Journal of Mathematics and Scientific Computing with Applications

E-ISSN : 2580-5754; P-ISSN : 2580-569X
Volume 7, Number 1, 2026
DOI: 10.53806/jmscowa.v7i1.1476
Page: 78–92

OPTIMIZING SPLIT-DELIVERY FRESH FRUIT BUNCH ROUTES USING A SAVING MATRIX-SIMULATED ANNEALING HYBRID APPROACH

Khairunnisa Ani Putri[1], **Ismail Husein**[2]

[1,2]Department of Mathematics, Universitas Islam Negeri Sumatera Utara, Medan, Indonesia

Article Info

Article history:
Received : May 16, 2026
Revised : June 15, 2026
Accepted : July 1, 2026

Keywords:
Optimization;
Route;
Saving Matrix;
SDMDCVRP;
Simulated Annealing

ABSTRACT

This study aims to minimize the total distribution distance of remaining Fresh Fruit Bunches (FFB) cargo at PTPN IV Regional II through the Split Delivery Multi-Depot Capacitated Vehicle Routing Problem (SDMDCVRP) approach. The proposed method combines the Saving Matrix (SM) to form the initial route and Simulated Annealing (SA) to optimize the route arrangement by considering split delivery, multi-depot, vehicle capacity, demand fulfillment, and consolidation of remaining cargo. The existing route has a total distance of 2,014.98 km with a transportation cost of IDR 1,370,186.40. The SM method reduces the distance to 1,739.53 km, while SM-SA produces the best distance of 1,536.22 km with a cost of IDR 1,044,629.60. These results indicate a distance efficiency of 23.76% compared to the existing route. Benchmarks against SM-Tabu Search show that SM-SA has better solution quality, stability, and computation time. This approach supports SDG 9, SDG 12, and SDG 13.

Corresponding Author:
Khairunnisa Ani Putri,
Department of Mathematics,
Universitas Islam Negeri Sumatera Utara,
Email: khairunnisa0703222030@uinsu.ac.id

1. INTRODUCTION

Crude Palm Oil (CPO) continues to play an important role in the Indonesian economy, as it generates foreign exchange, absorbs labor, and supports the sustainability of the national plantation sector. In this context, PTPN IV PalmCo is listed among the largest palm oil companies and has achieved significant performance milestones. Until October 2025, the company posted production of 2.20 million tons of CPO and net profit of IDR 3.76 trillion, an increase of 149 percent, reflecting solid production capacity [1], [2]. The increase in production volume also increases the complexity of the distribution system, while the industry's attention is still more focused on achieving output. In fact, the effectiveness of delivering garden products to factories is greatly influenced by route accuracy and mileage, as suboptimal routes can extend transportation time and reduce operational efficiency [3].

Operationally, the transportation of Fresh Fruit Bunches (FFB) at PTPN IV Regional II is generally carried out using a fleet of Colt diesel types with limited capacity. The distribution of crops that reach full volume (full truckload) is carried out directly from a single point of origin to a single destination, without stopping, at 100% capacity utilization. However, the problem arises with the residual load, the remaining crop that is less than the fleet's maximum capacity. If the residual load from each plantation is transported separately without route planning, it will result in underutilization or low utilization of transport capacity. This can increase the number of travel trips, leading to fuel waste and non-optimal total distribution costs. Thus, a Vehicle Routing Problem (VRP) approach is needed to determine routes to transport residual loads from several plantations, thereby optimizing fleet capacity utilization. The Split Delivery Multi-Depot Capacitated Vehicle Routing Problem (SDMDCVRP) was chosen because of the operational characteristics in the field, involving several mills (depots) and many plantations as transportation points (customers), where each fleet has a maximum carrying capacity. This study integrates methods to achieve optimal results using the Saving Matrix (SM) and Simulated Annealing (SA). The optimization criteria analyzed included minimizing mileage and increasing vehicle capacity utilization, without considering other external factors such as traffic conditions, weather, road damage, or operational disruptions outside the distribution system.

Various previous studies have attempted to optimize distribution routes using various approaches. The SM method operates on the principle of distance saving, identifying destination points that can be combined into a single travel route [4]. Another study also underscores the effectiveness of the SM in forming logical, structured route clusters before further optimization [5]. This is in line with other research showing that the SM produces more efficient distribution routes by reducing travel distance and the number of routes [6], [7]. More specifically, in the context of transporting palm oil, a study shows that the use of the SM yields a much more optimal distribution route for solving the VRP problem [8]. While the SM can provide a good starting route, heuristic methods often get stuck in local optima. To overcome this, metaheuristic algorithms such as SA are applied. The SA algorithm uses a probabilistic acceptance mechanism that occasionally accepts a worse solution to avoid local-optimum traps and continue exploring a wider solution space [9]. In line with this, other studies also show that SA is effective in solving complex multi-depot VRP problems [10]. Later research showed that SA has a significant advantage in refining the initial distribution route, enabling a much shorter final mileage [11]. In addition, this algorithm offers high flexibility and easy integration with other optimization methods, making it an ideal choice for solving complex logistics distribution route problems [12].

The novelty of this research does not lie solely in the combination of SM and SA, as this combination has been widely used in VRP studies. The main novelty of this study lies in the development of an SDMDCVRP framework for FFB distribution. Unlike conventional SM-SA applications, which generally focus on distance minimization, this study explicitly considers operational characteristics such as split delivery, multiple depots, vehicle capacity, consolidation of residual loads, and route feasibility validation to ensure that all plantation demand is met without exceeding vehicle capacity. The methodological contributions of this study encompass four aspects. First, this study formulates the transportation of residual FFB as an SDMDCVRP model, in which a single plantation can be served by more than one route or depot. Second, this study integrates a residual-load consolidation mechanism into the route optimization process, allowing small residual loads to be consolidated into other routes that still have available capacity. Third, this study applies stochastic evaluation to SA through 30 independent runs, reporting the best, worst, and average values, standard deviation, coefficient of variation, execution time, convergence graphs, and inter-run variations to assess solution stability. Fourth, to strengthen the experimental validation, this study added a standard Tabu Search as a benchmark. This benchmark was added to evaluate whether the proposed SM-SA approach is capable of producing better and more stable solutions compared to other standard metaheuristics in the SDMDCVRP case of FFB residual load distribution. Tabu Search (TS) was chosen because it is of widely used metaheuristic for route optimization problems. Furthermore, it is also due to its ability to avoid solution repetition by using a tabu list. The tabu list acts as a search memory, storing previously visited steps or solutions and preventing the algorithm from returning to the same search pattern in the near future. This mechanism makes TS relevant for comparison with SA, as both aim to improve the initial solution and avoid local solution traps, but use different search mechanisms.In this study, TS is not positioned as the main method, but rather as a benchmark method that uses the same initial solution, distance matrix, vehicle capacity, and operational constraints as SM-SA. Thus, the comparison between SM-SA and SM-TS can provide additional validation of the solution quality, stability, and computational efficiency of the proposed method.

In addition to its methodological contributions, this study also offers practical contributions toward improving logistics efficiency and operational sustainability for companies. Reducing travel distances and transportation costs supports SDG 9 by improving the efficiency of industrial infrastructure and logistics systems. Optimizing vehicle capacity utilization and reducing inefficient trips support SDG 12 through more responsible use of transportation resources. Furthermore, reducing vehicle mileage has the potential to support SDG 13 by curbing fuel consumption and carbon emissions from distribution activities. Thus, the proposed approach not only contributes to the development of route optimization methods but is also relevant to the sustainability agenda within the oil palm plantation logistics system.

