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Optimization of Palm Oil Distribution Routes Based on Saving Matrix and Genetic Algorithm

Evi Yuliza*, Yuli Andriani, Indrawati, Sisca Octarina, and Diah Putri Ramadani

Department of Mathematics, Universitas Sriwijaya, Indonesia

Abstract

The transportation of goods and services is a strategic issue in logistics systems, particularly in the palm oil industry. One of the main challenges of distribution optimization is the Split Delivery Vehicle Routing Problem (SDVRP), which involves determining the optimal distribution route considering vehicle capacity constraints. This study aims to identify the shortest distribution route for the transportation of fresh oil palm fruit bunches from collection points to palm oil mills, with the objective of minimizing the total vehicle mileage. A heuristic approach using the Saving Matrix method and a metaheuristic approach using Genetic Algorithm are applied separately to two regions: Block P and Block Q, each consisting of 14 collection points with a daily distribution schedule. The performance of both approaches is analyzed and compared in the context of region-based distribution.The results show that the total distance traveled against the Saving Matrix produces a more optimal solution than the Genetic Algorithm, resulting in 3845.2 km in Block P and 4093 km in Block Q. In comparison, the total distance traveled against the Genetic Algorithm reaches 4146 km in Block P and 4247.2 km in Block Q. These findings show that the Saving Matrix performs better than the Genetic Algorithm in completing the SDVRP distribution of fresh oil palm fruit bunches considering vehicle capacity and can be used as a basis for developing a more efficient distribution system using heuristic and metaheuristic approaches.

Keywords: capacitated vehicle; routing problem; distance; genetic algorithm; saving matrix

1 Introduction

Effective transportation and distribution management is crucial for companies to ensure the timely delivery of products to consumers. The process of distributing goods from the point of origin to various destinations is a complex challenge, particularly when distribution routes are not optimally planned. Inefficient distribution planning can lead to increased shipping costs, wasted time, and reduced service quality. In the context of agricultural product distribution, such as fresh oil palm fruit bunches (FFBs), determining efficient transportation routes is especially important. Deliveries of FFBs to processing mills must be completed within a short time frame to maintain product quality. This challenge is further complicated by the fact that many plantations do not have their own processing mills, leading to delays in the transportation process. FFBs are typically transported using dump trucks with a maximum capacity of 10 ton. The transportation area in this study consists of two regions, Block P and Block Q, each with 14 collection points.

*Corresponding author. E-mail: eviyuliza@mipa.unsri.ac.id

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Production at each collection point is assumed to be deterministic and occurs from Monday through Saturday. This study does not consider dynamic factors such as changes in production volume, road conditions, traffic, driver availability, vehicle types, service hours, or time windows. Nevertheless, the transportation of goods remains a critical and widely discussed issue in modern logistics. Efficient transportation and distribution systems are essential for ensuring product availability and customer satisfaction [1].

One of the most extensively studied topics in transportation and distribution management is the Vehicle Routing Problem (VRP). VRP is a combinatorial optimization model used to determine optimal vehicle routes from a central depot to a number of customers, subject to various constraints such as vehicle capacity [2], [3], [4]. The distribution of palm oil is a practical example of VRP implementation, involving multiple collection and delivery points. Route optimization in VRP plays a vital role in reducing logistics costs and maintaining product quality upon delivery. Due to its relevance in real-world logistics applications, VRP has attracted considerable attention from both researchers and practitioners. However, VRP is a complex computational problem that is difficult to solve optimally within a reasonable computation time [5], [6]. Consequently, numerous heuristic and metaheuristic approaches have been developed to efficiently solve VRP. These approaches aim to optimize a set of routes, all starting and ending at a central depot, while ensuring that all customer demands are met [7], [8], [9].

One specific type of VRP is the Split Delivery Vehicle Routing Problem (SDVRP), which considers vehicle capacity limitations [10], [11], [12]. SDVRP involves determining the optimal delivery routes from a central depot to multiple customers using vehicles with fixed capacities and customers can be served by multiple vehicle [8], [13], [14], [15]. It is a fundamental extension of the VRP and has various real-world applications, including smart logistics, pharmaceutical distribution, and disaster management [16]. The main objective of CVRP is to minimize the total distance traveled by vehicles while serving all customers within their capacity constraints.

The complexity of distributing products from a source to multiple destinations often results in high transportation costs. Poorly designed distribution systems can further increase these costs and lower customer satisfaction, ultimately eroding trust in the service provider. To address these issues, various heuristic methods have been applied to solve CVRP, including the Saving Matrix, Nearest Neighbor, and Sequential Insertion methods. These heuristics are known for their simplicity and ability to combine customers into efficient routes while considering vehicle capacity. Among them, the Saving Matrix is known for its computational speed but tends to yield more local (less optimal) solutions.

Fitriani [17] demonstrated that CVRP can be solved using the Saving Matrix, Nearest Neighbor, and Sequential Insertion methods. While the Saving Matrix is fast, it often produces less optimal solutions than the other two. Yuliza [18] applied the Saving Matrix as an initial solution, followed by optimization using the Nearest Neighbor method for waste transportation routing. The Nearest Neighbor approach selects the closest customer at each step, resulting in fast computation but also more localized solutions.

To enhance the performance of the Saving Matrix method, metaheuristic approaches such as the Genetic Algorithm (GA) can be employed for solving CVRP [19]. GA is a population-based global search technique inspired by the process of biological evolution, utilizing operations such as selection, crossover, and mutation [20], [21]. GA can explore the solution space more thoroughly, offering better optimization and reducing computation time compared to traditional heuristic methods. In the case of oil palm FFB distribution, the Saving Matrix can help reduce costs by grouping multiple collection points, while the GA can identify more optimal routes through a broader exploration of potential solutions. The purpose of this study is to solve the SDVRP for fresh oil palm fruit bunch distribution using both the Saving Matrix and GA approaches in order to minimize total travel distance. Additionally, the study aims to compare the total distances generated by each algorithm independently, to determine which method yields the most efficient routing solution.

