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Multi Trip Multi Compartment Vehicle Routing Problem with Alternative Fuel-powered Vehicles for Garbage Collection

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Abstract
The global sustainability effort forces us to treat waste as a valuable resource rather than a nuisance, making efficient management a critical urban priority. The theme of modern garbage collection is to significantly reduce greenhouse gas emissions, which necessitates the strategic integration of green vehicles into the logistics process. This paper considers a comprehensive garbage collection process in which Alternative Fuel-powered Vehicles (AFVs) with multiple compartments collect various waste streams across multiple daily trips. These multi-compartment vehicles allow for the simultaneous collection of different garbage types (e.g., recyclables and non-recyclables) in a single fleet visit to the customer, thereby increasing operational efficiency. In this proposed framework in this paper, each vehicle starts at a main depot and visits a disposal site equipped with specialized refilling stations for refueling. The vehicles then collect garbage from residential households, returning to the disposal site as needed either for refueling due to limited tank capacity or for disposing of the accumulated load. At the end of the day, the vehicles return to the main depot to conclude operations. We consider the known, deterministic values of all operational parameters to formulate this process as a rigorous mixed-integer programming model. The resulting NP-hard problem is solved and compared using both a heuristic Saving Algorithm and an intelligent Ant Colony System metaheuristic. To evaluate the performance of these proposed algorithms, new problem instances were generated based on standard benchmarks, providing a robust tool for designing sustainable and intelligent municipal waste collection systems.

Keywords: Vehicle Routing Problem; Multi-Compartment, Sustainability; Ant Colony; Metaheuristic.

1. Introduction

Global warming is an issue of global concern for all nations. It is required to have better cooperation among different countries to reduce the impact of global warming. On December 22nd, 2015, the United Nations Climate Change Conference finally negotiated a Paris Agreement, for slowing down climate change. In this agreement, the target was set as "Holding the increase in the global average temperature to well below 2 °C above pre-industrial levels and to pursue efforts to limit the temperature increase to 1.5 °C above pre-industrial levels" (UMFCCC, 2015). To achieve this target, every country is making efforts to reduce the Green House Gas (GHG) emissions. The reduction in usage of fossil fuels in transportation can reduce GHG emissions. Transportation accounted for 23% of global emissions in 2013 (IEA 2015). To achieve the world's sustainability goal, there is a desperate need to decrease the utilization of fossil fuel. This can be done by replacing fossil fuel with green energies like electricity, hydrogen etc. Motivated from this background, the Green Vehicle Routing Problem (GVRP) emerged in the literature of the Vehicle Routing Problem (VRP) research. In GVRP, Alternative Fuel-powered Vehicles (AFVs) are employed to fulfil the delivery process while reducing the GHG emissions. One of the targets of GVRP is to maintain sustainable transportation by incorporating social and ecological impacts along with the economic benefit. The issue of sustainability is also bringing awareness among the common people about recycling. Thus, the concerned citizens are seriously practicing the separation of recyclable items from non-recyclable items in their household garbage. Most of the municipal corporations are providing multi-bins to dump the recyclable and non-recyclable items separately. Enforcing such mechanism requires the use of multi compartment vehicles for household garbage collection with a multiple trip of vehicles in a day. To further reduce the negative environmental impacts brought by the conventional vehicles, some nation's municipal sanitation industries began to employ the AFVs with multi compartments to reduce the GHG emissions. Although the AFVs are more environmentally friendly than the conventional vehicles, they have the limitation in the fuel tank capacity. In addition, the number of Alternative Fuel Stations is limited.