2. RESEARCH METHOD

This research was conducted at the Head Office of PT Perkebunan Nusantara IV (PTPN IV) Regional II, which is located at Jl. Letjen Suprapto No. 2, Hamdan, Medan Maimun District, Medan City, North Sumatra. This research is included in the type of applied research. Applied research aims to apply, test, and evaluate a theory's ability to solve practical problems . The data in the study can be grouped based on several criteria, one of which is the nature of the data and the source [13]. Based on this grouping, the data used in this study are quantitative. Quantitative data is data expressed as numbers, obtained through measurement and calculation, and can be analyzed using a mathematical approach and further processed using statistical analysis techniques [13]. The data used in this study are classified into two categories:

a. Primary Data, which is data obtained directly through observation and interviews with Assistant Staff for Oil Palm Production and Planning in the Crop Section at PTPN IV Regional II.
b. Secondary data, namely data obtained from the company's internal documents and archives, especially from the Plant Section and the Engineering and Processing Section of PTPN IV Regional II. The secondary data used included the location and number of plantations, the location and capacity of mills, FFB production per plantation, distances between plantation locations and mills, transport vehicle capacity, and distribution routes.

In this study, the physical distance between distribution points (Palm Oil Mills/POM) is obtained based on real distance data through the actual road network accessed directly through the Google Maps application. This empirical approach was chosen because it is able to represent real geographic conditions in the field, including legal transportation routes for truck fleets, road geometry conditions, and applicable traffic restrictions. Through this method, each element of the distance matrix (d_{ij}) reflects the actual distance traveled in kilometers (km). The use of real distances from Google Maps ensures that the performance evaluation of the SM and SA methods in solving the SDMDCVRP case has a high level of accuracy and validity, and minimizes distance deviation bias that often occurs in theoretical approaches such as Euclidean Distance.

FFB data is processed using average daily production based on total annual production over 300 days of operation. This number is used as an estimate of effective working days in a year, after taking into account holidays, maintenance activities, and other operational constraints. This approach aims to obtain more stable distribution parameters in the route optimization process. Average daily production (q_i) is calculated using the following equation:

$$q_i = \frac{Total\ annual\ production}{300\ days} \tag{1}$$

2.1 Split Delivery Multi-Depot Capacitated Vehicle Routing Problem

In general, the Vehicle Routing Problem comprises several main components that are interrelated: depots, customers, vehicles, and routes [14]. Some commonly used VRP variants include Capacitated VRP, Multi-Depot VRP, VRP with Time Windows, and Open VRP. This study uses the Split Delivery Multi-Depot Capacitated Vehicle Routing Problem (SDMDCVRP). The split delivery approach in a multi-depot context has also been studied by other researchers in the Multiple Depot Split Delivery Vehicle Routing Problem with Separate Backhaul and Linehaul Customers (MDSDVRP-SBL) model, which shows that split delivery can improve route efficiency and vehicle utilization in large-scale distribution systms [15]. The SDMDCVRP problem involving several operational depots (POM) and a group of customer plantations with a fixed FFB production volume within a certain geographical area is the main focus of this study. The objective is to find the optimal shortest route framework for a homogeneous vehicle fleet with a certain carrying capacity to minimize the total distribution distance of the network. Furthermore, it is assumed that the transportation process strictly meets the following mathematical assumptions and constraints.

a. The physical distance traveled between all location points (nodes) in the network (from depot to plantation, between plantations, and vice versa) is known with certainty (deterministic) and is static.
b. The FFB demand (production volume) in each plantation must be transported in its entirety without any residue being left behind, where, based on the split-delivery characteristics, this load can be fulfilled by one or more vehicle visits.
c. The number of homogeneous transport vehicle fleets available at each depot factory is assumed to be sufficient to meet the total demand for all routes generated.
d. The initial departure depot and the final destination depot of each transport vehicle must be absolutely consistent; each vehicle must return to the same originating depot from which it first departed.
e. Logistics vehicles are strictly prohibited from traveling directly between different factory depots without first executing the cargo transport task at the customer's plantation point.

f. The total accumulated load of FFB plantations allocated to one vehicle in one series of its travel routes must not exceed the strict maximum carrying capacity limits of the vehicle.

Based on the assumptions and research limitations established above, the SDMDCVRP problem is then formulated into a formal mathematical model [16]. The definitions of the indices, sets, parameters, and decision variables used in this model are shown in Table 1.

Table 1: SDMDCVRP mathematical model notations

Category	Notation	Definitions
Indices	i, j, p	Index for location points (nodes) in the network
	d	Index for depot location points POM
	k	Index for vehicle fleet (trucks)
Sets	D	The set of all depot points, where $D = \{P_1, P_2, \ldots, P_{16}\}$
	C	The set of all customer points, where $C = \{K_1, K_2, \ldots, K_{29}\}$
	V	The universal set of all location points within the research coverage network, which is the combination of the depot and garden sets ($V = D \cup C$)
	K	A collection of all available fleets of transport trucks
Parameters	d_{ij}	Physical distance (in km) from location point i to location point j, where $i, j \in V$
	q_i	Total production volume of FFB produced by plantation i (in tons), where $i \in C$
	Q	The maximum transport capacity of each truck k fleet is 6 tons ($Q = 6$)
	C	Cardinality or total number of garden points registered in the network system (29 gardens)
Variables	x_{ijk}	A binary decision variable that has a value of 1 if vehicle k travels directly from point i to point j and a value of 0 otherwise, where $i, j \in V$ and $k \in K$
	y_{ik}	A non-negative continuous decision variable indicating the amount or quantity of FFB cargo (in tons) transported from plantation i by vehicle k, where $i \in C$ and $k \in K$
	u_{ik}	The auxiliary continuous variable, which states the sequence of visits to plantation i by vehicle k, is used specifically to fulfill the subtour elimination constraint

The SDMDCVRP model can be formulated as:

$$MinZ = \sum_{i \in V} \sum_{j \in V} \sum_{k \in K} d_{ij} x_{ijk} \tag{2}$$

Subject to:

$$\sum_{k \in K} y_{ik} = q_i, \quad \forall i \in C \tag{3}$$

$$\sum_{k \in K} y_{ik} = q_i, \quad \forall i \in C \tag{4}$$

$$\sum_{i \in C} y_{ik} \leq T, \quad \forall k \in K \tag{5}$$

$$\sum_{i \in V} x_{ipk} - \sum_{j \in V} x_{pjk} = 0, \quad \forall p \in C, \forall k \in K \tag{6}$$

$$\sum_{j \in C} x_{\delta(k)jk} = \sum_{i \in C} x_{i\delta(k)k} \leq 1, \qquad \forall k \in K \tag{7}$$

$$\sum_{j \in V} x_{ijk} \leq 1, \qquad \forall i \in C, \forall k \in K \tag{8}$$

$$x_{iik} = 0, \qquad \forall i \in V, \forall k \in K \tag{9}$$

$$y_{ik} \leq q_i \sum_{j \in V} x_{ijk}, \qquad \forall i \in C, \forall k \in K \tag{10}$$

$$u_{ik} - u_{jk} + |C|\, x_{ijk} \leq |C| - 1, \quad \forall i, j \in C, \; i \neq j, \forall k \in K \tag{11}$$

$$x_{ijk} \in \{0, 1\}, \; \forall i, j \in V, \forall k \in K; \quad y_{ik} \geq 0, \forall i \in C, \forall k \in K \tag{12}$$

The function of the objective (2) minimizes the total accumulated mileage across all operational vehicles globally across the multi-depot system network. Constraint (3) ensures that the entire volume of FFB production (q_i) generated in each plantation i must be transported in full without any waste. According to the nature of split-delivery, the fulfillment of this total demand can be divided and transported by one or more different vehicles, (4) ensures that the accumulated weight of FFB cargo transported by one vehicle k from all the plantations it visits must not exceed the maximum capacity limit of the truck, (5) ensures the continuity of the fleet's travel route. If a vehicle k enters a point in garden p, then the vehicle must exit from that point in garden p to the next point, (6) Ensures that vehicles assigned to a depot must start their journey from their originating depot and return to the same depot. Vehicles may be idled when not needed, limiting the number of departures and returns to a maximum of one, (7) limiting one vehicle from visiting the same plantation more than once on a single route. Split deliveries are still permitted because the same plantation can still be served by different vehicles, (8) prevent the formation of paths from one node to the same node, (9) ensure that a vehicle can only transport cargo from a plantation if the vehicle actually physically visits the plantation, (10) ensures that no isolated closed circular routes (subtours) are formed between garden nodes without connecting back to their parent depot node, (11) determines the feasibility properties of the values of the decision variables, where the travel route variable (x_{ijk}) must be of binary type (0 or 1), while the FFB transport quantity variable (y_{ik}) must have a non-negative continuous value.

