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Research Article

Route Optimization for Perishable Goods Distribution Using Ant Colony Optimization: A Capacitated Vehicle Routing Problem (CVRP) Case Study

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ABSTRACT

This study addresses inefficiencies in route planning for the distribution of perishable goods by a small-scale enterprise, Jaya Abadi Fruits, located in East Jakarta. The current manual delivery planning, reliant on driver experience, results in suboptimal distances, increased fuel usage, and inconsistent service quality. To overcome these challenges, the Ant Colony Optimization (ACO) algorithm was applied to a Capacitated Vehicle Routing Problem (CVRP) and implemented using MATLAB. The model incorporates real-world parameters such as delivery distances, box dimensions, demand volume, and vehicle capacities. Simulation results demonstrate significant improvements: for Vehicle 1, travel distance and distribution cost were reduced by 41.93% and 15.6%, respectively; for Vehicle 2, distance decreased by 30.96% and cost by 2.03%. These findings validate ACO as an effective, low-cost, and scalable decision-support tool for logistics operations in small enterprises lacking integrated digital infrastructure. The research contributes to the optimization of last-mile delivery in resource-limited supply chains, particularly in emerging economies.

Keywords: Capacitated Vehicle Routing Problem (CVRP); Ant Colony Optimization (ACO); Perishable Distribution; MATLAB; Small Enterprise Logistics; Route Optimization

1. INTRODUCTION

The rapid growth of logistics and supply chain management has heightened the demand for effective distribution channels, particularly regarding perishable items such as fruits, vegetables, and pharmaceutical products (Suryawanshi & Dutta, 2023). Such products are extremely sensitive to delays in delivery, temperature fluctuations, and mishandling, all of which tend to impact quality and result in financial losses. In small-scale urban distribution systems, routing planning is typically still manual, based on driver experience, and therefore contributes to inefficient deliveries and variable service quality (Yang, 2022). These inefficiencies are even more pronounced amidst the backdrop of increasing consumer demand and city traffic.

To overcome the above issues, the Vehicle Routing Problem (VRP) has been widely employed as a mathematical model for enhancing the distribution of routes from a central depot to geographically diverse customer locations (Puspitasari & Kurniawan, 2021). The VRP model takes into account various constraints, such as vehicle capacity, time delivery windows, and fuel-based constraints. Nevertheless, conventional exact approaches employed in solving the VRP are computationally costly when applied in dynamic or large real-world settings. Hence, scientists have applied more metaheuristic methods, including Genetic Algorithms (GA), Tabu Search, and Ant Colony Optimization (ACO), which provide adaptive and flexible search (Chen et al., 2025; Wang et al., 2025). According to (Syamil et al. (2023), SMEs require simplified yet adaptive supply chain systems that can function effectively without relying on complex digital infrastructures.

Ant Colony Optimization (ACO) is a swarm intelligence algorithm that draws inspiration from the way ants search for the optimum route between their nest and food sources. Originally developed in the early 1990s by Marco Dorigo, the algorithm has evolved to become one of the most widely used nature-inspired metaheuristic approaches in dealing with combinatorial optimization problems (Dorigo et al., 2006; Okwu & Tartibu, 2020). In logistics, ACO has been effective in resolving complex VRPs through efficiently searching solution spaces and adapting to changes in demand (Zheng et al., 2020). The algorithm uses pheromone-based probabilistic path selection, an aspect that renders it usable in routing problems with multiple variables. Also, ACO is able to produce almost optimal solutions more quickly compared to conventional algorithms, which is particularly crucial for time-sensitive distribution networks (Seyyedabbasi & Kiani, 2020; Tandon & Gupta, 2022).

Recent studies have applied ACO to various logistics contexts, Chen et al. (2025) put forward a multi-objective heuristic search algorithm for solving capacitated VRP with the aim of enhancing route efficiency as well as operational cost. Chai and Johar (2024) applied ACO to the process of blood distribution, with consideration of the criticality of timelines. Wang et al. (2025) solved the dynamic electric vehicle routing problem with Ant Colony Optimization (ACO) under the constraints of time windows. For instance, Syaifudin & Handayani (2024) implemented ACO in distribution route optimization for the delivery of snack foods in a local small and medium-sized enterprise (SME) in Indonesia. The study demonstrated that the application of ACO not only reduced the total delivery distance and fuel consumption but also supported environmental sustainability in the aspect of route efficiency, which complies with the green logistics concept.

Despite these advancements, many applications of Ant Colony Optimization (ACO) and several other metaheuristic methods still focus on large-scale logistics systems that are coupled with real-time monitoring, forecasting demand, and digital infrastructure (Juhászné Bíró & Németh, 2023). As such, this creates a lack of addressing the needs of small-scale distributors, particularly those operating within semi-manual environments that have limited technological support. They tend to be based on driver memory, experience uncertain daily demand, and do not have integrated route management tools (Yang, 2022). Furthermore, conventional algorithms like Genetic Algorithms or Tabu Search may require extensive tuning or memory mechanisms, making them less accessible to SMEs. ACO, by contrast, offers flexible, self-adaptive decision-making through pheromone-based feedback, which suits the dynamic and uncertain conditions of small logistics operations (Zhang et al., 2019).

