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A Hybrid Sweep-Nearest Neighbor-Tabu Search Method for Solving the CVRP in FMCG Distribution

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Abstract

This study addresses the Capacitated Vehicle Routing Problem (CVRP) in fast-moving consumer goods (FMCG) by proposing distribution using a hybrid approach that combines the Sweep algorithm, Nearest Neighbor method, and Tabu Search. The objective is to satisfy consumer demand and vehicle capacity restrictions while minimizing the overall journey distance. The Sweep algorithm is used to cluster customers based on polar coordinates, the Nearest Neigbor method determines initial delivery routes within each cluster, and Tabu Search refines those routes to find near-optimal solutions. Tested on a dataset of 248 stores in Malang, Indonesia, the method reduced clusters from 26 to 18 (30.77%) and improved route efficiency by 8.72% compared to the company's existing routes. These results demonstrate the practicality and computational efficiency of the proposed hybrid method for large-scale FMCG distribution networks.

Keywords: Capacitated Vehicle Routing Problem (CVRP); Fast Moving Consumer Goods (FMCG); Nearest Neighbor Method; Sweep Algorithm; Tabu Search Algorithm.

1 Introduction

Fast-Moving Consumer Goods (FMCG) are products with relatively low prices, short shelf life, and high turnover rates, such as food, beverages, detergents, cosmetics, and over-the-counter medicines [1]. Since these products are daily necessities, they must be consistently available in retail outlets and markets near residential areas. To ensure this availability, FMCG producers depend on extensive distribution networks involving distributors, retailers, and end consumers [2]. Distribution therefore constitutes a major component of operational costs, making efficiency in this sector a critical concern. As demand grows, companies are required to redesign their distribution systems to fulfill consumer needs in a timely and cost-effective manner [3].

One of the most pressing challenges in FMCG distribution systems is determining efficient delivery routes to minimize the overall cost of travel. The Capacitated Vehicle Routing Problem (CVRP), an optimization problem that seeks to minimize the overall distance traveled by multiple vehicles transporting commodities to customers with given demand, is the mathematical formulation of this issue [4]. A single vehicle may only service a client once under the CVRP; vehicle routes begin and end at the prime depot, and the total demand in a single route cannot be

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greater than the vehicle's maximum capacity [5]. The CVRP has been identified as an NP-hard issue, which means that as the number of clients increases, so does its complexity. This limits the effectiveness of exact algorithms—which are practically only capable of solving small-scale problems—and drives the use of heuristics and metaheuristics to obtain near-optimal solutions in reasonable computational time [6].

One of the most common and widely used approaches to solving the CVRP is the two-phase or cluster-first, route-second (CFRS) method, due to its simplicity in breaking the problem down into smaller parts and its relatively short computation time. In the first stage, all customer points are grouped into clusters based on spatial proximity, and in the second stage, the visit order within each cluster is determined [7]. One of the most well-known algorithms in this method is the Sweep Algorithm, which groups points based on their polar angle relative to the depot [8]. This method is widely applied in the literature due to its satisfactory results and simple implementation [9]. However, polar angle-based clustering has limitations, especially when customer points are radially dispersed or separated by geographical barriers such as rivers, mountains, or ring roads. Nevertheless, this method remains relevant as an initial step in constructing CVRP solutions, especially when combined with other algorithms to refine route sequences and improve the quality of the final solution.

After grouping customers into clusters using the Sweep algorithm, the next step in the two-phase method is to determine an efficient visit order within each cluster. For this stage, one of the most commonly used heuristic methods is the Nearest Neighbor algorithm [10]. This algorithm operates on a simple principle: starting from the initial point (depot), the vehicle always visits the nearest customer who has not yet been visited, and this process is repeated until all points within the cluster have been visited [11]. The main advantage of this method is its simplicity and computational speed, making it highly useful for large-scale problems and as an initial step in solution development [12]. Although it does not guarantee an optimal solution, this algorithm can generate a viable initial route in significantly less time compared to exact methods. In addition to being used as a standalone method, the Nearest Neighbor method is often employed as part of the initial population generation process in metaheuristic algorithms, thereby accelerating convergence toward the optimal solution. Its limitation lies in the possibility of getting stuck in local solutions, especially if the distribution pattern of customer points is uneven [13].

As a method for improving route solutions, Tabu Search (TS) is an effective metaheuristic algorithm for solving CVRP. TS works by searching for neighboring solutions and using tabu memory to avoid previously visited solutions, thereby avoiding local solution traps [14][15]. TS utilizes swap and sub-sequence reversal mechanisms to improve distribution routes [16]. Various studies show that TS is not only applied in logistics but also in energy optimization, power curve modeling, and image encryption. In the context of FMCG distribution, TS can improve the results of initial heuristics such as Nearest Neighbor, producing more efficient and accurate routes [17][18].

Each of the three methods offers complementary strengths that make their integration particularly effective for solving CVRP in FMCG distribution. The Sweep algorithm is advantageous for its simplicity and speed in clustering customer locations while considering vehicle capacity, ensuring scalable grouping in large networks. The Nearest Neighbor method, though heuristic in nature, provides a fast and practical way to generate feasible initial routes within clusters, reducing computation time and offering a reliable starting point for further refinement. Meanwhile, Tabu Search excels in escaping local optima by using memory structures to guide the search toward better solutions, allowing significant improvements over initial routes. Compared to hybrid methods that combine only two approaches, such as Sweep with Genetic Algorithm [9] or Nearest Neighbor with Ant Colony Optimization [19], the integration of Sweep, NN, and TS addresses the full cycle of the CVRP: efficient clustering, rapid route construction, and powerful iterative optimization. While the cluster-first, route-second paradigm is well established in VRP literature, the novelty of this study lies in its practical application to real-world FMCG distribution in Indonesia, where such integrations remain underexplored. By incorporating geospatial data from Google Maps and QGIS and addressing operational challenges such as delivery delays and the high cost of daily-paid drivers, this research demonstrates how classical methods can be effectively adapted to provide measurable economic and operational benefits in large-scale FMCG distribution systems.

2 Methods

This study integrates the Sweep algorithm, the Nearest Neighbour method, and the Tabu Search algorithm to optimize the distribution routes of FMCG at CV Putra Jaya Distribusi. The Nearest Neighbor heuristic was employed to construct the initial solution due to its simplicity, computational efficiency, and ease of implementation for large-scale datasets. Since the initial solution is subsequently refined through Tabu Search, NN provides a practical and reliable starting point [11]. The proposed method aims to minimize the total travel distance while ensuring that vehicle capacity constraints are satisfied and efficient routes are generated for each delivery cluster. The dataset used in this study comprises the coordinates of 248 retail stores and the central depot, along with the demand for each store. The delivery fleet consists of vehicles with fixed capacity Q, serving multiple stores across several route clusters.

The hybrid framework is divided into three sequential stages: (1) clustering with the Sweep algorithm, (2) initial route construction using the NN method, and (3) route optimization using TS. A research flowchart is presented in Figure 1.

2.1 Problem Formulation

Let $G = (V, E)$ be a complete undirected graph, where

- $V = \{v_0, v_1, \dots, v_n\}$ is the set of nodes with depot v_0 and customers $v_1, \dots, v_n$,
- E is the set of edges. Each edge $(i, j) \in E$ is associated with a distance d_{ij}.
- q_i is demand of each customer v_i
- Q is capacity of each vehicle.

