Optimization Of Vehicle Routing Problem With Time Windows (VRPTW) Using Hybrid Ant Colony Optimization (ACO) On Food Product Distribution Routes

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Abstract

The problem of vehicle scheduling and route optimization in food product distribution is a complex logistical challenge, especially when considering customer time window constraints and vehicle capacity. This study aims to implement a combination of Ant Colony Optimization (ACO) and Nearest Neighbor (NN) to solve the Vehicle Routing Problem with Time Windows (VRPTW) in the distribution system of HoneyBee Bakery & Cake. The Nearest Neighbor (NN) method is used to generate the initial solution, while Ant Colony Optimization (ACO) is applied to further optimize the route. The experimental results show that the Hybrid ACO approach reduced the initial NN solution from 72.55 km to 58.59 km, with four vehicle returns to the depot, representing a 19.24% reduction in travel distance. In comparison, standard ACO also obtained a final distance of 58.59 km with four vehicle returns to the depot. However, Hybrid ACO reached the final distance in 10 iterations, compared with 46 iterations for standard ACO in the conducted experiment. These results indicate that NN initialization can help reduce the number of iterations required to reach the final solution in the tested distribution case.

Keywords*—Vehicle Routing Problem with Time Windows, Ant Colony Optimization, Nearest Neighbor*

1. INTRODUCTION

In the logistics sector, efficient distribution is crucial to ensure timely product availability at various locations. In the food industry, the main challenge lies in optimizing delivery routes since products are highly sensitive to time and quality. Inefficient distribution may cause product spoilage and customer dissatisfaction. HoneyBee Bakery & Cake is a micro-enterprise specializing in bakery products such as donuts. It distributes its products daily across Palembang. The company experiences issues with delayed deliveries due to non-optimal route planning, highlighting the need for an intelligent routing solution.

The Vehicle Routing Problem with Time Windows (VRPTW) addresses the optimization of vehicle routes under constraints such as delivery time windows and vehicle capacities. A variant of the Vehicle Routing Problem (VRP), VRPTW is a combinatorial problem that seeks to minimize total travel cost while fulfilling constraints related to time and capacity. This research utilizes a hybrid approach by combining Nearest Neighbor (NN) and Ant Colony Optimization (ACO). NN serves as the initial solution constructor by quickly identifying nearby delivery points, while ACO optimizes these routes by simulating ant behavior using pheromone trails. The objective is to enhance delivery efficiency for HoneyBee Bakery.

According to [1], distribution is the process of delivering goods or services from producers to consumers at the time they are needed. This definition highlights the importance of timely delivery in ensuring customer satisfaction and maintaining product quality. In the food sector, delays in delivery can lead to freshness degradation or spoilage. Thus, a well-optimized routing strategy is essential to meet customer expectations and reduce operational inefficiencies.

2. LITERATURE STUDY

2.1. Distribution

Distribution refers to the process of delivering goods or services from producers to consumers. According to [2], it involves managing goods, determining delivery routes, and controlling delivery timing. In the context of food logistics, efficient distribution ensures products arrive fresh, in good condition, and on time, minimizing waste and maximizing customer satisfaction.

2.2 Vehicle routing problem

Vehicle Routing Problem (VRP), introduced by Dantzig and Ramser in 1959, is a generalization of the Traveling Salesman Problem (TSP). It is a combinatorial problem where a fleet of vehicles must serve a set of geographically scattered customers while minimizing total travel cost or time. According to [3], Vehicle Routing Problem (VRP) is a combinatorial problem aimed at determining distribution routes that can be applied to commodity distribution mechanisms, with the goal of finding efficient delivery routes. This perspective emphasizes the practical use of VRP in optimizing real-world logistics operations, especially in the distribution of goods or services.

Several variants of VRP have been developed to handle different real-world constraints, such as Capacitated VRP (CVRP), VRP with Pickup and Delivery (VRPPD), VRP with Time Windows (VRPTW), and Multi Depot VRP (MDVRP), each designed to solve specific distribution challenges in logistics systems.