The problem considered in this paper considers alternative fuel powered vehicles with multi compartments for collecting residential garbage. The customers have collection requests for different products which are collected using AFVs with multi compartments. These products are collected by one AFV, and they are stored in different compartments separately. In addition, the capacity of vehicles is limited, i.e. the total quantity of garbage carried by an AFV should not be greater than its capacity. We assume that only one fuel station is available and this fuel station is located at disposal site. The small fuel tank capacity of AFVs forces the vehicles to return to disposal site for refuelling. The AFVs also returns to disposal site for disposing of the garbage collected from customers. All AFVs start their trip from main depot, make multiple trips from disposal site and finally return to the main depot. The problem is further constrained by the driver's maximum working hours. Thus, the time for total trip of a vehicle is kept within the driver's maximum working hours. The objective of MCGVRP is to reduce the total travel distance of the AFVs. In this paper, this problem is referred to as a Multi-Trip Multi-Compartment Green Vehicle Routing Problem (MTMCGVRP). We propose two solution techniques based on Saving Algorithm (SA) and Ant Colony System (ACS) algorithm.

The structure of this paper is organized as follows. In section 2, related literature is presented. Section 3 provides detailed description of the problem. Section 4 presents two algorithms used to solve MTMCGVRP. Numerical experiments are presented in section 5, followed by the conclusions in section 6.

2. Literature Review

The Vehicle Routing Problem (VRP) is a well-known problem in Operations Research. The problem considered in this paper resembles the features of three Vehicle Routing Problems: Multi Compartment Vehicle Routing Problem (MCVRP), Green Vehicle Routing Problem (GVRP) and Multi Trip Vehicle Routing Problem (MTVRP). Thus, a brief review of these problems is presented.

The garbage collection process requires using vehicles with different compartments for storing different types of garbage. The need for different compartments arises because different types of garbage cannot be mixed together. The Vehicle Routing Problem with two compartments is called Multi-Compartment Vehicle Routing Problem (MCVRP). The first optimization models of MCVRP were built by Chajakis and Guignard (2003) for selecting the optimal delivery route for convenience stores. The MCVRP was used to design vehicle routes in many industries such as distribution of cattle foods (El Fallahi et al. (2008)); distribution of petrochemicals (Avella et al. (2009)) and Garbage collection problems (Muyldermans and Pang (2010); Reed et al. (2014) Abdulkader et al. (2015)). A branch and price algorithm was used by Avella et al. (2009) to solve the problem exactly while the other methods were based on either heuristic or metaheuristic. The guided local search-based metaheuristic was used by Muyldermans and Pang (2010). The ant colony-based metaheuristic was used by Reed et al. (2014) and Abdulkader et al. (2015) to solve MCVRP. More recently, metaheuristics have been proposed to address larger-scale and real-world MCVRP instances, particularly in waste collection and distribution logistics (Yang et al., 2022; Bouleft et al., 2023; Masmoudi et al., 2024).

The Vehicle Routing problem with multiple trips is an extension of the classical vehicle routing problem. The problem is extended to serve more practical situations where the availability of vehicles is limited. In this case, each vehicle performs more routes to make sure that all customers are visited. However, the total operational time for each vehicle is kept within the working hours duration. Many heuristics and meta-heuristics were proposed to solve the problem. Different algorithms include a tabu search by Taillard et al. (1996); a two-phase tabu-search by Brandão and Mercer (1998); a multi-phase constructive heuristic by Petch and Salhi (2004); an adaptive memory algorithm by Olivera and Viera (2007); a hybrid genetic algorithm by Salhi and Petch (2007); and a memetic algorithm by Cattaruzza et al. (2014). Mingozzi et al. (2012) described two set-partitioning formulations of the problem and provided linear relaxations to develop an exact solution method. Recent studies have further extended the MTVRP to include time-dependent travel times, time windows, and sustainability considerations, often using large neighbourhood search, exact approaches, and hybrid exact–heuristic approaches (Macrina et al., 2019; Vidal et al., 2020; Marques et al., 2022; Eltoukhy et al., 2025).

