A Genetic Algorithm Approach for Waste Collection Using Multi-trip Multi-period Capacitated Vehicle Routing Problem with Time Windows (MCVRPTW)

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Abstract

Waste collection and transportation processes are accounted for more than 50% of all total waste management costs then there is an urgency for a waste recycling company to minimize this activities-related total cost by any means. Route optimization in collecting those plastics wastes can be a good solution to addressing the problem. This research focuses on determining waste collection routes for multilayer plastic with the objective function of minimizing total transportation costs. The waste collection problem is modeled as Vehicle Routing Problem (VRP) with a certain capacity and constrained time windows but here the vehicle is allowed to travel multiple times, this model said as the Multi-Trip Multi-period Capacitated Vehicle Routing Problem with Time Windows (MCVRPTW). The model was solved by an exact method using mixed integer linear programming and a metaheuristic approach using the Genetic Algorithm (GA). The results showed that the exact method was able to solve problems on small data instances and required almost 100% higher computation time than of metaheuristic approach. The best GA solution with mutation and crossover rates of 0.75 and 0.1 provides savings of 30.2% compared to the total transportation cost for existing conditions.

Keywords
Genetic Algorithm, MCVRPTW, Mixed Integer Linear Programming, Route Optimization, and Waste Collection.

1. Introduction
More consumption means more waste plastic packaging dominating the world's pollution along with waste from these sectors: building and construction, textiles, transportation, electronics, industrial machinery, and others (Ritchie & Roser, 2018). Waste management has become a problem for all people, and Indonesia is no exception. Plastic waste management in Indonesia is considered unsuccessful yet where it is known that there are 4.8 million tons of them (National Plastic Action Partnership 2021). Regarding the potential for waste pollution, many companies are starting to adopt the Circular Economy (CE) business model and reverse logistics. Reverse logistics flow and process can be illustrated in Fig. 1. As stated by (Sureka, Bandara, & Wickramarachchi, 2018), one prominent factor some influencing others for efficient and effective reverse logistics is transportation, covering aspects of the driver, vehicle, road, geography, etc.

Waste management can be seen as a strategic supply chain issue as it consists of activities of collection, sortation, transportation, processing, and distribution where tactical, strategic, and operational decision-making requires coordination involving the entire actors (Mohammadi et al. 2019). Waste management activities have many challenges such as non-integrated upstream to downstream handling, inadequate processing infrastructure, and high investment and operational costs (Sutana 2021). The activities of collection and transportation contribute significantly up to 70% to the total cost of the waste management (Boskovic et al. 2016). Little moreover big improvements in waste collection and transport activities will give a big acceleration in overall waste management system which can be seen in the greater cost savings that can be gained. (Wu et al. 2020).

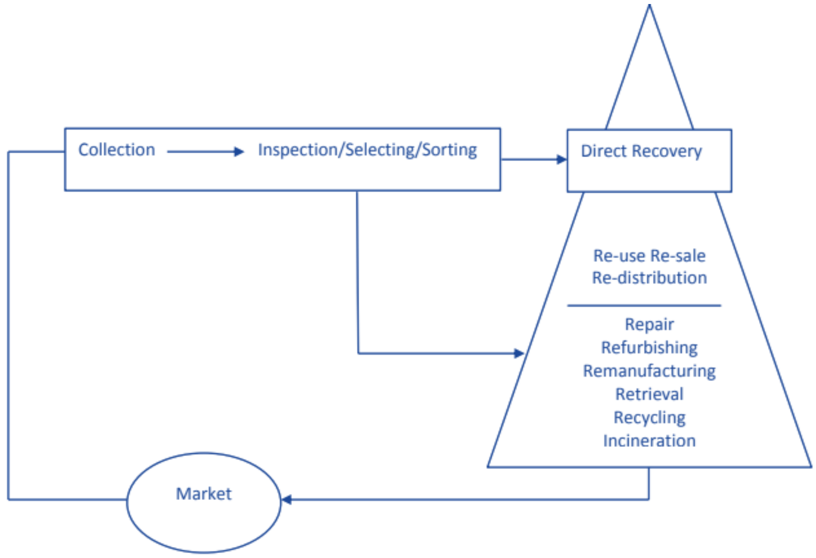

Figure 1. Reverse Logistics Flow (Reddy, 2011)

