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Optimization of Capacitated Vehicle Routing Problem for Municipal Solid Waste Collection Using Simulated Annealing Algorithm

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Abstract
Municipal Solid Waste collection is an essential component of waste management. Optimization of Municipal Solid Waste (MSW) collection and transportation becomes one of the key considerations in the design of the MSW management system. Generally, Vehicle Routing Problem (VRP) is one of the most prevelant methods to manage the MSW collection. Various garbage management companies use various strategies to construct their vehicle routes depending on existing information. Unfortunately, they may not achieve the desired results. This study proposes a meta-heuristic approach based on the Simulated Annealing (SA) method to solve the Capacitated Vehicle Routing Problem (CVRP). In CVRP, a vehicle with uniform capacity will service customers with varying needs. The objective of this study is to find the optimal routes in minimizing the cost function by reducing the travelling distance to collect the MSW with the aid of MATLAB programming. In this study, real data from GPS Coordinate Malaysia and three datasets, random (R1), cluster (C1), and random cluster (RC1), are used without exceeding capacity limits. Eventually, the proposed method effectively reduces the total distance travelled for MSW collection, resulting in minimizing the total cost function.

Keywords: Municipal Solid Waste Collection; Capacitated Vehicle Routing Problem (CVRP); Simulated Annealing (SA) Algorithm.

1. Introduction

Municipal Solid Waste (MSW) is characterized as the most complex type of solid waste, which excludes industrial, construction, and hazardous garbage and includes waste from residential, commercial, and institutional sources. According to [1], worldwide municipal solid waste generation is increasing. Due to rapid population growth, urbanization and economic growth, as well as consumer shopping habits, annual solid waste generation is expected to increase by 73% from 2.24 million tonnes in 2020 to 3.88 billion tonnes in 2050. Additionally, the effects of collecting municipal solid waste (MSW) have come under increasing scrutiny in recent years. Besides, an increase in human activity has harmed the environment because it generates large amounts of municipal solid waste (MSW), which could contain hazardous materials.

One of the most difficult combinatorial optimization problems is the Vehicle Routing Problem (VRP). Since its inception as the truck dispatching problem by Dantzig and Ramser in 1959, the VRP has grown in popularity due to its widespread applicability and economic importance in reducing operational costs in distribution systems. VRP is classified as a NP-hard problem with the objective of finding the optimal routes with minimum cost. In this study, a vehicle routing problem for the MSW collection is discussed to optimize the solid waste collection routes with minimum traveling cost and distance.

The vehicle routing problem involves customers with specific demands that must be met by one depot. To meet all customer demands, the vehicle must begin and end at the depot, with only one vehicle visiting each customer. Vehicle capacities are specified, and each vehicle has a maximum traveling distance. In addition, each customer may be given a drop allowance, which is added to the total distance traveled by the vehicle assigned to the customer. Therefore, a vehicle that visits many customers cannot travel as far as a vehicle that visits a small number of customers. Goals include seconding a set of routes that minimize total distance travelled and the number of vehicles required, and total distance traveled with this number of vehicles [2].

More constraints are usually involved in the problem to satisfy real-life VRP scenarios, such as multiple depots, different types of vehicles, different types of customer demand, road constraints, types of operations, and so on. All these constraints increase the complexity of the VRP problem significantly. Therefore, a variety of algorithms are available to solve different variations of VRP problems such as heuristic and metaheuristics. The heuristic algorithm is classified as the classic VRP that produces good quality solutions within modest computing times. While, the metaheuristics include Ant Algorithm, Constraint Programming, Genetic Algorithm, Particle Swarm Optimization and Tabu Search. Obviously, heuristics and meta-heuristics are preferable to exact methods. Heuristic algorithms can solve complex solid waste collection problems more quickly and efficiently by sacrificing optimality, accuracy, precision, or completeness for speed, whereas metaheuristics can provide a good solution for collection optimization even with incomplete information or limited computation capacity [3].

The objective of the study is to find the optimal solutions in minimizing the cost function and distance by using Simulated Annealing (SA) algorithm with the aid of MATLAB programming.

