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# Efficiency of Heuristic Algorithms in Solving Waste Collection Vehicle Routing Problem: A Case Study

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## Abstract

This paper investigated the efficiency of six heuristic algorithms from prior studies in the attempt to solve issues related to waste collection, namely: (i) Nearest Greedy (NG), (ii) Further from Depot (FFD), (iii) Different Initial Customer (DIC), (iv) Savings Approach, (v) Sweep Algorithm, and (vi) Different Initial Customer based on Sweep Algorithm. In fact, these heuristics have been employed to solve several routing problems in past studies, but the performance of each heuristic has never been compared. Hence, this paper looked into the efficiency of these heuristics by testing them on a real case study of waste collection problem in a district located at the north of Peninsular Malaysia. Several solutions obtained from these heuristics were compared with solutions implemented by the waste collection company, especially in terms of the total distance travelled. As a result, the computational results exhibited that DIC generated the best solutions, when compared to other heuristics, with a 12% reduction of the total travel distance.

**Keywords:** Case study; Heuristics; Vehicle routing problem; Waste collection problem.



## 1. Introduction

Solid waste management (SWM) has become a serious environmental issue for country and local governments worldwide. SWM is more than just collecting waste. It involves of six operational phases, start from waste generation at sources, handling and separation, storage, and processing, collection, separation and processing, and transformation, transfer and transport, and disposal (Tchobanoglous *et al.*, 1993). Various factors, involving environmental, economic, technical, regulation, and political issues, have to be considered. In managing solid waste, some important decisions need to be made. Among them is the opening of new landfills or the expansion of the current landfill, truck allocation to the disposal facilities and constructing efficient vehicle routes for collection process. Indeed, collection is the most important decision and costly aspect due to workload intensity and the massive use of trucks in the collection process (Beliën *et al.*, 2012). Eighty percent of the funds allocated for municipal solid waste management were spent on solid waste collection activities (Clark and Gillean, 1975).

In the past, solid waste collection was carried out based on traditional manner without analysing demand and the construction of the routes was left to the drivers. Nowadays, rapid development build our cities continue to grow. Therefore, the importance of efficient collection system is increasingly emphasized. Essentially, the collection of waste is classified as a vehicle routing problem (VRP). A VRP typically involves of a set of vehicles, customers, and a depot. A vehicle starts from the depot, visits a number of customers, and ends at the depot. Depending on the complexity of the problem, researchers can add some different constraints such as the type of vehicle and the number of disposal facilities (Beliën *et al.*, 2012).

In general, different types of models have been applied in previous studies to solve the VRP optimally, which are, mathematical programming and heuristic techniques. Mathematical programming is a technique developed to choose the optimal solution from a set of alternatives. Basically, it aims to maximize or minimize the objective function by choosing the values of real or integer variables (Beliën *et al.*, 2012). Likewise, a substantial number of prior studies pertaining to waste collection vehicle routing problem (WCVRP) had employed the heuristic techniques so as to solve the rising issue. Heuristic can be classified into two types: (1) constructive heuristic algorithms, and (2) iterative improvement heuristic algorithms. A constructive heuristic algorithm refers to the technique of generating an initial solution to the problem stage-by-stage until a viable solution is attained. Meanwhile, the iterative improvement heuristic algorithm, which is also known as metaheuristic, denotes a technique of improving an initial solution (Mat *et al.*, 2017). With that, this paper applied several constructive heuristic algorithms to construct several initial solutions for WCVRP.

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The rest of this paper is organized as follows: Section 2 reviews the techniques used in solving WCVRP. Next, Section 3 presents the dataset and the technique employed to solve the problem raised, whereas the retrieved computational results are discussed in Section 4. Lastly, some final remarks on conclusion and several suggestions for future work are presented in Section 5.

## 2. Literature Review

Several studies have reviewed a wide range of methods with varying characteristics and assumptions employed based on the demands related to solving VRP. For instance, the VRP literature published between 2009 and June 2015 had been classified based on several trends discovered in VRP studies (Braekers *et al.*, 2015) and the methods applied (Eksioglu *et al.*, 2009). In fact, quite a number of solution approaches have been sought to solve VRP, for instance, exact algorithms, constructive heuristics, classical improvement heuristics, metaheuristics, and hybridizations (Toth and Vigo, 2014). In fact, the most widely used approach when solving issues linked to vehicle scheduling is the constructive heuristics, in which a solution to the problem is constructed step-by-step throughout a procedure until a complete and feasible solution is achieved (Atkinson, 1994).