PT Tridi Oasis Group recycles plastic bottle waste to produce high-quality plastic flakes that can be used as raw materials for making electrical cables, furniture, sustainable packaging, textiles, and other industrial products. Tridi Oasis products are not only marketed to local factories but also exported abroad. Tridi Oasis was founded on the basis of concern for the huge plastic waste in Indonesia, especially the waste of polyethylene terephthalate (PET) plastic bottles and multi-layer plastic (MLP). The company receives raw materials in the form of waste plastic bottles sent by various suppliers (agreed partners) using own operational vehicle. Plastic waste received is stored in a warehouse for further processing using a special machine to separate one bottle from another. These bottles are then inspected, chopped, washed, separated from the bottle rings, packed, labeled before being loaded into containers to be sent to buyers.

Regarding waste collection for Tridi Oasis production, it is realized that there are 39 pick-up points of supplier where each point is visited once a day or a period. The pick-up process to all points usually takes 3 days due to the limited number of vehicles and operational time. In the existing collection process, there is no provision on which location should be visited first so the pick-up route is only determined based on the driver's intuition. Supply availability fluctuates depending on the partner's ability to collect MLP each week so the amount of MLP collection is also not fixed in terms of the number of points visited and the total volume of MLP collected. This causes the total transportation costs incurred by the company to tend to be high which further undermine other aspects of the business. Therefore, it is necessary to optimize the route for collecting MLP in order to minimize the total cost of transportation. This problem is modeled as Multi-trip Multi-period Capacitated Vehicle Routing Problem with Time Windows (MCVRPTW).

1.1 Objectives

This research focuses on a waste collection route that minimizes the total transportation costs covering fuel cost as a variable cost and driver wage as a fixed cost, at a recycling company, PT Tridi Oasis which is located in Tangerang district, West Java province, Indonesia. The waste type collected is the MLP from agreed partners nearby. The problem is modeled into MCVRPTW to be solved using exact and metaheuristic approaches. Comparison in terms of solution searching time and model output quality will be provided.

2. Literature Review

The Vehicle Routing Problem (VRP) is an extended development of the Traveling Salesman Problem (TSP). TSP is described as a routing problem where a salesman departs from one depot to visit several points and returns to the depot with the shortest route in which each point is visited once (Kusrini & Istiyanto 2007). VRP is a multiple TSP notated as n-TSP where there are n-salesmen who visit a number of points where each point can only be visited once by exactly one salesman (Kallehauge et al. 2001). Some objective functions used in VRP problems include minimizing total transportation costs related to travel distance and travel time, minimizing the number of vehicles, and balancing travel time and vehicle load (Toth & Vigo 2002). Multi-trip Multi-period Capacitated Vehicle Routing Problem with Time Windows (MTCVRPTW) is a VRP variant developed with the addition of vehicle capacity limitation, time windows, and the possibility to trip more than once for more than one period. As we know that in the basic VRP model, each vehicle will only form one route but in the multi-trip VRP, one vehicle will form several routes or trips as long as it does not exceed the maximum travel time of the vehicle that has been set.

This research uses a Genetic Algorithm metaheuristic approach to solving the vehicle routing problem. Metaheuristics should be used if the exact methods are not possible or inefficient to solve a VRP model, a complex optimization problem. Metaheuristics are also suitable for independent problems meaning that the method used does not depend on a particular type of problem. Even though it can be used for various types of problems, the adaptability of the chosen method for a specific problem will have a major effect on the quality of the output solution. Many previous studies applied analytical methods in finding optimum solutions for such VRP models, one of which is the metaheuristics, especially the GA. This GA approach is widely known to be one alternative to some evolutionary search techniques used to identify approximate solutions for the optimization problem. GA is proven to be effective and also efficient in solving combinatorial optimization problems (Chung & Kim 2016**)**. Inspired by chromosomes and genes that are present in nature, GA represents optimization problems as a set of variables. Each chromosome represents a solution to an optimization problem and each gene (genotype) represents a problem variable (Mirjalili et al. 2019). In searching best solution using GA, we need to follow some steps that are described below:

1) Initialization
   The process of generating an initial solution by representing the solution in chromosomes. This step is also called as an encoding process that is usually conducted by assigning a random value to each bit in the defined chromosome.
2) Evaluation
   Calculating the objective function value representing the fitness value for each chromosome. This value describes the compatibility of chromosomes in solving the problem.
3) Selection
   In this stage, we define the parent chromosomes. Parents selected will be utilized to produce a new individual or chromosome with the best fitness value to be used for the next GA process. There are several selection methods that can be implemented, some of the most used are the roulette wheel selection, ranked-based fitness, and tournament selection.
4) Crossover
   The crossover operation is executed by randomly selecting bits in a chromosome and then crossing those bits with bits on another chromosome. Crossover rate value range are between 0 and 1. There are several methods to operate crossover process including single-point crossover, multi-point crossover, and partially mapped crossover (PMX).
5) Mutation
   Mutation stage is carried out by randomly selecting bits on chromosomes and changing their values. Mutation value is ranged between 0-1. Some methods used to perform mutations are swap mutation, insertion mutation, and reversion mutation.

3. Methods
3.1 Exact Method
This paper mainly consists of three major stages. The first stage is solving this problem using exact method for small instance. The second stage is implementing Genetic Algorithm for solving the real problem which consist of large data. The last stage is analyzing the exact and GA result by comparing the value of objective function and computation time. The complete mathematical model is described below:

Input and Paremeters:
i, j : Set of customer location, $i, j = 1,2,3..N$
N : Set of depot and customers, $N = 0$ is depot
v : Set of vehicles, $v = 1,2..V$
t : Set of periods, $t = 1,2..P$
d_i : Demand at node i

tr_{ij} : Vehicle travel time from node i to node j
L_{ij} : Travel distances from node i to node j
C : Variabel cost (cost of fuel per km)
F : Fixed cost per period
Q : Maximum cehicle capacity
$[e, l]$: Earliest and latest time windows
E_{ivt} : Accumulative vehicle load before visiting point i

Decision Variabel
X_{ijvt} : Equal 1 if vehicle v visiting node j after node i at period t, otherwise equal 0
Y_{it} : Equal 1 if node j visited at period t, otherwise 0
u_t : Equal 1 if period t selected, otherwise 0
A_{ivt} : Service starting time vehicle v at node i and period t

Objective Function

$$\sum_{i \in N} \sum_{j \in N} \sum_{v \in V} \sum_{t \in P} CL_{ij} X_{ijvt} + \sum_{t \in P} u_t F \tag{1}$$

Constraints

$$\sum_{t \in P} \sum_{v \in V} \sum_{j \in N} X_{ijvt} = 1 \qquad \forall \text{ for } i \in N\backslash\{0\} \tag{2}$$

$$Y_{it} = \sum_{j \in N} X_{ijvt} \qquad \forall \text{ for } i \in N, v \in V, t \in P \tag{3}$$

$$u_t \geq X_{ijvt} \qquad \forall \text{ for } i \in N\backslash\{0\}, j \in N\ v \in V,\ t \in P \tag{4}$$

$$\sum_{j \in N} X_{0jvt} = \sum_{j \in N} X_{i0vt} \qquad \forall \text{ for } t \in P, v \in V \tag{5}$$

$$\sum_{i \in N} X_{ijvt} - \sum_{i \in N} X_{jivt} = 0 \qquad \forall \text{ for } t \in P, v \in V, j \in N\backslash\{0\} \tag{6}$$

$$E_{ivt} + d_j - M\left(1 - X_{ijvt}\right) \leq E_{jvt} \qquad \forall \text{ for } i \in N,\ j \in N\backslash\{0\}, t \in P, v \in V \tag{7}$$

$$E_{ivt} \leq Q \qquad \forall \text{ for } i \in N,\ v \in V,\ t \in P \tag{8}$$

$$A_i^v + M(1 - Y_i^v) \geq e \qquad \forall \text{ for } t \in P, v \in V, i \in N\backslash\{0\} \tag{9}$$

$$A_i^v - M(1 - Y_i^v) \leq l \qquad \forall \text{ for } i \in N\backslash\{0\}, v \in V, t \in P \tag{10}$$

$$A_{ivt} + S + tr_{ij} - A_{jvt} \leq M\left(1 - X_{ijvt}\right) \qquad \forall \text{ for } i \in N, j \in N\backslash\{0\}\ \ i \neq j, v \in V, t \in P \tag{11}$$

$$X_{ijvt} \in \{0,1\} \qquad \forall \text{ for } (i,j) \in N, v \in V, t \in P \tag{12}$$