The main features of the problem considered in this paper are to use AFVs to minimize the negative environmental impacts brought by vehicles. This feature of the problem resembles the features of GVRP. The AFVs use cleaner energy as power resource. The main disadvantage of AFVs is the limitation on low energy storage (e.g. low battery capacity of electric vehicles) requiring vehicles to visit alternate fuel stations (AFSs) whose availability can be limited too. Early studies on refueling problem of fossil energy based conventional vehicles could be found in the works of Mehrez and Stern (1985) and Mehrez et al. (1983). The study on the VRP with AFVs was first time considered by Erdoğan and Miller-Hooks (2012) in which Alternative Fuel-powered vehicles were used in the delivery process. This problem was then given a name as GVRP. Felipe et al. (2014) developed the VRP problem consisting with electric vehicles. Schneider et al. (2014) considered VRPTW for electric vehicles. They combined the tabu search heuristic and the nearest neighborhood search algorithm to solve VRPTW. Recent studies expanded the GVRP to incorporate charging station location decisions, partial recharging, battery degradation, and stochastic energy consumption (Montoya et al., 2016; Zhang et al., 2018; Pelletier et al., 2019; Basso et al., 2022; Yuan et al. 2026).

The garbage collection problem with AFVs was considered by the authors in Gajpal et al. (2017). However, this paper considers more realistic scenario in garbage collection process. Contrary to the previous work, this paper considers that the vehicle starts from the main depot and finally returns back to the main depot. The problem further considers the driver's working hours and thus vehicles are required to perform multiple trips each day. We call the proposed problem the Multi-Trip Multi-Compartment Green Vehicle Routing Problem (MTMCGVRP). Recent studies on sustainable waste collection routing have begun to explore integrated models that combine multi-compartment vehicles, electric fleets, multiple trips, and labor regulations, highlighting the growing relevance of the MTMCGVRP framework. However, comprehensive models that simultaneously address all these features remain limited.

3. Problem Description

The problem considered in this paper considers multi compartment alternate fuel powered vehicles which use multiple trips for collecting residential garbage. The proposed problem considers that the residential customers have collection requests for different types of garbage and the vehicles used in collection process are AFVs with multi compartments. Different types of garbage are collected from the customers having pre separated recyclable and non-recyclable items for collection. These different types of garbage are collected by only one of the AFVs and are required to be stored in different compartments separately. The vehicles have limited capacity, i.e. the total quantity of a particular type of garbage carried by an AFV should not be greater than the capacity of the compartment dedicated to that garbage.

The problem assumes that the AFV is using new technology power resources such as hydrogen, CNG or electric battery. Since this is new technology, only limited number of fuel/recharging stations are available. The problem assumes that there is only one refilling/recharging station available which is located at disposal site. Each vehicle starts from the depot every morning and visits the disposal site for refilling/recharging before proceeding to collect garbage. The vehicle then starts its trip from the disposal site to different customer locations and returns to the disposal site whenever it is required. The vehicle returns to the disposal site either because of the restriction on vehicle capacity or fuel tank capacity. Each vehicle makes several trips from the disposal site to customer locations. Finally, the vehicle returns to the main depot every evening before 8 working hours of drivers assigned workload is completed. The multi trip multi compartment vehicle routing problem with AFVs thus involves finding the route of vehicles with objective of minimizing total distance travelled by all the vehicles in such that: 1) A customer is visited only once by one vehicle, 2) all products are collected in a single visit, 3) the total amount of a particular type of garbage collected during a trip should not be more than the vehicle capacity of corresponding type of garbage, 4) The total time of the trip should be less than the driver's working hours.

The following notations have been used in the MTMCGVRP formulation:

C	Set of Customers
V	Set of Customers and Depot
k	Set of Trips
p	Set of products and their corresponding compartments
q_{ip}	Pickup quantity of product p from customer i
Q_p	Capacity of compartment p
$d_{i,j}$	Distance between customers i and j
Q_{ip}^k	The vehicle load of product p in trip k after leaving customer i
f_i	Remaining fuel level of vehicle before arrival at customer i
T	Fuel tank capacity
u	Vehicle speed
r	Fuel consumption rate

The problem is defined using an undirected graph $G = (V, E)$, in which V is a set of vertices and E is a set of edges between different vertices. The vertex set V contains all the nodes, including customers and the depot. The edge set $E = \{(i, j): i, j \in V, i \neq j\}$ stands for the edges that connect different nodes. The depot is used as a refueling station. Thus, the AFV refuels the tank up to the tank capacity T while unloading the garbage at the depot. The distance between customers i and j is denoted by $d_{i,j}$. The AFV travels with constant speed u, and it consumes fuel at a constant fuel consumption rate r.