2. Literature Review

2.1 *Vehicle Routing Problem (VRP)*

A closer look at the literature on the Vehicle Routing Problem (VRP) which was first developed in 1959 by George Dantzig and John Ramser [4]. The most popular method for discovering the best routes for a fleet of vehicles to travel to serve a population of clients is known as VRP. In general, the goal of the VRP is to identify the best routes that may be break into one or more depots to reduce the overall expenses of the number of vehicles while still meeting certain requirements. The VRP is the generalization of the Traveling-Salesman Problem (TSP), claims research by [5] entitled "The Truck Dispatching Problem". The TSP problem, which considers multiple cars, is used to identify the shortest-distance routes.

VRP has been extensively studied and applied, particularly in operations research. Numerous studies on various kinds of VRP exist. A case study of pertinent heuristic method applications for the five different vehicle routing problems, the Capacitated Vehicle Routing Problem, the Multi-Depot Vehicle Routing Problem, the Site-Dependent Vehicle Routing Problem, and the Open Vehicle Routing Problem by [6] is presented.

2.2 Capacitated Vehicle Routing Problem (CVRP)

Once the vehicle capacity is considered while using the VRP to determine the shortest routes, it transforms into the traditional VRP known as the vehicle routing problem with capacity limitations (CVRP), where each vehicle has a limited capacity [7]. The main goal of CVRP is to efficiently supply each customer by planning the best routes for vehicles to go. After Dantzig and Ramser's 1959 publication of VRP, numerous studies dealing with the CVRP issue have been conducted. CVRP refers to choosing a set of ideal routes that begin and terminate at the depot, provided that each customer is only visited once by the vehicle and vehicle's capacity is not exceeded. For large-scale capacitated vehicles, CVRP problems are NP-Hard and difficult to be solved [8]. The vehicle scheduling firms that need to find the best routes with the least amount of travel time and expense will find this study's alternate method for solving large-scale CVRP problems useful.

2.3 *Municipal Solid Waste (MSW) collection and transportation studies*

Residential, commercial, and industrial garbage are together referred to as municipal solid waste (MSW). Due to the rise in living standards and population, which is predicted to reach 37.4 million by 2030, municipal solid waste is the major problem for both small and large developing countries [9]. According to [10], managing MSW presents the greatest challenge for all nations, and it must be done in a way that is both technically and financially feasible. The current issues surrounding the optimization of MSW transportation and sorting are presented in [11].

Based on a study that was conducted on the subject and that addresses the issue of reducing the waste collection and transportation route length to the bare minimum, an MSW collection and transportation strategy is recommended by [12]**.** To optimize the MSW collection and transportation routes, this study focuses on the solid waste collection from any waste resources to the dump location utilizing TSP. To successfully address the transportation issue and achieve the objective of reducing MSW collection costs, [13] proposed a transportation model for optimizing municipal solid waste collection.

The Simulated Annealing (SA) Algorithm is the most popular metaheuristics because its simplicity of implementation and potential to find a global optimal after locating local minimum. This algorithm is commonly used to solve combinatorial problems, particularly TSP to reduce the route length. The goal of [14] is to identify the ideal solution that will increase the effectiveness of the waste management system and lower overall costs. Therefore, this study's primary goal in this research is to reduce overall travel distance. Using mixed-integer programming, the authors compared the simulated annealing approach to the large-neighborhood search and genetic algorithm. In comparison to SA and LNS approaches, GA provides poor results. As a result, the MSW collecting problems may be solved more effectively using the suggested SA method.

By examining the viability of utilizing smart bin data for effective solid waste collection, [7] updated Particle Swarm Optimization (PSO) method in a CVRP model. The major goal of this study is to reduce travel time and costs while optimizing the route within predetermined boundaries. This algorithm was created to enhance the ones already in use that take specific constraints into account. For instance, by converting the binary into an array of solid waste collection nodes, separate algorithmic steps can consider truck capacity and waste bin levels. The PSO method is a powerful metaheuristic optimization tool that draws its inspiration from flocks of birds. The core idea behind the PSO algorithm is to use randomly initialized velocity to produce the best solution from a set of particles toward the optimized value.

The collection vehicle routing problem of the garbage facilities (CVRPGF) is a new variant of the collection vehicle routing problem (CVRP) that is addressed in this study. It has the characteristics of full loads, multiple trips of the collection vehicles, and multiple demands on the garbage facilities. In this research, a parallel simulated annealing algorithm (Par-SAA) is proposed to solve a real CVRPGF situation in the Xuanwu District of Beijing. As a result, the number of vehicles and overall traveling time are reduced due to the efficiency of the algorithm [15].