2 Methods

The purpose of this study is to solve the SDVRP on the distribution route of fresh oil palm fruit bunches with the Saving Matrix and GA. Section 2.1 describes the mathematical model of SDVRP with its variables and parameters. Section 2.2 describes the saving matrix on the distribution of oil palm fruit bunches and section 2.3 describes GA on the distribution of oil palm fruit bunches. The overall steps of this research are illustrated in Fig. 1.

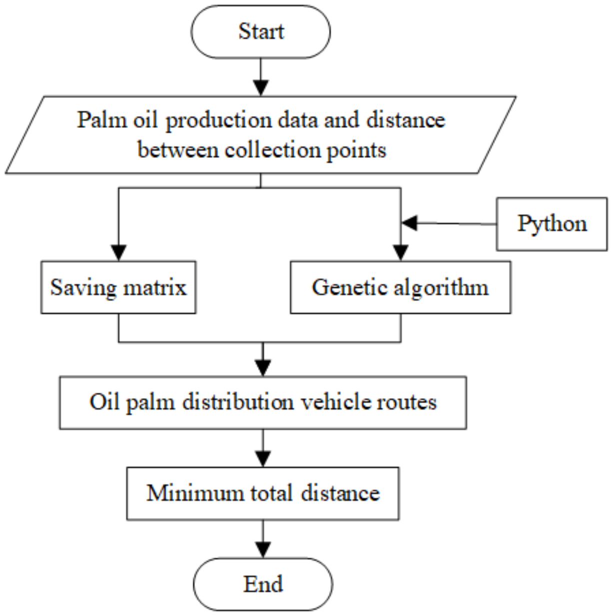

Figure 1: Research flow

2.1 Split Delivery Vehicle Routing Problem

SDVRP can be formally described as problem involving a set of nodes and a fleet of vehicles. It is modeled as a complete directed graph, where $G = (V, E)$ consists of a set of nodes $V = \{0, 1, 2, 3, \ldots, n\}$ as the set of vertices and a set of arcs $E = \{(i, j) \mid i, j \in V,\ i \neq j\}$. In this context, node 0 represents a palm oil mill (factory), and the remaining nodes represent the collection points. The SDVRP, as implemented in the FFB distribution problem, has the following characteristics:

1) Each collection point is served by only one dump truck.
2) Each route begins and ends at the palm oil mill, and each collection point is visited only once.
3) The total amount of FFB collected on each route must not exceed the vehicle's maximum capacity, thereby forming feasible sub-routes.

The following are all the variables and parameters used in this study. Variables:
y_{ij} : equals 1 if the vehicle travels from collection node i to j and equals 0 otherwise.
v_i : the continuous non-negative auxiliary variable used to eliminate tours passing through the collection node i.
v_j : the continuous non-negative auxiliary variable used to eliminate tours passing through the collection node j.

Parameter:

i, j	:	index of collection node, where $i, j \in V$
q_i	:	average production at each collection node i
Q	:	vehicle capacity
d_{ij}	:	distance between collection nodes i and j
N	:	maximum number of visits to a collection node

Mathematically, the SDVRP model is as follows :

$$\min \sum_{i\in V}\sum_{j\in V} d_{ij}\, y_{ij} \tag{1}$$

subject to

$$\sum_{i\in V} y_{ij} = 0, \quad j \in V \setminus \{0\} \tag{2}$$

$$\sum_{j\in V} y_{ij} = \sum_{i\in V} y_{ji}, \quad i, j \in V \setminus \{0\} \tag{3}$$

$$\sum_{j\in V}\sum_{i\in V} y_{ij} \le N \tag{4}$$

$$v_i - v_j \le Q(1 - y_{ij}) - q_j, \quad \forall\, i, j \in V,\, i \ne j \tag{5}$$

$$q_i \le v_i \le Q, \quad \forall\, i \in V \tag{6}$$

$$y_{ij} \in \{0, 1\}, \quad i, j \in V \tag{7}$$

Objective function (1) aims to minimize the total distance traveled by the vehicles. Constraints (2) ensures that the vehicle starts from its factory and terminates its route at the same factory. Constraints (3) ensures that each vehicle starts from the depot and ends its route at the depot. Constraint (4) ensures that each collection node can receive up to V vehicle visits to fulfill palm oil production. Constraint (5) ensures that the number of vehicles departing from the palm oil mill is equal to the number returning to it. Constraint (6) represents the capacity constraint, ensuring that the total amount of palm oil collected on each route does not exceed the vehicle's capacity. Constraint (7) enforces the integer condition. SDVRP on FFB distribution of oil palm fresh fruit bunches is only for reference and FFB distribution of oil palm fresh fruit bunches is solved using heuristic and metaheristic approaches. SDVRP is presented for reference purposes and is not used to solve this case. The proposed heuristic and metaheuristic approaches ensure actual solutions through their constructive mechanisms.

2.2 Saving Matrix

The Saving Matrix addresses the transportation problem by minimizing the total distance of palm oil distribution routes. It does so by merging several delivery routes, taking into account the capacity limitations of the vehicles used. The Saving Matrix is a heuristic approach designed to determine optimal distribution routes, aiming to deliver products on time while minimizing travel distances and transportation costs, all within the constraints of the problem [17], [18], [22], [23]. The following is the Saving Matrix procedure used to solve the SDVRP in the context of palm oil distribution:

The steps for saving the matrix are as follows:

1. Identify the distance matrix.
2. Calculate the saving matrix using the formula

$$s_{ij} = d_{fi} + d_{fy} - d_{ij} \tag{8}$$

where :

s_{ij} : the savings distance between collection node i to collection node j

d_{fi} : the distance between node 0 (factory) to collection node i

d_{fj} : the distance between node 0 (factory) to collection node j

3. Allocate fresh fruit bunches to a route by ordering them from the highest to the lowest savings value.
4. Combine routes, taking into account vehicle capacity.
5. Sort the collection points into predefined route and selecting the route with the minimum distance.