The objective is to minimize the total travel distance:

$$\min \sum_{i \in V} \sum_{j \in V} d_{ij}\, x_{ijk}. \tag{1}$$

subject to:

$$x_{ijk} = \begin{cases} 1, & \text{if vehicle } k \text{ travels from } i \text{ to } j, \\ 0, & \text{otherwise.} \end{cases} \tag{2}$$

$$\sum_{i \in V} q_i y_{ik} \leq Q, \quad \forall k, \tag{3}$$

$$\sum_{j \in V} x_{ij} = 1, \quad \forall i \neq 0, \tag{4}$$

$$\sum_{i \in V} x_{ij} = 1, \quad \forall j \neq 0, \tag{5}$$

where a binary variable x_{ij} takes the value 1 if vehicle k travels from node i to node j, and 0 otherwise, and y_{ik} indicates whether customer i is served by vehicle k. Each route starts and ends at the depot, every customer is visited exactly once, and the total demand per route must not exceed vehicle capacity Q.

2.2 Clustering with Sweep Algorithm

The Sweep algorithm clusters customers based on polar coordinates relative to the depot. Each customer location (x, y) is converted into polar coordinates:

$$r = \sqrt{x^2 + y^2} \tag{6}$$

$$\theta = arc \tan \frac{y}{x} \tag{7}$$

Customers are sorted by increasing θ and assigned to clusters sequentially until the accumulated demand reaches the vehicle capacity Q. A new cluster is then created, and the process continues until all customers are assigned. This ensures computational efficiency while respecting capacity constraints..

2.3 Route Construction with Nearest Neighbor

Within each cluster, a preliminary route is built using the Nearest Neighbor method. Starting from the depot, the algorithm iteratively selects the closest unvisited customer until all customers in the cluster have been served, and the vehicle then returns to the depot.

2.4 Route Optimization with Tabu Search

The Tabu Search (TS) algorithm was applied to refine the initial routes generated by the Nearest Neighbor method. Two neighborhood operators were used: swap (exchanging two customers) and reinsertion (relocating a customer within the route). The tabu tenure was set to 6 iterations, with the aspiration criterion allowing moves that improve the best solution. The search terminated after 100 iterations or when no improvement occurred over 20 iterations. These parameters were chosen to balance solution quality and computational efficiency.

The hybrid approach of Sweep, NN, and TS, supported by Google Maps and QGIS for clustering and MATLAB implementation for optimization, provides a practical and efficient solution for CVRP in real-world FMCG distribution.

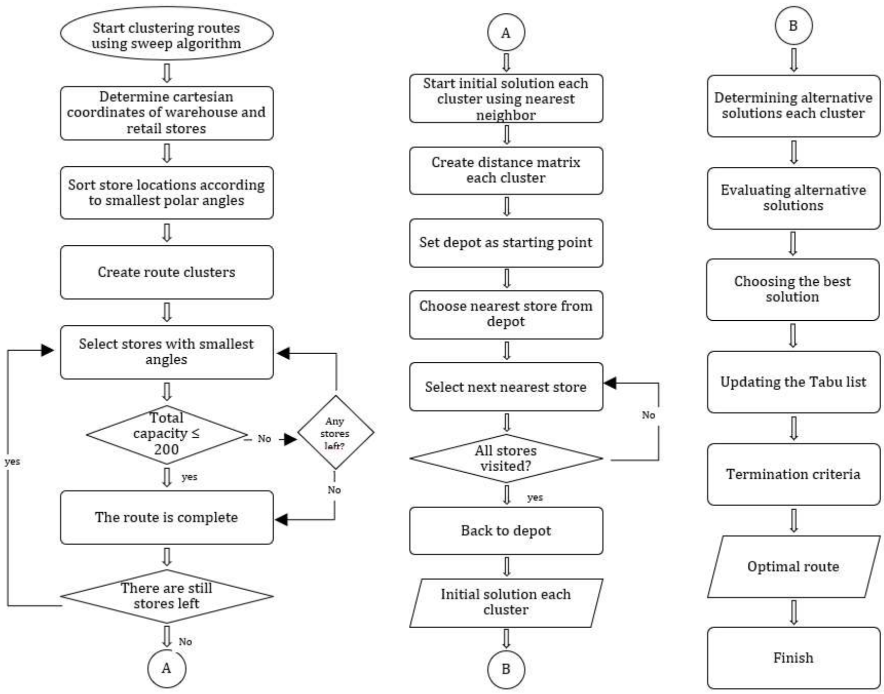

Figure 1: Flowchart of hybrid framework combining Sweep, Nearest Neighbor, and Tabu Search.

3 Results and Discussion

3.1 Clustering using the Sweep Algorithm

The sweep algorithm is one method that can be used to group customer stores based on their geographical location relative to the distributor's warehouse. The steps taken at the clustering stage with the sweep algorithm are

1. The sweep algorithm begins by determining each store's position in Cartesian coordinates and setting the warehouse location as the coordinate center, using the longitude and latitude obtained from Google Maps.
2. Next, the Cartesian coordinates are converted into polar coordinates. Given a customer point with Cartesian coordinates (x, y), the polar coordinates (r, θ) are determined by calculating each store according to Equations 6 and 7. A total of 248 stores were grouped based on their geographic coordinates. The latitude ranges from −7.83 to −8.31, while the longitude ranges from 112.37 to 112.81. The polar angles of the stores vary between 4.68° and 358.68°. The distribution of polar angles is illustrated in Figure 2, where the blue points represent the retail stores and the red star denotes the central depot, whereas the complete list of 248 stores is provided in the appendix.