3. Methodology

3.1 *Problem Formulation*

Let $G = (V, A)$ be a complete undirected graph, where V is the set of vertices and A is the set of edges, where vertex 0 represents the depot and set $V = [0,1,2, \dots, n\}$ represents N customers. With every edge (i, j) inside A, $i \neq j$ a non-negative cost C_{ij} is associated. The traveling cost represents the geographical distance between customers i and customer j. Next, assuming there are M vehicles at the depot that have uniform capacity Q. Furthermore, each customer has demand q_{ij} that refers to the units of waste from depot 0 to customer i and customer j. A set of identical M vehicles of capacity Q must begin and end at the depot. The total demands of any route must not exceed the vehicle capacity which is 200 units.

Parameters involved in CVRP:

N	Number of customers
M	Total number of vehicles
q_i	Unit of waste on vehicle at point i (demand of customer i)
q_j	Unit of waste on vehicle at point j (demand of customer j)
C_{ij}	raveling cost from customer i to customer j by M
x_{ij}	Traveling distance from customer i to customer j by M
Q	Capacity of vehicle
D_{ij}	Euclidean Distance

Decision Variables

$$x_{ij} = \begin{cases} 1 \; if \; customer \; i \; and \; j \; are \; continuously \; visited \\ 0 \; otherwise \end{cases}$$

Mathematical Model

The integer programming formulation of CVRP is given below:

Minimize

$$\sum_{M \in 1}^{M} \sum_{i \in 0}^{N} \sum_{j \epsilon 0}^{N} x_{ij} C_{ij} \tag{1}$$

Subject to:

$$\sum_{M \in 1}^{M} \sum_{i \in 0}^{N} x_{ij} \;, j = 1,2, \dots, N \tag{2}$$

$$\sum_{M\in 1}^{M}\sum_{j\in 0}^{N} x_{ij} \ , i = 1,2,\ldots,N \tag{3}$$

$$\sum_{i\in 0}^{N} x_{ij} \leq 1 \tag{4}$$

$$\sum_{j\in 0}^{N} x_{ij} \leq 1 \tag{5}$$

$$\sum_{j\in 0}^{N} q_{ij} \sum_{j\in 0}^{N} x_{ij}) \leq Q \tag{6}$$

$$x_{ij} \in 1 \ \ \forall i,j = 0,1,2,\ldots,N \tag{7}$$

$$d_{ij} = \sqrt{\left(x_i + x_j\right)^2 + \left(y_i + y_j\right)^2} \ \ \forall i,j = 0,1,2,\ldots,N \tag{8}$$

The objective function in (3.1) aims to minimize the total cost function for all vehicles. Equation (3.2) and (3.3) ensures that each customer (garbage bin) is only served once; equation (3.4) and (3.5) ensure that each customer is only served by one vehicle. Equation (3.6) ensures that the total demand by customer in any route must not exceed the capacity of the vehicle. Equation (3.7) ensures that the decision variables are binary, only the integer values 0 and 1 are considered. Since this problem involves the VRP with one depot, Equation (3.8) is the Euclidean distance matrix which calculates the distance between two points in Euclidean space.

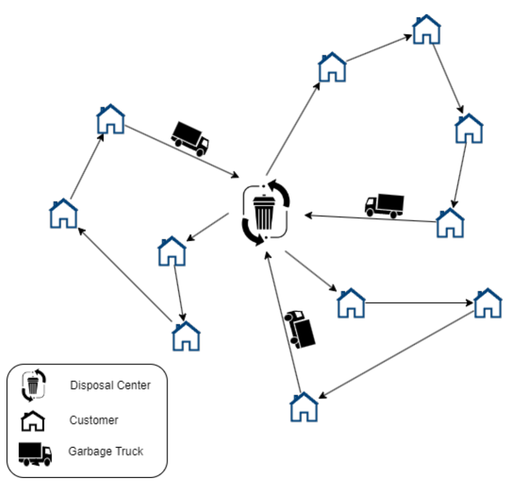

Figure 3.1 Vehicle Routing Diagram

3.2 *Data Sets and Problem Designed*

In this study, 15-customers instance of MSW real data from GPS Coordinate Malaysia and 50-customers instances of the Solomon benchmark problem were used. For the Solomon benchmark data, there are three categories which are Cluster (C1), Random (R1) and Cluster Random (CR1). These problem sets have a brief scheduling horizon and only allow approximately 5 to 10 customers per route. For the C1 problem set, the customers (garbage bins) are located in clusters while the customers are located randomly in problem set R1. The customers in problem set RC1 are in mixed cluster and random locations.