The significance of this research lies in the application of Ant Colony Optimization (ACO) algorithms in addressing the Vehicle Routing Problem (VRP) in a real-life, small-scale distribution channel of perishable items, with a focus on Jaya Abadi Fruits in East Jakarta. This study integrates real-life constraint parameters, including box sizes, delivery areas, and vehicle carrying capacities, into the optimization. The algorithm is implemented in MATLAB, and its outcome is contrasted with the existing delivery system, based on driver intuition. This research demonstrates that ACO is an effective decision support tool in low-infrastructure logistics environments. The proposed model makes a significant contribution to overall travel distance, delivery time, and fuel usage. Besides, the results give useful information to SMEs that aim to make their distribution more effective by using efficient computation methods with special attention to not investing much in digital infrastructure.

2. RESEARCH METHOD

This study was conducted at Jaya Abadi Fruits, a small-scale fruit distributor located in East Jakarta. The company distributes bananas and other tropical fruits to over 60 retail outlets using two delivery vehicles. Due to the absence of a systematic route planning method and reliance on driver memory, inefficiencies in delivery time, distance, and fuel cost were observed. To overcome these issues, the Ant Colony Optimization (ACO) algorithm was applied to solve the Vehicle Routing Problem (VRP). ACO was selected for its adaptability, simplicity, and proven ability to handle complex routing under uncertain conditions. The model integrates field-observed data such as demand volumes, delivery locations, vehicle capacity, and fuel consumption (Gaida & Mittal, 2022). The overall research procedure is illustrated in Figure 1, which outlines the steps taken from problem identification to analysis of results. The process begins with identifying the research problem followed by collecting the required data such as vehicle specifications, route distances, and demand per delivery point. Subsequently, the ACO heuristic is designed, particularly focusing on the pheromone update strategy for route learning.

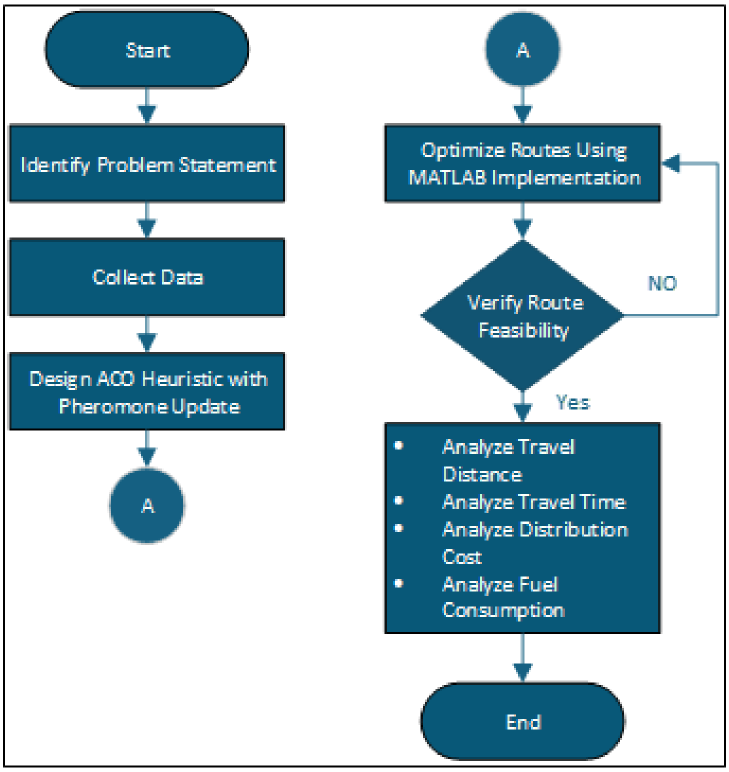

Figure 1. Research Process

The algorithm is then implemented using MATLAB, leveraging its matrix processing capabilities to simulate route construction and pheromone dynamics. A crucial step in the process is the Verification of Route Feasibility, which ensures that all proposed routes meet delivery constraints, such as maximum box capacity and full customer coverage. If a solution violates any constraint, the algorithm iteratively updates its pheromone paths until a feasible and optimized solution is found.Once feasibility is confirmed, final results are evaluated in terms of four main metrics: travel distance, delivery time (including unloading), distribution cost, and estimated fuel consumption. This structured approach not only improves distribution efficiency but also supports operational sustainability through data-driven decision-making.

2.1 Problem Formulation

The routing problem in this study is modeled as a Capacitated Vehicle Routing Problem (CVRP), where a set of delivery points must be served by a limited fleet of vehicles starting and ending at a central depot (Choudhari et al., 2022). Each customer has a known demand (in units of box), and each vehicle has a limited carrying capacity. The goal of this model is to minimize the total distribution distance, which directly correlates with fuel consumption and cost, while ensuring that all delivery points are visited exactly once and the vehicle capacities are not exceeded.