$$Y_{it} \in \{0,1\} \qquad \forall \text{ for } i \in N, t \in P \tag{13}$$

$$u_t \in \{0,1\} \qquad \forall \text{ for } t \in P \tag{14}$$

The objective function (1) used in this model is to minimize the total cost of transportation consisting of fixed costs and variable costs. The fixed cost comes from multiplying the fixed cost per period and the number of periods used while variable costs are obtained from the product of the cost of fuel per km by the total distance traveled. Constraint (2)-(3) ensure that each point must be visited once. Constraint (4) is used to find out in which period the vehicle performs service. Constraint (5)-(6) state that the vehicle starts and ends at the depot in each route. Constraints (7) and (8) ensure that the accumulative load does not exceed the maximum capacity of the vehicle for each route. Constraint (9)-(10) calculate that service time does not exceed the time windows allowed. Constraint (11) expresses that service starting time at node j must be greater than the sum of service starting time at node i, service time, travel time form node i to node j. Constraint (12)-(14) describe about the characteristics of decision variables.

3.2 Genetic Algorithm Procedure

The implementation of GA to find the best route follows some steps, there are:
Step-1: Initialization
In this step, the solution is represented in the form of chromosomes, called as encoding. In this case, the permutation is used in which each bit in chromosomes denoted by the number that represents a sequence. There are 39 bits chromosomes represent 39 destination points in waste collection.

Step-2: Selection
In this step, we select the parents based on the minimum fitness because the objective is to minimize total cost. Roulette wheel method is used to select the parents.

Step-3: Crossover
The selected parents will be crossed to get the new offspring. Partially Mapped Crossover (PMX) is used to crossover the parents.

Step-4: Mutation
Each offspring chromosome will be exchanged. The sweep mutation is used to exchange 2 random bit value. Mutation is done if the r lower than mutation rate. After mutation, evaluate fitness value. Then choose the lowest fitness value. Repeat step-1 to step-4 until the stopping criteria is reached.

4. Data Collection

4.1 General Data

This paper is based on primary and secondary data. The primary data consist of the vehicle used while the secondary data is the customers location and demand. The demand data are based on historical data provided by PT Tridi Oasis Group in average from January-March, 2022. Table 1 shows the attribute of each point that consist of latitude, longitude, and demand for each demand point.

Table 1. Location and Demand in Each Point

No.	Code	Latitude	Longitude	Demand (Kg)
0	D	-6,27661444	106,6036303	-
1	B01	-6,27568221	106,5973723	2,377
2	B02	-6,27721549	106,5963165	2,497
3	B03	-6,2724438	106,5987475	1,025
4	B04	-6,27077576	106,5996651	1,984
5	B05	-6,27145641	106,6017917	1,779
6	B06	-6,26658439	106,5961939	0,817
7	B07	-6,27152467	106,5991359	0,722
8	B08	-6,27613613	106,6039883	2,121
9	B09	-6,26205046	106,6070896	1,289
10	B10	-6,28319833	106,5939206	1,356
11	B11	-6,26613488	106,601817	0,685
12	B12	-6,28745366	106,591207	0,624
13	B13	-6,27353251	106,5981144	1,274

No.	Code	Latitude	Longitude	Demand (Kg)
14	B14	-6,27200752	106,5989489	1,240
15	B17	-6,27167006	106,601978	0,679
16	B18	-6,27226357	106,6028938	2,108
17	B19	-6,24284929	106,5836848	2,789
18	B20	-6,27199706	106,6025119	1,504
19	B22	-6,28766641	106,5938383	1,056
20	B23	-6,28781002	106,5937213	1,430
21	B24	-6,27819234	106,5821506	1,095
22	B25	-6,26351117	106,6162404	2,465
23	B26	-6,26334418	106,6171244	0,685
24	B27	-6,25782925	106,6208512	1,015
25	B29	-6,25710566	106,6169058	0,685
26	B30	-6,27276827	106,5985382	1,740
27	B31	-6,28937419	106,596444	2,315
28	B32	-6,27603788	106,598023	1,075
29	B33	-6,26293359	106,6172612	1,380
30	H01	-6,21139545	106,6104098	0,807
31	H02	-6,21125812	106,6104501	1,969
32	H03	-6,21159276	106,6104869	2,881
33	H04	-6,2111928	106,6105285	1,073
34	H05	-6,21109147	106,61021	1,743
35	H06	-6,21137811	106,6107357	1,191
36	H07	-6,21134878	106,6104755	1,608
37	H08	-6,21110214	106,6104675	1,317
38	H09	-6,21140611	106,6101134	0,907
39	H10	-6,21125146	106,6101564	1,301

