An Efficient Ant Colony Algorithm for Multi-Depot Heterogeneous Fleet Green Vehicle Routing Problem

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Abstract

Vehicle routing problem (VRP) is one of the most widely researched topics in the fields of transportation, distribution and logistics, mostly because of its capabilities for potential cost savings and improved service performance leading to better customer satisfaction. Nowadays, the rising concerns about global warming have forced companies to reduce their carbon emissions. In this paper, a framework for multi-objective multi-depot heterogeneous fleet green vehicle routing problem (MDHFGVRP) has been developed. The model maximizes revenue and minimizes costs, time and carbon emissions considering heterogeneous fleet. The heterogeneous fleet consists of different types of vehicles available to each depot. An efficient ant colony optimization algorithm (EACO), a population-based metaheuristic, has been applied to solve the problem. The EACO model is inspired by ant's behaviors in nature. The proposed EACO model uses a novel approach of applying *k*-NN Classification with traditional ant colony optimization (ACO), which ensures more efficient solutions with better accuracy. The results obtained through the proposed EACO shows better performance than the traditional methods existing in the literature and provides improved solution quality. Therefore, improved responsiveness and simplicity are achieved through the application of EACO algorithm for solving the MDHFGVRP problem.

Keywords:

Vehicle Routing Problem, Multi-Depot Vehicle Routing, Green Supply Chain, Heterogeneous Fleet, Ant Colony Optimization.

1. Introduction

In the fields of logistics, distribution, and transportation, VRP or Vehicle Routing Problem holds tremendous vitality. Among other things, one of the most pressing problems in operational level logistics is VRP, making it a matter of interest to be looked into. It is classified as an NP-hard problem. Under certain functional restrictions, the issue of estimating routes with the minimal cost where vehicles follow the fleet, about meet requirements of user satisfaction. In reality, logistics suggest that the vehicles in any fleet may have variable properties. E.g., a fixed expenditure of vehicles (for purchase or rental), Capacity of vehicles, Variable unit cost for transportation amongst two consumers, etc. Besides, various kinds of vehicles may be required to fit the freight needs and the consumer needs. Hence, companies are prioritizing route distribution identification and vehicle fleet selection regarding cost reduction of logistics. The considered vehicles are involved in the collection or distribution of those products on any route. VRP is one of the central and most common research subjects of combinatorial optimization. It addresses the optimal assignment and distribution of vehicles within a fleet, which provides better routing to the intended destinations. VRP models offer an essential role to deliver realistic solutions to the improved operations and better management of physical distribution systems. Supply chain networks have multiple departments and multiple delivery points that involve highly secure and systematic approaches such as MDVRP (multi - depot vehicle routing problems).

This paper presents a Multi-Depot Heterogeneous Fleet Green Vehicle Routing Problem (MDHFGVRP), considering a multi-depot distribution chain that achieves multiple goals such as maximum revenue, reduction of costs, travel time, and carbon emission at the same time. This paper considers a new and sophisticated version of the VRP. This version, in addition to the capacity restrictions, combines the following extensions: multiple depots, heterogeneous vehicle fleet, and multiple objectives. We propose an efficient ant colony optimization (EACO) approach to solve the problem and results are compared with traditional ant colony optimization (ACO). The

remaining of this paper is organized as follows. Chapter 2 presents a brief literature review of the relevant topics. Section 3 formulates the mathematical model and discusses the solution approach. Section 4 provides numerical examples and Section 5 summarizes the experimental results. Lastly, Chapter 6 presents the final findings and recommendations for further study.

2. Literature Review

This literature review is dedicated to resemble the importance of transportation in logistic management in contributing to economic development while keeping a balance with a sustainable logistics system to eliminate any negative externalities of their operation by explaining the innovation and purpose of VRP and the development of MDVRP (Y. Li et al. 2019). Dantzig & Ramser (1959) first introduced a model to serve the oil demand by a fleet of homogeneous trucks from a central hub with a minimum travel distance which is known as "Truck Dispatching Problem". After a few years of that, Clarke & Wright (1964) proposed a linear model that is widely researched in the area of logistics and transport. This research turned out to be known as the 'Vehicle Routing Problem' (VRP). It aims to incorporate real-life complexities, which is an increasing phenomenon (Braekers et al. 2015). The basic VRP involves a set of customers, who need to be serviced by a fleet of vehicles, and all vehicles start and return to the same depot. Multiple variations and specializations of the VRP exist.

The Capacitated Vehicle Routing Problem (CVRP) is one of the most implemented versions of the VRP. A set of identical vehicles having fixed capacities are considered here that fulfils customers' demand for a single commodity. Multi-Depot Vehicle Routing Problem (MDVRP) is the variant where several depots are considered to serve clients. Clients are usually assigned to depots using clustering strategies. Bae & Moon (2016) proposed an extended version of MDVRP to overcome the challenges in logistics and supply chain management by minimizing fixed costs related to installation, depot, delivery, travelling long distances etc. For solving MDVRP hazardous materials transportation, Du et al. (2017) developed fuzzy bi-level programming in their research. Stodola (2018) modified the MDVRP by altering the optimization criterion to minimize the total number of routes and the longest routes. Kumar & Yadav (2019) proposed an ant colony-based metaheuristic to solve MDVRP, which is significant for employing alternative fuel-powered vehicles to deal with the obstacles. This algorithm requires the shortest tour while considering the vehicle and its fuel tank capacity. On the other hand, in real-world optimization, several objectives need to be solved by providing a set of optimal solutions called Pareto front (Abido & Bakhashwain, 2005). This multi-objective approach performs better for solving the real-world complex problems (Ahmed & Ador, 2020). In the last few years, a lot of research has been done on multi-objective vehicle routing due to its rich real life applications (Sandhya & Goel, 2018).