2.3 Vehicle routing problem with time windows

Vehicle Routing Problem with Time Windows (VRPTW) is a well-known optimization problem that focuses on finding the optimal routes for a fleet of vehicles to serve customers within specified time windows, with the objective of minimizing the total cost or distance traveled [4].

According to [5], the main objective is to minimize the number of vehicles and total travel distance while meeting service time constraints. The mathematical model includes constraints such as vehicle capacity, service time alignment, and arrival within time windows.

Generally, there are two objectives in VRPTW. The primary goal is to minimize the number of vehicles (NV) and the secondary goal is to minimize the total distance (TD) with the same number of routes. VRPTW can be mathematically formulated as follows.

1. Minimize the number of vehicles used.

$$\min NV = K \tag{1}$$

2. Minimize the total travel distance.

$$\min TD = \sum_{i=0}^{M} \sum_{j=0}^{M} \sum_{k=1}^{K} c_{i,j} * x_{i,j}^{k} \tag{2}$$

Subject to the following constraints:

3. If customer (j) is served by vehicle (k), the vehicle must arrive at customer (j) from one of the preceding nodes (i), either the depot or another customer.

$$\sum_{i=0}^{M} x_{i,j}^{k} = y_{j}^{k} \quad \forall k = 1, \dots, K, \quad \forall j = 1, \dots, M \tag{3}$$

4. If vehicle (k) visits customer (i), the vehicle must leave customer (i) and proceed to the next node.

$$\sum_{j=0}^{M} x_{i,j}^{k} = y_i^k \quad \forall k = 1, \dots, K, \quad \forall i = 1, \dots, M \tag{4}$$

5. Each customer can only be visited and served by one vehicle.

$$\sum_{k=1}^{K} y_i^k = 1 \quad \forall i = 1, \dots, M \tag{5}$$

6. The total demand assigned to each vehicle must not exceed its capacity

$$\sum_{i=0}^{M} y_i^k * q_i \leq Q \quad \forall k = 1, \dots, K \tag{6}$$

7. Denotes that all routes start from the depot.

$$\sum_{k=1}^{K} y_0^k = K \tag{7}$$

8. After serving customer *i*, the vehicle must proceed to customer *j*, taking into account the service time and travel distance.

$$t_i + w_j + s_i + c_{i,j} = t_j \quad \forall i, j = 1, \dots, M, i \neq j \tag{8}$$

9. The vehicle's arrival time at each customer must fall within the customer's specified time window.

$$b_j \leq t_j \leq l_j \quad \forall j = 1, \dots, M \tag{9}$$

10. If the vehicle arrives before the beginning of the customer's time window, the vehicle must wait until the service time window opens.

$$w_j = \max\{b_i - (t_i + s_i + c_{i,j}), 0\} \quad \forall i = 1, \dots, M \tag{10}$$

The decision variables are defined as follows:

$$x_{i,j}^{k} = \begin{cases} 1, if\ vehicle\ k \text{ travels directly from } i \text{ to } j \\ 0, \text{otherwise} \end{cases}$$

$$and$$

$$y_i^k = \begin{cases} 1, if\ customer\ i\ is\ served\ by\ vehicle\ k \\ 0, \text{otherwise} \end{cases}$$

Where K and M are the numbers of vehicles and customers, respectively. The variable ti represents the vehicle's arrival time at node i;w_j denotes the waiting time incurred when the vehicle arrives at customer j; $S_i$indicates the service time at node i, and $c_{i,j}$represents the travel time between nodes $i$and j.

2.4 Metaheuristic

Metaheuristic algorithms are search methods inspired by social behavior or natural principles. Unlike traditional algorithms, they combine random processes with local search. The two main parts are exploration, which means searching widely for different solutions, and exploitation, which means focusing on improving good solutions in a local area [6]. According to [7] metaheuristics are computational approaches used to find near-optimal solutions to optimization problems by iteratively improving candidate solutions while considering solution quality constraints. This highlights the strength of metaheuristics in solving complex problems where exact methods are computationally impractical, especially in large-scale combinatorial optimization cases such as vehicle routing.