Constructive algorithms offer solutions by adding individual elements (e.g., nodes, arcs, and variables) one at a time until a feasible solution is attained (Zanakis *et al.*, 1989). The greedy algorithm is a constructive heuristic algorithm that has been widely used in the literature with varied problem applications. For example, the trucks from a depot to a number of customers had been scheduled by using an effective greedy heuristic based on the modified Dantzig and Ramser method after weighing in truck availabilities and capacities (Clarke and Wright, 1964). Other than that, the greedy look-ahead heuristic was applied for a real-life vehicle scheduling problem with time windows (Atkinson, 1994). Next, the greedy randomized heuristic and the tabu search algorithm were used to deal with the separation of capacity constraints for Capacitated VRP (Augerat and Belenguer, 1998). In addition, the Atkinson's greedy look-ahead heuristic Atkinson (1994) had been improved by taking into consideration all its problematic aspects, such as vehicle capacity, delivery time intervals, and costs in the model proposed by (Ioannou *et al.*, 2001).

On top of that, the issue regarding one-commodity pickup-and-delivery TSP was solved by using two heuristic approaches: (1) a greedy algorithm that was improved with a *k*-optimality criterion, as well as (2) a branch-and-cut procedure that determined the optimal local solution (Hernández-Pérez and Salazar-González, 2004). On the other hand, the greedy constructive heuristic approach was applied to segregate capacities inequalities to solve the capacitated VRP as a safety measure to shrink customers (Lysgaard *et al.*, 2004). Meanwhile, the performance of the proposed construction heuristics, such as the basic greedy heuristic and the regret heuristic, were evaluated for tuning instances related to VRP pickup and delivery with time windows (Ropke and Pisinger, 2006). In a similar vein, a new greedy-like heuristic algorithm was introduced to address the general multidimensional knapsack problem (Akcay *et al.*, 2007), whereas some modified versions of the Multiple Phase Neighborhood Search (MPNS) and the Greedy Randomized Adaptive Search Algorithm (GRASP) (MPNS-GRASP) had been proposed by Marinakis and Marinaki (2010) to generate good initial population for the VRP. Meanwhile, another study used the two-phase greedy algorithm to generate an initial solution for full truckloads multi-depot capacitated VRP in carrier collaboration (Liu *et al.*, 2010), while an iterated greedy algorithm was employed by Ribas *et al.* (2011) in the initial construction phase to solve the blocking flowshop scheduling problem. Additionally, a variable iterated greedy algorithm was proposed by Karabulut and Tasgetiren (2014), where it fundamentally relied on a greedy algorithm to produce several neighboring solutions based on the concept of neighborhood change in variable neighborhood search (VNS) algorithms so as to solve TSP issues with time windows. Furthermore, some greedy algorithms were enhanced to a polynomial-time approximation scheme for a single demand facility location problem (Cheung and Williamson, 2017). Table 1 presents current studies that had successfully solved waste collection vehicle routing problem.

**Table-1.** Current studies on waste collection vehicle routing problem

| Descriptions | References |
|---|---|
| Solved an integrated problem of shift scheduling and waste collection with service level constraint based on model enhancement procedures. | Bruecker *et al.* (2018) |
| Solved a waste collection VRP based on a biased-randomized version of a savings-based heuristic. | Gruler *et al.* (2018) |
| Solved capacitated VRP using a modified particle swarm optimization (PSO) algorithm to establish the best waste collection and route optimization solutions. | Hannan *et al.* (2018) |
| Solved time-dependent VRP with a vehicle travel speed model using current initial solution and different initial customer procedures for waste collection problem. | Mat *et al.* (2018) |
| Solved the inventory routing problem of waste vegetable oil collection using a shortest path based algorithm. | Montagné *et al.* (2018) |