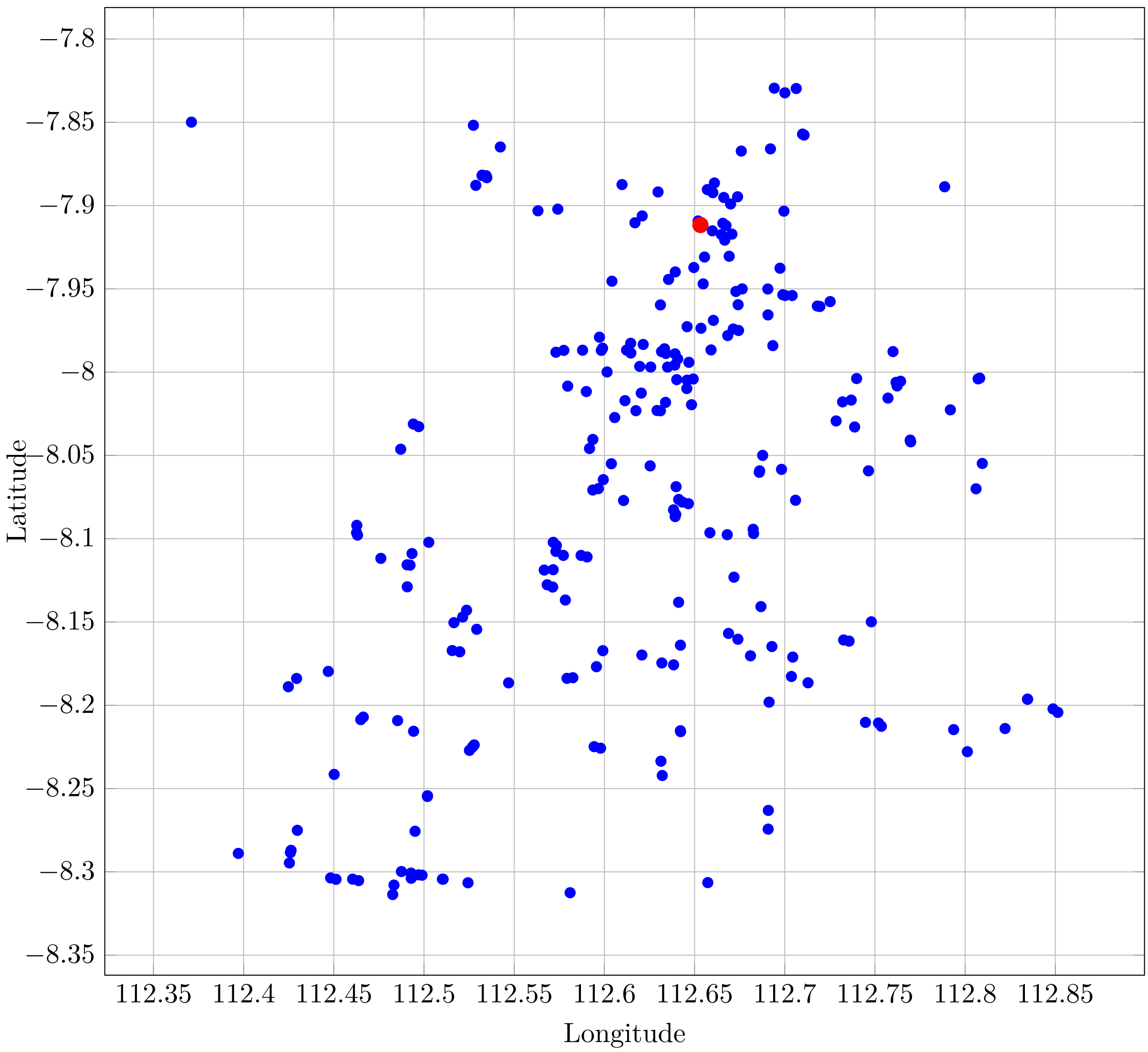

Figure 2: Distribution of store locations based on coordinates

3. A weighted graph is then created by defining vertices as store points and distributors and edges as connecting paths between store points and distributors or between stores, which represent the distribution network. The ranking of stores is then based on the smallest polar angle to the largest polar angle.
4. Cluster formation begins with the point having the smallest polar angle and proceeds to the customer point with the largest polar angle, until the vehicle's capacity limit is reached. Vehicle capacity given is 200.
5. When the next customer point entered exceeds the maximum vehicle capacity limit, clustering is terminated. Every customer chosen for a cluster must have a demand that is less than or equal to the vehicle's capacity.
6. The final cluster is satisfied, and the sweep is continued to build a new cluster. Until all of the client points have been added, the procedure of adding them to the cluster is repeated.

Table 1: Distribution routes of vehicles generated by sweep algorithm

Cluster to	Route	Demand
1	$v_1 \to v_2 \to v_3 \to v_4 \to v_5 \to v_6 \to v_7 \to v_8$	164
2	$v_9 \to v_{10} \to v_{11} \to v_{12} \to v_{13} \to v_{14} \to v_{15} \to v_{16} \to v_{17} \to v_{18} \to v_{19} \to v_{20} \to v_{21} \to v_{22}$	192
3	$v_{23} \to v_{24} \to v_{25} \to v_{26} \to v_{27} \to v_{28} \to v_{29} \to v_{30} \to v_{31} \to v_{32} \to v_{33}$	200
4	$v_{34} \to v_{35} \to v_{36} \to v_{37} \to v_{38} \to v_{39} \to v_{40} \to v_{41} \to v_{42} \to v_{43} \to v_{44} \to v_{45} \to v_{46} \to v_{47} \to v_{48} \to v_{49} \to v_{50} \to v_{51} \to v_{52} \to v_{53} \to v_{54} \to v_{55} \to v_{56} \to v_{57}$	196
5	$v_{58} \to v_{59} \to v_{60} \to v_{61} \to v_{62} \to v_{63} \to v_{64} \to v_{65} \to v_{66} \to v_{67} \to v_{68} \to v_{69} \to v_{70} \to v_{71}$	88
6	$v_{72} \to v_{73} \to v_{74} \to v_{75} \to v_{76} \to v_{77}$	192
7	$v_{78} \to v_{79} \to v_{80} \to v_{81} \to v_{82} \to v_{83} \to v_{84} \to v_{85} \to v_{86} \to v_{87} \to v_{88} \to v_{89} \to v_{90} \to v_{91} \to v_{92} \to v_{93} \to v_{94} \to v_{95} \to v_{96} \to v_{97}$	178
8	$v_{98} \to v_{99} \to v_{100} \to v_{101} \to v_{102} \to v_{103} \to v_{104} \to v_{105} \to v_{106}$	152
9	$v_{107} \to v_{108} \to v_{109} \to v_{110} \to v_{111} \to v_{112} \to v_{113} \to v_{114} \to v_{115} \to v_{116} \to v_{117} \to v_{118} \to v_{119} \to v_{120} \to v_{121} \to v_{122} \to v_{123} \to v_{124} \to v_{125}$	163
10	$v_{126} \to v_{127} \to v_{128} \to v_{129} \to v_{130} \to v_{131} \to v_{132} \to v_{133} \to v_{134} \to v_{135} \to v_{136}$	191
11	$v_{137} \to v_{138} \to v_{139} \to v_{140} \to v_{141} \to v_{142} \to v_{143} \to v_{144} \to v_{145} \to v_{146} \to v_{147} \to v_{148} \to v_{149} \to v_{150} \to v_{151} \to v_{152} \to v_{153} \to v_{154} \to v_{155}$	191
12	$v_{156} \to v_{157} \to v_{158} \to v_{159} \to v_{160} \to v_{161} \to v_{162} \to v_{163}$	128
13	$v_{164} \to v_{165} \to v_{166} \to v_{167} \to v_{168} \to v_{169} \to v_{170} \to v_{171} \to v_{172} \to v_{173} \to v_{174} \to v_{175} \to v_{176}$	192
14	$v_{177} \to v_{178} \to v_{179} \to v_{180} \to v_{181} \to v_{182} \to v_{183}$	195
15	$v_{184} \to v_{185} \to v_{186} \to v_{187} \to v_{188} \to v_{189} \to v_{190} \to v_{191} \to v_{192} \to v_{193} \to v_{194} \to v_{195}$	152
16	$v_{196} \to v_{197} \to v_{198} \to v_{199} \to v_{200}$	198
17	$v_{201} \to v_{202} \to v_{203} \to v_{204} \to v_{205} \to v_{206} \to v_{207} \to v_{208} \to v_{209} \to v_{210} \to v_{211} \to v_{212} \to v_{213} \to v_{214} \to v_{215} \to v_{216} \to v_{217} \to v_{218} \to v_{219} \to v_{220} \to v_{221} \to v_{222} \to v_{223} \to v_{224} \to v_{225} \to v_{226} \to v_{227} \to v_{228} \to v_{229}$	200
18	$v_{230} \to v_{231} \to v_{232} \to v_{233} \to v_{234} \to v_{235} \to v_{236} \to v_{237} \to v_{238} \to v_{239} \to v_{240} \to v_{241} \to v_{242} \to v_{243} \to v_{244} \to v_{245} \to v_{246} \to v_{247} \to v_{248}$	107
	Total demand for cartons	3079

The dataset comprises 248 retail stores with known geographic coordinates and product demand, clustered into feasible delivery groups using the Sweep algorithm. Table 1 presents the cluster allocation, ensuring that total demand within each cluster does not exceed vehicle capacity. The clustering stage successfully reduced the distribution network into manageable subproblems, demonstrating the efficiency of the cluster-first approach for large-scale FMCG delivery systems.