2.2 Saving Matrix

The Saving Matrix method, or Clarke and Wright multi-depot Algorithm, is a classic heuristic first proposed by Clarke and Wright in 1964 to determine vehicle routes. This method aims to construct distribution routes that are superior in efficiency by minimizing the accumulation of travel distance, time, or distribution costs through the combination of routes that yield the greatest savings [7]. This algorithm works based on the concept of distance saving. If the two routes are separate, the Depot→i→Depot and (Depot→j→Depot) combined into a single route (Depot→i→j→Depot), the value of savings (S_{ij}) is calculated by the equation:

$$S_{ij} = d_{0i} + d_{0j} - d_{ij} \tag{13}$$

S_{ij}: route savings between customers i and j
d_{0i}: travel distance from the depot to the customer i
d_{0j}: travel distance from the depot to the customer j
d_{ij}: distance between customers i and customers j

The steps for the matrix saving method are as follows:

a. Create a distance matrix
b. Calculate the savings using the formula in equation (12)
c. Sort the values from largest to smallest
d. Merge distribution points while considering capacity
e. Repeat the merging process
f. Obtain the initial distribution route

2.3 Simulated Annealing

Simulated Annealing (SA) is a metaheuristic algorithm first introduced by Kirkpatrick, Gelatt, and Vecchi (1983), which adopts the concept of the annealing process in solid materials to solve combinatorial optimization problems. This approach is stochastic because it uses a random search mechanism and an acceptance rule for solutions that is also opportunity-based [17]. Although it uses random elements, SA is designed to avoid getting stuck in local minima. During the iteration process, these algorithms not only accept solutions with better objective values but also accept poorer solutions. Such acceptance occurs with a probability that decreases as the search process progresses [12].

Steps of the simulated annealing method are as follows:

a. Define the main control parameters of SA, which include T_0, α, T_{end}, and L
b. Generate a new alternative route solution (E_n) by performing stochastic randomization in the form of garden point exchange or garden relocation across the factory depot area to the current route (E_c)
c. Calculate the total travel distance (in km) of the new route solution scheme that has been generated
d. Calculate the mathematical difference between the total distance of the new route and the total distance of the current route using the following formula:

$$\Delta E = E_n - E_c \tag{14}$$

e. The new alternative route solution is evaluated probabilistically and the acceptance decision is set as follows:

$$P = \begin{cases} 1 & , \Delta E < 0 \\ \exp\left(-\dfrac{\Delta E}{T_c}\right) & , \Delta E \geq 0 \end{cases} \tag{15}$$

Where T_c represents the local temperature parameter at the iteration stage. If $\Delta E < 0$, the new route results in a shorter (more economical) distance and is immediately accepted absolutely. Conversely, if $\Delta E \geq 0$ (the new route is worse), the route will only be accepted if the generated universal random number $R \in [0, 1]$ satisfies the condition $R < P$ (Acceptance)

g. During the iteration process, the algorithm will continuously track, update, and record the absolute best physical route solution throughout the running history (E_b)

h. The system temperature is systematically lowered at the end of each iteration stage using a predetermined geometric cooling scheme:

$$T_n = T_c \times \alpha \tag{16}$$

h. This stochastic-based iterative optimization process will continue to run repeatedly until the operational temperature parameters meet the stopping criteria

i. When the systematic temperature drop condition has reached the freezing threshold, namely when $T < T_{end}$, the algorithm will stop all its computation cycles automatically

The parameter definitions and notations used in the Simulated Annealing algorithm are shown in Table 2.

Table 2: Parameters and notation of Simulated Annealing (SA)

Parameter	**Description**
S_0	The initial solution of Saving Matrix
S_c	The current solution
S_n	The new solution
S_b	The best solution
T_0	The initial temperature
T_{end}	The final temperature
T_c	The current temperature
α	The cooling rate
L	The maximum number of iterations
R	The number of independent runs
P	The acceptance probability
E_n	The total distance of new solution
E_c	The total distance of current solution
E_b	The best total distance
ΔE	The difference in objective function values

2.4 Hybrid Saving Matrix and Simulated Annealing

The SDMDCVRP in FFB distribution is a complex NP-hard problem that integrates the optimization of vehicle fleet-factory depot combinations and the search for a sequence of transportation routes. The SA algorithm, a classical probability-based metaheuristic method with excellent global solution space exploration capabilities, has proven widely successful in solving various VRP cases [9], [12]. Therefore, in this study, a Hybrid Saving Matrix and Simulated Annealing (SM-SA) is proposed, based on the SA framework, to solve the presented palm oil distribution problem. In this SM-SA algorithm, we integrate the deterministic SM in the initial stage to generate efficient base routes in terms of geographical distance. Next, we design a mechanism for exchanging and relocating plantation points across different mill fleets (POMs) within a neighborhood search structure of SA. This alternative route search process is combined with adaptive metropolis criterion parameter control, so that the computational efficiency is increased and the algorithm is able to jump out of the local optima trap without violating the very strict maximum truck carrying capacity constraint of 6 tons. The flowchart of the proposed SM-SA hybrid algorithm is shown in full in Figure 1.

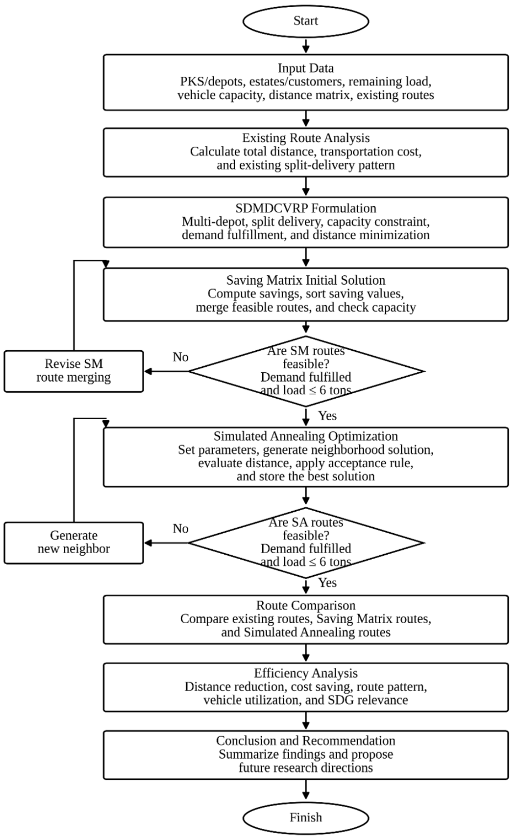

Figure 1. Research flowchart of FFB remaining load route optimization using SM-SA