The CVRP can be represented as a complete undirected graph $G = (V, E)$, where:

$V = \{v_0, v_1, \dots, v_n\}$ is the set of vertices, with v_0 representing the depot and the rest v_i the customer locations.

E is the set of edges representing the distances between each pair of nodes.

d_{ij} is the distance between node iii and node jjj.

q_i is the demand at customer iii.

Q is the maximum capacity of a vehicle.

K is the number of available vehicles.

The objective function to minimize is:

$$min \sum_{k=1}^{K} \sum_{i=0}^{n} \sum_{j=0}^{n} d_{ij} x_{ijk}$$

Subject to the following constraints:

1. Each customer is visited exactly once:

$$\sum_{k=1}^{K} \sum_{j=1}^{n} x_{ijk} = 1 \qquad \forall i = 1, \dots, n$$

2. Flow conservation:

$$\sum_{j=0}^{n} x_{ijk} - \sum_{j=0}^{n} x_{jik} = 0 \qquad \forall i = 1, \dots, n; \forall k$$

3. Vehicle capacity constraint:

$$\sum_{i=1}^{n} q_i \cdot x_{ijk} \leq Q \qquad \forall k$$

4. Binary decision variable:

$$x_{ijk} = \begin{cases} 1, & if\ vehicle\ k\ travels\ from\ i\ to\ j \\ 0, & Otherwise \end{cases}$$

This model captures the operational reality of Jaya Abadi Fruits, which needs to deliver perishable products to multiple outlets while dealing with vehicle load constraints and cost minimization. This mathematical structure follows the general CVRP formulation as described by Laporte (2009), which is widely applied in logistics and metaheuristic optimization studies

2.2 Vehicle Specifications and Operational Constraints

The delivery operation of Jaya Abadi Fruits makes use of two types of cars, a Grandmax Box and a Grandmax Blind Van, which have varying shipment volume as well as fuel expenditure. The Grandmax Box has an internal cargo space measuring 225 cm × 159 cm × 123 cm while the Grandmax Blind Van provides a space of 205 cm × 138 cm × 123 cm. Each fruit box used for packaging measures 48 cm × 40 cm × 22 cm and during transport they are stacked vertically up to six layers.

Considering the stacking arrangement and the volume calculation, the maximum loading capacity approximated is 60 boxes for the Grandmax Box and 55 boxes for the Blind Van. These values serve as benchmarks in the capacity limitation of the route optimization steps. In terms of fuel economy, the Grandmax Box consumes fuel at 10 km/L while the Blind Van performs better at 13.5 km/L. The Ant Colony Optimization (ACO) algorithm has to make certain that no route allocation surpasses vehicle capacity based on all the delivery points being serviced precisely once from the central depot. A dual constraint like this is fundamental to straddle a engineering approach to a mathematical problem, and remains typical in studies focused on distribution problems solved with ACO in Indonesia (Suryawanshi & Dutta, 2023). To aid understanding of the differences in structure and dimensional capacities of the two vehicles, the physical specifications of the two delivery vehicles are provided. These diagrams outline the external dimensions and the internal cargo area which was used to determine the box loading configuration. Fig. 2 shows the dimension of the Grandmax Box and Fig. 3 presents the technical layout of the Grandmax Blind Van with the cargo door open, which provides information on the internal height and width available for loading operations.

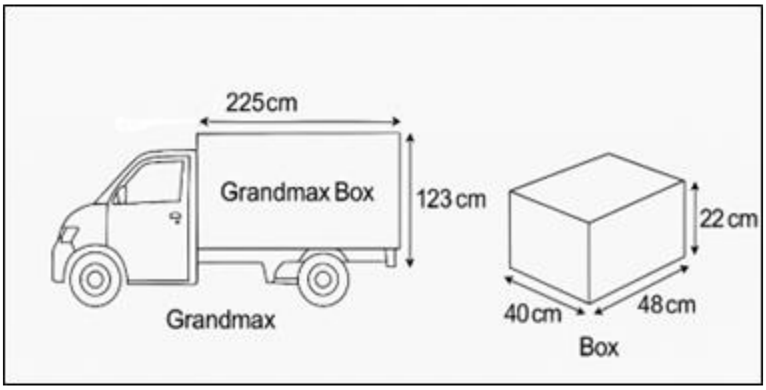

Figure 2. Vehicle (Grandmax Box) and Box Dimension Overview Used in Jaya Abadi Fruit

