Ant Colony Algorithm for Routing Alternate Fuel Vehicles in Multi-depot Vehicle Routing Problem

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Abstract A Multi-depot Green Vehicle Routing Problem (MDGVRP) is considered in this paper. An Ant Colony System-based metaheuristic is proposed to find the solution to this problem. The solution for MDGVRP is useful for companies, who employ the Alternative Fuel-Powered Vehicles (AFVs) to deal with the obstacles brought by the limited number of the Alternative Fuel Stations. This paper adds an important constraint, vehicle capacity to the model, to make it more meaningful and closer to real-world case. The numerical experiment is performed on randomly generated problem instances to understand the property of MDGVRP and to bring the managerial insights of the problem.

Keywords Vehicle routing · Multi-depot · Alternative fuel-powered vehicle operations · Fuel tank capacity limitation · Capacitated vehicle

1 Introduction

Recent years, green logistics has become a high-profile research field because of the growing environmental and of the pollution concern worldwide. The current production and distribution system has triggered various environmental problems, which lead to an unsustainable environmental situation.

Under this background, more and more researchers have concentrated on the Green Vehicle Routing problem (GVRP) [1–3]. Different from the classical Vehicle Routing Problem (VRP) which only focuses on the selection of the optimal route by minimizing total transportation cost generated in the process of distribution services, the GVRP emphasizes not only on the optimal economic cost of delivery, but also on addressing sustainable issues in delivery distribution of supply chains [2]. The design of GVRP requires the use of the Alternative Fuel-powered Vehicles (AFV),

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which relies on greener fuel source such as electricity, natural gas, hydrogen, etc. [1]. However, there are two main obstacles encountered when replacing the conventional vehicles with the AFVs: (1) the limited capacity of the fuel tank or batteries of AFVs, and (2) the scarcity of Alternative Fuel Stations (AFSs). Because of these obstacles, problem formulation and algorithm design of GVRP become more complex than those of VRP [1].

At the same time, the Multi-depot Vehicle Routing Problem (MDVRP) has also attracted a lot of attention [4–6]. In the MDVRP, the fleet of vehicles serves customers from several depots and returns back to the same depot [6]. Research about the MDVRP is meaningful for companies that have a wide range of business scope and have more than one depot because the solution of MDVRP could help these companies reduce their transportation costs and improve their financial performances.

In recent years, many large-scale multinational companies such as UPS, Coca-Cola, and GM have especially paid attention to their environmental sustainable performances and update their sustainability reports every year. They are exhausting their ability to keep a balance between economic performance and environmental protection. For these companies, the solutions for GVRP or MDVRP cannot provide an optimal solution they desired. Most of the GVRP solutions methods only work in situations where there is only one depot and most of the results for the MDVRP only focus on minimizing the transportation cost and ignore the sustainable issues.

Therefore, in this paper, a new variety of problem called the Multi-depot Green Vehicle Routing Problem (MDGVRP), is addressed. In the MDGVRP, the AFVs departure from different depots, serve customers, and at the end come back to original depots. Due to the limited capacity of the fuel tank of AFVs and the scarcity of AFSs, each AFV needs to go back its original depot or the nearest AFS to refuel. Based on the two main constraints above, the objective of MDGVRP is to minimize the route distance of the AFV fleets. Thus, compared with MDVRP or GVRP, MDGVRP has more constraints and subsequently, is more different to formulate and solve.

It is widely known that VRP is an NP-hard problem, which means that increasing the size of the problem leads to exponential growth in the computational effort required to find the corresponding solution. Because the MDGVRP is a special variant of the VRP, it can be determined that the MDGVRP is also NP-hard. Therefore, in this paper, the ant colony algorithm is proposed to find solutions for MDGVRP.

The structure of the rest of this paper is organized as follows. In Sect. 2, related literature review is presented. Section 3 describes the MDGVRP problem. Section 4 presents the proposed ant colony algorithm. Numerical experiments are presented in Sect. 5 and are followed by the conclusion in Sect. 6.

2 Literature Review

Because the MDGVRP is a quite new variety of problem, there is no literature focusing on this area. However, the MDGVRP is based on the GVRP and MDVRP; therefore, some important previous studies are reviewed in the following sections.