2.5 Benchmark with Tabu Search

To strengthen experimental validation, this study adds Tabu Search as a benchmark method to the main Hybrid SM-SA approach. Tabu Search (TS) is a metaheuristic method that explores neighboring solutions of the current solution and uses a memory structure in the form of a tabu list to prevent the search from returning to previously visited solutions or moves. With this mechanism, TS can reduce solution repetition and help the search process escape from local solutions. In route optimization problems such as VRP and CVRP, TS can be used to improve the initial solution through an iterative search process while still considering vehicle capacity constraints. The steps of the tabu search method are as follows:

a. Sets the SM result as the initial solution (S_0). This initial solution is used to ensure a fair comparison between SM-SA and SM-TS, as both start the optimization process from the same initial route. Once the initial solution is obtained, the total distance traveled is calculated as the initial objective function value.
b. Define the initial solution as the current solution (S_c) and the temporary best solution (S^*). Next, the tabu list (TL) is initialized as an empty list to store the movements or route changes made in the previous iteration.
c. Generating neighboring solutions (N(S)) from the (S_c). $N(S)$ are generated through swap and relocate operations. A swap operation exchanges two service points on different routes, while a relocate operation moves one service point from one route to another. The total distance of each candidate solution generated is then calculated.
d. Examine the feasibility of each candidate solution. A candidate solution is acceptable only if it meets operational constraints, namely maximum vehicle capacity, demand fulfillment, a multi-depot structure, and split-delivery requirements. Solutions that violate vehicle capacity are not selected as the next solution.
e. Check the tabu status of each move. If the move that produces a candidate solution is in the tabu list, it is not selected. However, if the tabu movement produces a better solution than (S^*), it can be accepted under the aspiration criterion.
f. Select the best candidate solution that is not tabu or meets the aspiration criterion. This candidate solution is then converted into the new current solution. The selected move is placed on the tabu list for a specified tabu tenure to prevent its immediate reuse in the next iteration.
g. Updating the best solution. If the current solution produces a lower total distance traveled than the previous best solution, then (S^*) is updated. This process is repeated until the maximum number of iterations is reached.

3. RESULT AND ANALYSIS

The analysis of FFB distribution route optimization in the operational area of PTPN IV Regional II began with identifying the characteristics of the locations involved in the distribution network. Based on secondary data obtained from the company, 16 POM points serve as operational depot, $P = P_1, P_2, P_3, \ldots P_{16}$, and 29 POM points which act as production or customer locations, $K = K_1, K_2, K_3, \ldots, K_{29}$. In this distribution activity, the fleet used is trucks with homogeneous characteristics, with a maximum carrying capacity of 6 tons for each vehicle.

To provide an initial overview of the spatial distribution of the network, the location of each POM is recorded using latitude and longitude coordinates. In addition, the company has established an initial connectivity pattern between the POM and the plantations, whereby each POM is responsible for receiving harvests from specific groups of surrounding plantations. For example, POM 1 receives supplies from six plantations, namely Plantations 1, 2, 4, 7, 25, and 26. Details regarding the identity of the depots and the initial linkages between POM and plantations are presented in Table 3.

Table 3: The relationship between POM and FFB supplier plantations

ID	Name of the POM	Latitude	Longitude	FFB Supplier Plantations	Total Gardens
P_1	POM Bah Jambi	2.98837	99.22055	$K_1, K_2, K_4, K_7, K_{25}, K_{26}$	6
P_2	POM Pasir Mandoge	2.76963	99.31810	K_4, K_5, K_6	4
P_3	POM Dolok Sinumbah	3.11215	99.32913	$K_3, K_4, K_7, K_8, K_9, K_{10}, K_{27}, K_{28}, K_{29}$	9
P_4	POM Dolok Ilir	3.12134	99.16006	$K_{25}, K_{27}, K_{28}, K_{29}$	4
P_5	POM Gunung Bayu	3.14539	99.37246	$K_8, K_9, K_{10}, K_{28}, K_{29}$	5
P_6	POM Mayang	3.03326	99.33305	K_9, K_{10}, K_{29}	3
P_7	POM Adolina	3.56854	98.94802	K_{20}	1
P_8	POM Pabatu	3.28678	99.10914	$K_{20}, K_{21}, K_{25}, K_{26}, K_{27}, K_{28}$	6
P_9	POM Sawit Langkat	3.70127	98.29362	K_{24}	1
P_{10}	POM Timur	0.36725	99.30769	K_{18}, K_{19}	2
P_{11}	POM Tinjowan	3.08295	99.51016	K_5, K_{22}, K_{29}	3
P_{12}	POM Air Batu	2.85983	99.63844	K_6, K_{11}	2
P_{13}	POM Pulu Raja	2.70205	99.62487	K_{12}, K_{13}	1
P_{14}	POM Berangir	2.22484	99.76018	K_{13}	1
P_{15}	POM Ajamu	2.45819	100.16169	K_{14}, K_{15}, K_{16}	3
P_{16}	POM Sosa	1.04878	100.01352	K_{17}	1

From this initial connectivity structure, it is evident that some plantations are not connected to just one POM but have supply relationships with more than one depot. This situation indicates the presence of a split delivery pattern within the company's existing distribution network. One example is K_4 which, in its operations, is recorded as sending its harvest to P_1, P_2, and P_3. This pattern indicates that split delivery practices are already occurring within the company's daily distribution system. However, the cargo allocation carried out so far is still largely based on administrative considerations and manual decisions. Consequently, there is a possibility of inefficient routes, either due to overlapping trips or suboptimal vehicle capacity utilization.

The analysis of the FFB distribution network optimization at PTPN IV Regional II began by processing annual production data into estimates of daily production volumes using Equation (1). Under current conditions, transportation is carried out directly from the plantations to affiliated palm oil mills using a homogeneous fleet of trucks. The processed data on daily production volumes and the accumulated remaining loads at each plantation are presented in Table 4.

Table 4: Average Daily Production of FFB and Remaining Load

No.	Combined ID	Annual Production (Tons)	Daily Production (Tons)	Total Trips (Direct)	Remaining Load (Tons)
1	POM 1–K_1	123,955.10	413.1836718	68	5.183671827
	POM 1–K_2	56,713.97	189.0465691	31	3.046569082
	POM 1–K_4	628.83	2.096115366	0	2.096115366
	POM 1–K_7	393.96	1.313184462	0	1.313184462
	POM 1–K_{25}	38,755.30	129.1843458	21	3.184345759
	POM 1–K_{26}	33,949.20	113.1640135	18	5.164013504
2	POM 2–K_4	7,247.55	24.15850999	4	0.158509986
	POM 2–K_5	136,848.12	456.1604004	76	0.160400441
	POM 2–K_6	70,265.60	234.2186562	39	0.218656239
	...	...	...	...	...
16	POM 16–K_{17}	112,220.58	374.0686	62	2.0686
	Total	**2,315,268.94**	**7,717.563133**	**1,266**	**121.5631333**

The data in Table 3 shows that out of a total daily production of 7,717.563.133 tons, 1,266 direct trips successfully evacuated full loads. However, there was an accumulated residual load of 121.5631333 tons spread across various plantation nodes. It is this residual cargo fraction that triggers the Split-Delivery feature in the constructed SDMDCVRP model. Through the SM-SA hybrid approach, this residual cargo is consolidated into multiple trip routes to optimize truck capacity utility without violating the maximum load constraint as per Equation (5).

