

Shortest Route Optimization for Waste Collection Using ACO-Based CVRP : Case Study of Banjar Basa and Banjar Tembau, Marga

Ida Bagus Kade Puja Arimbawa K. ^{1*}, I Gusti Ayu Novitasari², Putu Nanda Andika Permana³

^{1,3} Faculty of Technology and Health Sciences, Bali Dwipa University, Indonesia

² Faculty of Humanities and Social Science, Bali Dwipa University, Indonesia

*Corresponding Author. Email: kemenuh.puja@gmail.com

ABSTRACT

The increasing volume of household waste in rural areas has created challenges in transportation management, particularly in determining efficient waste collection routes. This study aims to optimize waste transportation routes in Marga Village, Tabanan Regency, focusing on Banjar Basa and Banjar Tembau, which have distinct topographical and settlement characteristics. The optimization process was formulated as a Capacitated Vehicle Routing Problem (CVRP) and solved using the Ant Colony Optimization (ACO) algorithm. The research began by modeling the waste collection points as graph vertices, with roads serving as edges weighted by distance. Simulation results showed that Banjar Basa, which has a larger area and more collection points, required two trips to cover all nodes, whereas Banjar Tembau required only one trip due to its smaller and denser topology. The ACO algorithm successfully identified the shortest and most efficient route configuration, with pheromone updates guiding the convergence toward the global optimum. The combination of parameters $\alpha=1.0$, $\beta=5.0$, $\rho=0.5$, $Q=100$ yielded stable convergence and effective route minimization. These results demonstrate that ACO is a robust and adaptive approach for optimizing waste transportation systems in rural regions, offering a sustainable solution for reducing operational costs and improving environmental quality.

Keywords: Ant Colony Optimization (ACO), Capacitated Vehicle Routing Problem (CVRP), Waste Collection, Route Optimization, Marga Village



This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution-NonCommercial 4.0 International License. Copyright © 2026 by the Author(s).

I. Introduction

Waste management remains one of the major challenges faced by many villages in Indonesia, including Marga Village, located in Marga District, Tabanan Regency. This village covers an area of 2.62 km² and has a population of 3,084 residents [1]. With the continuous growth of the population and the expansion of residential areas, the volume of household waste increases each year [2],[3]. This condition calls for the implementation of an efficient waste transportation system to prevent adverse impacts on the environment and public health.

This research focuses on Banjar Basa and Banjar Tembau in Marga Village, which are densely populated areas with narrow road access. The absence of fixed collection schedules and routes often causes waste collection workers to travel along non-optimal routes, leading to higher fuel consumption, increased operational costs, collection delays, and waste accumulation. Therefore, these conditions provide a basis for conducting shortest route optimization to generate more efficient collection routes, reduce travel distance, improve vehicle capacity utilization, and support a more systematic waste transportation process.

To address these issues, this study proposes the application of the Capacitated Vehicle Routing Problem (CVRP) approach, which considers vehicle capacity constraints in distributing waste loads. CVRP enables the design of efficient routes while ensuring that each vehicle operates within its load capacity limits. To solve the problem, the Ant Colony Optimization (ACO) algorithm is employed a metaheuristic inspired by the collective foraging behavior of ant colonies in discovering the shortest paths to food sources.

Ant Colony Optimization (ACO) and its variants have been extensively developed to enhance routing efficiency in combinatorial optimization problems. Okrah et al. demonstrated that incorporating velocity-based heuristics in Ant Colony System (ACS) improves convergence speed by up to 39% [4], while Li et al. showed that a hybrid APF-ACO approach effectively avoids local optimal in dynamic navigation scenarios through the integration of speed, positional, and geometric constraints [5].

For capacitated routing, several studies have refined ACS to address the Capacitated Vehicle Routing Problem (CVRP). Mutar et al. employed a subpath-based transition mechanism to reduce travel distance [6], whereas Ahmed et al. introduced the Enhanced ACS (EACS), combining KNN initialization and local search strategies to improve exploration and route quality. These advancements align with the growing adoption of multi-objective ACS frameworks to simultaneously optimize distance and fleet utilization [7].