2.5 Swarm Intelligence Algorithm

Swarm Intelligence Algorithm is a method inspired by how groups of animals like birds, fish, or insects work together in nature. The process starts with an initial setup, then each agent is evaluated using a fitness function. Based on this, agents are updated and guided to find better solutions until a stopping condition is met. In the end, the best solution found is taken as the final result [8]. These algorithms are widely used in optimization because they are good at finding the best solutions efficiently.

2.6 Nearest Neighbor

The Nearest Neighbor method is an algorithm used in the Vehicle Routing Problem (VRP) to determine delivery routes by selecting the nearest customer as the next destination from the current service point. This method is a simple and fast approach to solving VRP however, it does not guarantee an optimal solution as decisions are made solely based on the nearest customer at each step [9].

Due to its simple decision-making process, the Nearest Neighbor method can efficiently construct an initial feasible route based on the proximity of customers. The resulting route can provide a structured starting point for further optimization. However, because NN focuses on local distance at each step, the generated route may still be suboptimal when applied independently.

In this study, the Nearest Neighbor method is used to generate the initial solution for the Hybrid Ant Colony Optimization (ACO) approach. The initial route generated by NN is then improved through ACO to obtain a shorter distribution route while considering the vehicle capacity and customer time window constraints in the VRPTW. Therefore, NN serves as an initialization strategy that provides a feasible starting solution for the subsequent ACO optimization process.

2.7 Ant Colony Optimization

In the early 1990s, M. Dorigo and his team introduced Ant Colony Optimization (ACO), a method inspired by how ants find food. When ants find food, they leave a pheromone trail on the way back to the nest. Other ants follow this trail, and if the path is short and used often, the pheromone becomes stronger. This helps more ants choose the best path. If a path is not used much, the pheromone fades, and ants stop using it.

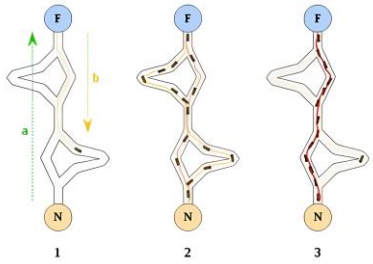

Figure 1. Illustration ants finding food

The more ants use a path, the more likely other ants will follow it. According to [4], here are the steps to solve problems using Ant Colony Optimization and the Vehicle Routing Problem with Time Windows:

1. Randomly choose nodes from depot.
2. Find the highest probability nodes from nodes i to nodes j. Check the distance, time and capacity constraints.

$$P_k(i,j) = \begin{cases} \dfrac{[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}}{\sum_{\text{unvisited customer}}[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}} & jika\ i \neq j \\ atau\ 0 \quad jika\ i = \text{j} \end{cases}$$

3. Update pheromone value

$$P_k(i,j) = \begin{cases} \dfrac{[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}}{\sum_{\text{unvisited customer}}[\tau(i,j)]^{\alpha}[\eta(i,j)]^{\beta}} & jika\ i \neq j \\ atau\ 0 \quad jika\ i = \text{j} \end{cases}$$

4. Find the next highest probability nodes for unvisited nodes and construct a vehicle route.
5. Calculate distance between two customer
6. Construct the final solution.

Ant Colony Optimization (ACO) for solving the Vehicle Routing Problem with Time Windows (VRPTW) is done using the following simple steps:.