The MTMCGVRP problem consists of a p number of garbage types (products) that need to be picked up from all n customers. The AFVs are divided into different compartments representing different garbage types. Each compartment has a limited capacity Q_p. Each customer i has a known quantity q_{ip} of garbage p to be picked up. All garbage quantities associated with a customer must be collected in a single visit and during the same trip by a single AFV. For each garbage type p, the total quantities collected from customers served by an AFV must not exceed the capacity Q_p of the compartment reserved for this garbage type p. Each AFV begins from the depot, visits a set of customers, and finally returns to the depot. The AFV ends its trip and returns to the depot for one of the following reasons: 1) if remaining fuel is not sufficient to serve additional customers, 2) if the remaining capacity of any compartment is not sufficient to serve additional customers, or 3) if all the customers are served. Let X_{ij}^k be a binary variable taking the value 1 if an AFV travels between customer i and j in the route of trip k, otherwise, the arc between customers i and j is not travelled in the route of trip k. Let Q_{ip}^k represent the AFV load of product p in trip k after leaving customer i. Let f_i represent the remaining fuel level when the vehicle arrives at customer i. Then the formulation of MTMCGVRP is given below:

$$Min \sum_{k\in K}\sum_{i\in V}\sum_{j\in V} d_{i,j}X_{ij}^k \qquad (1)$$

$S.t.$

$$\sum_{k=K}\sum_{j\in V} X_{ij}^k = 1 \qquad \forall\, i \in C \qquad (2)$$

$$\sum_{k=K}\sum_{i\in V} X_{ij}^k = 1 \qquad \forall\, j \in C \qquad (3)$$

$$\sum_{i\in V} X_{0i}^k = \sum_{j\in V} X_{j0}^k \qquad \forall\, k \in K \qquad (4)$$

$$q_{ip} \le Q_{ij}^k \le Q_p \qquad \forall\, i \in C, k \in K, p \in P \qquad (5)$$

$$Q_{ip}^k - Q_{jp}^k + Q_p X_{ij}^k \le Q_p - q_{jp} \qquad \forall\, i \in V, j \in V, i \ne j, k \in K \qquad (6)$$

$$f_j \le f_i - r \cdot d_{ij}X_{ij} + T(1 - X_{ij}) \qquad \forall\, j \in C, i \in V, i \ne j \qquad (7)$$

$$f_0 = T \qquad (8)$$

$$\sum_{i\in V}\sum_{j\in V} (d_{i,j}/u) X_{ij}^k \le L \qquad \forall\, k \in K$$

$$X_{ij}^k \in \{0,1\} \qquad \forall\, i \in V, j \in V, i \ne j, k \in K \qquad (9)$$

Eq. (1) is the objective function representing the total distance travelled by all AFVs in all trips. Eq. (2) and (3) ensure that each customer must be visited exactly once by one AFV and in a single trip. Eq. (4) ensures that each AFV begins every trip from the depot and returns to the depot at the end of every trip. Eq. (4) is the distinct characteristic that represents the multiple-trip characteristic of VRP. In the Capacitated VRP, Eq. (4) is set to 1 to represent that each vehicle will exit only once from the depot and enter only once into the depot. However, in the multiple-trip problem, a vehicle can exit the depot as many times as the number of trips, but it should be equal to the number of depot entries. Eq. (5) and (6) ensure connectivity between consecutive customer visits, satisfy AFV capacity constraints, and eliminate sub-tours. Eq. (7) and (8) ensure that each AFV has sufficient remaining fuel to visit all customers assigned to its route. Eq. (9) describes the binary variables X_{ij}^k.