To support the creation of consolidation routes for the remaining cargo, the actual travel distance (d_{ij}) between nodes was collected using the actual road network via Google Maps. This spatial representation includes a total of 45 nodes forming a 45×45 (2,025 cells). Given the limitations of publication space, a sample of the distance matrix representing the spatial relationships between several POM depots and customer farm nodes is presented in Table 5.

Table 5: Distance matrix between distribution points (km)

ID	P1	P2	P3	⋯	P16	K1	K2	K3	⋯	K29
P1	0	51	25	⋯	384	0.7	25	26	⋯	44
P2	51	0	68	⋯	334	50	47	66	⋯	86
P3	25	68	0	⋯	377	25	43	2.1	⋯	21
⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯
P16	383	333	374	⋯	0	383	365	374	⋯	360
K1	0.7	50	25	⋯	383	0	24	26	⋯	44
K2	25	47	43	⋯	365	24	0	42	⋯	86
K3	26	66	2.1	⋯	377	26	44	0	⋯	24
⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯	⋯
K29	44	86	21	⋯	364	44	86	22	⋯	0

To facilitate understanding of the distribution pattern of residual FFB under current conditions, transportation routes are visualized schematically for each POM. Overall, the total distance traveled under the current system is 2,014.98 km, and transportation costs amount to IDR 1,370,186.4. In the current multi-depot system, each palm oil mill operates independently and serves only the plantations within its respective area. Given that the system involves 16 palm oil mills and 29 plantations, displaying all routes on a single map would be too cluttered and difficult to read. Therefore, the visualization is presented separately for each palm oil mill so that the route connections between depots and plantations can be seen more clearly.

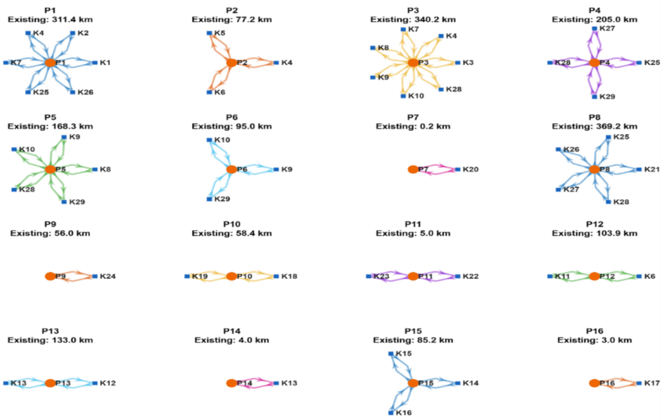

Figure 2. Visualization of existing transport routes for residual FFB by POM in a multi-depot system

Based on the network structure shown in Figure 2, the transportation of residual FFB under current conditions is still carried out independently by each POM. For example, P1 serves six affiliated plantations namely, K_1, K_2, K_4, K_7, K_{25}, and K_{26}, with a total existing distance of 311.4 km. This pattern indicates that transportation routes still tend to be separate from the depot to the plantation and back to the depot, meaning that unused vehicle capacity is not being utilized to combine service to other nearby plantations. This situation indicates potential inefficiencies in the existing multi-depot system. Therefore, these routes were optimized using the Saving Matrix and Simulated Annealing methods to more effectively consolidate routes, utilize vehicle capacity, and reduce travel distances.

3.1 Initial route generation using the Saving Matrix method (SM)

The initial stage in solving the SDMDCVRP model in this study involved generating initial routes using the SM method. In practice, the SM method gradually consolidates the remaining FFB cargo while adhering to vehicle capacity limits. Route consolidation is performed only if the total cargo transported does not exceed the fleet's maximum capacity, as stated in Equation (5). Through this mechanism, the SM method is able to form clusters of initial distribution routes across all POM, which serve as the basis for the subsequent optimization stage. Based on the computational results, the SM method successfully consolidated a total daily residual load of 121.563133 metric tons into several initial distribution routes. The calculation results show that the total distance traveled generated at this stage is 1,739.53 km and resulting in transportation costs of IDR 1,182,880.4. These results indicate that the SM method is capable of generating a more structured initial solution compared to the existing conditions, while also serving as the initial input for the improvement process using Simulated Annealing.

To provide a clearer picture of the results of the initial route formation using the SM method, the resulting routes are visualized as a distribution network for all POM. This visualization shows the relationships between each depot or POM and the plantations they serve after the route consolidation process has been carried out. Thus, the route consolidation patterns, the distribution of services among POMs, and the initial distribution structure resulting from the SM method can be observed more clearly before further optimization is performed using SA.

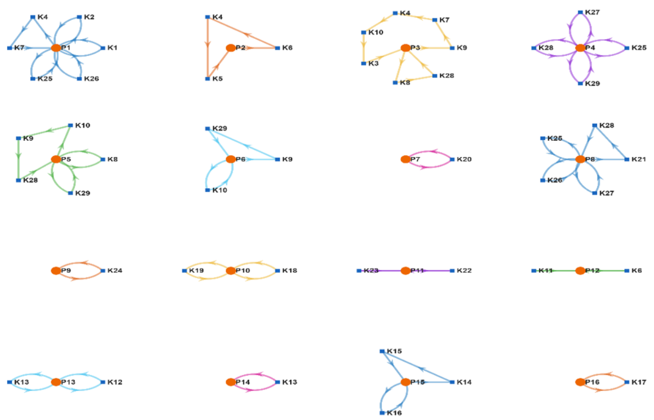

Figure 3. Visualization of the initial route based on the results of the Saving Matrix across all POM

Based on Figure 3, it can be seen that the SM method has formed a more consolidated route pattern across all oil palm plantations. Several plantations that were previously served separately have begun to be combined into a single route sequence, provided that the vehicle's capacity is not exceeded. This indicates that the Saving Matrix is capable of reducing single-trip patterns from the depot to the plantation and back to the depot, thereby producing a more efficient initial route structure. However, the solution generated by the Saving Matrix is still a preliminary one, so there is still room for further improvement through the Simulated Annealing optimization process, particularly in rearranging the order of visits, consolidating residual loads, and making more optimal use of vehicle capacity.

3.2 Route Optimization Using Simulated Annealing (SA)

The route results obtained from the SM method are used as the initial solution in the SA optimization process. The use of SM as the initial solution is intended to ensure that the SA search process does not start from a random solution, but rather from an initial route structure that has already taken distance savings into account. SA is then used as a route improvement method through the process of generating neighboring solutions. In this process, the route structure may undergo changes through the exchange of visit sequences, node relocation, the consolidation of residual loads, or adjustments to split deliveries. Each new solution is evaluated based on the objective function of minimizing total distance while adhering to the SDMDCVRP constraints, namely: fulfilling all farm demand (Equation 4), a maximum vehicle capacity of 6 metric tons (Equation 5), vehicle departure and return to the origin depot (Equation 7), and the prevention of subtours (Equation 9). The SA testing was conducted over 30 independent runs to account for the stochastic nature of the algorithm. Through repeated testing, the algorithm's performance can be analyzed more objectively using the best, worst, and average values, as well as the standard deviation and coefficient of variation. In each run, the search process was limited to 1,500 iterations so that the algorithm would have sufficient solution exploration space without excessively increasing computation time. T_0 was set to 50 to allow for the acceptance of worse solutions in the early stages of the search, thereby preventing the algorithm from getting stuck at a local optimum. Meanwhile, a cooling rate (α) of 0.96 was used to gradually lower the temperature, ensuring the search process remained stable and did not terminate prematurely. The statistical results of the SA testing are presented in Table 6.