1. Initialization: Set VRPTW parameters like customers, time windows, vehicle capacity, and depot. Place one ant for each vehicle and choose a random starting node from the depot.
2. Ant Movement: Each ant moves from the depot and picks the next customer based on probability, making sure the route still follows capacity and time window limits. This continues until all customers are visited or no more can be added.
3. Pheromone Update: After finishing their routes, ants leave pheromones on the paths they used. More pheromone means a higher chance other ants will follow the same path next time.
4. Iterations: Repeat the ant movements and pheromone updates several times or until a stopping condition is reached, to keep improving the route solution.

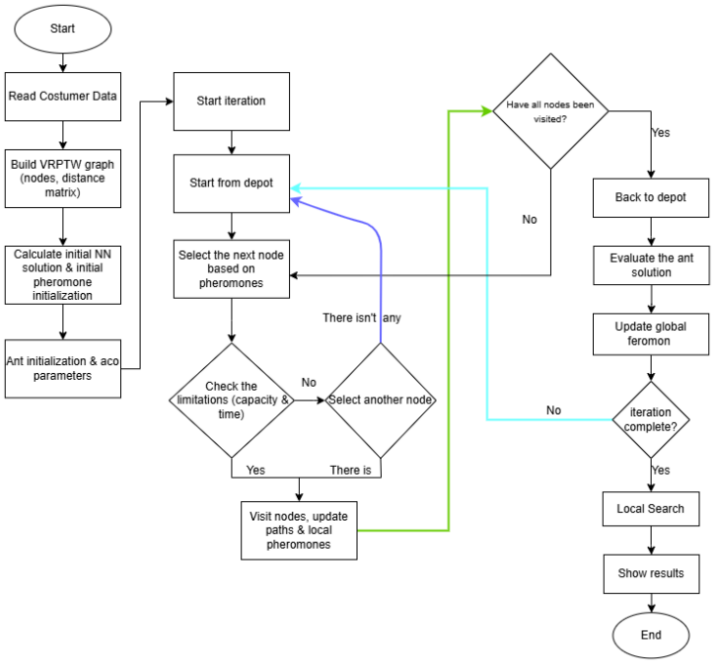

Figure 2. System flowchart of proposed hybrid Nearest Neighbor-Ant Colony Optimization for VRPTW optimization.

2.8 Efficiency

According to [10] efficiency can be defined as optimizing and maximizing an activity or operation appropriately and accurately in order to save or minimize costs, time, and effort. To measure efficiency, the initial distance is compared to the optimized distance, and the result is expressed as a percentage of savings. The following is the efficiency formula:

$$\text{Efficiency} = \frac{Initial\ Distance - \ Optimized\ Distance}{Initial\ Distance} \times 100$$

In this study, the efficiency value represents the percentage reduction in travel distance from the initial solution to the final optimized solution. Therefore, it is not used as a direct measure of superiority between standard ACO and Hybrid ACO.

3. RESEARCH METHODS

3.1. Research Workflow

The research workflow consists of several stages, including data collection, data preprocessing, problem formulation, algorithm implementation, and result evaluation. In the initial stage, distribution data were collected from HoneyBee Bakery & Cake, consisting of customer locations, demand quantities, vehicle capacity, and delivery time windows. The collected data were subsequently processed to ensure consistency and compatibility with the optimization procedure.

Following data preprocessing, the distribution problem was formulated as a Vehicle Routing Problem with Time Windows (VRPTW), aiming to determine efficient delivery routes while satisfying vehicle capacity and customer time window constraints. A hybrid optimization approach combining the Nearest Neighbor (NN) method and Ant Colony Optimization (ACO) was employed to solve the formulated problem.

The Nearest Neighbor method was applied to construct an initial feasible route by iteratively selecting the closest unvisited customer from the current location. The resulting route was then provided as the initial solution for the Ant Colony Optimization algorithm. ACO subsequently refined this solution through pheromone-based search mechanisms to reduce the overall travel distance while preserving the feasibility of vehicle capacity and customer time window constraints. The complete workflow of the proposed optimization approach is presented in Figure 3.