3.2 Route Determination Phase using Nearest Neighbors Method

Once clustering was completed, the Nearest Neighbor (NN) method was applied to construct initial routes. NN produced feasible tours with reasonable computational effort, yet the total travel distance remained relatively high due to its greedy nature, which often leads to suboptimal early decisions. The steps taken in the route determination phase for the initial solution using the nearest neighbor method are

1. Determine the distance matrix for each group by entering the distance between each location point in the graph. The distance matrix is presented in a table format, where the rows represent the origin locations and the columns represent the destination locations. The following is the distance matrix for cluster 1:

Table 2: Distance matrix for cluster 1

	v_0	v_1	v_2	v_3	v_4	v_5	v_6	v_7	v_8
v_0	0.00	2.98	23.13	7.01	3.39	4.11	11.38	11.26	8.84
v_1	3.27	0.00	23.08	6.96	1.41	4.06	11.33	11.21	8.79
v_2	23.72	22.67	0.00	16.12	20.04	19.22	24.58	24.46	25.33
v_3	7.60	6.55	16.12	0.00	3.92	3.10	5.84	5.95	6.72
v_4	3.81	2.76	20.04	3.92	0.00	0.87	9.83	9.71	7.29
v_5	4.70	3.65	19.22	3.10	0.87	0.00	8.99	8.86	6.44
v_6	11.98	10.93	24.61	5.84	9.59	8.96	0.00	0.13	4.61
v_7	11.85	10.80	24.49	5.95	9.47	8.84	0.13	0.00	5.14
v_8	9.43	8.38	25.36	6.72	7.04	6.41	4.61	5.16	0.00

2. Based on the distance matrix in Table 2, begin the travel route from the point designated as the starting point. The list of stores to be visited is $V = v_1, v_2, v_3, v_4, v_5, v_6, v_7, v_8$. The vehicle's capacity is sufficient to serve all customers on a single route.
3. Route building using the Nearest Neighbor method is performed in stages, starting from the depot (v_0), and selecting the closest unvisited customers. At each iteration, the route is temporarily updated until all customers have been visited and the vehicle returns to the depot. The route generated by the Nearest Neighbor method is as follows: $v_0 \to v_1 \to v_4 \to v_5 \to v_3 \to v_6 \to v_7 \to v_8 \to v_2 \to v_0$. The hybrid method consistently reduced total travel distance across clusters. For example, Cluster 1 experienced a 9.2% reduction, decreasing from 68.56 km to 62.23 km. This highlights the local optimization power of TS over NN. The process of calculating each route cluster using the nearest neighbor method is repeated with a similar pattern until the 18th cluster. The following are the results of route calculations using the NN, as shown in Table 3.

3.3 Tabu Search Algorithm

The Tabu Search Algorithm, which has six phases, is the next method. The following parameters were used in this study to guarantee reproducibility: With a tabu tenure of ten iterations, two neighbourhood structures were used, 2-opt and swap, to produce alternate solutions. By avoiding local optima through memory-based constraints and aspiration criteria, Tabu Search improves the initial routes created by the Nearest Neighbor method. This consistently reduces the overall distance between clusters, demonstrating the effectiveness of metaheuristic refinement in the hybrid framework. The following are the steps:

1. Determine the initial solution.
   The initial solution is determined by the nearest neighbor method, as shown in Table 3.

Table 3: Distribution routes of vehicles generated by Nearest Neighbor

Cluster	Route	Distance (km)
1	$v_0 \to v_1 \to v_4 \to v_5 \to v_3 \to v_6 \to v_7 \to v_8 \to v_2 \to v_0$	68.56
2	$v_0 \to v_{17} \to v_{18} \to v_{19} \to v_{16} \to v_{14} \to v_{15} \to v_9 \to v_{12} \to v_{13} \to v_{11} \to v_{10} \to v_{21} \to v_{20} \to v_{22} \to v_0$	88.08
3	$v_0 \to v_{32} \to v_{29} \to v_{33} \to v_{30} \to v_{31} \to v_{26} \to v_{25} \to v_{23} \to v_{24} \to v_{28} \to v_{27} \to v_0$	105.83
4	$v_0 \to v_{44} \to v_{54} \to v_{55} \to v_{43} \to v_{41} \to v_{38} \to v_{52} \to v_{53} \to v_{50} \to v_{48} \to v_{47} \to v_{49} \to v_{42} \to v_{40} \to v_{39} \to v_{37} \to v_{36} \to v_{34} \to v_{35} \to v_{51} \to v_{46} \to v_{45} \to v_{57} \to v_{56} \to v_0$	215.81
5	$v_0 \to v_{71} \to v_{70} \to v_{65} \to v_{58} \to v_{68} \to v_{69} \to v_{66} \to v_{59} \to v_{67} \to v_{60} \to v_{61} \to v_{62} \to v_{63} \to v_{64} \to v_0$	155.97
6	$v_0 \to v_{72} \to v_{73} \to v_{76} \to v_{74} \to v_{77} \to v_{75} \to v_0$	150.79
7	$v_0 \to v_{80} \to v_{84} \to v_{86} \to v_{79} \to v_{97} \to v_{83} \to v_{85} \to v_{91} \to v_{95} \to v_{94} \to v_{78} \to v_{87} \to v_{88} \to v_{89} \to v_{96} \to v_{92} \to v_{90} \to v_{93} \to v_{82} \to v_{81} \to v_0$	149.06
8	$v_0 \to v_{105} \to v_{104} \to v_{98} \to v_{102} \to v_{101} \to v_{100} \to v_{103} \to v_{106} \to v_{99} \to v_0$	117.28
9	$v_0 \to v_{125} \to v_{122} \to v_{121} \to v_{123} \to v_{117} \to v_{116} \to v_{115} \to v_{112} \to v_{110} \to v_{107} \to v_{111} \to v_{108} \to v_{119} \to v_{109} \to v_{124} \to v_{118} \to v_{120} \to v_{114} \to v_{113} \to v_0$	160.79
10	$v_0 \to v_{127} \to v_{130} \to v_{133} \to v_{132} \to v_{135} \to v_{136} \to v_{129} \to v_{134} \to v_{131} \to v_{128} \to v_{126} \to v_0$	82.97
11	$v_0 \to v_{144} \to v_{147} \to v_{138} \to v_{143} \to v_{142} \to v_{154} \to v_{152} \to v_{145} \to v_{155} \to v_{139} \to v_{149} \to v_{148} \to v_{151} \to v_{153} \to v_{150} \to v_{146} \to v_{141} \to v_{137} \to v_{140} \to v_0$	114.85
12	$v_0 \to v_{162} \to v_{156} \to v_{159} \to v_{161} \to v_{163} \to v_{160} \to v_{157} \to v_{158} \to v_0$	85.99
13	$v_0 \to v_{171} \to v_{168} \to v_{173} \to v_{164} \to v_{165} \to v_{170} \to v_{174} \to v_{176} \to v_{175} \to v_{172} \to v_{166} \to v_{167} \to v_{169} \to v_0$	123.01
14	$v_0 \to v_{180} \to v_{181} \to v_{183} \to v_{179} \to v_{182} \to v_{178} \to v_{177} \to v_0$	109.81
15	$v_0 \to v_{194} \to v_{192} \to v_{193} \to v_{191} \to v_{190} \to v_{195} \to v_{186} \to v_{185} \to v_{188} \to v_{187} \to v_{189} \to v_{184} \to v_0$	90.61
16	$v_0 \to v_{198} \to v_{199} \to v_{197} \to v_{196} \to v_{200} \to v_0$	99.34
17	$v_0 \to v_{221} \to v_{210} \to v_{207} \to v_{227} \to v_{229} \to v_{217} \to v_{204} \to v_{202} \to v_{208} \to v_{225} \to v_{228} \to v_{220} \to v_{219} \to v_{214} \to v_{218} \to v_{224} \to v_{223} \to v_{222} \to v_{211} \to v_{226} \to v_{203} \to v_{201} \to v_{205} \to v_{206} \to v_{209} \to v_{212} \to v_{213} \to v_{215} \to v_{216} \to v_0$	168.22
18	$v_0 \to v_{245} \to v_{246} \to v_{240} \to v_{247} \to v_{248} \to v_{244} \to v_{231} \to v_{235} \to v_{237} \to v_{238} \to v_{241} \to v_{239} \to v_{233} \to v_{234} \to v_{232} \to v_{242} \to v_{243} \to v_{230} \to v_{236} \to v_0$	104.11
	Total distance	**2191.08 km**