Nowadays, Green vehicle routing (GVRP) is becoming more popular as the concerns for climatic change are increasing worldwide. A GVRP with customer satisfaction criteria was investigated where pollution and customer satisfaction was taken into account while providing the decision-makers with the opportunity to select the appropriate route, heterogeneous fleet, speed and idle time of the vehicles (Afshar-Bakeshloo et al. 2016). Andelmin & Bartolini (2017) proposed an exact algorithm for GVRP to serve a set of geographically scattered customers via the optimal routing of an AFV. The assumption of a mixed vehicle fleet composed of electrical and conventional fleet creates an energy-efficient GVRP, and it was investigated by Macrina et al. (2019). To serve a subset of customers based on a single depot while minimizing the total travel distance, a path based solution approach for GVRP was proposed by Bruglieri et al. (2019). HVRP or Heterogeneous vehicle routing problem is a generalized derivation from classical VRP. Frequently, the broader usage of homogeneous fleet applied in VRP models does not meet realistic expectations. For dealing with many real-life scenarios of handling transportation of voluminous materials, Dominguez et al. (2016) proposed biased randomization for solving HFVRP. Pessoa et al. (2018) proposed enhanced branch and cut algorithm for solving heterogeneous fleet of VRP where the possibility in differing capacity, cost of the vehicles, depot allocations, subsets of customers are taken into account. Penna et al. (2019) proposed a hybrid heuristic approach for solving heterogeneous fleet VRP by combining with other attributes like backhauls, time windows, split deliveries and multi depot.

In recent years, researchers are benefited by applying advanced metaheuristics such as simulated annealing (SA), Tabu search (TS), genetic algorithm (GA), particle swarm optimization (PSO), artificial bee colony (ABC) algorithm, ant colony optimization (ACO) in different areas of supply chain management. For example, artificial bee colony (ABC) algorithm has been applied to partner selection for multi-echelon supply chain (Ahmed et al., 2020). Similarly, different metaheuristics have been applied extensively to VRP and its variants. For instance, Gao et al. (2016) proposed the ACO algorithm to solve multi depot vehicle routing problems with time windows effectively. An efficient algorithm based on ACO and neighborhood search for solving MDVRP with objectives of minimum route cost and emission rate was proposed by Jabir et al. (2017). Yao et al. (2019) proposed an ant colony optimization

(ACO) technique to solve the problem of fresh seafood delivery problems as an MDVRP where the models aim to find the routes with the least possible cost.

In particular, attempting to construct a model in which both heterogeneous fleets and green effect features of MDVRP have taken into consideration represents the context of this study. The main contributions of this paper are to incorporate prime objectives like maximizing revenue, minimizing cost including the reduction of CO_2 emission rate. Moreover, an efficient ant colony algorithm is proposed to solve the MDHFGVRP, in which the *k*-NN clustering technique is employed to traditional ant colony optimization (ACO) algorithm for improving the solution quality.

3. Methodology

3.1 Problem Definition

The objective of the proposed model is the determination of selecting supply sources, which maximizes potential revenues while reaching potential output, which as well as reduces associated costs and accumulated carbon emission rate to the least. Here, Figure1 demonstrates an example of the solution and embraces the main features of the problem whereas the green boxes represent customers at a different location; communication paths between customers and depots are presented as connecting arrows that also visualize the direction of the route. Asymmetric VRP is considered in our problem that assumes different distances in each opposite direction, which generates a directed graph. The assumption is more feasible in a real-life scenario. If an organization contains more than one depot from where the fleet starts and ends its journey, single depot VRP is not a proper solution. MD (Multi depot) VRP assumes several isolated depots that include more than one vehicle on purpose, and it eliminates the major limitation in designing and serves a broad point, making it more practicable to reality.