The steps of the Saving Matrix procedure are illustrated in Fig. 2. The corresponding pseudocode is provided in Algorithm 1.

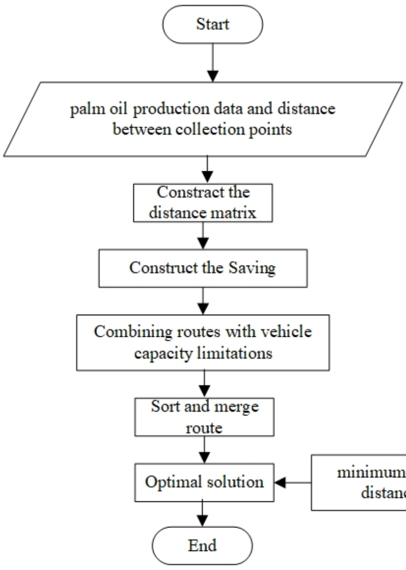

Figure 2: Flowchart of Saving Matrix

Algorithm 1 Saving Matrix

```
Start
Calculate savings s_ij
Sort the values of s_ij from largest to smallest
Form an initial route based on the highest savings
while not all customers are served do
    Parental selection
    Combine routes as long as vehicle capacity is not exceeded
end while
if optimum is achieved then
    Display final solution
end if
Stop
```

2.3 Genetic Algorithm

The Genetic Algorithm (GA) is an approach used to search for optimal solutions to complex optimization problems [24], [25], [26]. GA explore various possible vehicle routes simultaneously, and through the processes of selection, crossover, and mutation, they are capable of identifying the most efficient route combinations.

The process begins by initializing a number of individuals, referred to as a population. Each individual is a collection of genes, known as a chromosome, which represents a potential solution with an associated fitness value. The population is generated randomly using the following formula:

$$pop = random(n_k, N) \tag{9}$$

where *pop* represents the population, n_k represents the number of genes on one chromosome and N represents the number of chromosomes in one population.

Fitness is a measure of an individual's performance in terms of survival, used to assess the suitability of a chromosome for retention or elimination. Individuals with higher fitness values are more likely to survive and be selected for reproduction, while those with lower fitness are more likely to be discarded.A chromosome represents a set of routes R, which indicate the sequence of fresh oil palm fruit bunch collection points served by a vehicle. The fitness value of a chromosome and the penalty for infeasible chromosomes can be calculated based on the following criteria.

$$fitness\ value = \frac{1}{D_{total}(R)} \tag{10}$$

where $D_{total}(R)$ represents the total distance of each chromosome. The GA workflow is shown in Fig. 3.

Selection is the process of choosing individuals for crossover and mutation. Individuals with higher fitness values are more likely to be selected, resulting in higher-quality offspring. In this study, the selection method is based on random number generation. A chromosome may be selected more than once. The selected chromosomes form the parental population according to their fitness values. The steps involved in the random number selection process are as follows:

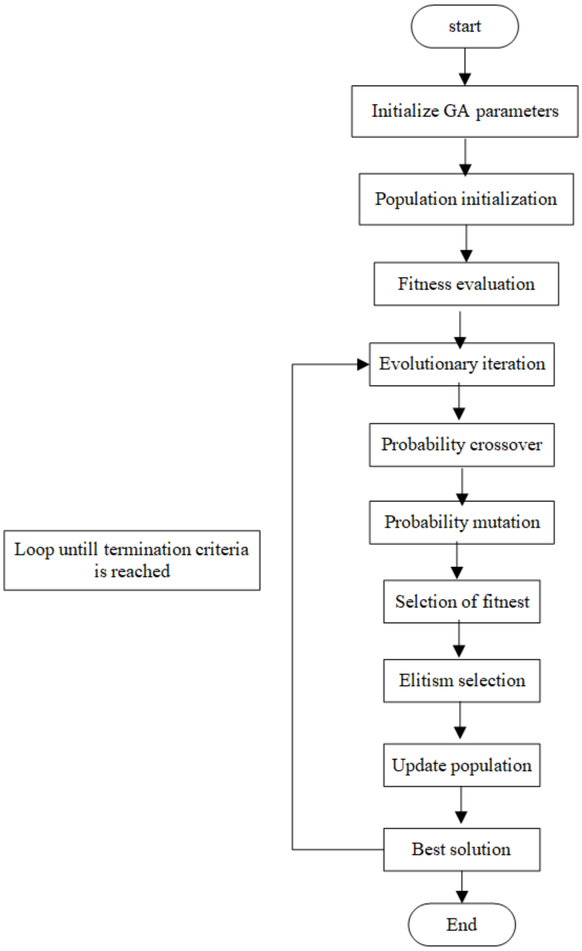

Figure 3: Flowchart of Genetic Algorithm

- Calculate the relative fitness values (p_k) of each chromosome using the following formula:

$$p_k = \frac{\text{fitness value}(i)}{\text{total fitness value}} \tag{11}$$

- Calculate the cumulative fitness value (q_k) from all individuals or chromosomes using the formula:

$$q_k = q_{k-1} + p_k \tag{12}$$

- Generate random numbers in [0,1] according to the population size of a problem to be solved. The k th chromosome will be selected as a surviving chromosome based on the following rules:

$$q_{k-1} \leq r_k \leq q_k \tag{13}$$

- Elitism copies the best chromosome (or a few best chromosomes) to a new population so that it can quickly improve the performance of Genetics, because it prevents the loss of the best solutions found.

Crossover is a GA operator that generates new offspring by combining two parent chromosomes. Not all chromosomes in the population undergo crossover; only those selected based on a predetermined crossover probability participate in the process. This study uses an ordered crossover technique, which begins by generating two random numbers. The genes located between these two positions (sub strings) are copied directly to the offspring in the same positions from each parent chromosome.