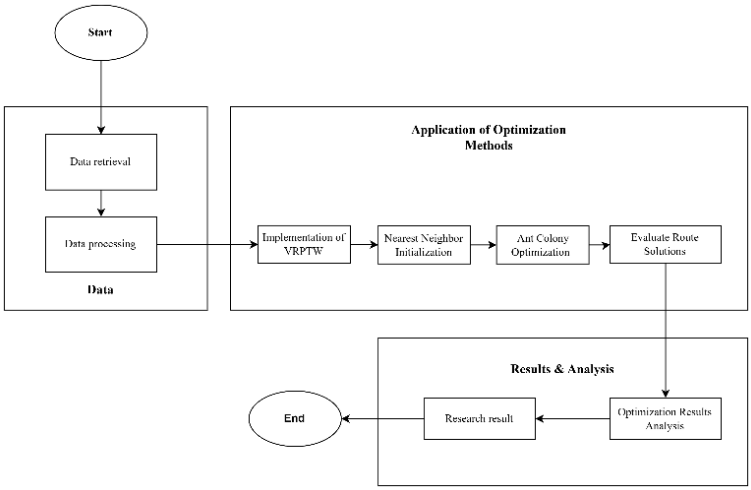

Figure 3. Research Workflow of the proposed hybrid Nearest Neighbor and Ant Colony Optimization Approach for VRPTW Optimization

3.2. Data Collection

This study uses primary data collected from HoneyBee Bakery & Cake. The data includes customer order information such as customer names, locations, distances between locations, number of products ordered, delivery schedule, and vehicle capacity. After collecting the data, it is processed and reformatted to match the needs of the analysis and the Ant Colony Optimization algorithm.

Table 1. Customer Location Data

Id	X	Y	Demand	Ready time	Due time
0	-2.967797	104.726648	0	00:00	00:00
1	-2.980148	104.755182	112	04:00	06:00
2	-2.953332	104.735306	70	04:00	05:00
3	-2.915004	104.680069	40	03:00	05:00
4	-2.997204	104.707322	90	05:00	06:00
5	-2.957643	104.726935	60	06:00	07:00

6	-2.993812	104.726361	30	06:00	07:00
7	-2.955790	104.748410	30	06:00	07:00
8	-2.967871	104.746621	25	06:00	08:00
9	-2.962252	104.749706	25	06:00	08:00

Table 1 presents the customer data utilized in this study, including geographic coordinates, product demand measured in boxes, and the corresponding service time windows. To provide a clearer representation of the spatial distribution of delivery points, the customer coordinates were plotted on a geographic map. This visualization illustrates the relative locations of the customers and the depot within the distribution area.

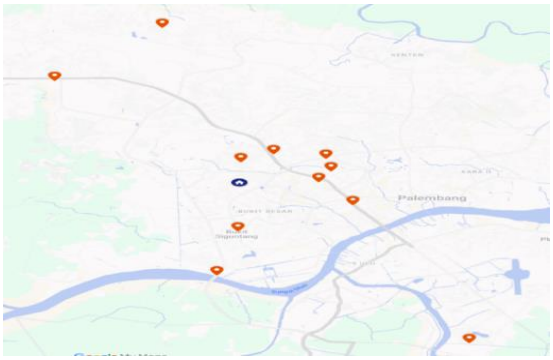

Figure 4. Customer Location Map

Figure 4 illustrates the geographical distribution of customer locations in Palembang. The map provides a visual representation of the delivery area and serves as a reference for constructing and optimizing delivery routes within the VRPTW model

4. RESULTS AND DISCUSSION

The developed application includes several key features such as a file upload option, display of the initial solution, display of the final optimized solution, and settings to adjust ACO parameters. The interface showcasing these features is presented in Fig.5.