Table 6: Statistical Results of the Simulated Annealing Test

Indicator	Value
Initial value of the Saving Matrix	1,739.53 km
Best distance	1,536.22 km
Best run	Run 7
Worst distance	1,687.53 km
Worst run	Run 25
Average distance	1,622.23 km
Standard deviation	38.31 km
Coefficient of variation	2.36%
Optimal descent distance relative to SM	203.31 km
The largest percentage decrease relative to the SM	11.69%
Average execution time	0.2345 seconds
Execution time range	0.2162–0.2834 seconds

Based on Table 5, the best result from SA yielded a total distance of 1,536.22 km on the 7th run, representing a decrease of 203.31 km and a percentage improvement of 11.69% compared to the initial SM solution. The average distance from 30 test runs was 1,622.23 km, representing an average reduction of 117.30 km and an improvement of approximately 6.74% over the initial solution. Even in the worst-case scenario, SA still produced a distance of 1,687.53 km in the 25th run, which is 52.00 km better—representing an improvement of approximately 2.99%compared to the SM solution. This indicates that all SA tests were able to improve upon the initial route generated by SM. A standard deviation of 38.31 km indicates variation in results across runs. This variation is to be expected because SA incorporates stochastic elements in the process of generating neighboring solutions and in its solution acceptance mechanism. However, the coefficient of variation of 2.36% indicates that the level of variation is relatively low compared to the average value. Thus, the test results show that SA performs quite stably in improving the initial SM solution for the SDMDCVRP problem.

In terms of computational efficiency, the average execution time of SA was 0.2345 seconds, with an execution time range of 0.2162–0.2834 seconds. This relatively narrow range indicates that the computational process across the 30 test runs exhibited consistent execution times. Thus, SA is not only capable of improving the quality of route solutions but also demonstrates good computational efficiency at the scale of the research data.

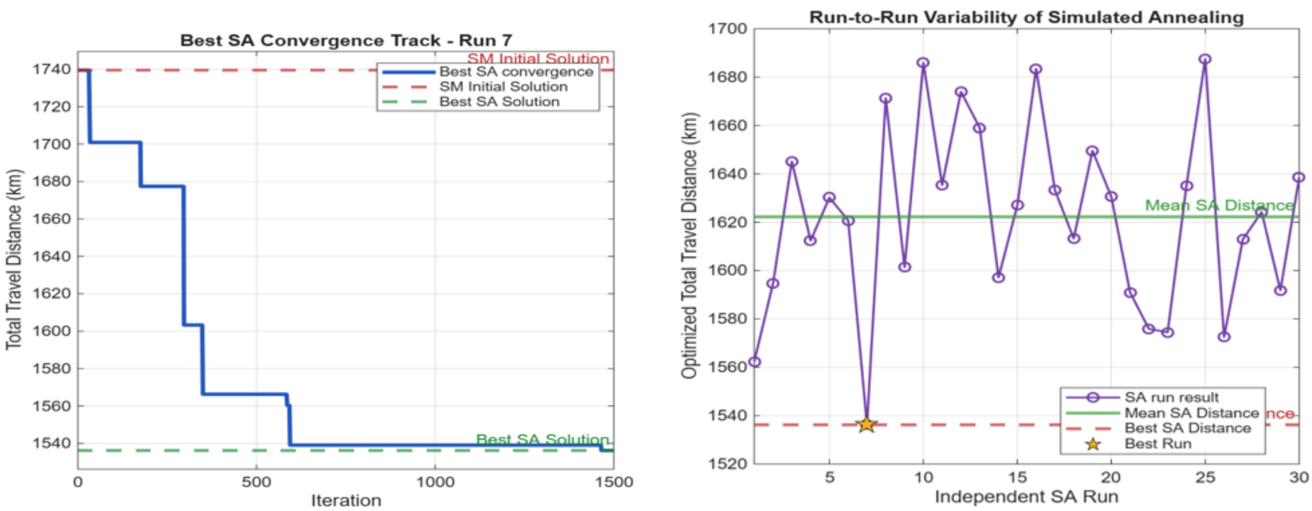

Figure 4. Convergence and Run-to-Run Variability of the Simulated Annealing

Figure 4 shows the validation results of the SA. The left graph shows the convergence pattern of the best-so-far values on the best run. Based on this convergence graph, the total distance value gradually decreases during the iteration process. At the start of the iteration, the distance value was still at the initial SM solution, which was 1,739.53 km. Subsequently, the algorithm gradually began to find better solutions until it reached the best value of 1,536.22 km on the 7th run. The stepped pattern of the decrease indicates that the best solution is not always found in every iteration, but is obtained when the algorithm successfully finds a new route combination that results in a shorter distance.

In some parts of the graph, a flat or stagnant phase is visible, indicating that the algorithm is performing a search but has not yet found a solution better than the current best solution. This condition is a common characteristic of SA, as the algorithm continues to explore neighboring solutions and may probabilistically accept worse solutions to avoid local optima. The subsequent decline in the next iteration indicates that this search mechanism is capable of finding a new, more efficient solution. Thus, the convergence graph shows that SA is able to progressively improve the initial SM solution until the optimal solution is obtained.

The stability of the SA results from 30 independent tests is shown in Figure 4 on the right. Each point on the graph represents the total distance from the optimization result in a single run. At the same time, the green line indicates the average SA distance of 1,622.23 km. The dotted red line indicates the best SA distance of 1,536.22 km, which was obtained in the 7th run and marked with an asterisk. Since the optimization objective is to minimize the total distance, points located lower on the graph indicate better results. The graph of inter-run variation shows that the SA results fluctuate in each test. These fluctuations occur because SA is a stochastic algorithm, meaning that the generation of neighboring solutions and the acceptance of solutions involve an element of randomness. However, based on the statistical results, a standard deviation of 38.31 km and a coefficient of variation of 2.36% indicate that the inter-run variation remains relatively low compared to the average value. Furthermore, the worst-case distance for SA, at 1,687.53 km, remains lower than the initial distance for SM, which was 1,739.53 km. This indicates that all SA runs were able to improve upon the initial solution.

Based on the convergence results and inter-run variations, it can be concluded that SA is effective in improving the initial route generated by SM in the SDMDCVRP problem. The convergence graph shows a decrease in distance during the iteration process. In contrast, the inter-run variation graph indicates that the results obtained are relatively stable despite the algorithm's stochastic nature. With a best distance reduction of 203.31 km or 11.69%, an average distance of 1,622.23 km, a coefficient of variation of 2.36%, and an average execution time of 0.2345 seconds, SA has proven capable of producing more efficient and stable route solutions that are suitable for use as an improvement method for the initial SM solution. To provide a clearer picture of the optimization results, the final route obtained from the best SA run is visualized in the form of a distribution network per POM. This visualization shows the relationships between depots or POM and the plantations they serve after the route refinement process is completed. Unlike the initial SM routes, the final SA results represent routes that have undergone a process of neighbor solution search, route structure reorganization, and consolidation of residual loads while still adhering to vehicle capacity limits and meeting plantation demand.