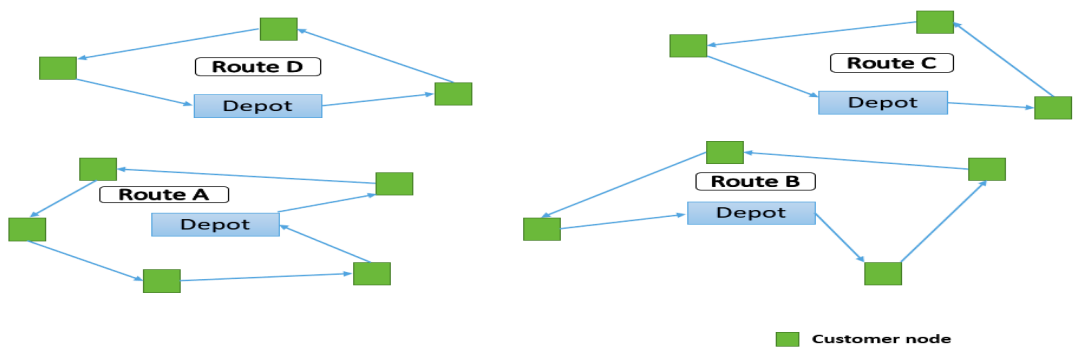

Figure 1. Representation of MDHFGVRP example

Logistics operations quite often recognize selections regarding heterogeneous fleets of vehicles. HVRP or Heterogeneous vehicle routing problem is a generalized derivation from classical VRP. In this occurrence, different kinds of vehicles with various features, such as capacity and pathway properties, serve customers accordingly. By assumption, there shall be fixed fleets and is known beforehand. Frequently, the broader usage of homogeneous fleet applied in VRP models does not meet realistic expectations. Regardless, maintenance of the balance of the sustainable logistics system to eliminate any negative externalities of their operation also requires significant concentration, which incorporates the necessity of Green VRP. Some assumptions considered to formulate the model are mentioned below:

- The problem is designed as an individual network
- Customer delivery will be completed by one trip of any one type of vehicle
- Each vehicle belongs to its departing depot and has to be returned for further service
- One product is loaded in each vehicle from one depot
- Heterogeneous vehicles are available
- Vehicles are assignable to only one depot
- The problem is designed as only one route constructed by each depot

3.2 Model Formulation:

By following the above criteria, a mathematical model of the problem is constructed based on linear programming model formulation regarding graph theory, where nodes connected to edges. Let, $G = (V_m, A)$ be a directed graph following asymmetric input data matrices, where $V_m = (V \cup V_o)$ is the set of nodes and $A=\{(i,j): i,j \in V, I \neq j\}$ is the set of arcs representing communication paths.

Index:

i, j, s : index of nodes
k : index of vehicles, $\{k = 1,...,|K|\}$

Parameters:

V : Set of all customers
V_0 : Set of all depots
A : Set of arcs (paths)
L_{ij} : Distance between node i and j
L_{sj} : Distance between node s and j
L_{is} : Distance between node i and s
D_j : Demand in node j
P : Per unit cost of product
E_k : Amount of produced emission by a vehicle of type k during transportation
t_{ij} : Travelling time of vehicle type k from node i to node j
t_{ij} : Travelling time of vehicle type k from depot s to node j
t_{ij} : Travelling time of vehicle type k from node i to depot s
T_{jk}^{out} : Unloading time at node j
T_{sjk}^{in} : Time of loading for shipping products from depot s to node j
C_{ijk} : Per unit transportation cost from node i to node j with vehicle type k
C_{sjk} : Per unit transportation cost from depot s to node j with vehicle type k
C_{isk} : Per unit transportation cost from node i to depot s with vehicle type k
K : Heterogeneous Fleet of vehicles
W_k : Capacity of the vehicle type k
F_k : Fixed cost of the vehicle of type k
Y_k : The number of vehicle type k used in the fleet
T_k : Available vehicles for each k type

Decisions Variables:

$Flow_{ijk}$: Total quantity of products of vehicle type k between node i and node j
$Flow_{sjk}$: Total quantity of products of vehicle type k between depot s and node i

$$x_{ijk} = \begin{cases} 1\text{: if a vehicles of type } k \text{ travels from node } i \text{ to node } j \\ 0\text{: otherwise} \end{cases}$$

$$x_{sjk} = \begin{cases} 1\text{: if a vehicles of type } k \text{ travels from depot } s \text{ to node } j \\ 0\text{: otherwise} \end{cases}$$

$$x_{isk} = \begin{cases} 1\text{: if a vehicles of type } k \text{ travels from node } i \text{ to depot } s \\ 0\text{: otherwise} \end{cases}$$

The proposed MDHFGVRP has the following objectives:

i. Revenue maximization (f_1):

$$\max f_1 = \sum_S \sum_{j\in N} \sum_{k\in K} Flow_{sjk} \,.\, P.\, x_{sjk}$$

ii. Cost minimization (f_2):

$$\min f_2 = \sum_S \sum_{j\in V} \sum_{k\in K} Flow_{sjk} . C_{sjk} \,.\, x_{sjk} + \sum_{i\in V} \sum_S \sum_{k\in K} C_{isk} \,.\, x_{isk} + \sum_{(i,j)\in V} \sum_{k\in K} Flow_{ijk} \,.\, C_{ijk} \,.\, x_{ijk} + \sum_{k\in K} F_k \,.\, Y_k$$

iii. Travel Time minimization (f_3):

$$\min f_3 = \sum_S \sum_{j\in V} \sum_{k\in K} t_{sjk} \,.\, x_{sjk} + \sum_{i\in v} \sum_S \sum_{k\in K} t_{isk} \,.\, x_{isk} + \sum_{(i,j)\in A} \sum_{k\in K} t_{ijk} \,.\, x_{ijk} + \sum_S \sum_{j\in V} \sum_{k\in K} T_{sjk}^{in} \,.\, x_{sjk} + \sum_{j\in V} \sum_{k\in K} T_{jk}^{out} \,.\, D_j$$