Next, to obtain the first offspring, the genes located after the second random number in the parent chromosome are sorted, followed by the genes located between the two random numbers, and then the genes before the first random number. This sorted sequence is compared with the first offspring, and any gene already present in the offspring is omitted. The resulting sequence is then inserted into the offspring at the positions before the first random number.

Mutation acts as an operator to recover potentially lost optimal solutions due to crossover and helps prevent the algorithm from getting trapped in local optimal. The purpose of mutation is to generate new chromosomes with improved fitness values by modifying one or more genes of selected parents. Multiple chromosomes undergo mutation based on a predetermined mutation probability. The mutation technique used in this study is insertion mutation, which begins by selecting two random positions; the gene at the first position is then inserted into the second position. The Genetic Algorithm for determining palm oil distribution routes is implemented using Python. The pseudo code of the proposed Genetic Algorithm is given in Algorithm 2.

Algorithm 2 Genetic Algorithm

```
Start
Parameter initialization
Evaluate each individual's fitness
while maximum generation not reached do
    Parental selection
    Crossover
    Mutation
    Evaluate the new population
end while
if optimum is achieved then
    Display final solution
end if
Stop
```

3 Results and Discussion

The oil palm harvest collection area is divided into two blocks, each consisting of 14 collection points. The first block, Block P, includes collection points such as P1 (variable P1), P2, P3, ...P14. This can be represented as Blok P = {P1, P2, P3, ..., P14}. The second block, Block Q, consists of collection points Q1, Q2, Q3, ...Q14, or Blok Q = {Q1, Q2, Q3, ..., Q14}. The palm oil mill is denoted by F. The transportation of fresh oil palm fruit bunches occurs from Monday to Saturday.

The production data for fresh oil palm fruit bunches represent the daily yields at each collection point within each block. The average daily production for Block P and Block Q is presented in Table 1 and Table 2, respectively.

Remaining load data for Monday in Block P and for Monday in Block Q, which shows the number of trips that must be made taking into account vehicle capacity and remaining load or load that cannot be carried. Table 3 and Table 4 are obtained from the average daily palm oil production data for Block P and Block Q on Monday.

Table 1: Average daily production of fresh oil palm fruit bunches in Block P

Area	Average Production per Day (ton)					
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
P1	32.79	39.10	119.17	138.21	119.85	82.66
P2	87.61	69.65	146.48	149.10	223.10	98.31
P3	99.34	39.88	41.87	129.68	144.01	221.90
P4	75.53	35.88	23.00	28.13	55.79	119.46
P5	80.34	67.11	16.52	12.06	41.86	80.74
P6	100.81	141.73	73.89	28.63	47.27	72.11
P7	69.88	133.05	115.80	93.33	22.35	33.44
P8	70.45	80.05	69.58	104.06	43.04	37.37
P9	30.28	23.44	53.82	54.86	76.32	31.11
P10	15.28	16.87	42.59	33.96	40.67	21.53
P11	11.3	19.30	34.21	20.44	51.02	19.16
P12	15.29	20.95	37.20	22.50	54.54	15.95
P13	39.11	32.77	49.64	31.29	65.21	17.05
P14	12	7.47	6.32	9.22	7.61	9.27
Total	740.01	727.25	830.09	855.47	992.64	860.06

Table 2: Average daily production of fresh oil palm fruit bunches in Block Q

Area	Average Production per Day (ton)					
	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday
Q1	67.20	119.16	78.98	102.93	101.53	56.13
Q2	107.11	204.65	118.17	168.03	96.59	62.26
Q3	91.37	197.36	147.74	103.16	57.10	145.05
Q4	112.83	100.53	132.13	117.27	115.31	169.41
Q5	53.82	93.33	121.40	109.68	182.33	154.95
Q6	46.21	137.53	116.86	156.41	100.41	31.90
Q7	83.13	162.43	109.08	128.01	22.62	43.58
Q8	207.56	112.11	88.24	83.38	32.05	69.04
Q9	142.57	71.31	61.89	45.90	96.53	121.48
Q10	76.10	54.61	44.20	73.09	106.46	151.70
Q11	38.14	49.08	47.76	94.35	83.91	128.24
Q12	34.08	37.21	76.01	121.34	84.81	49.70
Q13	5.08	60.94	41.81	83.86	68.48	72.79
Q14	6.75	13.26	3.86	11.30	6.01	12.50
Total	1071.95	1413.51	1109.15	1398.71	1154.14	1268.73

Table 3: Remaining load of Block P on Monday

Area	Fresh Fruit Bunch Production (ton)	Number of Trips	Remaining Cargo (ton)
P1	32.79	3	2.79
P2	87.61	8	7.61
P3	99.34	9	9.34
P4	75.53	7	5.53
P5	80.34	8	0.34
P6	100.81	10	0.81
P7	69.88	6	9.88
P8	70.45	7	0.45
P9	30.28	3	0.28
P10	15.28	1	5.28
P11	11.30	1	1.30
P12	15.29	1	5.29
P13	39.11	3	9.11
P14	12.00	1	2.00

Table 4: Remaining load of Block Q on Monday

Area	Fresh Fruit Bunch Production (ton)	Number of Trips	Remaining Cargo (ton)
Q1	67.20	6	7.20
Q2	107.11	10	7.11
Q3	91.37	9	1.37
Q4	112.83	11	2.83
Q5	53.82	5	3.82
Q6	46.21	4	6.21
Q7	83.13	8	3.13
Q8	207.56	20	7.56
Q9	142.57	14	2.57
Q10	76.10	7	6.10
Q11	38.14	3	8.14
Q12	34.08	3	4.08
Q13	5.08	-	5.08
Q14	6.75	-	6.75

Several trips were made and there was remaining cargo or cargo that could not be transported. The number of trips is determined based on palm oil production. It is assumed that the palm oil distribution route is determined by the residual load so that the palm oil harvesting place is only visited once without any residual load. Data on the distances between the palm oil mill and each collection point, as well as between the collection points themselves, were obtained from Google Maps. Table 5 and Table 6 present the distances for block P and block Q, respectively, in kilometers.