2. Determining alternative solutions,
   Finding alternate solutions, specifically by swapping or replacing two points within a single route group, is the second step in solving the tabu search algorithm. Table 3 shows that the sweep algorithm generates eighteen distribution routes, and each node on each route is then swapped to find a different solution that might have a more optimal value.

Table 4: Swap iterations and resulting paths with distances for cluster 1.

No	Swap	Path	Distance (km)
1	$v_1 - v_4$	$v_0 \to v_4 \to v_1 \to v_5 \to v_3 \to v_6 \to v_7 \to v_8 \to v_2 \to v_0$	73.51
2	...	...	...
21	$v_3 - v_8$	$v_0 \to v_1 \to v_4 \to v_5 \to v_8 \to v_6 \to v_7 \to v_3 \to v_2 \to v_0$	62.24

No	Swap	Path	Distance (km)
⋮	⋮	⋮	⋮
28	$v_8 - v_2$	$v_0 \to v_1 \to v_4 \to v_5 \to v_3 \to v_6 \to v_7 \to v_2 \to v_8 \to v_0$	73.58

The stage of determining alternative solutions is carried out up to the 6th iteration and applied to the 18th cluster.

3. Evaluating alternative solutions,
The third step is to evaluate alternative solutions based on the points that have been tried in previous iterations, and determine the solution as a temporary optimum. In route 1 iteration 1 based on Table 4, a temporary optimum solution was obtained by exchanging nodes v_3 and v_8, resulting in a distance of 62.24 km. This exchange led to the route $v_0 - v_1 - v_4 - v_5 - v_8 - v_6 - v_7 - v_3 - v_2 - v_0$. The stage of evaluating alternative solutions is carried out up to the 6th iteration and applied to the 18th cluster.
4. Selecting the best solution,
The fourth step is to choose the best optimum solution among all the alternative solution lists. If the solution is smaller than the initial solution, it will be selected as the new optimum solution. The value of the optimum solution in iteration 1 is smaller than that of the initial solution, so it is chosen as the new optimum solution. The stage of selecting the optimum solution is carried out until the 6th iteration and applied to the 18th cluster.
5. Updating the tabu list.
Updating the tabu list is the fifth step. The tabu list will be used as a solution for the following iteration until a new optimal solution is discovered. Table 5 displays the tabu list of the initial cluster route. The outcomes of alternate routes with the shortest distance at each iteration are stored in the tabu list. After then, every route in the tabu list is compared, and the one with the least distance is chosen. The route generated by the Tabu Search algorithm is $v_0 - v_1 - v_4 - v_5 - v_8 - v_6 - v_7 - v_3 - v_2 - v_0$ with a total distance of $62,23$ km.

Table 5: Tabu list for route cluster 1

Iteration	Swap	Route	Total distance
1	$(v_3 - v_8)$	$v_0 \to v_1 \to v_4 \to v_5 \to v_8 \to v_6 \to v_7 \to v_3 \to v_2 \to v_0$	62,23 km
2	$(v_6 - v_7)$	$v_0 \to v_1 \to v_4 \to v_5 \to v_8 \to v_7 \to v_6 \to v_3 \to v_2 \to v_0$	62,67 km
3	$(v_7 - v_6)$	$v_0 \to v_1 \to v_4 \to v_5 \to v_8 \to v_6 \to v_7 \to v_3 \to v_2 \to v_0$	62,23 km
4	$(v_3 - v_2)$	$v_0 \to v_1 \to v_4 \to v_5 \to v_8 \to v_6 \to v_7 \to v_2 \to v_3 \to v_0$	64,65 km
5	$(v_2 - v_3)$	$v_0 \to v_1 \to v_4 \to v_5 \to v_8 \to v_6 \to v_7 \to v_3 \to v_2 \to v_0$	62,23 km
6	$(v_6 - v_7)$	$v_0 \to v_1 \to v_4 \to v_5 \to v_8 \to v_7 \to v_6 \to v_3 \to v_2 \to v_0$	62,67 km

6. Termination criteria.
The sixth step is termination. If all criteria have been met, the search is terminated; otherwise, it will return to step 2.

Table 6: Optimal route using Sweep, Nearest Neighbor, and Tabu Search

Cluster to	Route	Distance (km)
Cluster 1	$v_0 \to v_1 \to v_4 \to v_5 \to v_8 \to v_6 \to v_7 \to v_3 \to v_2 \to v_0$	62,23
Cluster 2	$v_0 \to v_{17} \to v_{19} \to v_{18} \to v_{16} \to v_{14} \to v_{15} \to v_9 \to v_{12} \to v_{13} \to v_{11} \to v_{10} \to v_{22} \to v_{20} \to v_{21} \to v_0$	87,20
Cluster 3	$v_0 \to v_{29} \to v_{32} \to v_{33} \to v_{30} \to v_{31} \to v_{26} \to v_{25} \to v_{23} \to v_{24} \to v_{28} \to v_{27} \to v_0$	05,39
Cluster 4	$v_0 \to v_{44} \to v_{54} \to v_{55} \to v_{43} \to v_{38} \to v_{41} \to v_{52} \to v_{53} \to v_{50} \to v_{49} \to v_{47} \to v_{48} \to v_{42} \to v_{40} \to v_{37} \to v_{36} \to v_{35} \to v_{34} \to v_{39} \to v_{51} \to v_{46} \to v_{45} \to v_{56} \to v_{57} \to v_0$	207,38