iv. CO_2 Emission reduction (f_4):

$$\min f_4 = E_{pk} \left[\sum_S \sum_{j\in V} L_{sj} \,.\, x_{sjk} + \sum_{(i,j)\in A} L_{ij} \,.\, x_{ijk} + \sum_{i\in V} \sum_S L_{is} \,.\, x_{isk} \right]$$

f_1 is the total revenue obtained by multiplying total demand and price of the products. f_2 represents the total transportation costs between different nodes with different type of vehicle. f_3 is the total time for discharging, loading,

and even travelling between different nodes. Lastly, f_4 indicates the carbon emission function, which is the level of pollution by the vehicles. The final construction of the model is presented in equation (1) and (2).

1st objective function, Z_1 = maximize f_1 (1)

2nd objective function, Z_2 = minimize $(f_2 + f_3 + f_4)$ (2)

Here, the weighted sum approach has been used to solve the multi-objective optimization problem. The function is normalized for balancing the relative magnitude of the two objective functions is shown in equation (3).

$$\text{minimize } Z = -\omega \times \frac{Z_1 - Z_{1\_min}}{Z_{1\_max} - Z_{1\_max}} + (1-\omega) \times \frac{Z_2 - Z_{2\_min}}{Z_{2\_max} - Z_{2\_max}} \quad (3)$$

where ω is weight of the weighted sum approach. The maximum and minimum value for the respective functions is calculated considering extreme conditions running the optimization separately. The formulation of constraints are demonstrated as follows:

$$\sum_{j\in V} \sum_{k\in K} x_{ijk} = 1;\ \forall i \in V_0, \forall k \in K \quad (4)$$

$$\sum_{i\in V} \sum_{k\in K} x_{ijk} = 1;\ \forall j \in V_0, \forall k \in K \quad (5)$$

$$\sum_{S} \sum_{j\in V} \sum_{k\in K} Flow_{sjk} = \sum_{j\in V} D_j;\ \forall k \in K \quad (6)$$

$$D_j \times x_{ijk} \leq Flow_{ijk} \leq (W_k - D_j) \times x_{ijk};\ \forall (i,j) \in A, \forall k \in K \quad (7)$$

$$Flow_{ijk} \geq 0;\ \forall (i,j) \in A, \forall k \in K \quad (8)$$

$$Flow_{isk} = 0;\ \forall j \in V, \forall s \in S, \forall k \in K \quad (9)$$

$$\sum_{i\in V} Flow_{ijk} - \sum_{i\in V} Flow_{jik} = D_j;\ \forall j \in V \quad (10)$$

$$Flow_{ijk} \leq W_k \times x_{ijk};\ \forall (i,j) \in A,\ \forall k \in K \quad (11)$$

$$\sum_{j\in V} x_{ijk} - \sum_{j\in V} x_{jik} = 0;\ \forall k \in K, \forall i \in V_0 \quad (12)$$

$$x_{ijk} \in \{0,1\};\ \forall (i,j) \in A \quad (13)$$

$$Y_k \leq T_k;\ \forall k \in K \quad (14)$$

$$Y_k \geq 0 \text{ and } Y_k \text{ is integer};\ \forall k \in K \quad (15)$$

Constraints (4) and (5) presents the balance of flow of the network. Constraints (6) ensures that all the demand points are met. Constraints (7) checks the availability of product for the next delivery after satisfying demand. Constraints (8) ensures that flows are greater than or equal to zero. Constraints (9) consider that each vehicle belongs to their depot and returns to the departing depot. Constraints (10) checks that the available quantity after visiting customer *j* is exactly the load before visiting this customer minus its requirement. Constraints (11) indicate that the carrying capacity cannot be less than the total demand of the visited customers for each vehicle. Constraints (12) checks that a customer leaving a depot (or returning to a depot) is linked to the same depot respectively. Constraints (13) is the assignment constraint having binary value. Constraints (14) controls the number of vehicles of each type in the fleet must be less than or equal to the available number of vehicles of each type. Constraints (15) is the non-negativity and integrality constraint.

3.3 Solution Approach

ACO algorithm is the most widely used and well-recognized technique of algorithm that is employed with artificial ants following the behavior of real ants searching for food for finding the global solution for an optimization problem. The ant's communication methods, known as stigmergy, include information about the food source by deposition of pheromone. The paths involving higher pheromone level has a high possibility to be chosen. In comparison, the rest of the pheromone with a lower intensity level is disappeared by evaporation, providing the capability for shortest pathfinding (Garai et al. 2013). In this paper, an extended evolutionary algorithm called Efficient Ant Colony Optimization (EACO) is proposed to deal with multi depot heterogeneous fleet allocation for customers. In first step, the proposed method employs *k*-NN classification technique for classifying the depot to its relative closer customers. In *k*-NN classification, the output is a class membership. An object is classified by a plurality vote of its neighbors, with the object being assigned to the class most common among its *k* nearest neighbors. The objective function of *k*-NN is the sum of distances between clustering centers and data points, and to minimize the objective function, *k* means to divide a set of *n* points into *k* regions (Xu et al., 2018). In step 2, the Ant Colony optimization uses the results from step 1 and solve the weighted sum multi-objective optimization with optimal parameter setting for a particular weight. The iteration continues for different weight to provide a Pareto front solution of the problem. In figure 2, a flowchart has been provided for better under understanding the solution approach. The optimization will be terminated if the necessary termination criterion is realized. Therefore, the flow is considered as successful.