4. Solution methodology

In this paper, two obstacles are considered as important constraints in the problem. The first obstacle is related to the multi compartments for storing different items. The second obstacle is related to the small fuel tank capacity of the AFVs. We assume that only one fuel station is available and this fuel station is located at the disposal site. The objective function of the proposed problem is to minimize the total distance travelled by all AFVs. Two solution methods are proposed to solve the proposed problem. One is the Saving Algorithm (SA) and the other is the Ant Colony System (ACS) algorithm.

4.1. Saving Algorithm (SA)

The Saving Algorithm is one of the most popular algorithms to solve the CVRP. The main principle of this algorithm is to maximize the saving value when two routes are combined and served by a single vehicle instead of two different vehicles. We solve MTMCGVRP in two steps. In the first stage, a VRP problem is solved and in the second stage, the VRP solution is converted into a multi trip VRP solution. The two steps are described below:

Step 1: In this step the problem is converted into a MCVRP problem which consists of disposal site and customers. The disposal site is considered as a depot. This problem is solved using saving algorithm for CVRP (Clarke and Wright, 1964). The detailed description of saving algorithm can be found in Toth and Vigo (2002). The solution of saving algorithm for MCVRP creates different trips for different vehicles. Each trip starts from a disposal site, visits a set of customers and finally returns to the disposal site.

Step 2: The first step generates different trips for different vehicles. In the second step, these trips are combined in such a way that tour time of combined trip is less than the driver's working hours.

4.2. Ant Colony System (ACS) Algorithm

The ACS algorithm was proposed by Colorni et al. (1991) on the basis of food seeking process of ant colony. They found that ants were able to find the shortest route between food sources and home by using a chemical called pheromone. The ACS algorithm is widely used in solving VRP and its variants (e.g. Barán and Schaerer (2003), Bell and McMullen (2004), Y. Gajpal and P. Abad (2009a) and Y. Gajpal and P. L. Abad (2009b) etc.). In the ACS algorithm, artificial ants are used to find better solutions using the information from the solutions of previous iterations. At the end of each iteration, the solutions of previous iterations are stored in the trail intensity of each path in the form of pheromone. These pheromones are used to generate ant solutions in future iterations. The fundamental procedures of ACS are listed in the following:

Step 1: Initialize the trail intensity for n artificial ants.
Step 2: Do the following steps, while the termination condition is not fulfilled.
- By using trail intensity, generate a solution for each ant.
- Update the best solution.
- Based on the best solution, update trail intensity matrix.

Step 3: Report the best solution found from all generated solutions so far.

4.2.1. Trail Intensity Initialization

In ACS the trail intensity τ_{ij} determines the intensity of visiting customer j after customer i. In the beginning, all elements τ_{ij} in trail intensity are kept equal. In this paper, the initial trail intensity is kept as $\tau_{ij} = 1/L$, where L is the total length of the initial solution. The initial solution used to initialize the trail intensity is generated by visiting customers randomly without violating the vehicle compartment capacity and fuel constraints.

4.2.2. Ant Solution Generation

In each iteration, n number of ants generates n number of MTMCGVRP solutions. A solution starts from the depot and iteratively selects customers to build a complete solution. The attractiveness value is used to decide which customer should be selected as the next node. The attractiveness is calculated as:

$$\xi_{ij} = [\mu_{ij}]^{\alpha}[\tau_{ij}]^{\beta}$$

The desirability μ_{ij} is calculated as the inverse of the distance between customers i and j. Trail intensity τ_{ij} represents the intensity between customer i and j. In this equation, α is the desirability value bias and β is the trial intensity bias. These two parameters are fixed at the beginning of the algorithm.
Based on the attractiveness value, a customer is inserted from q number of feasible customer candidates as the next node in the route. Thus, the set of q feasible customers is created and denoted as Ω_q. Assume that the last customer in the partial route is customer x. The probability of choosing a customer y_i as the next node from set Ω_q is calculated by the following function:

$$P_{xy_i} = \frac{\xi_{xy_i}}{\sum_{j=1}^{q} \xi_{xy_j}}, 1 \leq i \leq q$$

where y_i is the i^{th}element of Ω_q. According to the probability function, the next customer is selected to insert in MCGVRP route. Insertion of customers continues till one compartment is filled up or the remaining fuel is only sufficient to return to the depot. The disposal site is visited to unload the collected garbage and to refill their tank. The AFV starts another trip by visiting a random customer and keeps on visiting unvisited customers. In this way an ant creates different trips till the driver's working hours are not violated. Once the complete trip of an AFV is built, the trip for new AFV is started. The trips of another vehicle are built to serve all remaining customers. The complete process finds a solution for MTMCGVRP. This solution is now improved using a 2-opt approach. The 2-opt approach is applied to each trip of the tour separately. The trip is broken into three parts and the sequence of customers in the middle part is inverted. The new trip is reconstructed by joining the three parts again. All possible 2-opt are investigated by trying all combinations of the three parts. The combination that provides shortest trip length is selected. The process continues till no more improvement is encountered.

4.2.3. Trail Intensity Update

The trail intensity is updated using the best solution found so far. The function to update the trail intensity τ_{ij} of the edge between customer i and j is:

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

In this equation, the first term stands for the old trail intensity which is reduced by amount φ, a trial persistence taking value between 0 and 1. In the second term, pheromone increase is brought by the best-found solution. The value of $\tau_{ij}^{\theta}$is determined by:

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

Here l^{θ} represents the route length of the θ^{th} best solution found so far.

5. Results and Discussion

The effectiveness of the proposed algorithm is tested by creating new problem instances. The problem instances are used to examine the viability and feasibility of the proposed algorithms, i.e. Saving algorithm and Ant Colony System algorithm. In experiment, we considered first 5 benchmark problems of VRP (Christofides et al., 1979) out of 14 benchmark problem instances. From each VRP instance, 2 MTMCGVRP problem instances are generated. We follow the procedure described by Reed et al. (2014) to create MTMCGVRP data set. The depot from original VRP problem instances is considered as a disposal site. We assume that main depot is located 15 miles from disposal site and it takes just 15 minutes to reach from main depot to disposal site. The basic setting for our problem instances is listed as follows. The compartment number of the AFV is $p = 2$; the fuel tank capacity of the AFV is 30 gallons; and the fuel consumption rate is 0.2 gallon/mile. The construction of algorithm is coded in C programming language and is implemented on AMD Opteron 2.3 GHz with 16 GB of RAM. The results of numerical experiments on the two proposed algorithms are shown in Table 1. The unit of computation CPU time is reported in seconds.

Table 1: Results of the SA and the ACS for MTMCGVRP

Problem	Number of Customers	ACS			Saving Algorithm		
		Total Distance	Number of Vehicles	CPU Time	Total Distance	Number of Vehicles	CPU Time
vrpnc 1a	50	552.32	2	60	606.51	2	<1
vrpnc 1b	50	564.38	2	62	606.51	2	<1
vrpnc 2a	75	727.07	2	138	765.87	2	<1
vrpnc 2b	75	731.57	2	130	762.74	2	<1
vrpnc 3a	100	903.08	3	231	888.94	3	<1
vrpnc 3b	100	895.61	3	237	888.94	3	<1
vrpnc 4a	150	1018.21	3	571	995.31	3	1
vrpnc 4b	150	1011.51	3	572	1001.64	3	1
vrpnc 5a	199	1246.96	4	992	1200.29	4	3
vrpnc 5b	199	1250.80	4	992	1195.64	4	3
Average		890.15	2.8	398.5	891.24	2.8	1.2

The performance and computation time of ACS algorithm are mainly affected by the number of ants. In this paper, for any particular problem instance, the ants' number is taken to be 20. In order to keep the reasonable CPU time, the number of iterations is set as 10000. In each iteration, 20 new ants are created to generate feasible solutions. The parameters α, β, and φ are set as: $\alpha = 1, \beta = 2$ and $\varphi = 0.9$. A sensitivity analysis with limited CPU time has been used to set the parameter values. We also notice that the algorithm's performance does not change significantly when changing the parameters.