2.1 GVRP

The research of the GVRP just began about 10 years before. However, the GVRP has received extensive attention from researchers because people are becoming aware of the importance of environment protection. According to the comprehensive literature survey on the GVRP of Lin et al. [2], there are mainly two categories of GVRP: Pollution-Routing Problem (PRP) and Green-VRP. Although both these two categories of GVRP focus on economic cost and environment cost simultaneously, the PRP reduces environment cost by minimizing the fuel consumption or minimizing the Green House Gas (GHG) emissions, while the Green-VRP alleviates the environmental damage by using AFVs instead of conventional vehicles. Erdoĝan and Miller-Hooks [1] first addressed that the conventional vehicles can be replaced by the AFVs. They proposed a model to help companies which apply the AFVs to optimize the transportation routes in order to overcome the limited capacity of fuel capacity of the AFVs. Based on their work, Schneider et al. [3] added the customer time window constraints to the VRP for electric vehicles. The MDGVRP considered in this paper is based on the Green-VRP of Erdoĝan and Miller-Hooks [1]. However, compared with their model, our model considers the demands of customers and can be used to solve the multi-depot problem instead of the single-depot problem.

2.2 MDVRP

The MDVRP was first described in the research of Cassidy and Bennett [4], and is a generalization of the standard VRP, in which there are multiple depots [5]. The MDVRP is very easy to be described. However, an NP-hard problem, the MDVRP is extremely difficult to solve. Therefore, the research of MDVRP mainly focuses on proposing and developing new methods and algorithms to solve the problem. The work of Montoya-Torres et al. [6] revealed that most researchers tend to solve the MDVRP by heuristics or meta-heuristics. For example, Vidal et al. [7] solved the MDVRP by using a hybrid genetic algorithm. In the research of Yu et al. [5], they changed the MDVRP to Single-depot VRP (SVRP) by adding a virtual depot in the first step, and then they applied an improved Ant Colony Optimization (ACO) to solve the SVRP. Therefore, the development of the research on MDVRP is followed by the continually improving the algorithms. In this paper, the ant colony algorithm is developed to solve the MDGVRP.

3 Problem Description

A standard MDGVRP can be described as the problem of designing least distance routes from the Ns' depots to a set of geographically scattered points (customers).

AFVs start from different depots and serve customers one by one, and finally, they return their original depots. Each customer $c_i \in C$ (customer set) is associated with a non-negative demand q_i to be delivered. To ensure the efficiency of delivery, each customer is visited by the AFVs one time and the demand of customer would be satisfied after this visit. During the service process, the AFVs need to return their original depots to reload to ensure that the remaining cargos always can satisfy the demand of the next customer. Besides, if it is necessary to refuel during the service process, the AFVs have to visit the AFSs or return their original depots to refuel. It is assumed that the number of AFSs visited by an AFV in a tour can be more than one. Besides, a particular AFS can be visited more than once on a given vehicle route. The objective of the problem is to minimize the total distance traveled by all vehicles.

4 Solution of MDGVRP

The proposed algorithm first assigns a customer to its nearest depot. Then a single-depot GVRP is solved for each depot using the Ant Colony System (ACS) algorithm.

4.1 Ant Colony System (ACS) Algorithm for Single-Depot GVRP

We solve the single-depot GVRP by using the Ant Colony System (ACS) algorithm. The problem consists of the depot and associated customers. Ants always can find the shortest route between their nest and the food. Through simulating the food-seeking behaviors of ant colonies in nature, the Ant Colony System (ACS) algorithm was developed [8]. During the past several years, the ACS algorithm has been successfully applied to solve the VRP and its variants (e.g., Lin et al. [2], Yu et al. [5], Montoya-Torres et al. [6], Dorigo et al. [8], Bell and McMullen [9], Gajpal and Abad [10], etc.).

In the ACS algorithm, some artificial ants are created to find the feasible solutions based on constraints and trail intensity generated or accumulated during previous iterations. The paths in solutions (routes) with a higher value of the objective function (shorter route distance) accumulate a higher level of trail intensity. The paths with a higher level of trail intensity have a higher chance to be selected by artificial ants in the next iteration. In this way, after several iterations, the near-optimal solution can be found. The fundamental procedures of ACS are as follows:

Step 1: Initialize the trail intensity matrix, create m artificial ants.
Step 2: Repeat the following steps until the termination condition is fulfilled.

- Generate a solution for each ant based on trail intensity.
- Optimize the solutions by local search.

- Update elitist ants.
- Update trail intensity matrix based on the elitist ant solutions.

Step3: Record the best solution of all generated solutions so far.

4.1.1 Ant Solution Generation

Every GVRP is first simplified as a Traveling Salesman Problem (TSP) and the ACS algorithm is applied to seek the feasible solutions. The feasible solutions of each TSP are the route set which only consists of the original depot and customers. Finally, in the third phase, the TSP solutions found in the second phase are used to build the routes of GVRP. The rules to build these routes are included: (1) insert an AFS or the original depot when the remaining fuel is not enough to support the AFV to reach the next customer on the TSP route or return its original depot and (2) insert the original depot when the remaining products are not able to satisfy the demand of the next customer on the TSP route. In this way, each GVRP can be solved.