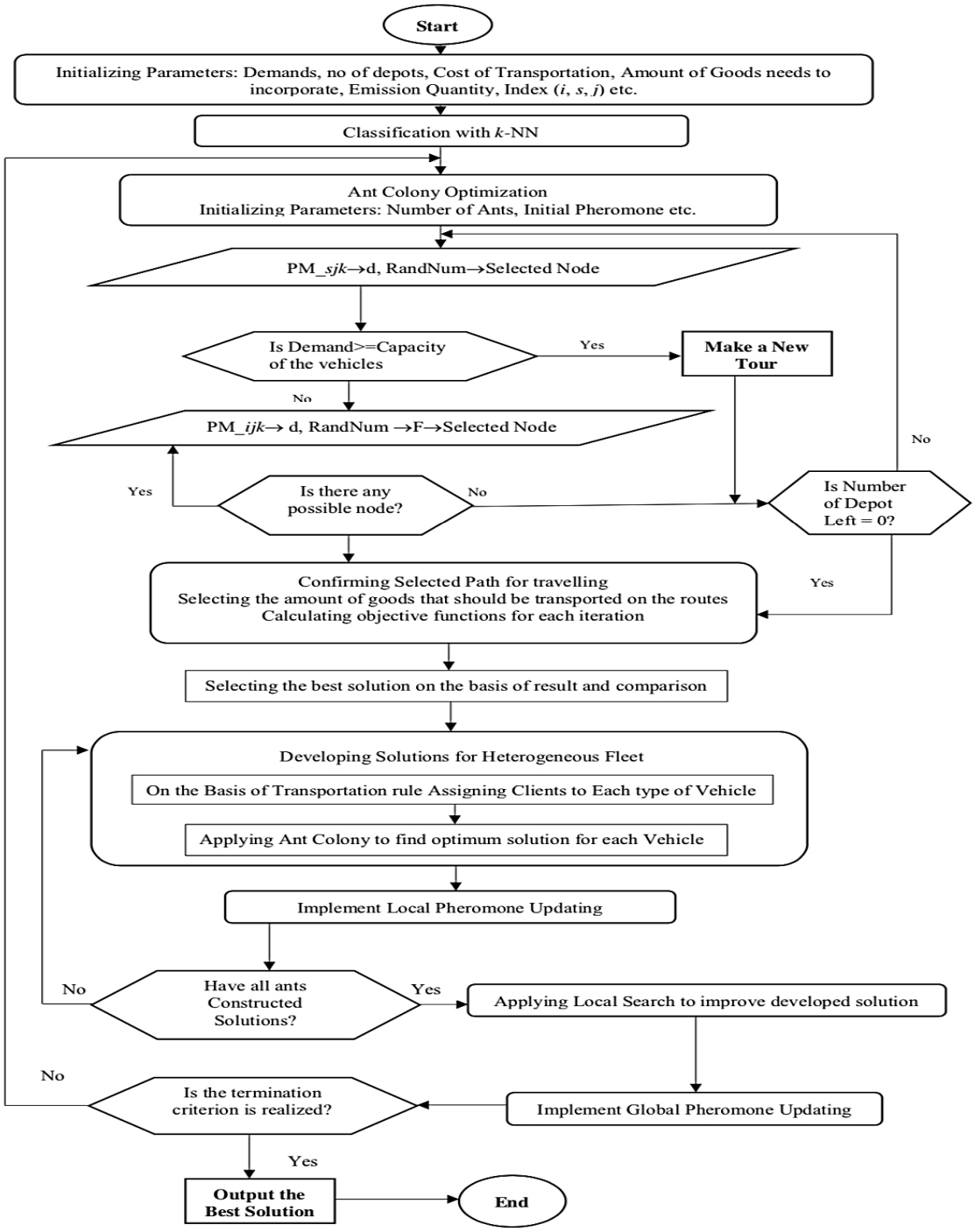

Figure 2. Flowchart of EACO algorithm for solving MDHFGVRP

4. Numerical Examples

In order to exemplify the application of EACO numerically, sixteen cases are considered with different specifications. The cases are further divided into small-scale and large-scale depending on their relative magnitude. The datasets are open and collected from Bagherinejad & Dehghani (2016). In Table 1, eight numerical examples in small-scale and eight numerical examples in large-scale, are provided to demonstrate the proposed method. For heterogeneous fleet, there are maximum three types of vehicle available in each depot. The specific type of vehicle will be assigned to each depot according to the optimized results.