The initial delivery routes for fresh oil palm fruit bunches in blocks P and Q each consisted of 14 routes. The total initial distances for Blocks P and Q were 1045.8 km and 1053.6 km, respectively.

Table 5: Distance matrix for Block P

	F	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
F	0	38.8	38.5	38.2	37.5	37.2	37.1	37	35.9	36.7	36.8	36.9	37.2	37.5	37.6
P1	38.8	0	0.9	2	2.5	3.1	3.7	4.5	5.2	5.6	6	6.3	6.5	6.8	7.1
P2	38.5	0.9	0	1	1.6	2.4	2.7	3.5	4.2	4.7	5.1	5.3	5.5	5.8	6.1
P3	38.2	2	1	0	0.6	1.4	1.7	2.5	3.2	3.7	4.1	4.3	4.5	4.8	5.1
P4	37.5	2.5	1.6	0.6	0	0.5	1.2	2	2.7	3.2	3.5	3.8	4	4.3	4.6
P5	37.2	3.1	2.4	1.4	0.5	0	0.7	1.5	2.1	2.6	3	3.2	3.5	3.8	4.1
P6	37.1	3.7	2.7	1.7	1.2	0.7	0	0.8	1.4	1.9	2.3	2.5	2.8	3.1	3.4
P7	37	4.5	3.5	2.5	2	1.5	0.8	0	0.7	1.2	1.5	1.8	2	2.3	2.6
P8	35.9	5.2	4.2	3.2	2.7	2.1	1.4	0.7	0	0.5	0.9	1.1	1.3	1.6	1.9
P9	36.7	5.6	4.7	3.7	3.2	2.6	1.9	1.2	0.5	0	0.4	0.6	0.9	1.1	1.4
P10	36.8	6	5.1	4.1	3.5	3	2.3	1.5	0.9	0.4	0	0.2	0.5	0.8	1.1
P11	36.9	6.3	5.3	4.3	3.8	3.2	2.5	1.8	1.1	0.6	0.2	0	0.2	0.5	0.8
P12	37.2	6.5	5.5	4.5	4	3.5	2.8	2	1.3	0.9	0.5	0.2	0	0.3	0.6
P13	37.5	6.8	5.8	4.8	4.3	3.8	3.1	2.3	1.6	1.1	0.8	0.5	0.3	0	0.3
P14	37.6	7.1	6.1	5.1	4.6	4.1	3.4	2.6	1.9	1.4	1.1	0.8	0.6	0.3	0

Table 6: Distance matrix for Block Q

	F	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14
F	0	38.6	38.4	38.2	38	37.7	37.4	37.1	36.8	37	37.2	37.4	37.6	37.8	37.6
Q1	38.6	0	0.9	2	3	4	5	5.9	6.7	7.6	8.3	9	9.7	10.3	10.6
Q2	38.4	0.9	0	1	2.1	3.1	4.1	5	5.8	6.7	7.5	8.2	8.8	9.4	9.7
Q3	38.2	2	1	0	1.1	2.1	3	3.9	4.8	5.6	6.4	7.1	7.8	8.4	8.7
Q4	38	3	2.1	1.1	0	1	2	3	3.8	4.6	5.4	6.1	6.7	7.3	7.6
Q5	37.7	4	3.1	2.1	1	0	1	1.9	2.7	3.5	4.4	5.1	5.7	6.3	6.7
Q6	37.4	5	4.1	3	2	1	0	0.9	1.8	2.6	3.4	4.1	4.7	5.3	5.7
Q7	37.1	5.9	5	3.9	3	1.9	0.9	0	0.8	1.7	2.5	3.2	3.8	4.4	4.7
Q8	36.8	6.7	5.8	4.8	3.8	2.7	1.8	0.8	0	0.8	1.6	2.3	3	3.5	3.9
Q9	37	7.6	6.7	5.6	4.6	3.5	2.6	1.7	0.8	0	0.8	1.5	2.1	2.7	3.1
Q10	37.2	8.3	7.5	6.4	5.4	4.4	3.4	2.5	1.6	0.8	0	0.7	1.4	2	2.3
Q11	37.4	9	8.2	7.1	6.1	5.1	4.1	3.2	2.3	1.5	0.7	0	0.6	1.2	1.6
Q12	37.6	9.7	8.8	7.8	6.7	5.7	4.7	3.8	3	2.1	1.4	0.6	0	0.6	0.9
Q13	37.8	10.3	9.4	8.4	7.3	6.3	5.3	4.4	3.5	2.7	2	1.2	0.6	0	0.3
Q14	37.6	10.6	9.7	8.7	7.6	6.7	5.7	4.7	3.9	3.1	2.3	1.6	0.9	0.3	0

3.1 Vehicle Route Determination Using the Savings Matrix

The Savings Matrix calculations for each route, obtained using formula Eq. 8, are presented in Table 7, in kilometers.