In existing condition, waste collection uses a motorcycle with capacity of 8 Kg. In this research we assume that the velocity of the vehicle is constant, 30 Km/Hour. The transportation cost considers two component-fixed and variable cost. Fixed cost is the daily cost spent for driver wage while fuel cost is assumed as variable cost. The value of fuel cost depends on the total travel distance. Here is the detail of transportation cost component at Table 2:

Table 2. Transportation Cost Component

No.	Cost Component	Cost (IDR)
1.	Fixed Cost	125.000/vehicle/day
2.	Variable Cost	147,71/KM

4.2 Genetic Algorithm Parameter Setting

GA parameter testing needs to be done to determine the optimal GA parameter that can produce the best fitness. In GA, there are 4 parameters-population size, number of iterations, crossover rate, and mutation rate. Population size is one of the most important parameters in GA. To get the best fitness score, the population size must be set correctly. If the population size is too small, the search space is limited so the chances of getting the best solution are smaller. If the population size is too large, the search area is wider and the chances of getting the best solution are greater, but it will take a longer computational time. According to (Sarmady 2007), in solving the problem using the GA population size that can be used is equal to 1.5 – 2 times the number of bits or genes on the chromosome.

The crossover rate (Cr) and mutation rate (Mr) determine how many opportunities individuals in a population have for crossing over and mutation. If the crossover rate is low, then exploration for optimal solutions is limited and narrow. A high mutation rate value will cause a random search so that the search for a solution becomes more difficult. In this study, a combination of parameters was used based on previous research where the optimal crossover rate and mutation rate values were 0.9 and 0.05 and 0.75 and 0.1.

Each instance is run for 31 times to choose the best combination. Table 3 shows that based on the trial of parameter combined the best fitness is 402.903 which is instance 6. Therefore, the selected parameter combination is population size 100, Cr 0,75, Mr 0,1, and iteration 100.

Table 3. Parameter Setting

Instance	Population Size	Crossover rate	Mutation Rate	Iteration	Average Fitness
1	60	0,75	0,05	100	403.935
2	60	0,75	0,1	100	403.685
3	60	0,9	0,05	100	403.467
4	60	0,9	0,1	100	403.316
5	100	0,75	0,05	100	403.130
6	100	0,75	0,1	100	402.903
7	100	0,9	0,05	100	403.013
8	100	0,9	0,1	100	402.975

5. Results and Discussion

5.1 Numerical Result

We implement our proposed GA in LINGO and Python by using an Intel(R) core i3 6006U CPU and 4 GB of RAM under Microsoft Windows 10 Pro Operating System. This research was conducted using exact method and GA to compare the result in term of objective function and computation time. In this section, the existing condition, the problem solving with exact metod and the implemetation of GA will be explained.

5.1.1 Existing Condition

In existing conditions, there are no rules or regulations regarding which points should be visited first in the MLP collecting process. The determination of the MLP collecting route is determined by the driver. Determination of the route only based on the intuition of the driver with consideration of adjacent locations are within the same route. Table 4 shows the existing MLP collection routes.

Table 4. Existing Condition

<table>
<tr><th>Period</th><th>Routes</th><th>Cost (IDR)</th></tr>
<tr><td rowspan="3">Day 1</td><td>0-9-16-18-15-6-0</td><td rowspan="3">131.634,90</td></tr>
<tr><td>0-5-7-13-27-10-0</td></tr>
<tr><td>0-3-14-4-1-28-0</td></tr>
<tr><td rowspan="3">Day 2</td><td>0-12-21-20-19-2-11-0</td><td rowspan="3">134.993,67</td></tr>
<tr><td>0-8-17-23-29-24-0</td></tr>
<tr><td>0-25-22-26-0</td></tr>
<tr><td rowspan="2">Day 3</td><td>0-30-31-33-36-37-38-0</td><td rowspan="2">132.253,01</td></tr>
<tr><td>0-32-34-35-39-0</td></tr>
<tr><td colspan="2">Total</td><td>398.881,58</td></tr>
</table>

5.1.2 Optimization Using Exact Method

Route determination with exact method is done by using LINGO 18.0 software. Referring to previous research (Wildan & Setyanto Nasir, 2017), to solve linear programming problems using LINGO with 9 constraint functions and 15 index points requires computing time up to 55 hours. Therefore, taking this into account, in this study the exact method is used for data with small instance of 6 points, 10 points and 15 points. Table 5 illustrates the results of three different instances. The result obtained from data instance 6 points and 10 points are the global optimal solution. While the result from data instance 15 points is feasible solution which is solution could be better if the calculation time is longer.

