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Application of Greedy Algorithm and Simulated Annealing Algorithm on the Asymmetric Capacitated Vehicle Routing Problem Model in Designing Optimal Garbage Transportation Routes

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ABSTRACT

Waste management remains a recurring issue, particularly in large urban areas. An optimal waste collection route is essential to prevent the problem from becoming more severe and persistent. This study aims to determine the minimum distance and route for waste collection in the Seberang Ulu 1 District, Palembang, using the Greedy and Simulated Annealing algorithms. The calculations were carried out by dividing the district into four work zones. The results show that, using the Greedy algorithm, the minimum distances and routes for work zones 1 through 4 were 24.655 km, 29.7 km, 22.7 km, and 24.705 km, respectively. Meanwhile, using the Simulated Annealing algorithm, the minimum distances and routes for each work zone were 24.325 km, 32.45 km, 22.5 km, and 22.385 km. On average, SA reduces the total distance traveled by 2.1% compared to Greedy, but it requires a longer computation time due to its iterative process of finding the global optimum. These indicate that both algorithms are equally effective in solving the ACVRP problem, with different advantages. SA's advantage in optimizing more complex routes and Greedy's advantage in computation speed for practical implementation. These findings indicate that the Simulated Annealing Algorithm and the Greedy Algorithm almost the same results in solving the Asymmetric Capacitated Vehicle Routing Problem in Seberang Ulu 1 District, Palembang.

1. INTRODUCTION

Waste management in Indonesia faces significant challenges, particularly in major cities and provincial capitals. South Sumatra is one of the largest provinces on the island of Sumatra, with its capital city, Palembang, having a population of 1,686,073 resulting in substantial waste generation [1][2]. The waste problem has escalated as more people gain the capacity to produce waste, while there has been no significant improvement in waste management practices [3]-[6]. The city of Palembang generates approximately 1,000 tons of waste per day, and most of the collection process is still carried out using traditional methods without route optimization. This condition can result in excessive time, fuel wastage, and inefficient working time for waste collection personnel [7]-[10]. It is necessary to implement route optimization efforts to determine the most efficient collection paths, thereby reducing waste accumulation, improving operational effectiveness, and supporting the implementation of technology-based smart waste management systems in urban areas [11].

The Model Vehicle Routing Problem (VRP) is a general term for the optimization problem [12]-[14]. VRP can minimize the excess time, it can be used to minimize route time [15][16]. VRP is a general term for the problem of garbage collection vehicles [17]-[19]. Most VRP studies only consider travel time (or travel distance) as the optimization objective, because this objective fully demonstrates the performance of the

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solution and fully traffic must be minimized [20]-[23]. VRP is used to identify shipping routes by fleet to fulfill one or more customers from a company that depends on one or more existing depots [24]-[26]. The classic VRP is the Capacitated Vehicle Routing Problem (CVRP), which determines delivery routes in which each vehicle on duty follows only one route [27]-[29]. The amount of goods that can be transported via the CVRP is limited; it cannot exceed the fleet capacity. The purpose of CVRP is to reduce the total distance traveled or travel time [30]-[35].

The Asymmetric Capacitated Vehicle Routing Problem (ACVRP) is a form of CVRP in which the path from the origin to the destination differs from the path from the destination to the origin, resulting in an asymmetric distance matrix [36]. Each vehicle can perform at most one route. In the ACVRP model, there are various ways to find the shortest route, for example, using exact, heuristic, and metaheuristic methods [37]. A method that uses the Greedy algorithm generates a step-by-step solution. At each step, the optimal decision will be selected. The decision cannot be changed in the next step, and there is no need to pay attention to the next decision. Then, it is expected that the global optimum, covering all steps from start to finish, is achieved when using local-optimum values at each step [38][39]. Previous research about the application of greedy algorithms in waste transportation routes has been widely used [40][41]. Simulated Annealing (SA), Genetic Algorithms, Cross-Entropy, Particle Swarm Optimization, and Tabu Search Algorithms are some examples of metaheuristic methods [42][43]. Metaheuristic methods are used to find optimal solutions [44]. The SA algorithm performs a search by providing solutions that are considered worse than the conditions currently accepted in the search process, and gradually reduces the probability of solutions that are worse than the conditions currently accepted [45].