If all vehicles travel at the same constant speed, one unit of cost equals one unit of distance. In terms of numbers, the travel cost, travel time, and distance between two nodes are all the same. Each data instance contains the number of customers, customer nodes, customer demand, ready time, due time and service time. Customer number 0 represents the depot where all the vehicles must begin and end. The ready time means the earliest time where the due time means the latest time that service may begin at the given customer/depot. In this data set, the traveling time has the same value as traveling distance. The Euclidean distance is used to calculate the distance between two nodes.

3.3 *Simulated Annealing (SA) Algorithm*

The Simulated Annealing (SA) algorithm is a random search algorithm proposed by Kirkpatrick et al. (1983) which is one of efficient metaheuristics to be applied in solving CVRP [16]**.** Despite the fact that Simulated Annealing algorithm frequently produces only an approximation of the global minimum, the SA algorithm is commonly used in many real-world problems where exact techniques fall short. Kirkpatrick, et al. explained how the SA works. At high temperatures, liquid molecules have high energy levels, making them relatively easy to move towards other molecules. When the temperature is reduced, the molecules arrange themselves to seek configurations or with lower energy levels. By gradually reducing the temperature, the molecules are allowed to self-regulate, resulting in a stationary or stable state with a low energy level. The gradual decrease in temperature is known as the annealing process. Therefore, it can be used to solve the VRP problem in order to obtain an optimal solution [17].

3.3.1 Simulated Annealing Algorithm Implementation

In this study, T_0 represents the initial temperature, while T denotes the final temperature at which the process fulfils the stopping condition. The cooling factor, α denotes the coefficient in the cooling schedule. In this SA algorithm, the stopping condition is when the temperature is reduced until T approached zero. In this study, the number of iterations, $MaxIt$ will be set to 500 to obtain the optimal solution (Best Cost).

3.3.2 Simulated Annealing Flowchart

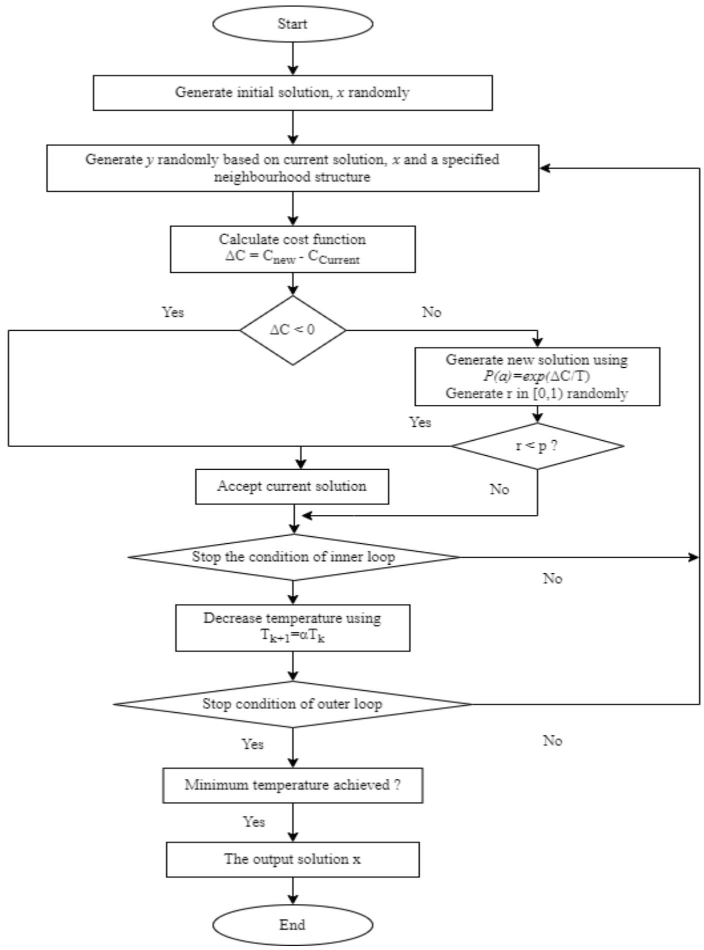

Figure 3.2 Simulated Annealing (SA) Algorithm Flowchart

4. Results and discussion

The data was conducted based on the data from GPS Coordinate Malaysia and the residential area is focused on Bidor region [20]. This set data is classified as cluster data and the locations are scattered as below.