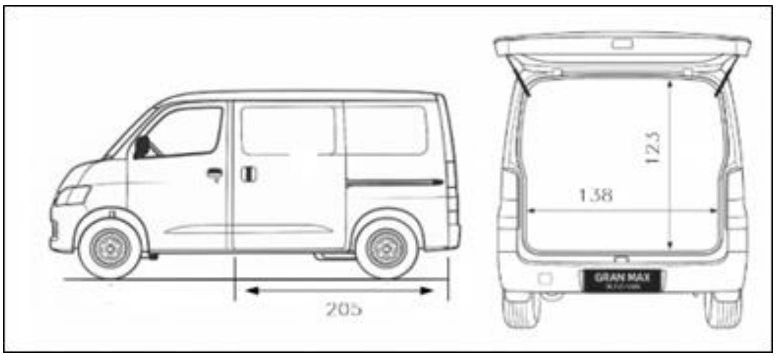

Figure 3. Vehicle (Grandmax Blindvan) Dimension

2.3 Ant Colony Optimization

Ant Colony Optimization (ACO) is a metaheuristic algorithm based on the probabilistic approach that simulates the real-life foraging or scavenging activities of an ant colony. The algorithm was first suggested by Marco Dorigo in his doctoral dissertation in 1992, and it has enabled the development of a widespread class of swarm intelligence algorithms (Dorigo et al., 2006). It is known that ants are capable of discovering the shortest routes connecting their nests and the food sources. They do this by depositing pheromones on the segments of the route they traverse. Subsequent ants can perceive those pheromone trails, and they tend to seek paths with greater probabilities where pheromones are more concentrated. While the environment still fluctuates, through constant iteration and subsequent updates of pheromones, the colony finds ways to reach paths that are optimal or close to optimal.

The nature-inspired ACO algorithm implements a sophisticated biological system for resolving problems in combinatorial optimization, including the Vehicle Routing Problem (VRP), Traveling Salesman Problem (TSP), and network design problems (Valdez et al., 2020). The algorithm uses a colony of artificial ants that construct solutions iteratively according to a probabilistic model based on a weighted combination of pheromone strength reflecting historical solution quality and heuristic desirability, usually representing distance or cost. ACO utilizes these rules to efficiently navigate the constrained dynamic solution spaces in the presence of time windows, capacity restrictions, or route length limitations (Ivkovic et al., 2023).

In the logistics and supply chain management areas, ACO captures attention because it can model real-world uncertainties and constraints. It works best for scenarios involving perishables, last-mile delivery, and dynamic routing since, unlike heuristic or exact methods, traditional ones are computationally infeasible (Zeng, 2022). When compared to other metaheuristics such as Genetic Algorithms or Tabu Search, ACO stands out due to its lack of centralization, gleaning capabilities, adaptability, and iteration driven self-improvement, which makes it suitable for near real-time or loosely structured decision settings. Its ease of use and high-quality outcomes mount its reliance across scholarly circles and industries. When compared to other metaheuristics such as Genetic Algorithms or Tabu Search, ACO stands out due to its lack of centralization, gleaning capabilities, adaptability, and iteration driven self-improvement, which makes it suitable for near real-time or loosely structured decision settings. Its ease of use and high-quality outcomes mount its reliance across scholarly circles and industries.

The core of ACO lies in the construction of routes by artificial ants based on a combination of pheromone intensity and heuristic visibility (typically, inverse distance). The probability $P_{ij}^{k}(t)$ that ant k moves from node iii to node j at time t is defined as:

$$P_{ij}^{k}(t) = \frac{[\tau_{ij}(t)]^{\alpha} \cdot [\eta_{ij}]^{\beta}}{\sum_{l \in \text{allowed}_k} [\tau_{il}(t)]^{\alpha} \cdot [\eta_{il}]^{\beta}}$$

where:

$t_{ij}(t)$ is the pheromone intensity on edge ij at time t

$\eta_{ij} = 1/d_{ij}$ is the heuristic desirability (inverse of distance)

α and β control the relative importance of pheromone and heuristic information

After all ants complete their tours, the pheromone trails are updated according to:

$$\tau_{ij}(t+1) = (1-\rho) \cdot \tau_{ij}(t) + \sum_{k=1}^{m} \Delta\tau_{ij}^{k}(t)$$

where ρ is the pheromone evaporation rate, and $\Delta\tau_{ij}^{k}(t)$ is the pheromone deposited by ant k on edge ij, defined as:

$$\Delta\tau_{ij}^{k}(t) = \begin{cases} \frac{Q}{L_k}, & \textit{if ant k uses edge } (i,j) \\ 0 \quad , & \textit{otherwise} \end{cases}$$

New research shows how ACO is a viable option to solve logistical distribution challenges, especially when it comes to commodities with a limited lifespan, sparse infrastructure, and dynamic routing. Qi & Li (2024) did a study that shows how ACO has developed to help with the logistics of electric vehicle cold chain deliveries, especially when traffic conditions are unpredictable. Feng et al. (2023) used ACO to optimize delivery routes for fresh products in cold storage, considering fuel efficiency and environmental impact.

Shi et al. (2024) integrated electric and conventional vehicle routing to manage and control the delivery of temperature-sensitive products using ACO. (He et al., 2024) proposed an Improved ACO (IACO) algorithm for multi-temperature product co-distribution and flexible time windows in urban contexts, showcasing marked improvements in vehicle and energy use.