Although it has advantages over other methods, such as speed in producing near-optimal solutions, this meta-heuristic method has rarely been used in previous studies. Because the solutions generated by the heuristic method often get stuck in the optimal locale, this metaheuristic method is developed to overcome this problem. Furthermore, this method was chosen because it can produce results close to the optimal global solution in a very large, highly complex solution space. Previous research on the application of Simulated Annealing in waste transportation routes has been widely used [46]-[49]. However, when there is a duality gap, a subgradient-based solution may be incorrect, and the iteration must be continued until a feasible solution is obtained. Then, finding vehicle routes with more than 4 variables in one solution really requires a long calculation time. Judging from previous research, it is rare to obtain distance data for garbage vehicles modeled as ACVRP under real-world route conditions, and problem-solving using two methods, namely the Greedy algorithm and the Simulated Annealing algorithm, is also rare for ACVRP.

The ACVRP method will then be applied using the Greedy and Simulated Annealing algorithms to optimize waste collection routes in the Seberang Ulu 1 District, Palembang. Seberang Ulu 1 is one of the districts in Palembang with the largest population, totaling 91,166 people and a population density of 11,010 per km², with an area of approximately 8.28 km². Based on these data, this district has a high population density, which may be a major contributing factor to waste collection problems. This research can provide theoretical and practical contributions. Theoretically, this research expands the application of the Asymmetric Capacitated Vehicle Routing Problem (ACVRP) model by comparing two optimization algorithms, the Greedy Algorithm and the Simulated Annealing Algorithm, in the context of urban waste management in Indonesia. This research provides new insights into network conditions for efficient routes and demonstrates the potential of metaheuristic algorithms in solving optimization problems in waste management. In practice, the results of this research can be used by the government to design data policies and technology-based waste transportation systems. The results of this research are expected to improve operational efficiency, reduce fuel consumption and emissions, and support the transition to a smart and sustainable urban waste management system.

2. METHOD

In this section, we discuss the method used in this research. This part describes the greedy and simulated annealing algorithms. The steps taken to complete the ACVRP model are as follows:

1. Collect the data on the vehicle, location, Temporary Shelters (TPS), and Initial Point (IP) from District Seberang Ulu 1, Palembang
2. Calculate the distance of each waste transport vehicle route from IP to TPS, TPS to TPS, and TPS to IP in each Working Area (WK) of Seberang Ulu 1 District, Palembang, using *Google Maps*.
3. Defining the parameters and variables in modeling the distances from IP to TPS, TPS to TPS, and TPS to IP.
4. Formulate the ACVRP model
5. Complete the ACVRP model with Greedy Algorithm steps.
6. Complete the ACVRP model with the Simulated Annealing Algorithm steps.
7. Analyze and compare the solutions of the Greedy Algorithm and the Simulated Annealing algorithm.

2.1. Greedy Algorithm

The Greedy Heuristic Algorithm is one of the algorithms used to solve optimization problems. Greedy's algorithm aims to locate facilities without capacity, known as deletion. This algorithm is executed by determining the optimal facility location point. Determining the optimal point is defined as the marginal cost of the objective function when each double route of transportation is removed from the facility location [50]-[53]. This algorithm is the most feasible way to generate solutions. There are several steps in the Greedy Heuristic Algorithm, including determining candidate sites that include demands, then looking for facilities to make replacements, if and only if more than one facility has been located.

The steps in the Greedy Heuristic algorithm to get the optimal solution are

1. If $c_i = 0\ and\ a_i = 1$, where c_i is the objective function coefficient, then eliminate all constraints a_i which has a coefficient of 1 and $i = 1, 2, \cdots, n$.
2. If $c_i > 0\ and\ a_i$ don't have an equation where c_i is the objective function coefficient, then eliminate all constraints a_i don't have an equation and $i = 1, 2, \cdots, n$.
3. For the remaining variables, calculate $\frac{c_i}{d_i}$ where d_i is the number of constraints a_i, which appears with a coefficient of 1.
4. Choose the minimum variable $\frac{c_i}{d_i}$ and the set of a_i have a coefficient of 1.
5. If there are no more constraints, all variable sets remaining 0 are terminated; otherwise, repeat Step (1).

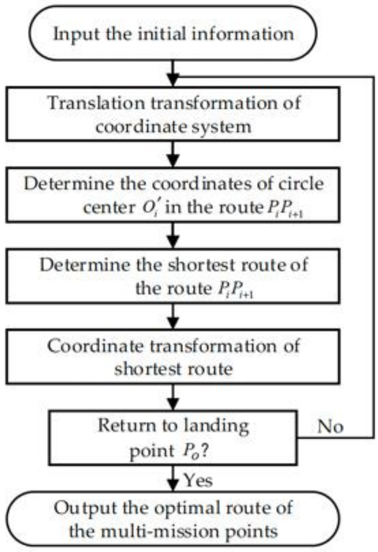

Figure 1. Greedy Algorithm Flowchart

2.2. Simulated Annealing (SA) Algorithm

The Simulated Annealing (SA) method is based on an analogy to the cooling of liquid metal to form crystals, known as annealing. Annealing is a metallurgical technique that uses the science of scheduling the cooling process to optimize the use of energy and produce metals efficiently [54]-[57]. The working principle of SA is that, at high temperatures, liquid molecules have high energy levels, making them relatively easy to move towards other molecules. If the temperature is lowered, the molecules will arrange themselves into configurations with lower energy levels.