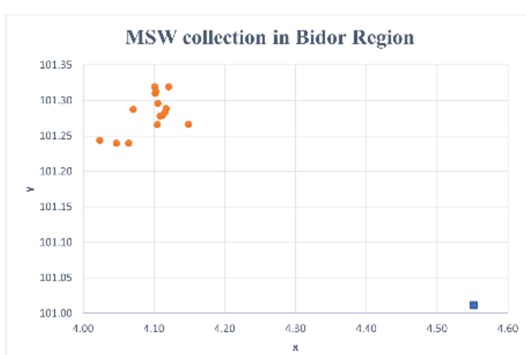

Figure 4.1 MSW real data from GPS Coordinate Malaysia

Table 4.1 CVRP for MSW Collection in Bidor Residential Area Data

Result	CVRP	MTVRP as {24}
Best Cost	259.6743	475.988
Total Distance	368.9923	390.25
Number of Vehicles	3	3

Table 4.1 demonstrates that the best cost obtained for CVRP is 259.6743 but in MTVRP case, the best cost obtained is 475.888. In MTVRP, it consists of more constraints such as time windows, penalty, and multi-trip. Therefore, the cost required for MTVRP is logically higher than CVRP in this study. However, the total distance for CVRP and MTVRP is 368.9923 and 3.9025 units (390.25) respectively. This implies that the total distance obtained is almost the same. Besides, the number of vehicles acquired in both cases is the same, which is three.

Next, three different instances which are Random (R1), Cluster (C1) and Random Cluster (RC1) from Solomon Benchmark is discussed.

Random (R1) data **Cluster (C1) data** **Random Cluster (RC1) data**

Figure 4.2 Random (R1), Cluster (C1) and Random Cluster (RC1) data from Solomon Benchmark

4.1 *Data Comparison of three instances*

All the results shown are coded in MATLAB Programming and tabulated in Microsoft Excel. 50-instances data from the Solomon benchmark are used in this project to solve the CVRP using simulated annealing (SA) algorithm. In this section, we compare the three different classes which are random, cluster and random cluster data. Generally, the greater the distance between customers, the greater the total distance. Therefore, the total traveling distance of the cluster will be the shortest due to the shortest distance between customers.

Table 4.2 Comparison of Random, Cluster and Random Cluster data

Data	Number of routes	Total Load (Unit)	Total Distance Travelled (Unit)
Random (R1)	5	721	1094.1456
Cluster (C1)	3	860	650.1044
Random Cluster (RC1)	7	970	1354.0845

According to Table 4.2, cluster data has the fewest routes, the highest total load, and the shortest total travelling distance compared to random and random cluster data. This is due to the characteristics of cluster data being close to each other as well as the depot 0. Therefore, the vehicle needs shorter travelling distance and time to reach each customer and collect the municipal solid waste. The most significant result is shown in the shortest total traveling distance at 650.1044 units. Then, followed by random and random cluster data with total traveling distance of 1094.1456 units and 1354.0845 units respectively.

The highest number of routes is needed by the random cluster area since the demand for the load is quite high compared to random and cluster data. However, the number of routes taken and total load cannot be further compared based on the distance travelled. This is due to the different categories of data which will affect the total travelling distance.

Conclusion

This study is conducted to generate the optimal routes for MSW collection by minimizing the travelling cost without neglecting the vehicle capacity by using proposed SA algorithm with the aid of MATLAB programming. This study is conducted based on the data from GPS Coordinate Malaysia and Solomon Benchmark which includes random, cluster and random cluster data. Referring to the result for the data in Bidor Region, the total travelling distance and best cost in this study which focused on CVRP is better than the MTVRP since there are less constraints considered in this study. Next, by comparing the three main types of data, which are random, cluster, and random cluster data, the findings show cluster data gives the shortest journey distance and the lowest travel cost, followed by random and random cluster data. This is due to the locations and demand of customers. It is incontrovertible that the shorter the distance between customers, the shorter the distance travelled, and the expense incurred. In the nutshell, this study achieved all the objectives which were to use MATLAB programming to construct the Simulated Annealing (SA) algorithm to find the optimal route schedule in minimising the cost function and travelling distance. Overall, by using this proposed method, the travelling cost and distance could be reduced. This method is also useful to solve more complicated problems.

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