Table 1. Specifications of MDHFGVRP examples

Specification for Small-scale Cases				Specification for Large-scale Cases			
Example No.	**Number of depots**	**Number of Customers**	**Types of Vehicles**	**Example No.**	**Number of depots**	**Number of Customers**	**Types of Vehicles**
1	7	21	3	1	7	32	3
2	3	8	2	2	11	40	3
3	3	15	2	3	8	34	2
4	4	10	2	4	9	70	3
5	5	12	2	5	9	62	3
6	6	14	3	6	7	80	3
7	5	20	2	7	11	68	3
8	4	26	2	8	10	60	3

4.1 Parameter Selection

Selecting the appropriate parameters for each scenario can intensify the global search ability of the algorithm while considering the enhancement of the convergence speed (P. Li & Zhu, 2016). Weight of Pheromone (α), Weight of visibility (β), Evaporation rate of pheromone (ρ), Initial Crossover Threshold (t), Number of Ants (nAnt) and Maximum Number of Iterations (N) provide a significant impact on the path selection of the ant. In this paper, optimum values for these parameters are selected from the range provided by P. Li & Zhu (2016). Different parameter play different role in convergence of the algorithm, for example, Weight of Pheromone (α) which is also known as information elicitation factor, reflects the relative importance of the pheromone and the accumulation of the pheromone that is required for ant's appropriate path selection, Weight of visibility (β) is also known as expected heuristic factors that involve the importance of heuristic information regarding path selection by the ants, Evaporation rate of pheromone (ρ) reflects the degree of pheromone evaporation and the degree of mutual influence between the ants. The selected values for different parameter of the proposed EACO method is shown in table 2. There are two levels of selected values for the parameters for solving small-case and large-case examples from the optimum range for better performance of the optimization.

Table 2. Selected values for parameters of EACO

Parameter	Description	Value for small-case	Value for large-case
nAnt	Number of Ants	40	100
α	Weight of Pheromone	1	2
β	Weight of Visibility	1	1
ρ	Evaporation rate of Pheromone	0.8	0.9
t	Initial Crossover Threshold	1	1
N	Maximum Number of Iterations	300	500

5. Experimental Results and Discussions

In this section, the results obtained from the efficient ant colony optimization (EACO) for solving the example MDHFGVRP problems are presented. By a number of experiments based on two different scales of data sets, we analyze the performance of the proposed algorithm by solution quality and convergence characteristics. The Pareto front is shown in table 3 and table 4 for problem 6 of both small-case and large-case example, respectively. By the help of the Pareto front, the performance of the efficient ant colony optimization (EACO) and traditional ant colony optimization has been assessed. Figure 3 and Figure 4 illustrates the relative comparison of Pareto front between EACO and ACO for small-scale and large-scale respectively. As both objective functions are normalized, the respective values remain within 0 to 1. The Pareto front has a positive slope because of the nature of the two objective functions. The first objective function tends to maximize the revenue, whereas the second objective function tends to minimize the associated costs and carbon emissions. From figure 3 and 4, it can be observed that our proposed EACO performed slightly better than the traditional ACO.

In order to show the efficiency of our proposed EACO model with respect to the traditional ACO, the convergence characteristics are illustrated in figure 5 and figure 6 for the small-scale and large-scale example, respectively. From figure 5, it can be said that the performance of EACO and ACO is almost same in terms of finding the best cost for

Table 3. Comparison of Pareto front for ACO and EACO (small-scale)

Weight	**ACO**		**EACO**		**Percentage Difference between ACO and EACO**	
ω	**Objective Function 1**	**Objective Function 2**	**Objective Function 1**	**Objective Function 2**	**Objective Function 1**	**Objective Function 2**
0.1	0.4258	0.0465	0.4339	0.0352	1.90	24.41
0.2	0.4939	0.0953	0.5033	0.0851	1.90	10.72
0.3	0.5705	0.1803	0.5835	0.1692	2.26	6.10
0.4	0.6442	0.2274	0.6537	0.2018	1.47	11.24
0.5	0.6962	0.2597	0.6896	0.2390	0.94	7.96
0.6	0.7469	0.3007	0.7418	0.2771	0.68	7.83
0.7	0.7995	0.3669	0.7730	0.3683	3.31	0.36
0.8	0.8630	0.4165	0.8959	0.4258	3.80	2.23
0.9	0.8880	0.4565	0.9021	0.4541	1.59	0.52
1	0.9468	0.4939	0.9711	0.4663	2.57	5.59

Table 4. Comparison of Pareto front for ACO and EACO (large-scale)

Weight	**ACO**		**EACO**		**Percentage Difference between ACO and EACO**	
ω	**Objective Function 1**	**Objective Function 2**	**Objective Function 1**	**Objective Function 2**	**Objective Function 1**	**Objective Function 2**
0.1	0.5653	0.0875	0.5824	0.0839	3.02	4.04
0.2	0.6126	0.1281	0.6221	0.0962	1.54	24.93
0.3	0.6712	0.1414	0.6833	0.1401	1.80	0.94
0.4	0.6919	0.1670	0.6862	0.1491	0.81	10.68
0.5	0.7273	0.2096	0.7071	0.1627	2.77	22.36
0.6	0.7612	0.2321	0.7483	0.2182	1.69	6.01
0.7	0.7779	0.2899	0.7696	0.2375	1.06	18.06
0.8	0.8253	0.3194	0.8268	0.2869	0.18	10.16
0.9	0.8260	0.3570	0.8324	0.3306	0.77	7.41
1	0.9361	0.4955	0.9403	0.5010	0.45	1.0