By slowly lowering the temperature, the molecules are allowed to self-regulate, resulting in a stationary, stable state at a minimum energy level. The gradual decrease in temperature is called annealing, which is used to solve the VRP problem and obtain an optimal solution. The implementation of SA for VRP is as follows. First, the proposed SA starts with a random initial X. Then, the initial parameter is set, and it is noted that the current best solution X best is equal to the initial solution X.

The following process is to find a better solution using neighborhood moves such as swap, insert, and reverse. The probability of choosing each neighborhood is treated equally, at 1/3. If the new solution Y is better than the current solution X, then replace X with Y. Otherwise, a small probability of accepting a worse solution (Perwira Redi et al., 2020; Redi & Redioka, 2019).

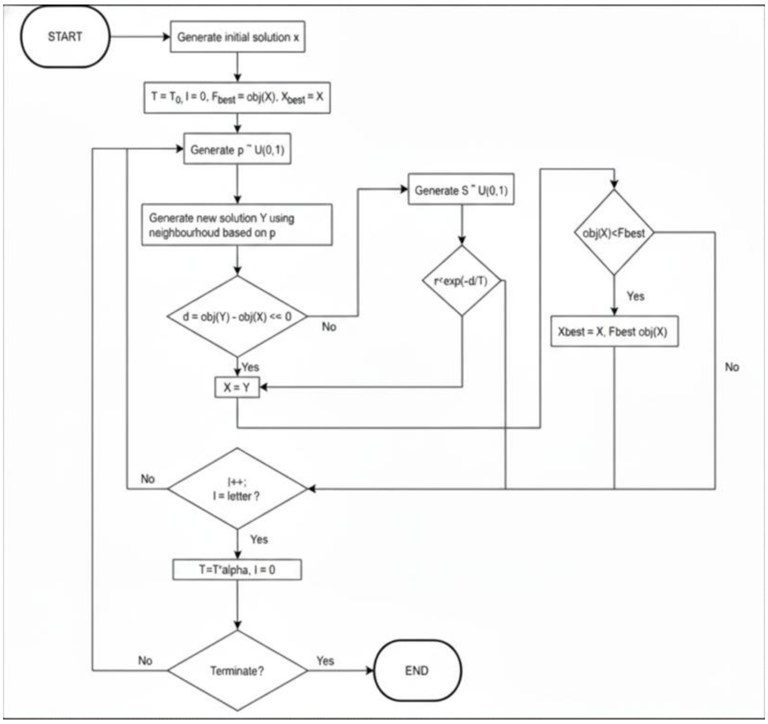

Figure 2. Simulated Annealing Algorithm

3. RESULTS AND DISCUSSION

This research was conducted in the Seberang Ulu 1 sub-district, one of the districts in Palembang. This sub-district consists of four Working Areas (WK) and nineteen Temporary Shelters (TPS), based on data from the official BPS Palembang City website for 2022, in which each WK is served by one waste transport vehicle with a maximum capacity of 4 tons. The Seberang Ulu 1 sub-district is divided into 4 working areas as presented in Tables 1 to 4.

Table 1. The distance between IP and TPS in WK 1

	IP	TPS				
		1	2	3	4	5
IP	0	11.9	12	11.4	10.7	11.4
Next to SPBU Bungaran (TPS 1)	11	0	0.12	0.7	0.26	0.6
In front of Alfamart Sebelum Tugu KB (TPS 2)	10.9	1.1	0	0.55	0.14	0.45
Depan Panca Usaha (TPS 3)	10.3	2.5	2.6	0	1.3	2
Along Street Media Tengah Mulia Tugu KB to Panca Usaha (TPS 4)	10.8	1.2	1.3	0.4	0	0.35
Next to Jl. Panca Usaha (TPS 5)	10.4	2.6	2.7	0.085	1.4	0