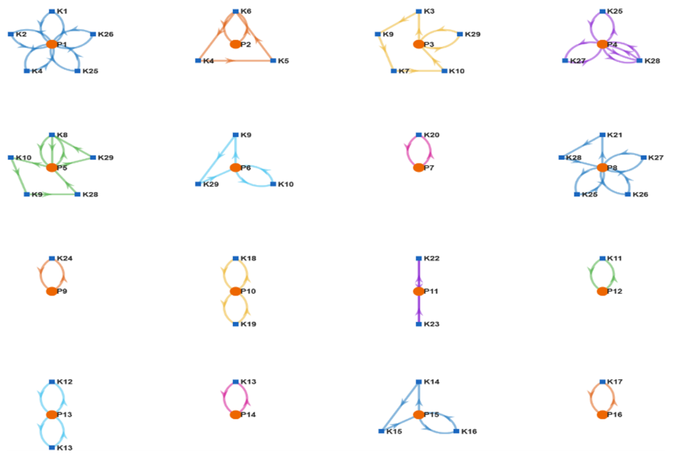

Figure 5. Visualization of the final route resulting from Simulated Annealing optimization across all POM

Based on Figure 5, the SA optimization results show a final route pattern that has been consolidated compared to the initial SM route. This visualization demonstrates that some orchards can be combined into a single trip, while others continue to be served separately according to vehicle capacity and cargo requirements. For example, in cluster P_1, several plantations such as K_1, K_2, K_4, K_{25}, and K_{26} are grouped into a single service cluster, indicating route consolidation at that depot. A similar pattern is observed in P_8, which serves several plantations including $K_{21}, K_{25}, K_{26}, K_{27}$, and K_{28} within a more consolidated route structure. Additionally, the figure shows that some plantations appear in more than one POM cluster; for example, K_{25} appears in clusters P_1, P_4, and P_8, and K_{28} appears in clusters P_4, P_5, and P_8. This does not indicate a duplication error but rather reflects a characteristic of the distribution system that has allowed for split deliveries since the existing conditions were established. In the SDMDCVRP model, a single plantation can be served by more than one route or depot if there is load splitting, partial demand transfer, or consolidation of residual loads, as long as vehicle capacity is not exceeded and all of the plantation's demand is still met. Thus, the visualization results of the final SA route show that the optimization process does not eliminate the split-delivery nature of the existing route, but rather reorganizes the service pattern to make it more efficient. The optimization was performed by considering travel distance reduction, vehicle capacity utilization, and operational feasibility in a multi-depot system. As long as all demand is met and maximum vehicle capacity is not exceeded, the occurrence of the same stop on multiple routes remains valid and consistent with the characteristics of the SDMDCVRP model used in this study.

To clarify the impact of optimization on distribution performance, a comparison was conducted between the existing conditions, the initial route results from SM, and the final results from SA. This comparison includes total distance traveled, transportation costs, distance reduction, distance efficiency, and the cost savings resulting from each optimization stage. The results of the efficiency comparison are presented in Table 7.

Table 7: Comparison of Efficiency Between Existing Conditions, Saving Matrix, and Simulated Annealing

Route	Total Distance (km)	Transportation Costs (IDR)	Reduction in Distance (km)	Distance Efficiency (%)	Cost Savings (IDR)
Existing	2,014.98	1,370,186.00	–	–	–
Saving Matrix	1,739.53	1,182,880.40	275.45	13.67	187,306.00
Simulated Annealing	1,536.22	1,044,629.60	478.76	23.76	325,556.80

After obtaining the comparison results between the existing route, Saving Matrix, and Hybrid SM-SA, this study conducted an additional benchmark using Tabu Search. In this study, TS is not positioned as the primary method, but rather as a benchmark. Therefore, the TS results are not directly compared with the existing route but with the SM-SA results. To ensure a fair comparison, SM-TS and SM-SA use the same initial solution, namely the Saving Matrix results, the same distance matrix, the same vehicle capacity limit of 6 tons, and the same operational constraints. Both methods were also run independently 30 times, with 1,500 iterations per run. In the Tabu Search implementation, the parameters used include a candidate list size of 50, a tabu period of 25 iterations, and neighbor operations consisting of swaps and relocations. A tabu period of 25 iterations means that the selected move will be temporarily stored in the tabu list for that duration, preventing its immediate reuse in subsequent searches. This parameter prevents the search process from repeating the same solution pattern and encourages it to continue exploring alternative solutions.

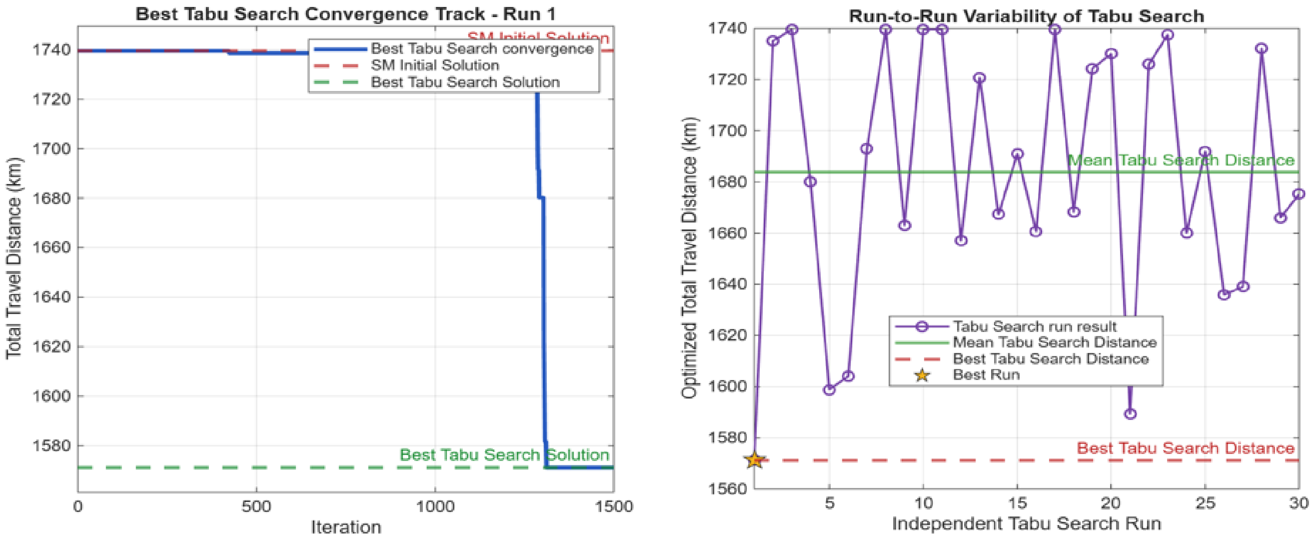

Figure 6. Convergence and Run-to-Run Variability of Tabu Search as a Benchmarking Method

Figure 6 shows the results of testing SM-TS as a benchmark method. The left graph shows the convergence pattern of the best-so-far value on the best run, run 1. In this run, the initial SM solution was at a distance of 1,739.53 km, then improved during the iteration process to obtain the best solution, TS at 1,571.20 km. The decrease in the best-so-far value indicates that TS improved the initial solution through the process of searching for neighboring solutions until it reached its best solution. The right graph shows the variation in optimization results from 30 independent runs. Based on the graph, the best SM-TS result was obtained in run 1 at a distance of 1,571.20 km, while the average across the 30 runs was 1,683.84 km. The difference between the best and average values indicates that TS performance still varies between runs. Therefore, the SM-TS results were subsequently used as a benchmark to assess whether the primary SM-SA method is capable of producing better and more stable solutions. The benchmark results between SM-SA and SM-TS are presented in Table 8.

Table 8: Benchmark Comparison Between SM-SA and SM-TS

Route	Best Distance (km)	Worst Distance (km)	Mean Distance (km)	Std. Dev (km)	CV (%)	Mean Runtime (s)
SM-SA	1,536.22	1,687.53	1,622.23	38.31	2.36	0.234
SM-TS	1,571.20	1,739.53	1,683.84	50.22	2.98	1.782

Based on Table 8, SM-SA demonstrates superior performance compared to the benchmark method, SM-TS. In terms of solution quality, SM-SA produces a lower best distance by a margin of 34.98 km compared to SM-TS. For the worst distance, SM-SA also outperforms it by a margin of 52 km, while for the mean distance, the difference is 61.61 km. This indicates that SM-SA not only produces a shorter best solution but also has better average performance across 30 independent runs. In terms of stability, SM-SA has a lower standard deviation by a margin of 11.91 km and a smaller coefficient of variation by 0.62 percentage points compared to SM-TS. These values indicate that SM-SA optimization results are more stable and have less variation between runs. Furthermore, in terms of computation time, SM-SA is more efficient, with a mean runtime difference of 1.548 seconds compared to SM-TS. Thus, the benchmark results show that SM-SA achieves better solution quality, greater stability, and higher computational efficiency than SM-TS. These findings reinforce the conclusion that SM-SA is suitable as the primary method for solving the SDMDCVRP case of distributing residual FFB loads.