Table 7: Saving matrix for Block P

	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P11	P12	P13	P14
P1	0													
P2	76.4	0												
P3	75	75.7	0											
P4	73.8	74.4	75.1	0										
P5	72.9	73.3	74	74.2	0									
P6	72.2	72.9	73.6	73.4	73.6	0								
P7	71.3	72	72.7	72.5	72.7	73.3	0							
P8	69.5	70.2	70.9	70.7	71	71.6	72.2	0						
P9	69.9	70.5	71.2	71	71.3	71.9	72.5	72.1	0					
P10	69.6	70.2	70.9	70.8	71	71.6	72.3	71.8	73.1	0				
P11	69.4	70.1	70.8	70.6	70.9	71.5	72.1	71.7	73	73.5	0			
P12	69.5	70.2	70.9	70.7	70.9	71.5	72.2	71.8	73	73.5	73.9	0		
P13	69.5	70.2	70.9	70.7	70.9	71.5	72.2	71.8	73.1	73.5	73.9	74.4	0	
P14	69.3	70	70.7	70.5	70.7	71.3	72	71.6	72.9	73.3	73.7	74.2	74.8	0

The routes are sorted by ordering the savings values from the largest to the smallest. Based on Table 7 the largest savings value occurred in the P1-P2 route which was 76.4 km and the smallest savings value occurred in the P1-P14 route which was 69.3 km. Based on Table 3, the remaining load table on Monday is used to combine routes from the highest savings value to the lowest savings value. If the remaining load does not exceed the vehicle capacity, the routes proceed to the next highest savings value and can be combined into one route.

The combined route ranking for Monday in Block P is then adjusted by considering vehicle capacity, as shown in Table 8.

Table 8: Vehicle routes on Monday in Block P based on the Saving Matrix

	Route	Destination (km)	Combined Load (ton)
Route 1	F-P11-P12-P14-F	75.3	8.59
Route 2	F-P1-P4-P5-P6-F	79.6	9.47
Route 3	F-P8-P9-P10-F	73.6	6.01
Route 4	F-P2-F	77	7.61
Route 5	F-P3-F	76.4	9.34
Route 6	F-P7-F	74	9.88
Route 7	F-P13-F	75	9.11

Furthermore, the arrangement of collection points along a predetermined route aims to minimize the total vehicle distance traveled. Organizing the sequence of visits within a route helps determine the first, intermediate, and final stops, taking into account the shortest possible distance. The same data processing is performed for Tuesday through Saturday. Total distance traveled, number of routes and average remaining load in blocks P and Q against the saving matrix per day as in Table 9 and Table 10.

Table 9: Savings matrix results in Block P for each day

Days	Mileage (km)	Numbe of Routes	Average Remaining Load (ton)
Monday	530.9	7	8.57
Tuesday	680	9	8.58
Wednesday	749.1	10	8.01
Thursday	679.1	9	8.39
Friday	529.5	7	8.95
Saturday	676.6	9	7.78
Total	3845.2		50.26

Table 10: Savings matrix results in Block Q for each day

Days	Mileage (km)	Number of Routes	Average Remaining Load (ton)
Monday	681.5	9	7.99
Tuesday	610.4	8	7.94
Wednesday	755.9	10	7.81
Thursday	682	9	7.63
Friday	681.2	9	7.12
Saturday	682	9	7.62
Total	4093		50.26

3.2 Vehicle Route Determination Using the Genetic Algorithm

The distribution routes for palm oil harvest collection points were determined using GA implemented with Python. The Genetic Algorithm formulation incorporates data on the distances between the palm oil mill and each collection point, as well as distances between the collection points themselves. The parameters used in this study are as in Table 11. The stability results of the average distance and average time on Block P and Block Q using GA are as in Table 12.

Table 11: Parameters in Genetic Algorithm

Notation	Parameter	Value
Q	Vehicle Capacity	10
N_p	Population Size	93.68
P_c	Crossover Probability	0.8
P_m	Mutation Probability	0.01
$MaxIter$	Maximum Iterations	100
e	Elitism Rate	2
n_{trial}	Number of Independent Trials	30

Table 12: Comparison of distance and time stability in Block P and Block Q on Monday

	Block P	Block Q
Average Distance	530.52	535.63
Standard Deviation of Distance	0.49	0.47
Best	529.6	535
Worst	532.2	537.4
Average Time	0.059	0.051
Standard Deviation of Time	0.014	0.004

The average distance, standard deviation, best/worst, and average time are used to assess the stability and permissibility of the GA. A small standard deviation means the results do not spread far from the average distance, so the GA is stable (results are consistent). Summary of convergence to the average total distance traveled and average processing time of the Savings Matrix and GA on Monday as in Table 13

Table 13: Summary of convergence between Genetic Algorithm and Saving Matrix on Monday

	Block P		Block Q	
	Saving Matrix	GA	Saving Matrix	GA
Average Distance (km)	530.6	530.5	535.4	535.64
Average Time (s)	0.000989	0.000977	0.059154	0.050621

The results of the combined routes for Monday in Block P, based on the GA, are presented in Table 14.

Table 14: Vehicle routes on Monday in Block P based on Genetic Algorithm

	Route	Destination (km)	Combined Load (ton)
Route 1	F-P5-P4-P1-F	79	8.66
Route 2	F-P2-F	77	7.61
Route 3	F-P3-F	76.4	9.34
Route 4	F-P6-F	74.2	0.81
Route 5	F-P7-F	74	9.88
Route 6	F-P9-P10-F	73.9	5.56
Route 7	F-P13-F	75	9.11
Route 8	F-P14-P12-P11-P8-F	75.4	9.04

Table 15: Daily performance results of the Genetic Algorithm for Block P

Days	Mileage (km)	Number of Routes	Average Remaining Load (ton)
Monday	604.9	8	7.5
Tuesday	680.6	9	8.58
Wednesday	749.5	10	8.01
Thursday	754.2	8	7.55
Friday	603.9	8	7.82
Saturday	752.9	10	7.78
Total	4146		46.47

Distance traveled, number of routes and average remaining load in Blocks P and Q against GA every day as in Table 15 and Table 16.

Table 16: Daily performance results of the Genetic Algorithm for Block Q

Days	Mileage (km)	Number of Routes	Average Remaining Load (ton)
Monday	756.9	10	7.2
Tuesday	685.2	9	7.05
Wednesday	755.9	10	7.81
Thursday	684.5	9	7.53
Friday	682.2	9	7.13
Saturday	682.9	9	7.64
Total	4247.2		44.36

Comparison of initial travel distance and travel distance per block with Saving Matrix and GA as in Table 17.