Table 2. The distance between IP and TPS in WK 2

	IP	TPS							
		1	2	3	4	5	6	7	8
IP	0	11.9	12.3	10.4	10.4	12	11.4	8.9	10.1
Next to the Palembang City Parliament Building (TPS 1)	12.5	0	0.75	3.9	3.2	1.2	1.3	5.4	3.8
Along Jl. from DPRD to BKN (TPS 2)	12.4	1.3	0	3.8	3.1	1.4	1.4	5.3	3.6
Market 2 Ulu (TPS 3)	11.5	2.8	3.3	0	0.75	2.2	1.7	2.2	1.4
Market 3 – 4 Ulu (TPS 4)	12.2	2.1	2.6	0.75	0	2.2	1.7	2.2	1.4
In the Al-Fathur Akbar Mosque (TPS 5)	12	0.4	0.9	2.7	2.7	0	0.6	4.6	3.3
Before the Jakabaring Flyover (TPS 6)	11.4	1.6	2.1	2.2	2.2	1.7	0	4	2.7
Jl. 1 North Pole (TPS 7)	12.7	2.9	3.4	1.5	1.5	3.1	2.5	0	1.2
In front of the Muhajirin 2 Ulu Laut Mosque (TPS 8)	11.9	2.8	3.3	1.4	1.4	3	2.4	1.2	0

Table 3. The distance between IP and TPS in WK 3

	IP	TPS	
		1	2
IP	0	9.4	10.7
Jl. KH Wahid Hasyim (PT. ALI) (TPS 1)	9.5	0	1.4
Beside PBK Office 3/4 Ulu (TPS 2)	11.9	2.3	0

Table 4. The distance between IP and TPS in WK 4

	IP	TPS			
		1	2	3	4
IP	0	10.9	10.1	10.1	10.1
In front of Sub-District Office SU.1 (TPS 1)	11.6	0	2	2	1.9
Side Sect SU.1 (TPS 2)	12.5	0.053	0	2	2
Start going down the Ogan Bridge to the Sub-district Office SU.1 (TPS 3)	12.6	0.071	0.052	0	2
Front RM. Mega Raya (TPS 4)	12.6	0.13	0.11	0.58	0

3.1. Calculating the Route of IP to TPS

3.1.1. Calculating with the Greedy Algorithm

Calculation Process Using the Greedy Algorithm on the ACVRP Model in Seberang Ulu 1 District, Distance and Route of IP to TPS and between TPS in WK 1. In Table 1, there are 5 TPS, namely S = {1, 2, 3, 4, 5}, which must be visited, with *i* being the point of origin and *j* being the point of destination. IP is denoted 0, and TPS is denoted as 1, 2, 3, 4, 5.

Starting from the starting point (IP). Take all the points that can be visited. The local maximum is at TPS 4, because the distance to TPS 4 is the shortest. Mark the IP as visited, then move to TPS 4. After that, repeat steps 1-3. Take all points that can be visited from TPS 4. The local maximum is at TPS 5 because the distance to TPS 5 is the shortest. Mark TPS 4 as the visited point, then move to TPS 5. Repeat steps 1 to 3 again. Take all points that can be visited from TPS 5. The local maximum is at TPS 3 because the distance to TPS 3 is the shortest. Mark TPS 5 as the visited point, then move to TPS 3. Repeat steps 1 to 3. Take all points that can be visited from TPS 3. The local maximum is at TPS 1, because the distance to TPS 1 is the shortest. Mark TPS 3 as the visited point, then move to TPS 1. Repeat steps 1 to 3. Take all points that can be visited from TPS 1. The local maximum is at TPS 2, because the distance to TPS 2 is the shortest. Mark TPS 1 as the visited point, then move to TPS 2. Repeat step 1 until you return to the IP. Take all points that can be visited from TPS 2, because all points have been visited, TPS 2 will return to IP.

a. Distance and Route of IP to TPS and between TPS in WK 1

Based on the calculations, the minimum distance traveled by vehicles is 24.655 km. With the minimum route for the vehicle's journey, namely IP (Jl. IP II Lorong Karya 1) – TPS 4 (Along Jl. Median Tengah Mulia Tugu KB to Panca Usaha) – TPS 5 (Across from Jl. Panca Usaha) – TPS 3 (Front of Panca Business) – TPS 1 (Opposite Bungaran 1 gas station) – TPS 2 (Front of Alfamart before the KB Monument) – IP (Jl. IP II Lorong Karya 1).

b. Distance and Route of IP to TPS and between TPS in WK 2

Using the same method, the minimum distance traveled by the vehicle is 29.7 km. With the minimum route for the vehicle's journey, namely IP (Jl. IP II Lorong Karya 1) – TPS 7 (Jl. 1 Ulu Laut) – TPS 8 (Front of Muhajirin Mosque 2 Ulu Laut) – TPS 3 (Pasar 2 Ulu) – TPS 4 (Pasar 3 – 4 Ulu) – TPS 6 (Before Jakabaring Flyover) – TPS 1 (Next to Palembang City DPRD Building) – TPS 2 (All the way from DPRD to BKN) – TPS 5 (In Al-Fathur Akbar Mosque) – IP (Jl.IP II Lorong Karya 1).