The practicality of ACO has been validated through various real-world spatial routing scenarios. Teguh et al. and Suryana et al. successfully optimized multi-destination travel routes using ACO with high computational efficiency, demonstrating its adaptability to preference-based, multi-stop routing environments [8], [9].

In the field of waste collection logistics, ACO has been applied under both indoor and outdoor operational constraints. Tomitagawa et al. developed an energy-aware ACO framework for indoor robotic waste collection by integrating path distance and waste load into the heuristic function [10]. Furthermore, Okrah et al. applied a modified bi-objective ACS model for urban waste management in the Shama District, achieving an optimal route of 11 km with an externality cost of GHS 2100, thus highlighting the relevance of ACS in minimizing both operational distance and socio-environmental impact [11]. More recently, Arimbawa K. demonstrated the effectiveness of ACO in designing a single-trip CVRP-based waste collection route in sparse urban networks while accounting for variable waste volumes and vehicle capacity constraints [12]. Overall, these findings confirm that ACO remains a robust, adaptive, and effective metaheuristic approach for route optimization, particularly in waste collection systems with heterogeneous geographical characteristics, such as those found in Banjar Basa and Banjar Tembau of Marga Village. The main contribution of this study is the development of a graph-based CVRP model combined with the ACO algorithm for village-scale waste collection route optimization. This approach incorporates field-based distance data, waste volume variations, and vehicle capacity constraints to generate feasible and efficient collection routes.

II. Method

This study is an applied research employing a computational quantitative approach. The primary objective is to optimize the waste collection routes in Banjar Basa and Banjar Tembau, located in Marga Village, by formulating the problem as a Capacitated Vehicle Routing Problem (CVRP) solved using the Ant Colony Optimization (ACO) algorithm. This approach

was chosen because ACO has proven effective in generating near-optimal solutions efficiently for routing problems that involve vehicle capacity constraints.

The study was conducted in Banjar Basa and Banjar Tembau, located in Marga Village, Marga District, Tabanan Regency. The data were collected through field observations, measurements of distances between waste collection points, and interviews with waste collection personnel. The collected data included the coordinates of each waste collection point, the average waste volume per point (m^3), and the capacity of the waste collection vehicle (m^3). These data were represented as a weighted undirected simple graph $G = (V, E)$, where V denotes the set of vertices (waste collection points) and E denotes the set of edges connecting the vertices, with the weight d_{ij} representing the distance between points.

The waste collection routing problem is formulated as a Capacitated Vehicle Routing Problem (CVRP) that considers vehicle capacity limitations. The main objective of the CVRP is to minimize the total travel distance of all vehicles, subject to the following constraints:

$$\text{Minimize } Z = \sum_{i=0}^n \sum_{\substack{j=0 \\ j \neq i}}^n d_{ij} x_{ij} \quad (1)$$

Subject to:

$$\forall i, j \quad \sum_{i=0, i \neq j}^n x_{ij} = 1, \quad \sum_{j=0, j \neq i}^n x_{ij} = 1, \quad \sum_{i \in V} q_i x_{ij} \leq K$$

where:

$$x_{ij} = \begin{cases} 1, & \text{if the vehicle travels along the edge}(i, j) \\ 0, & \text{otherwise.} \end{cases}$$

d_{ij} = represents the distance between vertices i and j ;

q_i = denotes the waste volume at vertex i ; and

K = the maximum capacity of the vehicle.

The Ant Colony Optimization (ACO) algorithm was first introduced by Dorigo, Maniezzo, and Colomi (1996), inspired by the collective foraging behavior of real ant colonies in finding the shortest path to a food source[13]. In the context of the Capacitated Vehicle Routing Problem (CVRP), ants are modeled as agents that iteratively construct vehicle routes based on pheromone information and the desirability level between vertices. Each ant probabilistically selects the next vertex to visit according to the pheromone intensity and heuristic information, enabling the colony to collectively converge toward an optimal or near-optimal routing solution over multiple iterations.