In this study, the ACO algorithm is applied to solve a Capacitated Vehicle Routing Problem (CVRP) for the distribution of perishable fruit products by Jaya Abadi Fruits, East Jakarta. The goal is to reduce the total distance traveled as long as each customer is visited once and no vehicle overloads the capacity. The algorithm was carried out in MATLAB R2023b on account of its excellent performance with matrix calculations and display capabilities. Ant behaviors such as pheromone updates and route convergence computations along the logistics paths can be executed – and modeled – in real time using pheromone simulation in small-scale logistics systems. Therefore, ACO has been chosen not only for its potential to obtain a solution but also for its adaptability to non-fully automated distribution systems. This section describes the detailed configurations of ACO regarding the settings of parameters, pheromone policies, and methods of route building used in this research.

2.4 ACO Parameters and Implementation Configuration

To ensure effective solution performance in optimizing perishable goods distribution, the proper configuration of Ant Colony Optimization (ACO) parameters is essential. This study implements the ACO algorithm using MATLAB R2023b, leveraging its powerful numerical processing capabilities and visualization tools for simulating heuristic algorithms. The selection of ACO parameters in this research was guided by established practices in logistics optimization and adjusted based on preliminary experiments. The chosen parameter set reflects configurations commonly adopted in medium-scale Vehicle Routing Problem (VRP) scenarios and is summarized in Table 1 below:

Table 1. Ant Colony Optimization (ACO) Parameter Settings

Parameter	Symbol	Value	Justification
Number of Iterations	–	200	Provides sufficient convergence opportunity while maintaining computational efficiency for problems with ≤ 20 delivery nodes.
Number of Ants	–	200	Helps avoid premature convergence and improves solution diversity during early iterations.
Pheromone Importance	α	1	Balances historical path preference (exploitation) and exploratory behavior; widely adopted default in VRP-ACO studies.
Heuristic Importance	β	2	Assigns greater weight to visibility (inverse distance), which is critical in minimizing travel distance in perishable goods delivery.
Pheromone Evaporation Rate	ρ	0.5	Prevents pheromone over-concentration on early paths and sustains exploration potential across iterations.
Initial Pheromone Level	τ_0	0.01	Encourages uniform exploration of all routes during early iterations, reducing bias toward any specific edge.

These parameter values are based on prior research and fine-tuned to the practical constraints of this study. For instance Zheng et al. (2020) demonstrated that $\alpha = 1$ and $\beta = 2$ provide stable convergence behavior in routing problems, while Ivkovic et al. (2023) emphasized the importance of pheromone decay (ρ) in sustaining solution variability and avoiding local minima traps. In this implementation, each ant begins its route at the depot and probabilistically selects the next delivery point based on the combined influence of pheromone trail intensity and heuristic visibility (usually the inverse of distance). A roulette-wheel selection mechanism governs the decision process. After all ants complete their tours, global pheromone updates reinforce efficient routes. The best-known route is updated iteratively if a better solution emerges.

Additionally, the model integrates real-world constraints, such as vehicle capacity and customer demand. Using delivery distance matrices and demand data collected over 22 days, this parameter configuration effectively reduced total distance, delivery time, and cost. These findings confirm that ACO, when properly tuned, can significantly enhance the performance of small-scale logistics systems lacking integrated digital tools.

2.5 ACO-Based Route Optimization in MATLAB

The implementation of the Ant Colony Optimization algorithm in this study is carried out using MATLAB R2023b. MATLAB is selected due to its strong numerical computation capabilities, flexibility in modeling, and ease of integrating custom algorithms. The distance matrix for each vehicle is represented in matrix form, and artificial ants are simulated to iteratively build routes based on the probabilistic transition rules.Each iteration consists of three key stages: solution construction, pheromone update, and route evaluation. The algorithm tracks the shortest distance obtained in each iteration, and updates pheromone levels accordingly to reinforce better routes. MATLAB's plotting tools are also used to visualize route convergence and pheromone intensity across iterations. This implementation enables practical route optimization that reflects real-world delivery constraints and supports operational decision-making for small-scale logistics networks.

3. RESULTS AND DISCUSSION

3.1 Existing Distribution System Analysis

This study was conducted at Jaya Abadi Fruits, a sub-distributor of the Sunpride brand based in East Jakarta. The company delivers fresh fruits, primarily bananas, to approximately 40–60 retail stores per day using two vehicles: a Grandmax Box (Vehicle 1) and a Grandmax Blind Van (Vehicle 2). Each vehicle operates on a fixed daily route, but these routes are determined based on driver memory and experience, without the aid of any route optimization tool. This manual planning results in inefficiencies, such as increased fuel usage, longer delivery times, and inconsistency in service. The existing routing patterns for each vehicle were analyzed based on historical tracking and delivery records. Vehicle 1 serves eight major delivery regions, while Vehicle 2 serves ten regions. The delivery operations are structured to begin and end at the central depot (DC), with multiple stops in each zone. **Table 2** shows the complete distance matrix between delivery points for Vehicle 1, while Table 3 illustrates the same for Vehicle 2. These matrices serve as the input for the route optimization process using the ACO algorithm.