In every iteration, there are n number of artificial ants to create n number of TSP solutions (n is the number of customers in the problem). The artificial ants select the next customer mainly based on two factors: the saving value and the trail intensity between two customers.

The saving value S_{ij} represents the saved traveling distance between the customers i and j who are served by one AFV instead of two. The following function shows how to calculate S_{ij} and d_{ij} denotes the distance between the customer i and j:

$$S_{ij} = d_{0i} + d_{j0} - d_{ij}$$

The trail intensity τ_{ij} is defined as the intensity of serving customer j from the customer i and the trail intensity records the information on the visit between two customers. Therefore, at the beginning, all elements in the τ_{ij} matrix are same and are set to 0.01 in this paper.

The saving value (S_{ij}) and trail intensity (τ_{ij}) between two customers constitute the attractiveness value ξ_{ij} between these two customers. And,

$$\xi_{ij} = \left[S_{ij}\right]^{\alpha}\left[\tau_{ij}\right]^{\beta}$$

In this equation, α and β are the biases of saving value and trail intensity, respectively. These two parameters are set at the beginning of the algorithm execution and the values of them need to be altered according to different problem scenarios.

Based on the attractiveness value, the probability of selecting customer j as the next customer from customer i is calculated by the following function:

$$P_{ij} = \frac{\xi ij}{\sum_{k=1}^{q} \xi i x_k}, 1 \le k \le q$$

In this function, X_k represents the element of unvisited customer set Ω_q. The set Ω_q contains q number of elements, which means that there are q numbers of unvisited customers. x_k represents the kth element of set Ω_q.

According to the probability calculation function, the m number of artificial ants generates m number of TSP routes in every generation. In the next step, m number of GVRP routes would be generated from TSP route based on the following rules:

1) Insert the depot if the remaining load of the vehicle cannot satisfy the demand of the next customer;
2) Insert the nearest available fuel station if the remaining fuel level is not enough to get the next customer.

However, sometimes, the quality of the solutions generated in this way is not good enough. To improve the quality of these solutions, the local search is necessary. Local search improves the quality (objective function value) of a solution (a GVRP route) by changing the visiting consequence of a customer to check whether the value objective function can decrease and local search is applied in every iteration after the artificial ants generating new solutions. In this way, the solutions of every iteration can be improved.

4.1.2 Trail Intensity Update

At the end of every iteration, the trail intensity between two customers τ_{ij} needs to be updated to ensure the artificial ants can generate high-quality solutions in the next iteration. To update trail intensity, the elitist ant set which contains λ number of ants (represent λ best solutions in the past iterations) need to be set first. Then, τ_{ij} will be updated according to the solutions of elitist ant set. The function to change τ_{ij} is as follows:

$$\tau_{ij}^{\text{new}} = \tau_{ij}^{\text{old}} \times \varphi + \sum_{\theta=1}^{\lambda} \tau_{ij}^{\theta},\ i \neq j \text{ and } i, j = 1, 2, \ldots, n$$

In this equation, τ_{ij}^{old} represents the old trail intensity accumulated until the last iteration and φ is the trail persistence which is between 0 and 1. The number of φ determines the decreasing speed of pheromone density, and is set as 0.95. The second term of the equation represents the pheromone increase brought by the elitist ant θ. And the value of τ_{ij}^{θ} is determined by

$$\tau_{ij}^{\theta} = \begin{cases} 0 & \text{if the edge between customer } i \text{ and } j \text{ is not in the elitist ant route.} \\ \frac{1}{l^{\theta}} & \text{otherwise.} \end{cases}$$

l^{θ} represents the route length of θth elitist ant solution.

Table 1 Strategic location of AFS

Pattern	Number of AFSs	Details
1	2	The grid is horizontally divided into two equal sections with each AFS randomly assigned to the two sections
2	4	The grid was divided into four equal sections with each assigned an AFS
3	6	This is similar to pattern 2 except that the two additional AFSs are distributed using pattern 1
4	8	This is similar to pattern 3 with the grid vertically divided into two equal section and the two additional AFSs are randomly assigned to each section

5 Numerical Experiment and Analysis

To test the validity of the proposed algorithm, the numerical experiment is designed. Totally, 48 problem instances are created. In every instance, the different participants in the MDGVRP are set in a 330 by 300 miles grid. The first 24 instances (MDGVRP1-24) have 4 depots and other instances (MDGVRP25-48) have 6 depots. Two locating schemes of AFSs are considered. To be specific, in the instances MDGVRP1-12 and MDGVRP25-36, the AFSs are located strategically according to the principles shown in Table 1. In the instance MDGVRP 13-24 and MDGVRP37-48, the AFSs are located randomly. In addition, each instance has different numbers of customers and AFSs. The detailed characteristics of instances are given in Table 2.