c. Distance and Route of IP to TPS and between TPS in WK 3

Using the same method, the minimum distance traveled by the vehicle is 22.7 km. With the minimum route of the vehicle trip, namely IP (Jl. IP II Lorong Karya) – TPS 1 (Jl. KH Wahid Hasyim) – TPS 2 (Next to the PBK Office 3 – 4 Ulu) – IP (Jl. IP II Lorong Karya).

d. Distance and Route of IP to TPS and between TPS in WK 4

Using the same method, it is found that the minimum distance traveled by the vehicle is 24.705 km. With the minimum route for the vehicle's journey, namely IP (Jl. IP II Lorong Karya 1) – TPS 3 (Starting down the Ogan Bridge to the Sub-district Office SU.1) – TPS 4 (In front of RM. Mega Raya) – IP (Jl. IP II Lorong Karya 1).

The Greedy Algorithm uses a deterministic process that selects the best solution at each step. At the first step, it obtains a local optimal solution, and at the final step, it obtains the global optimal solution. The best solution at each step is optimal. In this study, the best route selection within each WK follows a Greedy Algorithm, starting from each work area, then visiting all TPS and returning to the IP. The process continues until all TPS have been visited and stops when the optimal route is reached.

Table 5. Results of the Greedy Algorithm in the ACVRP Model in Seberang Ulu District 1

Working Area	Minimal Routes	Minimal Distance (km)
WK 1	IP – TPS 4 – TPS 5 – TPS 3 – TPS 1 – TPS 2 – IP	24.655
WK 2	IP – TPS 7 – TPS 8 – TPS 3 – TPS 4 – TPS 6 – TPS 1 – TPS 2 – TPS 5 – IP	29.7
WK 3	IP – TPS 1 – TPS 2 – IP	22.7
WK 4	IP – TPS 3 – TPS 2 – TPS 1 – TPS 4 – IP	24.705

Results show the Greedy Algorithm can provide a fast and easy-to-implement solution, but it does not necessarily produce a global optimum solution because of its nature of only considering the best local decision at each step.

3.1.2. Calculating with the Simulated Annealing Algorithm

The Calculation Process Using the Simulated Annealing Algorithm in the ACVRP Model in Seberang Ulu 1 District

In Table 1, there are 5 TPS, namely S = {1, 2, 3, 4, 5}, which must be visited, with *i* as the point of origin and j as the destination. IP is denoted 0, and TPS is denoted as 1, 2, 3, 4, 5.

Completion:

1) Determine the initial route, which is assumed to be the shortest route temporarily.

Initial route ie 0 – 1 – 2 – 3 – 4 – 5 – 0.

2) Calculates the current route mileage(Z_c).

$$Z_c = 11.9 + 0.12 + 0.55 + 1.3 + 0.35 + 10.4 = 24.62$$

3) Determine the initial T value with $\alpha = 0.05$ and $i = 0$.

$$T_0 = (1 - 0.05)(24.62) = 23.389$$

4) Calculate the maximum number of iterations.

$$\frac{(n-1)!}{2} = \frac{(6-1)!}{2} = \frac{5!}{2} = \frac{(5)(4)(3)(2)(1)}{2} = \frac{120}{2} = 60 \text{ iteration}$$

5) Iteration 1

Determine the location of TPS 1, TPS 2, TPS 3, TPS 4, and TPS 5 by means of 1 divided by 5 in the interval [0,1] so that each TPS location has a class interval length of 0.20.

0.00 – 0.19	Initial transport route to TPS 1
0.20 – 0.39	Initial transport route to TPS 2
0.40 – 0.59	Initial transport route to TPS 3
0.60 – 0.79	Initial transport route to TPS 4
0.80 – 0.99	Initial transport route to TPS 5

Selection of random numbers is done with Microsoft Excel, namely $r_1 = 0.217$, so that the initial route to TPS 2. Then determine the location of TPS 1, TPS 3, TPS 4, and TPS 5, with 1 divided by 4 in the interval [0,1], then each TPS location has a class interval length of 0.25.