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Cluster to	Route	Distance (km)
Cluster 5	$v_0 \to v_{71} \to v_{70} \to v_{65} \to v_{58} \to v_{68} \to v_{69} \to v_{66} \to v_{67} \to v_{59} \to v_{60} \to v_{61} \to v_{62} \to v_{63} \to v_{64} \to v_0$	155,97
Cluster 6	$v_0 \to v_{72} \to v_{73} \to v_{76} \to v_{75} \to v_{77} \to v_{74} \to v_0$	150,48
Cluster 7	$v_0 \to v_{80} \to v_{84} \to v_{86} \to v_{79} \to v_{97} \to v_{83} \to v_{85} \to v_{91} \to v_{95} \to v_{94} \to v_{78} \to v_{87} \to v_{88} \to v_{89} \to v_{96} \to v_{92} \to v_{90} \to v_{81} \to v_{82} \to v_{93} \to v_0$	149,06
Cluster 8	$v_0 \to v_{105} \to v_{104} \to v_{98} \to v_{102} \to v_{101} \to v_{99} \to v_{103} \to v_{106} \to v_{100} \to v_0$	117,28
Cluster 9	$v_0 \to v_{125} \to v_{122} \to v_{121} \to v_{123} \to v_{117} \to v_{116} \to v_{115} \to v_{112} \to v_{124} \to v_{118} \to v_{110} \to v_{107} \to v_{108} \to v_{111} \to v_{119} \to v_{109} \to v_{120} \to v_{114} \to v_{113} \to v_0$	132,96
Cluster 10	$v_0 \to v_{127} \to v_{130} \to v_{133} \to v_{135} \to v_{132} \to v_{136} \to v_{129} \to v_{134} \to v_{131} \to v_{128} \to v_{126} \to v_0$	82,97
Cluster 11	$v_0 \to v_{144} \to v_{147} \to v_{138} \to v_{143} \to v_{142} \to v_{154} \to v_{152} \to v_{155} \to v_{145} \to v_{139} \to v_{149} \to v_{148} \to v_{151} \to v_{153} \to v_{150} \to v_{146} \to v_{140} \to v_{137} \to v_{141} \to v_0$	114,31
Cluster 12	$v_0 \to v_{162} \to v_{156} \to v_{159} \to v_{161} \to v_{163} \to v_{160} \to v_{158} \to v_{157} \to v_0$	85,99
Cluster 13	$v_0 \to v_{171} \to v_{168} \to v_{173} \to v_{164} \to v_{165} \to v_{170} \to v_{174} \to v_{176} \to v_{172} \to v_{175} \to v_{166} \to v_{167} \to v_{169} \to v_0$	122,49
Cluster 14	$v_0 \to v_{180} \to v_{181} \to v_{183} \to v_{179} \to v_{177} \to v_{178} \to v_{182} \to v_0$	109,81
Cluster 15	$v_0 \to v_{194} \to v_{192} \to v_{193} \to v_{191} \to v_{190} \to v_{195} \to v_{186} \to v_{185} \to v_{187} \to v_{189} \to v_{188} \to v_{184} \to v_0$	90,53
Cluster 16	$v_0 \to v_{198} \to v_{199} \to v_{197} \to v_{200} \to v_{196} \to v_0$	99,34
Cluster 17	$v_0 \to v_{221} \to v_{210} \to v_{207} \to v_{227} \to v_{229} \to v_{217} \to v_{204} \to v_{202} \to v_{208} \to v_{225} \to v_{228} \to v_{220} \to v_{219} \to v_{214} \to v_{218} \to v_{224} \to v_{226} \to v_{223} \to v_{222} \to v_{211} \to v_{203} \to v_{201} \to v_{205} \to v_{206} \to v_{209} \to v_{212} \to v_{216} \to v_{215} \to v_{213} \to v_0$	165,07
Cluster 18	$v_0 \to v_{245} \to v_{246} \to v_{240} \to v_{248} \to v_{247} \to v_{244} \to v_{231} \to v_{235} \to v_{237} \to v_{238} \to v_{241} \to v_{239} \to v_{233} \to v_{232} \to v_{234} \to v_{243} \to v_{242} \to v_{236} \to v_{230} \to v_0$	102,82
	Total distance	**2141,31 km**

The Nearest Neighbor heuristic is prone to local optima because it always chooses the closest next node, often ignoring global efficiency. Tabu Search improves this by diversifying the search through memory structures and prohibiting recently visited solutions, which prevents cycling. For instance, in Cluster 5, NN produced a detour that increased distance by 12%, while TS corrected this by relocating nodes across adjacent routes, reducing total distance. This indicates that TS not only improves solution quality but also balances load across vehicles, which is particularly valuable in FMCG distribution where delivery frequency is high.

3.4 Comparison with Existing Routes

The company's existing routes are constructed manually by drivers based on their experience and practical knowledge of the delivery area, without the aid of optimization algorithms. This manual approach often results in a large number of clusters, which in turn leads to delivery delays and higher operational costs, since each cluster requires a driver who is compensated on a daily basis. Table 7 shows the results of the route distance recap for one period implemented by the company.

Table 7: Existing route of the company

Route	Path	Distance
1	$v_0 \to v_{105} \to v_0$	24.94km
2	$v_0 \to v_{18} \to v_{125} \to v_{164} \to v_0$	34.72 km
3	$v_0 \to v_{132} \to v_{107} \to v_{134} \to v_{131} \to v_{128} \to v_{126} \to v_{88} \to v_{103} \to v_{106} \to v_{92} \to v_0$	125.13 km
4	$v_0 \to v_9 \to v_7 \to v_6 \to v_{168} \to v_{173} \to v_{154} \to v_{145} \to v_{155} \to v_{162} \to v_{139} \to v_0$	61.53 km
5	$v_0 \to v_{86} \to v_{71} \to v_{70} \to v_{44} \to v_{43} \to v_{121} \to v_{135} \to v_{139} \to v_{161} \to v_{163} \to v_{160} \to v_{119} \to v_{124} \to v_{118} \to v_0$	106.24 km
6	$v_0 \to v_{84} \to v_{127} \to v_{130} \to v_{33} \to v_0$	32.16 km
7	$v_0 \to v_{54} \to v_{41} \to v_{38} \to v_{58} \to v_{117} \to v_{115} \to v_{112} \to v_{129} \to v_{66} \to v_{73} \to v_{76} \to v_0$	95.20 km
8	$v_0 \to v_{28} \to v_{27} \to v_0$	97.25 km
9	$v_0 \to v_{195} \to v_{187} \to v_{196} \to v_{201} \to v_{205} \to v_{206} \to v_{209} \to v_{212} \to v_{213} \to v_{215} \to v_{216} \to v_{199} \to v_0$	135.73 km
10	$v_0 \to v_{246} \to v_{245} \to v_1 \to v_4 \to v_{14} \to v_{16} \to v_{15} \to v_{72} \to v_{136} \to v_{214} \to v_{218} \to v_{223} \to v_{222} \to v_{224} \to v_{211} \to v_{230} \to v_{226} \to v_0$	103.60 km
11	$v_0 \to v_{116} \to v_{74} \to v_{67} \to v_{59} \to v_{57} \to v_{51} \to v_{46} \to v_{45} \to v_{60} \to v_{89} \to v_{99} \to v_{96} \to v_{90} \to v_{93} \to v_{114} \to v_0$	151.72 km
12	$v_0 \to v_{227} \to v_{237} \to v_{194} \to v_{31} \to v_{22} \to v_{25} \to v_{23} \to v_{24} \to v_{26} \to v_0$	63.43 km
13	$v_0 \to v_{108} \to v_{146} \to v_{150} \to v_{166} \to v_{167} \to v_{157} \to v_{178} \to v_{177} \to v_{169} \to v_{182} \to v_0$	126.19 km