Table 17: Comparison of the initial and mileage for each block

	Initial Mileage		Mileage on Block P		Mileage on Block Q	
Days	Block P	Block Q	Saving Matrix	GA	Saving Matrix	GA
Monday	1045.8	1053.6	530.6	604.9	681.5	752.9
Tuesday	1045.8	1053.6	680.0	680.6	610.4	685.2
Wednesday	1045.8	1053.6	749.1	749.5	755.9	755.9
Thursday	1045.8	1053.6	679.1	745.2	682.0	684.5
Friday	1045.8	1053.6	529.5	603.9	681.2	682.2
Saturday	1045.8	1053.6	676.6	752.9	682.0	682.5
Total			3845.2	4146	4093	4247.2

Table 18: Comparison of mileage efficiency percentage per block

	Mileage Efficiency Percentage on Block P (%)		Mileage Efficiency Percentage on Block Q (%)	
Days	Saving Matrix	GA	Saving Matrix	GA
Monday	49.23	42.16	35.32	28.16
Tuesday	34.97	34.92	42.06	34.96
Wednesday	28.37	28.33	28.25	28.25
Thursday	35.06	27.88	35.27	35.03
Friday	49.37	42.25	35.34	35.25
Saturday	35.30	28.00	35.27	35.22
Total	38.72	33.92	35.25	32.81

Comparison of the percentage of efficiency of distance traveled per block with Savings Matrix and GA as in Table 18. Based on the calculation results, it shows that the total distance traveled against the saving matrix produces a more optimal solution than GA, resulting in 3845.2 km in Block P and 4093 km in Block Q. In comparison, the total distance traveled against GA reached 4146 km in Block P and 4247.2 km in Block Q. In addition, the percentage of total distance traveled using the Saving Matrix in Blocks P and Q is better than that achieved using GA. The total percentage of distance savings with the Saving Matrix is 38.72% for Block P and 35.25% for Block Q, compared to using GA which is 33.92% for Block P and 32.81% for Block Q. The largest percentage of distance savings with the Savings Matrix and GA occurred in Block P and Block. These results indicate that the Saving Matrix produces a more optimal solution to minimize the total distance traveled by vehicles in the distribution of fresh oil palm fruit bunches compared to GA.

In completing the SDVRP distribution of oil palm fruit bunches, Saving Matrix relies solely on savings value at each collection point, limited by vehicle capacity. The Savings Matrix is practical because this enables cost savings by combining multiple collection points and producing optimal solutions with respect to vehicle capacity and faster computing times. In contrast, GA includes such parameters such as population size, maximum iterations, crossovers, and mutations, which allow it to explore a wider range of solutions and generally provide better results. GA tends to have longer computing times than the Savings Matrix. Furthermore, a simple hybrid can be carried out, namely using the Savings Matrix results as an initial solution for GA as an improvement. In addition, sensitivity analysis can be carried out to test how much influence changes in GA parameters have on the results so that the results (for example: travel distance or computing time) change in significance.

4 Conclusion

The solution of the SDVRP in palm oil distribution using a metaheuristic approach, namely the Genetic Algorithm, and a heuristic approach, namely the Saving Matrix, produces optimal vehicle routes. This study shows that the Saving Matrix performs better in solving SDVRP on practical implications for the distribution of fresh oil palm fruit bunches and can serve as a foundation for developing distribution systems using heuristic and metaheuristic approaches to a variety of scenarios. Future research can be expanded by incorporating additional real-world constraints such as dynamic demand changes, road conditions, traffic, driver availability, vehicle types, service times, and time windows to better reflect practical logistics scenarios.

CRediT Authorship Contribution Statement

Evi Yuliza: Conceptualization, Methodology, Resources. **Yuli Andriani:** Data Curation, Formal Analysis, Writing–Review. **Indrawati:** Software, Validation. **Sisca Octarina:** Supervision, Project Administration, Editing. **Diah Putri Ramadani:** Software, Visualization, Writing–Original Draft.

Declaration of Generative AI and AI-assisted Technologies

No generative AI tools were used for data analysis, result generation, or figure creation.

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Data and Code Availability

The operational data on fresh oil palm fruit bunch production and transportation used in this study are owned by the plantation company and are therefore not publicly available due to confidentiality constraints.

References

[1] A. A. Ibrahim, N. Lo, R. O. Abdulaziz, and J. A. Ishaya, "The Capacitated Vehicle Routing Problem," *International Journal of Research-Granthaalayah*, vol. 7, no. 3, pp. 310–327, 2019. DOI: 10.5281/zenodo.2636820.

[2] M. Anderson, S. Sumarsono, and A. Mahendra, "Vehicle Routing Problem In A Medical Facility Waste Collection Company: A Comparative Analysis Of Guided Local Search, Simulated Annealing And Tabu Search," *International Journal of Technology*, vol. 16, no. January 2023, pp. 423–432, 2018. Available online.

[3] E. Solano-Charris, C. Prins, and A. C. Santos, "Local Search Based Metaheuristics for the Robust Vehicle Routing Problem with Discrete Scenarios," *Applied Soft Computing Journal*, vol. 32, pp. 518–531, 2015.

[4] E. Yuliza, S. Octarina, N. Eliyati, and F. Maya, "Application of The Robust Capacitated Vehicle Routing Problem with Time Windows Model on Gallon Water Distribution," *AIP Conference Proceedings*, vol. 020076, no. 2577, pp. 13–19, 2022.

[5] A. Hottung and K. Tierney, "Neural Large Neighborhood Search For the Capacitated Vehicle Routing Problem," *Frontiers in Artificial Intelligence and Applications*, vol. 325, pp. 443–450, 2020. DOI: 10.3233/FAIA200124. arXiv: 1911.09539.

[6] E. Queiroga, R. Sadykov, and E. Uchoa, "A POPMUSIC Matheuristic For The Capacitated vehicle Routing Problem," *Computers and Operations Research*, vol. 136, no. July, p. 105 475, 2021. DOI: 10.1016/j.cor.2021.105475. Available online.