# 3. Methodology

## 3.1. Sample Dataset of WCVRP

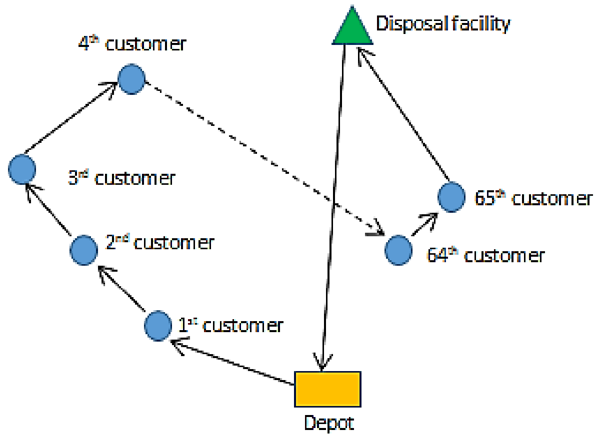
In this paper, a sample dataset of the waste collection problem in a district located at the North of Peninsular Malaysia had been selected, which consisted of six areas with varied numbers of customers, as displayed in Table 2. The problem involved one depot and one disposal facility. Besides, the capacity of vehicle used to serve the customers was 7 tons, whereby each vehicle must start and end at the depot. In fact, a single vehicle was assigned to serve customers from every area and multiple trips were made to the disposal facility in order to complete the collection before the vehicle returned to the depot with empty load.

**Table-2.** Sample data for waste collection problem

| Area | Total customers |
|---|---|
| **1** | 65 |
| **2** | 68 |
| **3** | 48 |
| **4** | 53 |
| **5** | 103 |
| **6** | 78 |

A vehicle route for area 1 is illustrated in Figure 1. In this example, the driver would leave the depot with an empty vehicle. Then, he would begin collecting waste from the first customer until the $65^{th}$ (last customer) by following the route constructed for him. Before returning to the depot, he would unload the waste at the disposal facility to empty the vehicle. The quality of the route constructed for the driver was evaluated based on the total distance travelled to serve all customers.

**Fig-1.** Example of vehicle route for area 1




## 3.2. Heuristic Algorithms

This paper refers to an extended version of a work published in Mat *et al.* (2017). Hence, one of our many previous works is extended by testing the same dataset with other heuristic algorithms. Six heuristics from Benjamin (2011) were applied to solve a sample data of a district located at the north of Peninsular Malaysia. The first heuristic; Nearest Greedy (NG) technique, was used to construct an initial solution by completely utilizing a vehicle over the day (thereby minimizing the total number of vehicles used). Once a vehicle cannot be used any more, a new vehicle route is constructed for a new vehicle. This heuristic had successfully solved a benchmark waste collection VRPTW with very good solutions, as published in Benjamin and Beasley (2010); (Mat *et al.*, 2018).

The second heuristic is a modified algorithm of NG known as Further from Depot (FFD). In NG, every vehicle route starts with a customer closest to the depot, whereas in FFD, the first customer on the route is a customer far from the depot. Then, further customers on the route are added using the same procedure as employed in NG.

The third heuristic is Different Initial Customer (DIC), which was used in a separate study to solve a benchmark waste collection VRPTW introduced by Kim *et al.* (2006), whereby the results were compared with those from past works in terms of the total number of vehicles used and the total distance travelled (Benjamin and Beasley, 2013).

The fourth heuristic is the Clarke and Wright Savings Algorithm, which appears to be a well-known heuristic for VRP. Since its inception by (Clarke and Wright, 1964), it has been widely applied to solve issues related to unfixed number of vehicles for both directed and undirected conditions.

The fifth heuristic is Sweep Algorithm, which was introduced by Gillett and Miller (1974). This algorithm divides a single terminal vehicle dispatch problem into two sub-problems; one assigns locations to routes, while the other minimizes the length of each route by using a traveling salesman algorithm.

Lastly, the sixth heuristic is Different Initial Customer based on Sweep Algorithm (DICSA). The efficiency of DICSA was tested on a benchmark waste collection VRP by Kim *et al.* (2006) and the computational results are presented in Benjamin (2011).

All vehicle routes constructed from these heuristics were compared in order to identify the heuristic algorithm that produced the minimum total distance travelled in solving the issue that emerged in waste collection VRP real data set.

## 4. Computational Results

In this paper, the tested heuristic algorithms were run on a Pentium® Dual-Core CPU T4300 @ 2.10GHz with 3.00 GB memory using C++ language. The solutions were compared with the real distance obtained from the local authorities. The related computational results of six heuristic algorithms are presented in Table 3.