the small-scale case. However, from figure 6, it can be observed that EACO performed better than ACO in finding the best cost for the large scale case. The relative differences between the values of both objective functions are shown in table 3 and table 4 for small-scale and large-scale respectively. The relative difference of values of objective function 1 obtained from ACO and EACO is very negligible. In case of values of objective function 2, there are some variations between ACO and EACO. However, in most of cases, the differences are not significant. Therefore, it can be concluded that both the method is capable of finding the best cost. However, our proposed EACO algorithm is more efficient than the traditional ACO in finding the best cost without affecting the solution quality. Finally, the solution of the problem is shown in table 5 and table 6 for small and large cases, respectively. From table 5 and table 6, the details of customer allocation to each depot can be observed. The particular type of vehicle also has been assigned to each depot based on the optimization results. The customer allocation is presented sequentially so that the route of the vehicle can be easily understood. In table 5, it is shown that total of 14 customers are served from six depots for the small-scale case. Again in table 6, it is shown total of 80 customers are served from the seven depots for the large-scale case. Similarly, all the allocation for each eight examples of both small-scale and large-scale are conducted by applying our proposed method. However, due to space constraints, only the results obtained from example 6 of each case have been shown in this paper. From all the results obtained, it can be concluded that our proposed EACO algorithm is found to be more efficient than the ACO algorithm. In particular, the results obtained through our proposed model performed better when the size of the network increases involving more depots and more customers to be served from each depot.

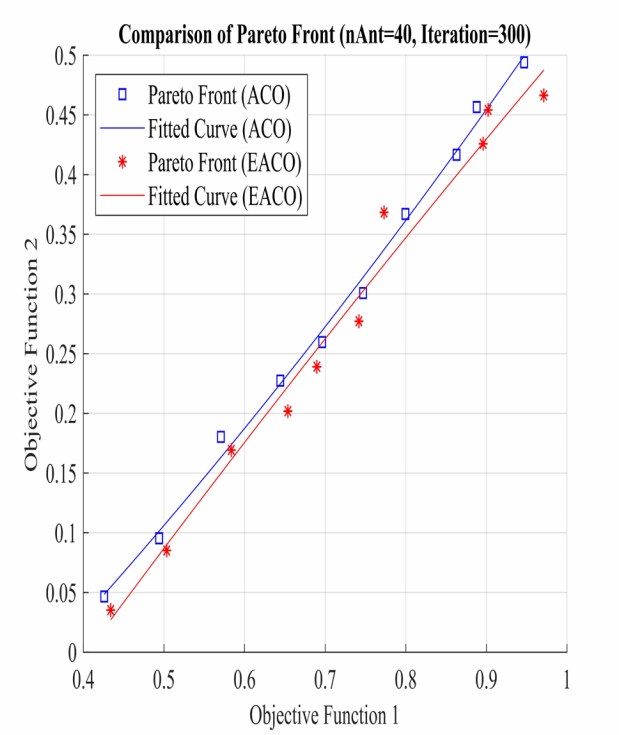

Figure 3. Comparison of Pareto front for problem 6 (small-scale, No. of Ant = 40, Max. iterations = 300)

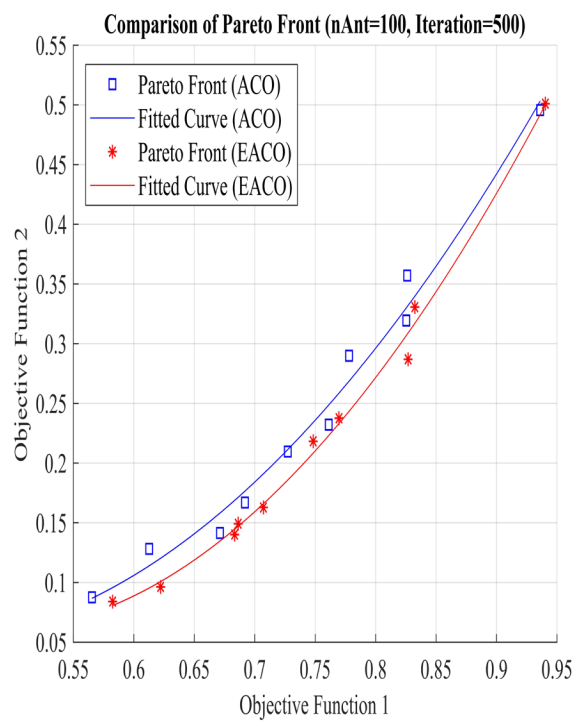

Figure 4. Comparison of Pareto front for problem 6 (large-scale, No. of Ant = 100, Max. iterations = 500)