Continued on next page

Table 7 – *continued from previous page*

Route	Path	Distance (km)
14	$v_0 \to v_5 \to v_{239} \to v_{228} \to v_{220} \to v_{219} \to v_{193} \to v_{190} \to v_{191} \to v_{198} \to v_{186} \to v_{185} \to v_{170} \to v_{156} \to v_{149} \to v_{52} \to v_0$	90.46 km
15	$v_0 \to v_{68} \to v_{69} \to v_{53} \to v_{50} \to v_{48} \to v_{47} \to v_{49} \to v_{42} \to v_{40} \to v_{39} \to v_{37} \to v_{36} \to v_{34} \to v_{35} \to v_0$	112.52 km
16	$v_0 \to v_{144} \to v_{221} \to v_{210} \to v_{207} \to v_{181} \to v_{217} \to v_{235} \to v_{241} \to v_{234} \to v_{233} \to v_{232} \to v_{242} \to v_{243} \to v_{236} \to v_2 \to v_0$	124.05 km
17	$v_0 \to v_{122} \to v_0$	23.55 km
18	$v_0 \to v_{80} \to v_{171} \to v_{147} \to v_{138} \to v_{142} \to v_{192} \to v_{244} \to v_{238} \to v_{225} \to v_{65} \to v_{32} \to v_{29} \to v_0$	87.00 km
19	$v_0 \to v_{194} \to v_{104} \to v_{97} \to v_{83} \to v_{85} \to v_{98} \to v_{78} \to v_{137} \to v_{141} \to v_{158} \to v_{140} \to v_{21} \to v_0$	171.48 km
20	$v_0 \to v_9 \to v_{19} \to v_{30} \to v_{26} \to v_{20} \to v_0$	50.97 km
21	$v_0 \to v_{79} \to v_{123} \to v_{91} \to v_{95} \to v_{110} \to v_{94} \to v_{111} \to v_{189} \to v_{197} \to v_{203} \to v_{200} \to v_0$	119.40 km
22	$v_0 \to v_{240} \to v_{247} \to v_{229} \to v_{231} \to v_{202} \to v_{208} \to v_{154} \to v_{143} \to v_{152} \to v_{133} \to v_0$	43.36 km
23	$v_0 \to v_{108} \to v_{109} \to v_{102} \to v_{101} \to v_{100} \to v_{87} \to v_{113} \to v_{120} \to v_{82} \to v_{81} \to v_{75} \to v_{77} \to v_{64} \to v_{63} \to v_{62} \to v_{61} \to v_{56} \to v_{184} \to v_0$	165.18 km
24	$v_0 \to v_{248} \to v_{12} \to v_8 \to v_6 \to v_7 \to v_{13} \to v_{11} \to v_{10} \to v_3 \to v_0$	46.79 km
25	$v_0 \to v_{183} \to v_{175} \to v_{172} \to v_{179} \to v_{188} \to v_0$	78.14 km
26	$v_0 \to v_{17} \to v_{180} \to v_{204} \to v_{156} \to v_{159} \to v_{165} \to v_{148} \to v_{151} \to v_{153} \to v_{174} \to v_{186} \to v_{176} \to v_0$	75.15 km
	Total distance	**2345.90 km**

The company's existing routes, which serve as the primary benchmark, are constructed manually by drivers based on their practical knowledge rather than formal optimization techniques. This manual approach often produces a large number of clusters, leading to delivery delays and increased operational costs, as each cluster requires a daily-paid driver. The proposed hybrid method reduced the total travel distance from 2,345.90 km to 2,141.31 km (an improvement of 8.72%) while also decreasing the number of clusters, thereby lowering labor costs and enhancing delivery reliability. Although the distance reduction may appear modest, in the FMCG distribution context such improvements are practically significant because they directly translate into financial savings and more consistent service performance. While the present study focuses on comparing the hybrid approach with the real-world baseline of the company's manual system, future research may extend the evaluation by benchmarking against well-established VRP heuristics such as the Clarke and Wright Savings algorithm to further validate the robustness of the method.

Table 8: Comparison of the combination of the three methods and the existing route

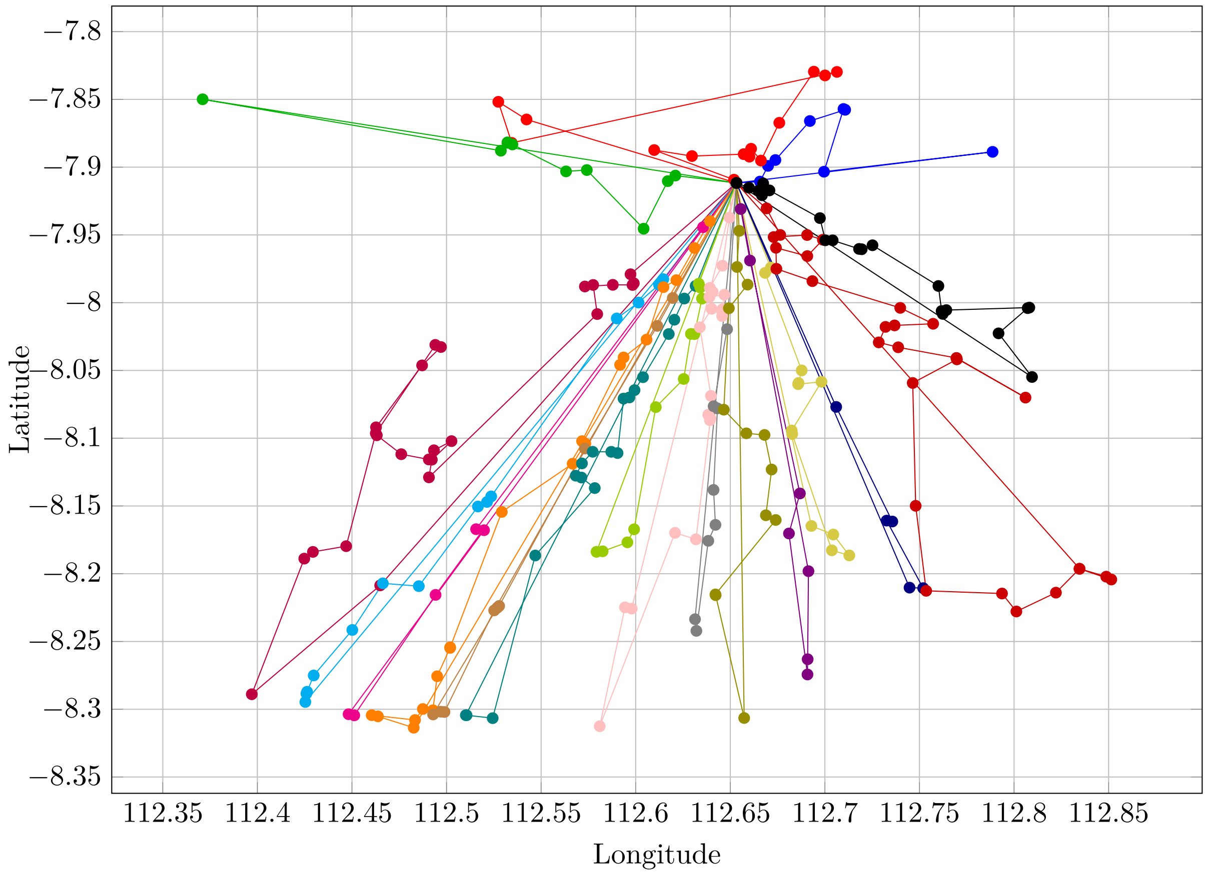
Metric	Existing System	Proposed Method	Improvement
Number of Clusters	26	18	↓ 30.77%
Total distance (km)	2345.90	2141.31	↓ 8.72%

The visualization of the distribution routes is presented in Figure 3, which presents the optimized distribution routes generated using a combination of the Sweep Algorithm, Nearest Neighbor, and Tabu Search.

