td>
<td>10</td>
<td>2</td>
<td>70</td>
<td>5378.20</td>
<td>5378.2</td>
<td>5378.2</td>
<td>0.0000</td>
<td>5366.9</td>
<td>5366.9</td>
<td>5366.9</td>
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<td>15</td>
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<td>7739.30</td>
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<td>70</td>
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<td>10538.0</td>
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<td>0.0000</td>
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<td>5476.6</td>
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<td>50</td>
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<td>70</td>
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<td>10202.0</td>
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<td>10140.0</td>
</tr>
</tbody>
</table>

(PI = Problem Instance; \(N\)-Number of Customers; \(M\)-Number of Depots; \(Q_v\)-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**

<table>
<thead>
<tr>
<th>PI</th>
<th>(n)</th>
<th>(m)</th>
<th>Cost(_{\text{Economic\ cost}})</th>
<th>Cost(_{\text{Emission\ cost}})</th>
<th>Cost(_{\text{Total\ cost}})</th>
<th>%change in \text{Economic\ cost}</th>
<th>%change in \text{Emission\ cost}</th>
<th>%change in \text{Total\ cost}</th>
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**Figure 5.1** comparative studies of ACO and ACO-VNS Result

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