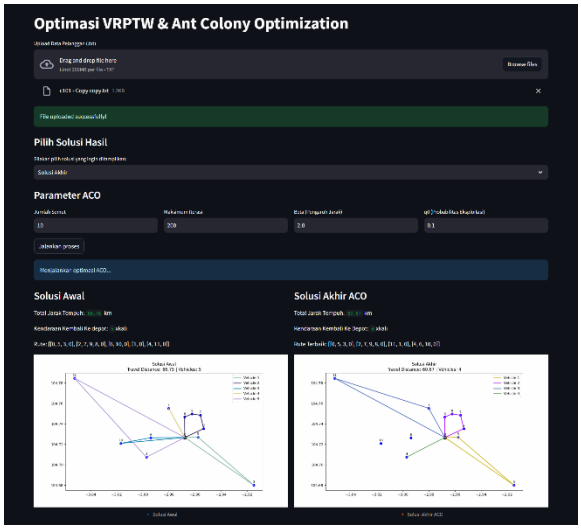

Figure 5. System Interface

4.1. Trial configuration

The experiment uses customer data from HoneyBee Bakery & Cake, including customer locations, demand quantities, and service time. The Hybrid ACO combines Nearest Neighbor (NN) to generate the initial solution with Ant Colony Optimization (ACO) to optimize the route.
The experiments tested different numbers of ants (100, 50, 20, 10, and 5) and Q values (2.0, 1.0, 0.5, 0.3, and 0.1), while the maximum iterations and β were set to 200 and 1.0, respectively. The performance was evaluated based on total travel distance and the number of vehicle returns to the depot.

4.2. Test Result

Table 2. Results of ACO+NN for Different Q Values

Test	**1**	**2**
Number Ant	100	100
Max Iterations	200	200
Beta	1.0	1.0
Q	2.0	1.0
Total Distance	75.77 km	75.77 km
Vehicle Returning to Depot	6 times	6 times

Table 3. Results of ACO+NN for Different Numbers of Ants at Q = 0.5

Test	**1**	**2**	**3**	**4**	**5**
Number Ant	100	50	20	10	5
Max Iterations	200	200	200	200	200
Beta	1.0	1.0	1.0	1.0	1.0
Q	0.5	0.5	0.5	0.5	0.5
Total Distance	59.93 km	59.93 km	60.27 km	61.02 km	59.68 km
Vehicle Returning to Depot	4 times	4 times	4 times	4 times	4 times

Table 4. Results of ACO+NN for Different Numbers of Ants at Q = 0.3

Test	**1**	**2**	**3**	**4**	**5**
Number Ant	100	50	20	10	5
Max Iterations	200	200	200	200	200
Beta	1.0	1.0	1.0	1.0	1.0
Q	0.3	0.3	0.3	0.3	0.3
Total Distance	59.93 km	58.59 km	59.93 km	61.02 km	60.76 km
Vehicle Returning to Depot	4 times	4 times	4 times	4 times	4 times

Table **5.** Results of ACO+NN for Different Numbers of Ants at Q = 0.1

Test	**1**	**2**	**3**	**4**	**5**
Number Ant	100	50	20	10	5
Max Iterations	200	200	200	200	200
Beta	1.0	1.0	1.0	1.0	1.0
Q	0.1	0.1	0.1	0.1	0.1
Total Distance	58.59 km	58.59 km	58.59 km	58.59 km	59.63 km
Vehicle Returning to Depot	4 times	4 times	4 times	4 times	4 times

Table **6.** Results of Standard ACO for Different Q Values

Test	**1**	**2**	**3**	**4**	**5**
Number Ant	100	100	100	100	100
Max Iterations	200	200	200	200	200
Beta	1.0	1.0	1.0	1.0	1.0
Q	2	1	0.5	0.3	0.1
Total Distance	67.97 km	63.98 km	59.93 km	59.93 km	58.59 km
Vehicle Returning to Depot	6 times	4 times	4 times	4 times	4 times

The test results in Table 2 show that Q values of 2.0 and 1.0 produced the same total travel distance of 75.77 km with six vehicle returns to the depot. These results indicate that, under the tested configuration, both Q values produced a higher travel distance than the lower Q values evaluated in the subsequent experiments.