[7] S. Izar, S. Suwilo, and Sutarman, "The Vehicle Routing Problem with Discrete Split Delivery and Time Windows Time Windows," *Bulletin of Mathematics*, vol. 08, no. September, pp. 169–177, 2016. Available online.

[8] L. Liu, K. Li, and Z. Liu, "A Capacitated Vehicle Routing Problem with Order Available Time in e-commerce Industry," *Engineering Optimization*, vol. 49, no. 3, pp. 449–465, 2017. DOI: 10.1080/0305215X.2016.1188092.

[9] M. Nazari, A. Oroojlooy, M. Takáč, and L. V. Snyder, "Reinforcement learning for solving the vehicle routing problem," *Industrial and Systems Engineering*, pp. 9839–9849, 2018. arXiv: 1802.04240.

[10] N. J. Z. Mamat, S. H. Jaaman, and R. Ahmad, "Vehicle Routing Problem and Capacitated Vehicle Routing Problem Frameworks in Fund Allocation Problem," in *AIP Conference Proceedings*, vol. 1784, American Institute of Physics, 2016, pp. 050001–1–050001–7. DOI: 10.1063/1.4966820.

[11] P. Sitek and J. Wikarek, "Capacitated Vehicle Routing Problem with Pick-Up and Alternative Delivery (CVRPPAD): Model and Implementation Using Hybrid Approach," *Annals of Operations Research*, vol. 273, no. 1-2, pp. 257–277, 2019. DOI: 10.1007/s10479-017-2722-x. Available online.

[12] J. Zhang, Y. Zhu, X. Li, M. Ming, W. Wang, and T. Wang, "Multi-trip time-dependent vehicle routing problem with split delivery," *Mathematics*, vol. 10, no. 19, p. 3527, 2022.

[13] K. M. Ferreira, P. Munari, T. Alves de Queiroz, C. Archetti, and R. Morabito, "Exact methods for the split delivery vehicle routing problem with two-dimensional loading constraints," *Networks*, 2025.

[14] M. Sajid et al., "Article a Novel Algorithm for Capacitated Vehicle Rrouting Problem for Smart Cities," *Symmetry*, vol. 13, no. 10, pp. 1–23, 2021. DOI: 10.3390/sym13101923.

[15] E. Yuliza and F. Puspita, "Branch and Cut Method for Solving Capacitated Vehicle Routing Problem (CVRP) Model of LPG Gas Distribution Routes," *Science and Technology Indonesia*, vol. 4, no. 4, p. 105, 2019. DOI: 10.26554/sti.2019.4.4.105-108.

[16] F. Alesiani, G. Ermis, and K. Gkiotsalitis, "Constrained Clustering for the Capacitated Vehicle Routing Problem (CC-CVRP)," *Applied Artificial Intelligence*, vol. 36, no. 1, 2022. DOI: 10.1080/08839514.2021.1995658. Available online.

[17] N. A. Fitriani, R. A. Pratama, S. Zahro, P. H. Utomo, and T. S. Martini, "Solving Capacitated Vehicle Routing Problem Using Saving Matrix, Sequential Insertion, and Nearest Neighbor of Product 'X' in Grobogan District," *AIP Conference Proceedings*, vol. 2326, 2021. DOI: 10.1063/5.0039295.

[18] E. Yuliza, B. Suprihatin, P. B. Jaya Bangun, F. M. Puspita, S. Octarina, and Nuraina, "Saving Matrix Method and Nearest Neighbor Method for Garbage Transport Route Problems," *AIP Conference Proceedings*, vol. 3046, no. 1, 2024. DOI: 10.1063/5.0194590.

[19] D. G. Rossit, A. A. Toncovich, and M. Fermani, "Routing in waste collection: A simulated annealing algorithm for an argentinean case study," *Mathematical Biosciences and Engineering*, 2021.

[20] A. K. Ariyani, W. F. Mahmudy, and Y. P. Anggodo, "Hybrid genetic algorithms and simulated annealing for multi-trip vehicle routing problem with time windows.," *International Journal of Electrical & Computer Engineering (2088-8708)*, vol. 8, no. 6, 2018.

[21] S. Octarina, F. M. Puspita, S. S. Supadi, R. Afrilia, and E. Yuliza, "Set covering location problem and p-median problem model in determining the optimal temporary waste disposal sites location in seberang ulu i sub-district palembang," in *AIP Conference Proceedings*, AIP Publishing LLC, vol. 2577, 2022, p. 020 046.

[22] C. Kamthornsawat, A. Wayuparb, and S. Chain, "An Application of the Savings Method to A Vehicle Routing Problem," *The Journal of Supply Chain Management: Research and Practice*, vol. 11, no. 2, pp. 56–68, 2017.

[23] R. M. Sari, J. C. P, A. Ishak, and M. M. Tambunan, "Analysis of Goods Delivery Routes Using Saving Matrix and Clarke & Wright Savings Methods," *Jurnal Sistem Teknik Industri*, vol. 27, no. 1, pp. 1–7, 2025.

[24] J. Carr, "Introduction to Genetic Algorithms," *Artificial Intelligence Methods in the Environmental Sciences*, pp. 103–125, 2009. DOI: 10.1007/978-1-4020-9119-3_5.

[25] L. Haldurai, T. Madhubala, and R. Rajalakshmi, "A Study on Genetic Algorithm and Its Applications," *International Research Journal of Modernization in Engineering Technology and Science*, no. 10, pp. 139–143, 2023. DOI: 10.56726/irjmets32980.

[26] S. D. Immanuel and U. K. Chakraborty, "Genetic Algorithm: An Approach on Optimization," *Proceedings of the 4th International Conference on Communication and Electronics Systems, ICCES 2019*, no. Icces, pp. 701–708, 2019. DOI: 10.1109/ICCES45898.2019.9002372.