Table 2. Distance Matrix Between Stores (Vehicle 1)

No.	From/To	0	1	2	3	4	5	6	7	8
		DC	T1	T2	T3	T4	T5	T6	T7	T8
0	DC	0	6,6	8,5	3,7	11,2	13,7	11,6	19,6	15.1
1	T1	9,1	0	3,4	5	11,2	13,5	2	13,5	16,1
2	T2	9	6,3	0	6,8	13	15,4	8,5	13,1	18,2
3	T3	4,4	3	6	0	7,9	10,3	5,1	16,1	12,9
4	T4	11,8	9	10,4	9,7	0	4,6	10,7	9,9	7,5
5	T5	12,7	11	14	11,8	5,5	0	10,2	14,1	4,3
6	T6	8,2	3,2	6,2	3,9	10,1	12,5	0	15,7	17,9
7	T7	15	9,6	8,9	12,8	9	12,9	12	0	16,7
8	T8	15,6	13,9	13,8	13,7	4,9	5,2	12,8	14	0

Table 3. Distance Matrix Between Stores (Vehicle 2)

No	From/To	0	1	2	3	4	5	6	7	8	9	10
		DC	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18
0	DC	0	16,1	17,1	15,7	14,7	14,4	10,7	8,2	8,3	3,1	5,4
1	T9	16,8	0	1,9	3,6	4,6	4,9	10,1	8,9	9,9	18,7	19,2
2	T10	16,2	2	0	3	4	4,3	9,5	8,2	9,2	18	18,6
3	T11	14,8	3,6	3	0	1	1,3	8,1	6,8	7,8	16,7	17,2

No	From/To	0	1	2	3	4	5	6	7	8	9	10
		DC	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18
4	T12	13,8	5,9	5,3	1	0	0,2	7	5,8	6,8	15,6	16,1
5	T13	13,5	4,9	4,2	1,3	0,2	0	6,8	5,6	6,6	15,4	15,9
6	T14	11,8	9,8	9,1	7,7	6,6	6,4	0	3,8	4,8	13,6	14,2
7	T15	8	9	8,3	6,9	5,8	5,6	3,5	0	1,3	9,8	10,4
8	T16	9,5	10,2	9,5	8	7	6,8	4,7	1,7	0	10,3	9
9	T17	2,9	19	18,3	16,8	15,8	15,6	11,5	9,4	8,4	0	2,3
10	T18	5,4	19,3	18,6	17,2	16,1	15,9	14,3	9,7	8,8	2,3	0

The existing route structure for Vehicle 1 follows the sequence: DC – T1 – T2 – T3 – T4 – DC – T5 – T6 – T7 – T6 – T2 – T8 – DC, with a total travel distance of 100.4 km, an estimated fuel cost of Rp100.400, and total distribution cost of Rp270.400. The working time required to complete this route is approximately 8.01 hours, including loading/unloading time.Vehicle 2 follows the sequence: DC – T9 – T13 – T12 – T15 – T14 – T16 – T11 – T13 – T10 – T17 – T18 – DC, covering a distance of 69.1 km, with a fuel cost of Rp51.200, and a total distribution cost of Rp221.200. The total time to complete this route is 7.2 hours. Both routing patterns show inefficiencies, with several repetitive paths and suboptimal zone groupings. To complement the route distance and cost data, demand volume at each delivery region was collected based on historical shipment records. This demand represents the number of boxes delivered to each zone and directly influences vehicle loading decisions. Since each vehicle has a strict maximum capacity (60 boxes for Vehicle 1 and 55 boxes for Vehicle 2), careful distribution planning is required to avoid exceeding capacity while maximizing delivery efficiency. **Table 4** summarizes the daily average demand and store count for each delivery point handled by Vehicle 1 (Grandmax Box). The route includes eight delivery regions and a total of 31 stores. The highest demand is recorded in T1 (Penggilingan) with 13 boxes and T2 (Pulo Gebang) with 18 boxes, accounting for over 60% of the total vehicle load. These areas should be prioritized and optimally sequenced in the routing model. Table 5 presents the demand data for Vehicle 2 (Grandmax Blind Van), covering ten delivery regions and 34 stores. The largest demand is observed at T9 (Gedong) with 13 boxes, followed by T11 (Makasar) and T13 (Cililitan) with 7 boxes. The cumulative demand of 53 boxes approaches the vehicle's capacity limit, thus requiring strict adherence to vehicle constraints during optimization.