Based on Table 5 shows that the small instances can visit all the demand points within single day. Instances 6 and 10 are found the optimum solution and the computation times are still within acceptable duration, but the result shows different manner when we add the demand point into 15, the result is feasible, has not yet reached the optimum value even though it has been running for 10 hours.

Table 5. Exact Solution

Instance	**Objective**	**Routes**	**Period**	**Computation Time**	**Solver Status**
6 points	127.495	0-4-2-1-6-5-3-0	1	1 second	Global Optimum
10 points	126.132	0-2-4-3-10-6-0	1	11 minutes 12 second	Global Optimum
		0-5-1-8-9-7-0			
15 points	127.320	0-5-15-4-7-14-13-0	1	10 hours	Feasible
		0-8-9-11-6-3-0			
		0-10-12-2-1-0			

5.1.3 Route Optimization Using Genetic Algorithm

To obtain the MLP collection route, GA is run with the setting parameters selected from the parameter test results. Routing using GA is done for 6-point, 10-point, 15-point, and 39-point data instances. The search for solutions in each data sample for MCVRPTW and MTCVRPTW problems was carried out as many as 31 replications to ensure that the fitness obtained was normally distributed and the resulting solutions were stable. Fitness value indicates the value of the destination function that is the total cost of transportation.

Table 6. Result of Genetic Algorithm

Instance	**Objective Function**	**Routes**	**Period**	**Computation Time (Second)**
6 points	127.495	0-6-5-4-2-1-3-0	1	4
10 points	127.924	0-3-4-1-6-9-0	1	9,3
		0-5-10-2-7-8-0		
15 points	127.718	0-1-12-10-2-0	1	14
		0-5-14-6-9-15-0		
		0-4-7-3-13-11-0		
39 points	277.710	0-4-30-24-21-20-0	1	44
		0-8-17-14-26-0		
		0-2-12-9-5-28-11-0		
		0-36-25-18-23-19-6-0		
		0-32-35-31-3-7-0	2	
		0-39-37-15-10-27-0		
		0-16-1-13-29-0		
		0-22-34-33-38-0		

5.2 Graphical Result

Figure 2 to Figure 5 show the convergence of genetic algorithm during 100 iteration. X-axis show the iteration number and the Y-axis show the fitness value of each iteration. A good genetic algorithm will produce a stable fitness value and convergent solution.