0.00 – 0.24	Final transport route to TPS 1
0.25 – 0.49	Final transport route to TPS 3
0.50 – 0.74	Final transport route to TPS 4
0.75 – 0.99	Final transport route to TPS 5

Selection of random numbers is done with Microsoft Excel, namely $r_1 = 0.217$, so that the final route is to TPS 1. Then exchanging the two locations, namely TPS 2 and TPS 1, will produce a new route, namely 0 – 2 – 1 – 3 – 4 – 5 – 0. Calculation of the distance traveled for the new route (Z_n) :

$$Z_n = 0 - 2 - 1 - 3 - 4 - 5 - 0$$
$$Z_n = 12 + 1.1 + 0.7 + 1.3 + 0.35 + 10.4$$
$$Z_n = 25.85$$

The current route distance is known $(Z_c) = 24.62$ so obtained $Z_n = 25.85 > Z_c = 24.62$ Then the new route can be expressed as the current route with probability.

$$p = e^{\frac{Z_c - Z_n}{T_0}} = e^{\frac{24.62-25.85}{23.389}} = e^{-0.053} = 0.949$$

Because $r_1 = 0.217 < p = 0.949$ Then the new route can be approved as the current route.

6) Initialize it $T_{i+1} = (1-\alpha)(T_i)$ According to the annealing schedule with $T_1 = (1-0.05)(T_0)$ as follows:

$$T_1 = (1-0.05)(23.389) = 22.220$$

Repeat steps 5 and 6.

5) Iteration 2

Determination of TPS 1, TPS 2, TPS 3, TPS 4, and TPS 5 locations by 1 divided by 5 at intervals [0,1), each TPS location has a class interval length of 0.20.

0.00 – 0.19	Initial transport route to TPS 1
0.20 – 0.39	Initial transport route to TPS 2
0.40 – 0.59	Initial transport route to TPS 3
0.60 – 0.79	Initial transport route to TPS 4
0.80 – 0.99	Initial transport route to TPS 5

Selection of random numbers is done with Microsoft Excel, namely $r_2 = 0.037$, so that the initial route to TPS 1. Then determine the location of TPS 2, TPS 3, TPS 4, and TPS 5, with 1 divided by 4 in the interval [0,1), then each TPS location has a class interval length of 0.25.

0.00 – 0.24	Final transport route to TPS 2
0.25 – 0.49	Final transport route to TPS 3
0.50 – 0.74	Final transport route to TPS 4
0.75 – 0.99	Final transport route to TPS 5

Selection of random numbers is done with Microsoft Excel, namely $r_2 = 0.037$, so that the final route is to TPS 2. Then, by exchanging the two locations, namely TPS 2 and TPS 1, it produces a new route 0 – 2 – 1 – 3 – 4 – 5 – 0. Calculation of the distance traveled for the new route (Z_n):

$$Z_n = 0 - 2 - 1 - 3 - 4 - 5 - 0$$
$$Z_n = 12 + 1.1 + 0.7 + 1.3 + 0.35 + 10.4$$
$$Z_n = 25.85$$

The current route distance is known $(Z_c) = 24.62$ so obtained $Z_n = 25.85 > Z_c = 24.62$ Then the new route can be expressed as the current route with probability.

$$p = e^{\frac{Z_c - Z_n}{T_0}} = e^{\frac{24.62-25.85}{23.389}} = e^{-0.053} = 0.949$$

Because $r_2 = 0.288 < p = 0.949$ Then the new route can be approved as the current route.

6) Initialize it $T_{i+1} = (1-\alpha)(T_i)$ According to the annealing schedule with $T_2 = (1-0.05)(T_1)$ as follows:

$$T_2 = (1-0.05)(22.220) = 21.109$$

Next, for iterations 3 to 60, it uses the same calculation.

a. Distance and Route of IP to TPS and between TPS in WK 1

Based on the calculations, the minimum distance traveled by vehicles is 24.325 km. With the minimum route for the vehicle's journey, namely IP (Jl. IP II Lorong Karya 1) – TPS 2 (Front of Alfamart before the KB Monument) – TPS 4 (All along Jalan Median Tengah Mulia Tugu KB to Panca Usaha) – TPS 1 (Across from the gas station Bungaran 1) – TPS 5 (Opposite Jl. Panca Usaha) – TPS 3 (Front of Panca Usaha) – IP (Jl. IP II Lorong Karya 1).

b. Distance and Route of IP to TPS and between TPS in WK 2

Using the same method, the minimum distance traveled by vehicles is 32.45 km, found in iterations 57, 61, and 63. With the minimum routes of the three vehicle trips, namely the first iteration 57 includes IP (Jl IP II Lorong Karya 1) – TPS 1 (next to the Palembang City DPRD Building) – TPS 2 (All the way from DPRD to BKN) – TPS 5 (Inside the Al-Fathur Akbar Mosque) – TPS 6 (Before the Jakabaring Flyover) – TPS 4 (Pasar 3 – 4 Ulu) – TPS 8 (In front of Muhajirin Mosque 2 Ulu Laut) – TPS 7 (Jl. 1 Ulu Laut) – TPS 3 (Pasar 2 Ulu) – IP (Jl. IP II Lorong Karya 1).