**Table-3**. Computational results using heuristic algorithms

| Algorithm | Comparison | Area | | | | | | Total |
|---|---|---|---|---|---|---|---|---|
| | | 1 | 2 | 3 | 4 | 5 | 6 | |
| Real | Distance (km) | 61.61 | 66.83 | 56.84 | 59.47 | 55.53 | 59.01 | 359.29 |
| *NG | Distance (km) | **59.71** | **57.71** | 53.16 | 49.87 | 49.64 | **49.41** | 319.52 |
| | Improvement (%) | 3.07 | 13.65 | 6.47 | 16.15 | 10.60 | 16.26 | 11.07 |
| FFD | Distance (km) | 63.97 | 65.05 | 51.38 | 55.81 | 60.09 | 56.53 | 352.82 |
| | Improvement (%) | -3.83 | 2.67 | 9.61 | 6.15 | -8.21 | 4.20 | 1.80 |
| DIC | **Distance (km)** | **59.71** | **57.71** | **51.26** | **48.68** | **49.39** | **49.41** | **316.17** |
| | **Improvement (%)** | **3.07** | **13.65** | **9.81** | **18.15** | **11.07** | **16.26** | **12.00** |
| Savings | Distance (km) | 58.11 | 76.27 | 69.74 | 55.66 | 65.71 | 59.89 | 385.38 |
| | Improvement (%) | 5.67 | -14.11 | -22.70 | 6.40 | -18.33 | -1.49 | -7.26 |
| Sweep | Distance (km) | 70.15 | 95.35 | 73.86 | 73.34 | 107.47 | 79.93 | 500.11 |
| | Improvement (%) | -13.87 | -42.67 | -29.94 | -23.32 | -93.52 | -35.47 | -39.19 |
| DICSA | Distance (km) | 70.15 | 95.35 | 73.86 | 80.74 | 107.47 | 79.93 | 507.51 |
| | Improvement (%) | -13.87 | -42.67 | -29.94 | -35.77 | -93.52 | -35.47 | -41.25 |

*NG: Nearest greedy
FFD: Further from depot
DIC: Different initial customer
DICSA: Different initial customer based on sweep algorithm

Table 3 displays the combination of computational results for six heuristic algorithms, which are NG, FFD, DIC, Savings algorithm, Sweep algorithm, and DIC based on Sweep algorithm. Based on the results shown above, it can be concluded that the computational results from DIC portrayed the best solution in terms of total distance travelled, in comparison to other heuristic algorithms.

Nonetheless, as depicted above, based on the solutions proposed by NG and DIC, three areas required similar distance to serve the customers. For example, the total distances travelled for Areas 1 and 2 are 59.71km and 57.71km, respectively, while Area 6 needed 49.41km. Thus, the local authorities have several options to choose from as the solution, but with varying sequence of customers visited for each solution presented.

The total distance travelled to serve 415 customers (65 + 68 + 48 + 53 + 103 + 78) covering 6 areas is presented in the last column of Table 3. The best solution for the hurdle presented in this sample data is highlighted (yellow) in Table 3. Based on the solution presented by DIC, the driver would only need to travel 316.17km to serve 415 customers, while the present system takes about 359.29km to serve the same amount of customers.

With that, improvement in the distance travelled over the real distance proposed by the local authorities is highlighted (green) in Table 3. The positive percentage indicates a reduction in the total travel distance of vehicles, in comparison to the real distance. The percentage was calculated as following: ((real distance - proposed algorithm solution distance)/(real distance distance))*100. The results showed that the DIC algorithm generated the highest reduction (12%) in distance, when compared to the real distance proposed by the local authorities. Meanwhile, the negative percentages displayed for Savings, Sweep, and DICSA algorithms indicate increment in the total travel distance by 7.26%, 39.19%, and 41.25%, respectively, over the present system proposed by the local authorities.

## 5. Conclusion

This paper looked into the efficiency of six heuristic algorithms derived from prior studies in solving a real case study of waste collection problem in a northern part of Malaysia. The sample data used in this paper consisted of six areas that involved up to 103 customers with only one depot and one disposal facility. The computational results showed that DIC had generated the best solution with 12% less distance travelled compared with the real solution. In the near future, we would like to conduct a similar study by testing the same data set with consideration of several resource elements so as to reflect the real life situation in waste collection applications.

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