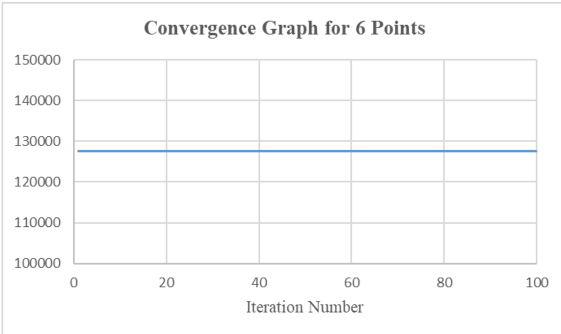

Figure 2. Covergence Graph for 6 Points

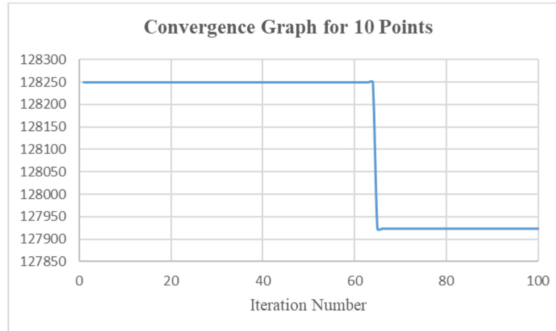

Figure 4. Convergence Graph for 10 Points

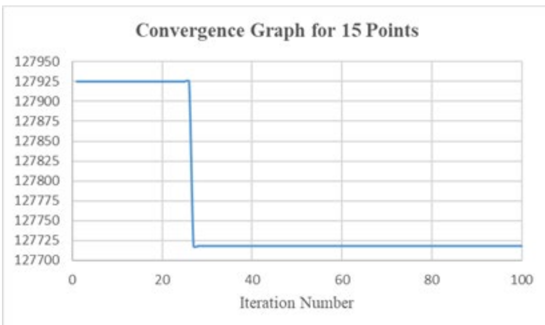

Figure 3. Convergence Graph for 15 Points

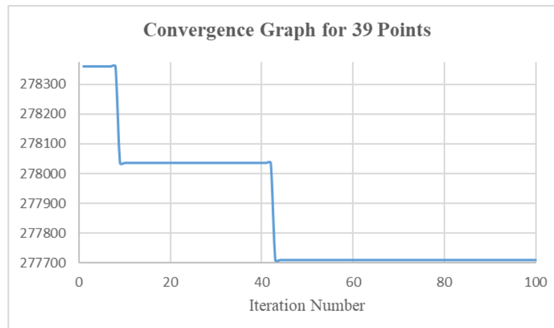

Figure 5. Convergence Graph for 39 Point

For 6 points intance data, the fitness value is stable during 100 iterations and the solution obtained is optimal from iteration-1. For 10, 15 and 39 points intance data, fitness value decreased and show a tendency to approach an increasingly optimal value during 100 iterations. In this research, the built genetic algiorthm is considered good because because it produces stable fitness value and convergent solutions.

5.3 Discussion

The tradeoff of GA is the result of GA does not guarantee to get the optimum result, but the computation time is faster than exact method. To understand how good the GA that has been developed, it is necessary to compare its results with the results from the exact method. The comparison is made in terms of objective function and computation time. Table 7 shows the comparison of the results between two methods.

Table 7. The Comparison between Exact and GA

Instance	Exact Method		GA		Delta	
	Objective Function	Computation Time	Objective Function	Computation Time	Objective Function	Computation Time
6 points	127.495	1 second	127.495	4 second	0%	-99%
10 points	126.510	11 minute 12 second	127.924	9,3 second	-1,4%	99%
15 points	127.270	10 hour	127.718	14 second	-0,03%	100%

Based on Table 7, the value of objective function there is small difference, but in term of computation time there is significant difference between exact method and GA. GA provides faster computation time. In numerical experiment with 6 points shows that there is no difference in term of fitness value, but the GA needs longer computation time than exact method, because of the procedure of GA to find the best solution is more complex and in this experiment GA

search for 100 iterations and 100 number of populations. But this condition is more efficient for larger instance such as 10 points and 15 points. The computation time for both 10 and 15 points using GA is faster than exact with acceptable objective function. GA is more suitable to solve large scale problem, because its capability to solve the problem in an efficient time and with the near optimum solution.
This paper contributes to solve the real world's problem. So, we compare the cost of transportation between existing condition and GA result. The existing condition needs IDR 398.881 to collect the waste while GA results IDR 277.710. Based on these results the company can save 30.3% in transportation cost without any additional investment cost. But the company needs two days to collect the waste from all the suppliers. This idea can be an alternative solution for the company if they have no concern about collecting time within two days and does not expecting any investment in the near future.

6. Conclusion

Finding the optimal route for collecting MLP on the MCVRPTW model using the exact method is considered inefficient in terms of computation time. Determining the route on an instance of 15 points takes up to 10 hours of computing time but has not yet obtained a global optimal. The application of the Genetic Algorithms (GA) method in finding the optimal route for collecting MLP on the MCVRPTW model has a computation time of 44 seconds. The best parameters selected for GA to obtain the optimal solution are 100 population, 100 iterations, 0.75 crossover rate, and 0.1 mutation rate. The optimal route based on GA has obtained 8 routes where 4 routes are served in period 1, 3 routes are served in period 2, and 1 route is served in period 3 with an objective function of IDR 277.710. The optimal solution generates savings of 30.3% compared to the existing conditions. This research has limitations so there are some suggestions for future research. The first suggestion is to consider other cost components in the formula of total transportation costs that have not been considered in this research. The second suggestion is might be considered for adding a new objective function such as minimizing the cost of carbon emissions.

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