4. CONCLUSION

This study successfully formulated the Fresh Fruit Bunch (FFB) waste distribution problem at PTPN IV Regional II as a Multi-Depot Separate Delivery Capacity Vehicle Routing Problem (SDMDCVRP). The proposed Saving Matrix–Simulated Annealing approach can generate more efficient distribution routes by considering multiple depots, separate deliveries, vehicle capacity, demand fulfillment, and waste consolidation. The results show that the company's existing route has a total distance of 2,014.98 km with a transportation cost of IDR 1,370,186.40. The SM method reduces the total distance to 1,739.53 km, while the SA solution further reduces it to 1,536.22 km with a transportation cost of IDR 1,044,629.60. Overall, the proposed approach reduces the total distance by 478.76 km (23.76%) compared to the existing route. These findings indicate that the SM-SA approach is effective in improving the efficiency of FFB waste distribution. Experimental validation is also strengthened through a benchmark comparison between SM-SA and SM-Tabu Search (SM-TS). The benchmark results show that SM-SA outperforms SM-TS in terms of solution quality, stability, and computational efficiency. SM-SA produces lower best distance, worst distance, average distance, standard deviation, coefficient of variation, and average execution time than SM-TS. Thus, these benchmark results confirm that SM-SA is not only capable of improving existing routes and Saving Matrix results but also of achieving superior performance compared to other metaheuristic methods. In addition to reducing transportation distances and costs, the proposed approach supports more sustainable logistics practices by increasing vehicle utilization and reducing unnecessary trips, aligning with SDG 9, SDG 12, and SDG 13. Future research is recommended to compare SM-SA with other metaheuristic methods, such as Genetic Algorithm, Particle Swarm Optimization, Ant Colony Optimization, and hybrid methods, to evaluate the relative performance of SM-SA in more complex distributed cases. Furthermore, future research could consider additional operational constraints, such as heterogeneous vehicle capacity, vehicle availability, road conditions, dynamic travel times, and time windows. The model could also be expanded into a multi-objective optimization approach by considering distance, transportation costs, vehicle utilization, fuel consumption, and carbon emissions to strengthen its contribution to sustainable logistics.

REFERENCES

[1] M. Harianto. (2025) Palmco catat produksi cpo meningkat jadi 2,2 juta ton hingga oktober. Antara News.

[2] PTPN IV PalmCo. (2025) Laba ptpn iv palmco tembus rp3,76 triliun. PT Perkebunan Nusantara IV.

[3] M. N. Fauzi and M. Tohir, "Optimizing multimodal transportation and the role of freight forwarding in the palm oil (cpo) supply chain in indonesia," *Jurnal Siber Transportasi dan Logistik*, vol. 3, no. 1, pp. 24–46, 2025.

[4] Y. H. Sidiq, D. Candrahadinata, and E. J. Hayat, "Perencanaan rute transportasi pengangkutan sampah menggunakan metode saving matrix dalam program bank sampah amal haqiqi," *Jurnal Kalibrasi*, vol. 23, no. 1, pp. 126–136, 2025, https://doi.org/10.33364/kalibrasi/v.23-1.2389.

[5] 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, 2022, https://doi.org/10.3390/math10193527.

[6] A. Y. Sitompul and I. Husein, "Application of the clarke and wright savings algorithm to solve the vehicle routing problem in optimizing chip distribution," *Kubik: Jurnal Publikasi Ilmiah Matematika*, vol. 10, no. 1, pp. 78–86, 2025, https://doi.org/10.15575/kubik.v10i1.49162.

[7] N. Hafizah and I. Husein, "Determining the shortest route for lpg gas cylinder distribution using the clarke and wright savings algorithm," *Zero: Jurnal Sains, Matematika dan Terapan*, vol. 7, no. 2, pp. 175–181, 2023, https://doi.org/10.30829/zero.v7i2.19269.

[8] E. Yuliza, Y. Andriani, Indrawati, S. Octarina, and D. P. Ramadani, "Optimization of palm oil distribution routes based on saving matrix and genetic algorithm," *Cauchy: Jurnal Matematika Murni dan Aplikasi*, vol. 10, no. 2, pp. 1251–1265, 2025, https://doi.org/10.18860/cauchy.v10i2.36371.

[9] H. Liu and H. Zhang, "Application of an improved simulated annealing algorithm in satellite network routing," *Journal of Physics: Conference Series*, vol. 2807, no. 1, 2024, https://doi.org/10.1088/1742-6596/2807/1/012028.

[10] S. Lin, V. F. Yu, L. Zhou, and R. Baldacci, "A fast simulated annealing heuristic for the multi-depot two-echelon vehicle routing problem with delivery options," *Transportation Letters*, pp. 921–932, 2023, https://doi.org/10.1080/19427867.2023.2257923.

[11] F. Cardenas-Mariño, E. A. P. Quiroz, R. C. Vilca, E. I. Cahuata, H. R. Enriquez, and R. A. A. Rentería, "Generation of distribution routes with shorter distances and fewer vehicles using the simulated annealing algorithm," *Indonesian Journal of Electrical Engineering and Computer Science*, vol. 40, no. 2, pp. 707–718, 2025, https://doi.org/10.11591/ijeecs.v40.i2.

[12] S. Xiao, P. Peng, P. Zheng, and Z. Wu, "A hybrid adaptive simulated annealing and tempering algorithm for solving the half-open multi-depot vehicle routing problem," *Mathematics*, vol. 12, no. 7, 2024, https://doi.org/10.3390/math12070947.

[13] M. Darwin *et al.*, *Metode Penelitian Pendekatan Kuantitatif.* Bandung: Penerbit Media Sains Indonesia, 2021.

[14] W. M. Fernando, A. Thibbotuwawa, H. N. Perera, P. Nielsen, and D. K. Kilic, "An integrated vehicle routing model to optimize agricultural products distribution in retail chains," *Cleaner Logistics and Supply Chain*, vol. 10, 2024, https://doi.org/10.1016/j.clscn.2023.100137.

[15] P. Pongmanawut, S. Phonin, and C. Likasiri, "Multiple depot split delivery vehicle routing problem with separate backhaul and linehaul customers," *IEEE Access*, vol. 14, pp. 61 262–61 276, 2026, https://doi.org/10.1109/ACCESS.2026.3685172.

[16] A. M. Rajagukguk, E. S. M. Nababan, and P. Gultom, "Logistics distribution optimization model using multi-depot capacitated vehicle routing problem," *Desimal: Jurnal Matematika*, vol. 8, no. 2, pp. 215–224, 2025, https://doi.org/10.24042/cazand26.

[17] A. Z. A. Muhammad, M. E. P. Kaf, N. R. Hasibuan, N. A. Rahmawatie, and A. P. Rifai, "Optimasi open location routing problem menggunakan metode metaheuristik simulated annealing, large neighborhood search, dan adaptive large neighborhood search," *Jurnal Optimasi Teknik Industri*, vol. 7, no. 1, pp. 9–16, 2025, https://doi.org/10.30998/joti.v7i1.24873.