In the experiment, the capacity of fuel tank is set as 60 gallons. The vehicle capacity is assumed to be 300 units of particular cargos. The fuel consumption rate is set at 0.2 gallons per mile. One of the rules for generating the data used in the experiment is that one tank of fuel is enough for a vehicle to reach to a customer from depot via an AFS.

The construction of algorithm is coded in C programming and implemented on AMD Opteron 2.3 GHz with 16 GB of RAM. The result of instances with strategic AFS location and random AFS location are shown in Tables 2 and 3 respectively. All problem instances are solved in seconds.

The results reported in Tables 2 and 3 show that the ACS can solve the MDGVRP in seconds. The solved instances vary in terms of the number of customers, AFSs, and depots and show the scalability of the proposed ACS on solving the MDGVRP. Further, the results show that the strategic location of AFSs can minimize the total route length, because the average route length of instances with the strategic AFSs location is less than that of instances with random AFSs locations. However, this observation does not hold for every instance used.

It is also worth to mention that the growth in the number of depots leads to the decrease in the route length. However, more depots can raise the maintenance costs

Table 2 Results of instances with strategic AFS location

Instance	Quantity of customers	Quantity of AFSs	Number of depots	Distance
MDGVRP1	25	2	4	958.933
MDGVRP2	50	2	4	1420.91
MDGVRP3	75	2	4	1870.26
MDGVRP4	25	4	4	1072.3
MDGVRP5	50	4	4	1499.85
MDGVRP6	75	4	4	1714.51
MDGVRP7	25	6	4	974.518
MDGVRP8	50	6	4	1418.11
MDGVRP9	75	6	4	1845.3
MDGVRP10	25	8	4	1106.49
MDGVRP11	50	8	4	1336.83
MDGVRP12	75	8	4	1817.46
MDGVRP25	25	2	6	815.249
MDGVRP26	50	2	6	1494.85
MDGVRP27	75	2	6	1876.56
MDGVRP28	25	4	6	1106.16
MDGVRP29	50	4	6	1354.45
MDGVRP30	75	4	6	1683.09
MDGVRP31	25	6	6	1022.31
MDGVRP32	50	6	6	1300.97
MDGVRP33	75	6	6	1746.58
MDGVRP34	25	8	6	871.961
MDGVRP35	50	8	6	1235.61
MDGVRP36	75	8	6	1788.41
Average				1388.81

and increase the vehicle used in delivery. Therefore, future research can focus on determining the optimal quantity of depots in the distribution network.

6 Conclusion

In this paper, the formulation of the MDGVRP is proposed and the algorithm based on the ACS is designed to solve this problem. The ACS algorithm seeks the shortest tour when considering the vehicle capacity and the fuel tank capacity.

Numerical experiments illustrate that the proposed algorithm performs well and can be used to deal with different instances. The results of numerical experiments also show some implications to the company who has employed the AFVs or intends

Table 3 Results of instances with random AFS location

Instance	Quantity of customers	Quantity of AFSs	Number of depots	Distance
MDGVRP13	25	2	4	1166.79
MDGVRP14	50	2	4	1417.87
MDGVRP15	75	2	4	2269.84
MDGVRP16	25	4	4	976.786
MDGVRP17	50	4	4	1451.22
MDGVRP18	75	4	4	1778.68
MDGVRP19	25	6	4	1151.4
MDGVRP20	50	6	4	1466.59
MDGVRP21	75	6	4	1886.86
MDGVRP22	25	8	4	1028.35
MDGVRP23	50	8	4	1497.78
MDGVRP24	75	8	4	1631.41
MDGVRP37	25	2	6	1149.69
MDGVRP38	50	2	6	1433.49
MDGVRP39	75	2	6	2193.64
MDGVRP40	25	4	6	900.919
MDGVRP41	50	4	6	1433.75
MDGVRP42	75	4	6	1846.76
MDGVRP43	25	6	6	1125.36
MDGVRP44	50	6	6	1394.92
MDGVRP45	75	6	6	1863.23
MDGVRP46	25	8	6	945.133
MDGVRP47	50	8	6	1486.94
MDGVRP48	75	8	6	1671.45
Average				1465.37

to use in the future. The first implication is that the company has to decide the number of depots based on the calculation of benefits induced by the AFSs and the additional costs induced by depots maintenance. In addition, we also find that the limited fuel tank capacity of AFVs creates more complexity to the routing problem. This situation is quite different from the classic routing problem where the traditional fuel tank capacity is large enough traveling for a fairly long distance.

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