In Table 3, with Q = 0.5, the number of ants was varied from 100 to 5. The results ranged from 59.68 km to 61.02 km. The configurations with 100 and 50 ants produced 59.93 km, while 20 and 10 ants produced 60.27 km and 61.02 km, respectively. The configuration with 5 ants produced

59.68 km. Thus, the results did not show a consistent relationship between the number of ants and the obtained travel distance.

In Table 4, with a Q value of 0.3, the obtained travel distances varied across the tested numbers of ants. The shortest distance was 58.59 km with 50 ants, while the other configurations produced distances between 59.93 km and 61.02 km. These results show that the obtained solution varied across the tested parameter configurations.

In Table 5, using Q = 0.1, the tested configurations with 100, 50, 20, and 10 ants produced the same travel distance of 58.59 km. The configuration with 5 ants produced a slightly higher distance of 59.63 km. These results show that, among the tested configurations, Q = 0.1 with at least 10 ants produced the shortest observed travel distance.

To further evaluate the effect of Q on the standard ACO without NN initialization, an additional experiment was conducted using 100 ants, 200 maximum iterations, and $\beta = 1.0$. The results are presented in Table 6. The standard ACO results show that decreasing the Q value from 2.0 to 0.1 was associated with a reduction in the obtained travel distance. The shortest distance obtained in this experiment was 58.59 km at Q = 0.1, with four vehicle returns to the depot.

Based on the parameter testing results, the configuration selected for the subsequent comparison was 100 ants, 200 maximum iterations, $\beta = 1.0$, and Q = 0.1. This configuration was selected because it achieved the shortest observed travel distance while maintaining four vehicle returns to the depot.

4.3. Comparison of ACO and Hybrid ACO

This study compares two approaches for solving the Vehicle Routing Problem with Time Windows (VRPTW): standard Ant Colony Optimization (ACO) with its original initialization process and Hybrid ACO, which combines the Nearest Neighbor (NN) method with ACO. The comparison focuses on the initial route distance, final optimized distance, number of iterations required to reach the final solution, and vehicle returns to the depot.

The standard ACO generated an initial route with a total travel distance of 64.09 km, while the Hybrid ACO generated an initial route of 72.55 km using the Nearest Neighbor method. After optimization, both approaches obtained the same final travel distance of 58.59 km and required four vehicle returns to the depot. The main difference was the number of iterations required to reach the final solution. Standard ACO required 46 iterations, whereas Hybrid ACO reached the same final distance after 10 iterations.

Table 7. Comparison of Standard ACO and Hybrid ACO

Method	*Standard ACO*	*Hybrid ACO (ACO+NN)*
Initial distance	64.09 km	72.55 km
Final distance	58.59 km	58.59 km
Iterations Required	46 iterations	10 iterations
Vehicle Returns to Depot	4 times	4 times

$$\text{Efficiency} = \left(\frac{72{,}55 - 58{,}59}{72{,}55}\right) \times 100 = 19.24\%$$

$$\text{Efficiency} = \left(\frac{64.09 - 58{,}59}{64.09}\right) \times 100 = 8.58\%$$

Based on Table 7, standard ACO reduced its initial travel distance from 64.09 km to 58.59 km, corresponding to a reduction of 5.50 km or 8.58%. Meanwhile, Hybrid ACO reduced the initial NN solution from 72.55 km to 58.59 km, corresponding to a reduction of 13.96 km or 19.24%. These percentages represent the reduction from the respective initial solutions to the final solution and should not be interpreted as a direct measure of superiority between the two methods. Both methods achieved the same final distance and the same number of vehicle returns. The main difference observed in this experiment was the number of iterations required to reach the final distance.

The standard ACO provides flexibility in exploring route combinations without relying on a predetermined heuristic initial route. In the present experiment, it generated an initial route of 64.09 km and required 46 iterations to reach the final distance of 58.59 km.