Table 4. Delivery Points and Average Demand for Vehicle 1

Code	Location	Demand (Box)	Number of Stores
DC	Jaya Abadi Fruits, Jl Pondok Kelapa Barat III No.A18		
T1	Pasar Jaya Mulya Penggilingan, Jl Raya Penggilingan No. 16	13	7
T2	Jl. Raya Pulo Gebang, Pulo Gebang, Kec. Cakung, Kota Jakarta Timur	18	10
T3	Pasar Perumnas Klender, Jl Teratai Putih Raya No. 19	8	4
T4	Jl. Pinang Raya Rawamangun, Kec. Pulo Gadung, Kota Jakarta Timur	2	1
T5	Jl. Klp. Sawit Raya Kec. Matraman, Kota Jakarta Timur	1	1
T6	Komp. Taman Puspa, Perumahan Jatinegara Baru, Kota Jakarta Timur	3	2
T7	Jl.sukapura jaya, Kec. Cilincing, Jkt Utara.	4	4
T8	Jl. Murtado 13, Kec. Senen, Kota Jakarta Pusat	2	2
	Total	51	31

Table 5. Delivery Points and Average Demand for Vehicle 2

Code	Location	Demand (Box)	Number of Stores
DC	Jaya Abadi Fruits, Jl Pondok Kelapa Barat III No. A18		
T9	Gedong, Kota Jakarta Timur, Daerah Khusus Ibukota Jakarta	13	6
T10	Jl. Raya Inpres. Kramat jati, Kota Jakarta Timur	4	9
T11	Jl. Pusdiklat Depnaker No.21 Kec. Makasar, Kota Jakarta Timur	7	5
T12	Jl. Squadron No.06, RT.007, Halim Perdana Kusumah, Kota Jakarta Timur	5	2
T13	Jl. Cililitan Besar No..62, Makasar, Kota Jakarta Timur	7	2
T14	Kios Pasar Mini Indah No. D-6, Halim Perdana Kusumah,Kota Jakarta Timur	4	2
T15	Jl. Cipinang Bali I, RT.2/RW.13, 13, Cipinang Muara, Kota Jakarta Timur	3	1
T16	Pd. Bambu, Kec. Duren Sawit, Kota Jakarta Timur	4	3
T17	Jl. Bintara Jaya No.55, RT.006/RW.009, Kec. Bekasi Bar.	4	2
T18	Jl. Perumahan pondok cipta, Bintara, Kec. Bekasi Bar	2	2
Total		53	34

These demand values are used as constraints in the Ant Colony Optimization (ACO) algorithm to ensure that each generated route remains feasible in terms of load capacity, while covering all delivery points.

3.2 ACO Simulation Result in MATLAB

The Ant Colony Optimization (ACO) algorithm was implemented in MATLAB R2023b using 200 ants and 200 iterations for both delivery vehicles. The algorithm iteratively constructed routes by simulating pheromone-based decision-making to identify near-optimal paths, while adhering to capacity and distance constraints. The optimization aimed to reduce total travel distance, fuel cost, and delivery time. The comparison between the existing manually planned routes and those generated through ACO reveals significant improvements across all key performance indicators, including distance, time, and cost.Figure 4 displays the routes produced by the Ant Colony Optimization (ACO) algorithm for each delivery vehicle. These routes were generated through simulations in MATLAB, considering real-world operational constraints such as maximum vehicle capacity, total daily demand, and minimization of travel distance. Each route begins and ends at the central depot (DC) and includes all assigned delivery locations in an optimized service order.

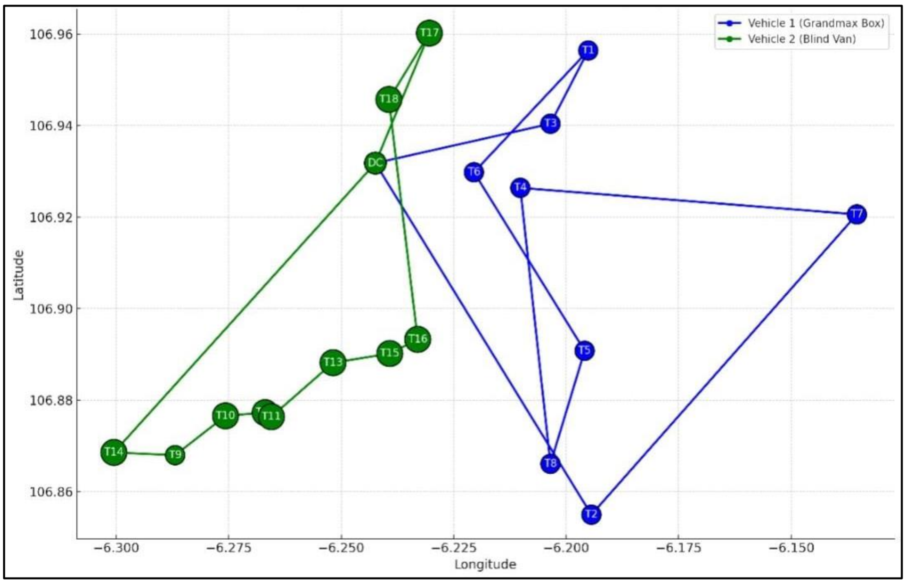

Figure 4. Route Visulization with ACO Algorithm

The delivery locations span multiple districts in East Jakarta and surrounding areas. This spatial distribution is useful for assessing how well the algorithm clusters deliveries and avoids unnecessary travel. Compared to the previously used manual routing, the ACO-optimized routes show enhanced path continuity, elimination of redundant loops, and better grouping of service zones. This further reinforces the effectiveness of ACO in optimizing small-scale distribution operations for perishable goods.