The second route, namely iteration 61, includes IP (Jl. IP II Lorong Karya 1) – TPS 3 (Pasar 2 Ulu) – TPS 7 (Jl. 1 Ulu Laut) – TPS 4 (Pasar 3 – 4 Ulu) – TPS 8 (Front of the Mosque) Muhajirin 2 Ulu Laut) – TPS 1 (next to Palembang City DPRD Building) – TPS 2 (All the way from DPRD to BKN) – TPS 5 (Inside Al-Fathur Akbar Mosque) – TPS 6 (Before Jakabaring Flyover) – IP (Jl. IP II Lorong Karya 1).

The third route, namely iteration 63 includes IP (Jl. IP II Lorong Karya 1) – TPS 3 (Pasar 2 Ulu) – TPS 8 (Front of Muhajirin Mosque 2 Ulu Laut) – TPS 4 (Pasar 3 – 4 Ulu) – TPS 7 (Jl 1 Ulu Laut) – TPS 1 (next to Palembang City Parliament Building) – TPS 2 (All the way from DPRD to BKN) – TPS 5 (Inside Al-Fathur Akbar Mosque) – TPS 6 (Before Jakabaring Flyover) – IP (Jl. IP II Lorong Karya 1).

c. Distance and Route of IP to TPS and between TPS in WK 3

Using the same method, the minimum distance traveled by the vehicle is 22.5 km. With the minimum route of the vehicle trip, namely IP (Jl. IP II Lorong Karya) – TPS 2 (Next to the PBK Office 3 – 4 Ulu) – TPS 1 (Jl. KH Wahid Hasyim) – IP (Jl. IP II Lorong Karya).

d. Distance and Route of IP to TPS and between TPS in WK 4

Using the same method, the minimum distance traveled by the vehicle is 22.385 km. With the minimum route for the vehicle's journey, namely IP (Jl. IP II Lorong Karya 1) – TPS 4 (In front of RM. Mega Raya) – TPS 3 (Start down the Ogan Bridge to the Sub-district Office SU.1) – TPS 2 (Beside Sekta SU. 1) – TPS 1 (Front of District Office SU.1) – IP (Jl. IP II Lorong Karya 1).

Table 6. Results of the Simulated Annealing Algorithm in the ACVRP Model in Seberang Ulu District1

Working Area	Minimal Routes	Minimal Distance (km)
WK 1	IP – TPS 2 – TPS 4 – TPS 1 – TPS 5 – TPS 3 – IP	24.325
WK 2	First : IP – TPS 1 – TPS 2 – TPS 5 – TPS 6 – TPS 4 – TPS 8 – TPS 7 – TPS 3 – IP Second : IP – TPS 3 – TPS 7 – TPS 4 – TPS 8 – TPS 1 – TPS 2 – TPS 5 – TPS 6 – IP Third : IP – TPS 3 – TPS 8 – TPS 4 – TPS 7 – TPS 1 – TPS 2 – TPS 5 – TPS 6 – IP	32.45
WK 3	IP – TPS 2 – TPS 1 – IP	22.5
WK 4	IP – TPS 4 – TPS 3 – TPS 2 – TPS 1 – IP	22.385

3.2. Comparison of the Greedy Algorithm and the Simulated Annealing Algorithm in the ACVRP Model in Seberang Ulu District 1

The results of the comparison of the Greedy algorithm and the Simulated Annealing algorithm in the ACVRP model in the Seberang Ulu 1 sub-district are presented in Table 7 as follows:

Table 7. Comparison Results Rute of the Greedy Algorithm and the Simulated Annealing Algorithm in the ACVRP Model in Seberang Ulu District 1

Working area	Minimum Route		Minimum Distance (km)	
	Greedy Algorithm	Simulated Annealing Algorithm	Greedy Algorithm	Simulated Annealing Algorithm
WK 1	IP – TPS 4 – TPS 5 – TPS 3 – TPS 1 – TPS 2 – IP	IP – TPS 2 – TPS 4 – TPS 1 – TPS 5 – TPS 3 – IP	24.655	24.325
WK 2	IP – TPS 7 – TPS 8 – TPS 3 – TPS 4 – TPS 6 – TPS 1 – TPS 2 – TPS 5 – IP	First: IP – TPS 1 – TPS 2 – TPS 5 – TPS 6 – TPS 4 – TPS 8 – TPS 7 – TPS 3 – IP Second: IP – TPS 3 – TPS 7 – TPS 4 – TPS 8 – TPS 1 – TPS 2 – TPS 5 – TPS 6 – IP Third : IP – TPS 3 – TPS 8 – TPS 4 – TPS 7 – TPS 1 – TPS 2 – TPS 5 – TPS 6 – IP	29.7	32.45
WK 3	IP – TPS 1 – TPS 2 – IP	IP – TPS 2 – TPS 1 – IP	22.7	22.5
WK 4	IP – TPS 3 – TPS 2 – TPS 1 – TPS 4 – IP	IP – TPS 4 – TPS 3 – TPS 2 – TPS 1 – IP	24.705	22.385