The results reported in Table 1 show that the performance of SA and ACS algorithms are comparable in terms of solution quality. The average route length for 10 problem instances is 890.15 for ACS and 891.24 for SA. The performance of SA is significantly better than the performance of ACS in terms of CPU time. The average CPU time (for 10 problem instances) reported in Table 1 shows that ACS takes 398.5 seconds while SA takes just 1.2 seconds. The performance of a meta-heuristic is usually better than the performance of a heuristic and thus the results reported in Table 1 are surprising. Usually, metaheuristics consume more CPU time to produce better results, however, this is not the case for solving MTMCGVRP. The small CPU time taken by SA proves the effectiveness of SA to solve MTMCGVRP. VRP literature shows that the saving algorithm produces very good results for different variants of VRP. The solution reported in this paper for SA further verify the superiority of saving algorithm for solving variants of the VRP.

The results reported in Table 1 further show that the CPU time of ACS increases as the number of customers grows. This phenomenon is reasonable because the increase in number of customers increases the complexity of the problem. Therefore, the computing time also increases apparently when the number of customers grows. The interesting part of this result is the poor performance of ACS. The ACS could produce the results comparable with SA even after spending 395.5 seconds. The poor performance of ACS can be mainly attributed to the poor construction rule of ACS. It seems that the construction rule used in this paper is not suitable for multi trip VRP. The successful application of metaheuristics requires the adoption of problem specific features to solve a particular problem efficiently. The current construction rule of ACS tries to utilize driver's working hours. The greediness of utilizing driver's working hours forces the solution to generate the last trip of vehicle to be very small with just one or two customers. Another reason for such small last trip is due to sequential way of generating solutions. While generating a solution for an ant, trips for different vehicles are generated sequentially. The problem of small last trip can be avoided by generating the trips of different vehicles in parallel. This construction rule might help ACS to perform efficiently. Another way the performance of ACS can be improved through the hybridization of ACS with some local search procedures. The literature on use of ACS for solving VRP indicates that the good performance of ACS is obtained only after hybridizing it with local search schemes. The main contribution of this paper is to design a logistic system for garbage collection performed by alternate fuel vehicles (AFVs). Future research can explore the improvement of ACS performance through the adoption of problem specific construction rules.

6. Conclusions

In this paper, based on the garbage collection process in real world, we first describe a Multi-Trip Multi-Compartment Green Vehicle Routing Problem (MMCGVRP). In this problem, vehicles use alternative fuel and have several compartments to store different kinds of garbage items (e.g. recyclable garbage and unrecyclable garbage). These items are collected using multiple trips starting from the disposal site. The main contribution of this paper is the inclusion of garbage recycling and GHG emission from the angle of sustainability. The goal is to optimize the real-life garbage collection process.

We have proposed two algorithms to solve this problem. One is the Ant Colony Algorithm, and the other is the Saving Algorithm. We conducted numerical experiments on newly generated benchmark problems to evaluate the performance of different algorithms. The numerical results show that the solution of saving algorithm and ACS are comparable in terms of solution quality. The solution of saving algorithm is very impressive since it produced good solution with fraction of seconds. On the other hand, the solution of ACS is poor. ACS consumed significantly more CPU time to produce the results just comparable with SA. For future research, the performance of ACS can be improved by adopting the problem specific construction rule. The future research could also involve adding more constraints into the model to vividly mimic the real-life cases. One of the limitations of our model is the assumption that fuel consumption is in proportion to the distance travelled. While in real life, fuel consumption can be dependent on the vehicle load, road condition and many other factors. The future research can be extended to consider realistic fuel consumption in the model. The future research can also be extended by vehicle utilization or trip balance to reflect more realistic assumptions and create practical solutions.

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