These results confirm the advantage of combining simple heuristics with metaheuristic refinement in FMCG distribution. While NN provides a quick and feasible baseline solution, TS leverages iterative search to significantly enhance efficiency without incurring prohibitive computational costs. For FMCG companies, such improvements translate into tangible operational benefits, including reduced fuel consumption, lower distribution costs, and potentially shorter delivery times—factors critical in maintaining competitiveness in fast-moving consumer sectors.

4 Conclusion

This study demonstrates that a Sweep–Nearest Neigbor–Tabu Search hybrid framework can significantly reduce the number of routes and total distribution distance in FMCG distribution. The approach reduced both the number of clusters (by 30.77%) and total distance traveled (by 8.72%) compared to the existing system. Beyond confirming its practical benefits, the study



Route 1: $v_0 \to v_1 \to v_4 \to v_5 \to v_8 \to v_6 \to v_7 \to v_3 \to v_2 \to v_0$

Route 2: $v_0 \to v_{17} \to v_{19} \to v_{18} \to v_{16} \to v_{14} \to v_{15} \to v_9 \to v_{12} \to v_{13} \to v_{11} \to v_{10} \to v_{22} \to v_{20} \to v_{21} \to v_0$

Route 3: $v_0 \to v_{29} \to v_{32} \to v_{33} \to v_{30} \to v_{31} \to v_{26} \to v_{25} \to v_{23} \to v_{24} \to v_{28} \to v_{27} \to v_0$

Route 4: $v_0 \to v_{44} \to v_{54} \to v_{55} \to v_{43} \to v_{38} \to v_{41} \to v_{52} \to v_{53} \to v_{50} \to v_{49} \to v_{47} \to v_{48} \to v_{42} \to v_{40} \to v_{37} \to v_{36} \to v_{35} \to v_{34} \to v_{39} \to v_{51} \to v_{46} \to v_{45} \to v_{56} \to v_{57} \to v_0$

Route 5: $v_0 \to v_{71} \to v_{70} \to v_{65} \to v_{58} \to v_{68} \to v_{69} \to v_{66} \to v_{67} \to v_{59} \to v_{60} \to v_{61} \to v_{62} \to v_{63} \to v_{64} \to v_0$

Route 6: $v_0 \to v_{72} \to v_{73} \to v_{76} \to v_{75} \to v_{77} \to v_{74} \to v_0$

Route 7: $v_0 \to v_{80} \to v_{84} \to v_{86} \to v_{79} \to v_{97} \to v_{83} \to v_{85} \to v_{91} \to v_{95} \to v_{94} \to v_{78} \to v_{87} \to v_{88} \to v_{89} \to v_{96} \to v_{92} \to v_{90} \to v_{81} \to v_{82} \to v_{93} \to v_0$

Route 8: $v_0 \to v_{105} \to v_{104} \to v_{98} \to v_{102} \to v_{101} \to v_{99} \to v_{103} \to v_{106} \to v_{100} \to v_0$

Route 9: $v_0 \to v_{125} \to v_{122} \to v_{121} \to v_{123} \to v_{117} \to v_{116} \to v_{115} \to v_{112} \to v_{124} \to v_{118} \to v_{110} \to v_{107} \to v_{108} \to v_{111} \to v_{119} \to v_{109} \to v_{120} \to v_{114} \to v_{113} \to v_0$

Route 10: $v_0 \to v_{127} \to v_{130} \to v_{133} \to v_{135} \to v_{132} \to v_{136} \to v_{129} \to v_{134} \to v_{131} \to v_{128} \to v_{126} \to v_0$

Route 11: $v_0 \to v_{144} \to v_{147} \to v_{138} \to v_{143} \to v_{142} \to v_{154} \to v_{152} \to v_{155} \to v_{145} \to v_{139} \to v_{149} \to v_{148} \to v_{151} \to v_{153} \to v_{150} \to v_{146} \to v_{140} \to v_{137} \to v_{141} \to v_0$

Route 12: $v_0 \to v_{162} \to v_{156} \to v_{159} \to v_{161} \to v_{163} \to v_{160} \to v_{158} \to v_{157} \to v_0$

Route 13: $v_0 \to v_{171} \to v_{168} \to v_{173} \to v_{164} \to v_{165} \to v_{170} \to v_{174} \to v_{176} \to v_{172} \to v_{175} \to v_{166} \to v_{167} \to v_{169} \to v_0$

Route 14: $v_0 \to v_{180} \to v_{181} \to v_{183} \to v_{179} \to v_{177} \to v_{178} \to v_{182} \to v_0$

Route 15: $v_0 \to v_{194} \to v_{192} \to v_{193} \to v_{191} \to v_{190} \to v_{195} \to v_{186} \to v_{185} \to v_{187} \to v_{189} \to v_{188} \to v_{184} \to v_0$

Route 16: $v_0 \to v_{198} \to v_{199} \to v_{197} \to v_{200} \to v_{196} \to v_0$

Route 17: $v_0 \to v_{221} \to v_{210} \to v_{207} \to v_{227} \to v_{229} \to v_{217} \to v_{204} \to v_{202} \to v_{208} \to v_{225} \to v_{228} \to v_{220} \to v_{219} \to v_{214} \to v_{218} \to v_{224} \to v_{226} \to v_{223} \to v_{222} \to v_{211} \to v_{203} \to v_{201} \to v_{205} \to v_{206} \to v_{209} \to v_{212} \to v_{216} \to v_{215} \to v_{213} \to v_0$

Route 18: $v_0 \to v_{245} \to v_{246} \to v_{240} \to v_{248} \to v_{247} \to v_{244} \to v_{231} \to v_{235} \to v_{237} \to v_{238} \to v_{241} \to v_{239} \to v_{233} \to v_{232} \to v_{234} \to v_{243} \to v_{242} \to v_{236} \to v_{230} \to v_0$

Figure 3: Visualization of optimal route

highlights the importance of combining constructive heuristics with metaheuristic refinements to overcome local optima. Future research could extend this work by integrating multi-depot or time-window constraints, exploring adaptive Tabu tenure mechanisms, or hybridizing with evolutionary algorithms such as Genetic Algorithm or Particle Swarm Optimization to further enhance robustness. Additionally, testing on dynamic datasets with fluctuating demand would provide stronger validation for real-world logistics environments.

CRediT Authorship Contribution Statement

Sikhatun Naimah Evary: Conceptualization, Methodology, Writing–Original Draft. **Sobri Abusini:** Data Curation, Formal Analysis, Writing–Review & Editing. **Mohamad Muslikh:** Software, Validation, Visualization.

Declaration of Generative AI and AI-assisted technologies

No generative AI or AI-assisted technologies were used during the preparation of this manuscript.

Declaration of Competing Interest

The authors declare no competing interests

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Data and Code Availability

The data supporting the findings of this study are available from the corresponding author upon reasonable request and subject to confidentiality agreements

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