3.3 Route Optimization Results Using ACO

In the ACO (Ant Colony Optimization) Algorithm, 200 ants and 200 iterations were set. The MATLAB implementation ran smoothly, optimizing routing for both delivery trucks. With respect to delivery efficiency, turnaround time, cost, monetary value, and operational expenses, the results achieved were significantly better than the previous iteration. For Vehicle 1 (Grandmax Box), the optimized route sequence is:

DC → T3 → T1 → T6 → T5 → T8 → T4 → T7 → T2 → DC

The total travel distance was reduced from 100.4 km to 58.2 km, which is a 41,93% reduction. Fuel expenditures decreased to Rp58,200, and the overall estimated distribution expenditure dropped to Rp228.200. The total operational time was also reduced to 5.46 hours. For Vehicle 2 (Grandmax Blind Van), the optimized sequence is:

DC → T14 → T9 → T10 → T11 → T12 → T13 → T15 → T16 → T17 → T18 → DC

The travel distance was reduced from 69.1 km to 47.7 km, which is an improvement of 30,96%. The fuel expenditure was optimized to Rp36,692, which brought the total distribution expenditure down to Rp216.692. The total completion time was 6.19 hours. These performance improvements are visualized in Figure 5, which illustrates the convergence of the total distance during the 200 iterations, indicating the algorithm's stability and ability to achieve optimal results.

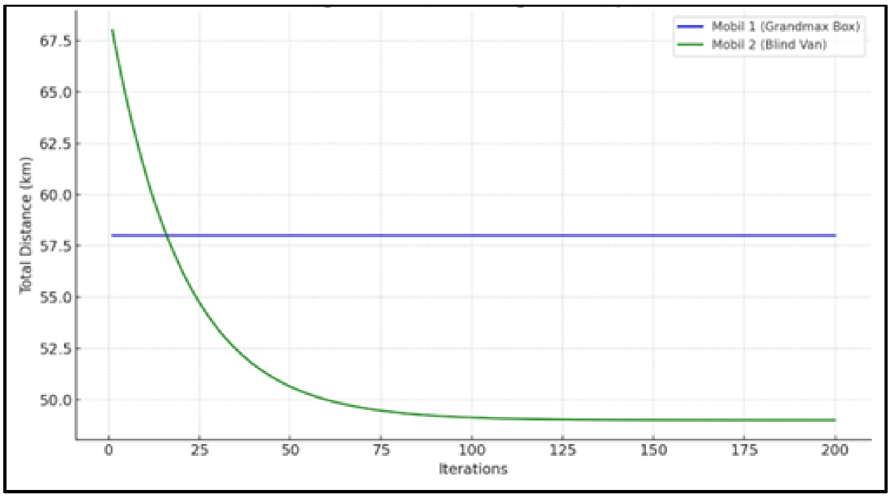

Figure 5. ACO Convergence Graph

Table 6 presents a comparative analysis between the existing and optimized delivery routes for both vehicles used by Jaya Abadi Fruits. The implementation of the Ant Colony Optimization (ACO) algorithm significantly improved the distribution performance across multiple dimensions, particularly in travel distance, delivery time, and operational cost.

Table 6. Route and Cost Comparison Before and After Optimization

Components	Vehicle 1	Vehicle 2
Existing Distance (km)	100.4	69.1
Optimized Distance (km)	58.2	47.7
Distance Reduction (%)	41.93%	30.96%
Existing Time (hrs)	8.01	7.2
Optimized Time (hrs)	5.46	6.19
Time Reduction (%)	31,83%	14,02%
Existing Cost (Rp)	270.400	221.200
Optimized Cost (Rp)	228.200	216.692
Cost Reduction (%)	15.6%	2.03%

4. CONCLUSION

This study implemented the Ant Colony Optimization (ACO) algorithm on Jaya Abadi Fruits' distribution network in Perishable Goods East Jakarta as a case study on the Capacitated Vehicle Routing Problem (CVRP). The actual box-sized MATLAB containers, vehicle specifications, delivery points, and distances were measured and filed accordingly. ACO showed noticeable improvements in vehicle routing, optimally decreasing the diameter of travel, associated costs, fuel, delivery time, and total costs for distribution. This study compares the drivers' dependent heuristic routes to the optimized metaheuristic algorithm-guided routes to demonstrate the power of metaheuristic algorithms to enhance distribution management decision support systems for SMEs lacking integrated digital solutions. The case of Jaya Abadi Fruits illustrates how ACO can be effortlessly integrated into smaller corporations. Additions to enhance delivery performance refinement could include real-time traffic data and additional windows of time. ACO has diminished the distance for Vehicle 1 by 41.93%, reduced delivery time by 31.83%, and lowered overall distribution costs by 15.6%. Vehicle 2 showed a reduction in distance and time by 30.96% and 14.02%, respectively, for a cost reduction of 2.03%. These outcomes affirm ACO's metaheuristic competencies concerning optimal routing.

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