In contrast, the Hybrid ACO uses the Nearest Neighbor method to construct an initial solution before the ACO optimization process. Although the initial route was longer at 72.55 km, the NN method provided a structured starting point for the ACO search. As a result, the Hybrid ACO reached the same final distance of 58.59 km in only 10 iterations, compared with 46 iterations for the standard ACO.

The larger distance reduction obtained by the Hybrid ACO does not necessarily indicate a better initial solution. Instead, it reflects the difference between the initial and final routes. The Hybrid ACO reduced its initial distance by 13.96 km, while the standard ACO reduced its distance by 5.50 km. Thus, the main difference observed in this experiment was in the optimization process, particularly the number of iterations required to reach the same final distance.

The standard ACO offers flexibility in exploring different route combinations, while its stochastic initialization may produce different initial routes across repeated runs. Meanwhile, the Hybrid ACO provides a structured initial route through the Nearest Neighbor method. Although this route was longer, the structured initialization enabled the ACO process to reach the obtained final distance in fewer iterations.

Overall, both ACO and Hybrid ACO obtained the same final distance of 58.59 km and required four vehicle returns to the depot. The main difference was the number of iterations required to reach the final distance, with Hybrid ACO requiring 10 iterations compared with 46 iterations for standard ACO. These findings indicate that Nearest Neighbor initialization provided a structured starting point that required fewer iterations to reach the obtained solution in the tested distribution case.

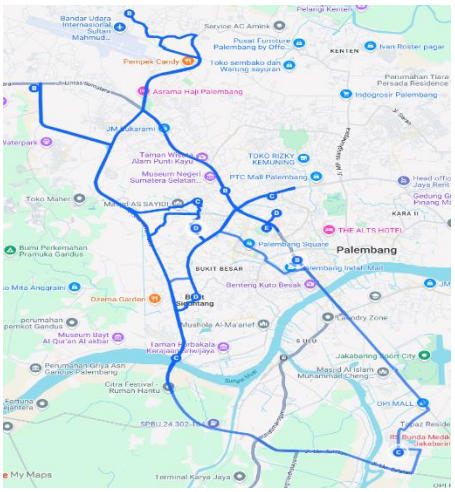

Figure 6. Customer Routes

The visualized routes indicate that both approaches generate feasible delivery routes while satisfying the required distribution constraints. Differences can be observed in the route configurations and customer sequences between the two approaches. However, both approaches obtained the same final travel distance of 58.59 km and four vehicle returns to the depot.

5. CONCLUSION

The results of this study show that the Hybrid Ant Colony Optimization (ACO) approach can be used to solve the Vehicle Routing Problem with Time Windows (VRPTW) for the food product distribution case of HoneyBee Bakery & Cake. Using Nearest Neighbor (NN) to generate the initial solution and ACO for further optimization, the Hybrid ACO obtained a final travel distance of 58.59 km with four vehicle returns to the depot.

In the comparison with standard ACO, both methods obtained the same final travel distance of 58.59 km and the same number of vehicle returns. However, Hybrid ACO reached the final distance in 10 iterations, while standard ACO required 46 iterations in the conducted experiment. The Hybrid ACO reduced the initial NN solution from 72.55 km to 58.59 km, corresponding to a distance reduction of 19.24%.

These findings indicate that Nearest Neighbor initialization can provide a structured starting solution that helps reduce the number of iterations required to reach the obtained solution in the tested distribution case. However, the results are limited to the HoneyBee Bakery & Cake case and the tested parameter configurations, and therefore do not establish the general superiority of Hybrid ACO for VRPTW.

6. SUGGESTED

Suggestions for Future Research:

1. Conduct research using other metaheuristic algorithms such as Particle Swarm Optimization (PSO) and Genetic Algorithm (GA) to evaluate the advantages of each algorithm.
2. Integrate the route optimization system into a mobile application.
3. Develop the system to display visualization results in map form, similar to Google Maps.

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