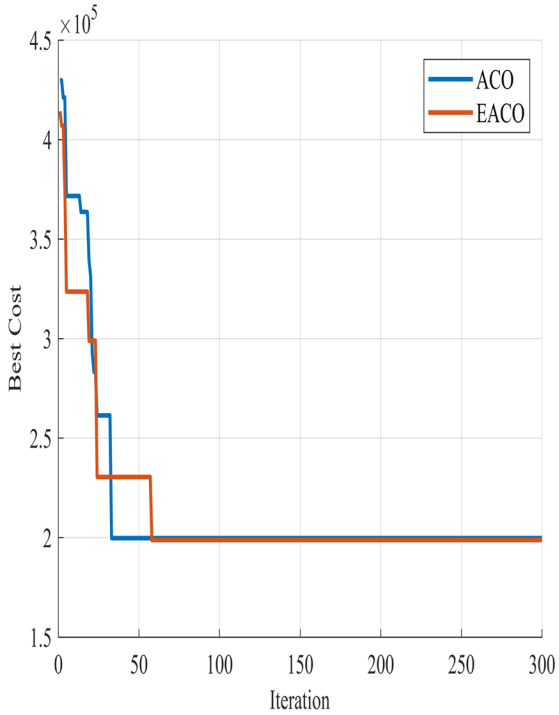

Figure 5. Convergence characterstics for problem 6 (small-scale, No. of Ant = 40, Max. iterations = 300)

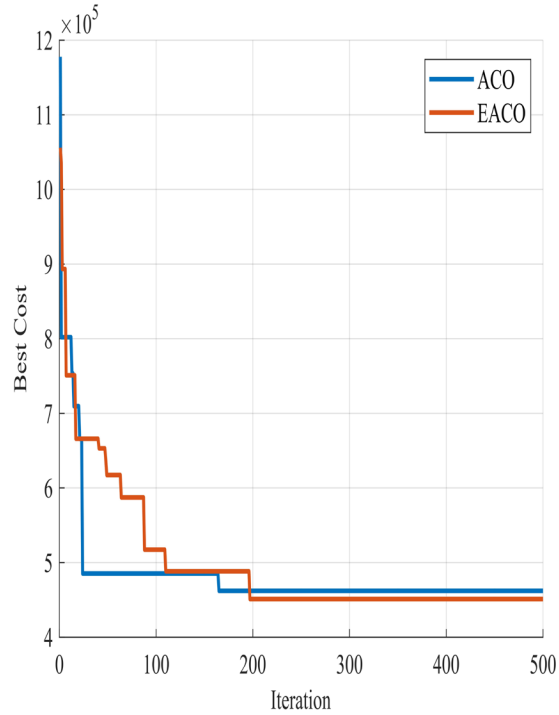

Figure 6. Convergence characterstics for problem 6 (large-scale, No. of Ant = 100, Max. iterations = 500)

Table 5. Allocation of customers to each depot for example 6 (small-scale)

Depot	Customers Allocated	Total Number of Customer served	Selected Vehicle Type
1	14-7	2	1
2	8 - 6	2	3
3	2 – 13 - 10	3	2
4	4 -3- 9	3	3
5	12 -5 - 11	3	2
6	1	1	3

Table 6. Allocation of customers to each depot for example 6 (large-scale)

Depot	Customers Allocated	Total Number of Customer served	Selected Vehicle Type
1	3-4-5-6-26-27-29-30-32-34-37-39-78-79	14	3
2	10-11-14-19-31-38-53-54-59-65-66-77	12	2
3	40-44-45-47-48-50-51-55-60-67-68-70-75	13	2
4	2-16-21-24-28-33-36-49-62-63-69-71-73-74	14	3
5	1-22-23-41-42-43-56-61-64-76	10	2
6	18-20-25-7- 8-13-35-46-52-57-58-72	12	3
7	9-12-15-17-80	5	1

6. Conclusion and Future research

The thoroughly recognized service in an emulative business environment for customers has proven to be efficient and swift, holding immense importance. To make sure the flow of commodities and materials stay abetted between producers and consumers, distribution centers carry out the task effectively. Traditionally, a considerable effort went in to handle cost reduction while researching efficiency in transport systems. In contemporary business environments, the success of a transport system includes many major factors that hold a crucial position and are on increasing demand by stakeholders like - environmental impact minimization. In this paper, a multi-objective model is presented for solving a green multi-depot heterogeneous fleet vehicle routing problem. The optimization objectives are to maximize revenue and minimize associated costs as well as carbon emissions. Since the model is considering a heterogeneous fleet of vehicles, this represents a more realistic approach for solving the proposed model.

Moreover, an evolutionary algorithm named efficient ant colony optimization (EACO) is proposed for solving the model more efficiently. The proposed methodology is based on using a *k*-NN classification for aiding the traditional ant colony optimization. To validate the efficacy of our EACO model, eight small-scale and eight large-scale networks were used to demonstrate the performance of the model in real-world scenarios. The experimental results obtained through EACO showed satisfying performance in developing optimal Pareto front. In addition, the results show that both EACO and ACO algorithms are capable of solving the model and does not differ much. However, the EACO algorithm is more efficient than ACO in terms of finding the best cost, optimization performance, and convergence. In particular, it can be concluded that with the increasing complexity of the problem, the proposed model performs better than the traditional method.

The proposed model considers a single product with deterministic parameters. It is recommended that future research may consider multi-product scenarios and extended to deal with different real-world uncertainties in demand, transportation time and price. Therefore, the future works may consider fuzzy, stochastic, chaos or other approaches available in the literature.

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