Based on Table 6, the two algorithms produce nearly the same distance. The majority of the minimum distances are obtained with the Simulated Annealing algorithm, which requires more iterations. The mean distance for the greedy algorithm is 25.43875, and for the simulated annealing algorithm is 25.415.

Table 8. Comparison Results of the Greedy Algorithm and the Simulated Annealing Algorithm in the ACVRP Model in Seberang Ulu District 1

Working Area	Greedy (km)	Simulated Annealing (km)	Difference (km)
WK 1	24.655	24.325	0.330
WK 2	29.700	32.450	-2.750
WK 3	22.700	22.500	0.200
WK 4	24.705	22.385	2.320

The total distance results obtained by both algorithms are shown in Table 8. The results show that both algorithms perform comparably across the four work areas, with variations depending on route complexity and road conditions. The Simulated Annealing (SA) algorithm produced a shorter total distance in WK 1, 3, and 4, but a slightly longer one in WK 2. It means that the Simulated Annealing (SA) algorithm can find a more efficient solution than Greedy, because it can escape local optima by accepting worse temporary solutions during the annealing process. The Greedy algorithm always chooses the most locally optimal decision, namely, the nearest unvisited TPS, making it fast but potentially resulting in a suboptimal global route. In contrast, the Simulated Annealing (SA) Algorithm sometimes accepts worse temporary solutions early on to avoid a local minimum.

In WK 2, the Simulated Annealing (SA) Algorithm produced a longer total distance (32.45 km) compared to Greedy (29.7 km). This could be due to the stochastic nature of SA, where poorer solutions accepted early in the cooling process did not have time to consolidate into better routes before the temperature reached the termination threshold. Conversely, in WK 4, Simulated Annealing (SA) Algorithm showed significant improvement, reducing the route distance from 24.705 km (Greedy) to 22.385 km—a savings of 9.39%. This result shows that the Simulated Annealing (SA) Algorithm's ability to explore a wider solution space and escape local solution traps in certain route structures. The Greedy algorithm is much faster, generating routes in seconds, while the Simulated Annealing (SA) Algorithm requires multiple iterations and is computationally expensive. However, the additional time is justified by the better solution quality it provides in most cases.

Differences in results between regions are also influenced by the degree of route asymmetry. Regions with more one-way streets and irregular road patterns (such as WK 4) provide conditions where the Simulated Annealing (SA) Algorithm probabilistic search mechanism performs better because it can adapt the route configuration. The differences of regions with more symmetrical road layouts, such as WK 2, are more easily solved by deterministic methods like Greedy, as the search space for solutions is more limited. The research results show that optimizing waste transportation routes using the ACVRP approach and metaheuristic algorithms such as Simulated Annealing can improve vehicle travel time and distance efficiency. Mileage savings range from 0.3–2.3 km per work area, directly impacting fuel efficiency, reducing carbon emissions, and increasing field worker productivity.

4. CONCLUSION AND LIMITATION

4.1. Conclusion

Based on the results and discussion described, several conclusions can be drawn regarding the problem of waste transportation routes in the Seberang Ulu 1 District. The application uses the greedy algorithm for each Working Area, the minimum vehicle distance and route is obtained: WK 1 is 24.655 km, WK 2 is 29.7 km, WK 3 is 22.7 km, and WK 4 is **24.705** km. In comparison, using the Simulated Annealing algorithm for each WK, the minimum vehicle distance and route are obtained: WK 1 is 24.325 km; WK 2 is 32.45 km; WK 3 is 22.5 km; WK 4 is **22.385** km.

The Simulated Annealing algorithm generally yields shorter vehicle route distances than the Greedy algorithm in the ACVRP model for the Seberang Ulu 1 District, Palembang. Consequently, both algorithms can be used, depending on specific requirements, to determine the most efficient waste transportation routes.

4.2. Limitation

The limitation of this research was not adding busy time. For further research, other metaheuristic algorithms, such as the Genetic Algorithm or Particle Swarm Optimization, could be applied to compare their efficiency. Furthermore, integrating real-time data from GPS or vehicle sensors could improve the accuracy of dynamic routing.

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