At the initial stage, a number of ants m are placed on the starting vertex. The parameters used in the Ant Colony Optimization (ACO) algorithm include: α = the influence level of pheromone intensity on the probability of path selection; β = the influence level of visibility (η_{ij}); ρ = the pheromone evaporation rate ($0 < \rho < 1$); Q = the pheromone constant for global updating; and t_{max} = the maximum number of iterations[14]. Each ant selects the next

vertex to visit based on a combination of pheromone intensity τ_{ij} and visibility $\left(\eta_{ij} = \frac{1}{d_{ij}}\right)$ with the probability of moving from vertex i to vertex j expressed as follows[15]:

$$P_{ij}(t) = \frac{[\tau_{ij}(t)]^\alpha [\eta_{ij}]^\beta}{\sum_{k \in N_i} [\tau_{ik}(t)]^\alpha [\eta_{ik}]^\beta} \quad (2)$$

where:

$P_{ij}(t)$ = probability of an ant moving from vertex i to j at iteration t ;

$\tau_{ij}(t)$ = pheromone intensity on edge (i, j) ;

$\eta_{ij}(t)$ = heuristic value (desirability) of edge (i, j) ; and

N_i = the set of vertices that can be visited.

After each ant constructs its route, the total travel distance is calculated using the following equation:

$$L_k = \sum_{(i,j) \in V_k} d_{ij} \quad (3)$$

where L_k represents the total route length ant k and V_k denotes the set of edges (i, j) traversed by that ant. The ant with the smallest L_k value is considered to have produced the best solution in that iteration. After all ants complete their routes, the pheromone intensity is updated in two stages: evaporation and deposition. In the evaporation phase, the existing pheromone levels are reduced proportionally to the evaporation rate, as expressed by the following equation:

$$\tau_{ij}(t) \leftarrow (1 - \rho)\tau_{ij}(t) \quad (4)$$

The purpose of this process is to prevent excessive pheromone accumulation on specific paths and to maintain diversity in the search space. Subsequently, each ant deposits new pheromone on the edges it has traversed, which is formulated as follows:

$$\tau_{ij}(t) \leftarrow (1 - \rho)\tau_{ij}(t) + \sum_{k=1}^m \Delta\tau_{ij}^k \quad (5)$$

where:

$$\Delta\tau_{ij}^k = \begin{cases} \frac{Q}{L_k}, & \text{if ant } k \text{ passes through edge } (i, j); \\ 0, & \text{otherwise.} \end{cases} \quad (6)$$

Paths with shorter total distances receive greater pheromone reinforcement, thereby increasing their probability of being selected by other ants in subsequent iterations. This iterative process continues until the algorithm reaches the maximum number of iterations t_{max} following the flowchart below:

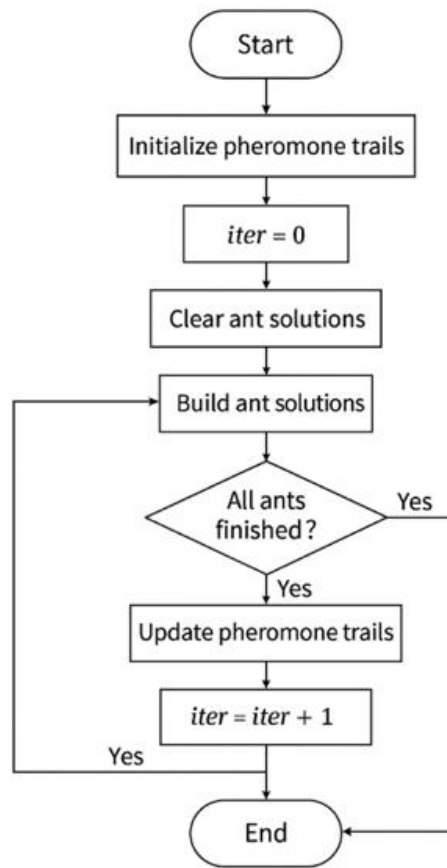


Figure 1. ACO Flowchart

III. Result

The research began with the construction of graph models representing the waste transportation networks of Banjar Basa and Banjar Tembau. The input data used in this study include the number of waste collection points, waste volume at each point, road distance between connected points, and vehicle capacity. A summary of the input data for Banjar Basa and Banjar Tembau is presented in Table 1.

Table 1. Summary of Waste Collection Input Data

Area	Number of vertexs	Number of collection points	Waste volume range (m ³)	Edge distance range (m)	Vehicle capacity (m ³)
Banjar Basa	15	14	0.31–0.50	50.10–240.43	1,20
Banjar Tembau	9	8	0.31–0.46	84.01–217.55	1,20

Source: Data processed by the authors (2025)

Banjar Basa area was modeled as a graph $G_B = (V_B, E_B)$ consisting of $|V_B| = 15$ denoted as $V_B = \{b_1, b_2, \dots, b_{15}\}$, which include 14 temporary waste collection points and one main depot (b_1). Meanwhile, Banjar Tembau was modeled as a graph $G_D = (V_D, E_D)$ with $|V_D| = 9$ denoted as $\{d_1, d_2, \dots, d_9\}$ where d_1 serves as the main depot. The set of edges E connects two vertices if there is a road accessible by waste collection vehicles. For each edge (i, j) the

distance d_{ij} (in meters) was recorded. The resulting graph G_B and G_D are illustrated in following Figure 2.

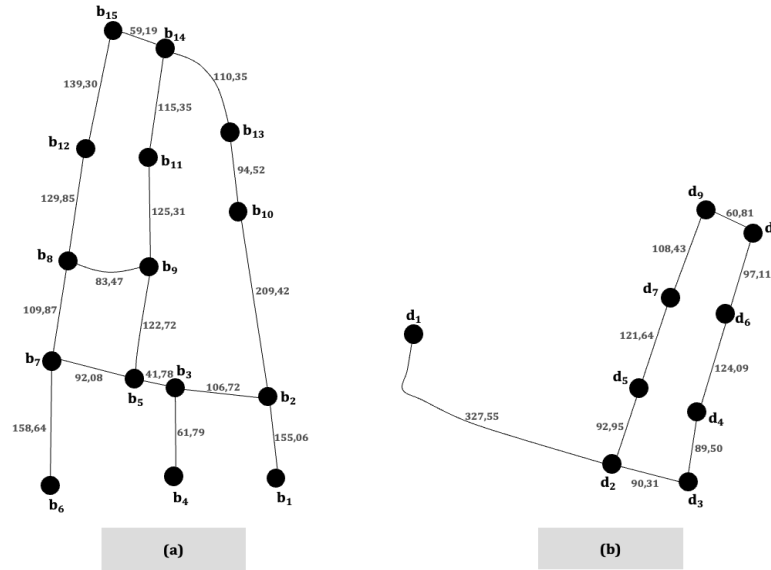


Figure 2. (a) Graph G_B ; (b) Graph G_D

After the graph structures for Banjar Basa and Banjar Tembau were established, the next step was to construct the corresponding weighted adjacency matrices as a numerical representation of the relationships between vertices in the graphs. Based on graphs G_B and G_D the weighted adjacency matrices $A_B = [a_{ij}] \in \mathbb{R}^{15 \times 15}$ and $A_D = [a_{ij}] \in \mathbb{R}^{9 \times 9}$ were generated under the following conditions:

$$a_{ij} = \begin{cases} d_{ij} & \text{if conected} \\ 99999 & \text{otherwise} \end{cases} \quad (7)$$

From Equation (7), the adjacency matrix is obtained as follows:

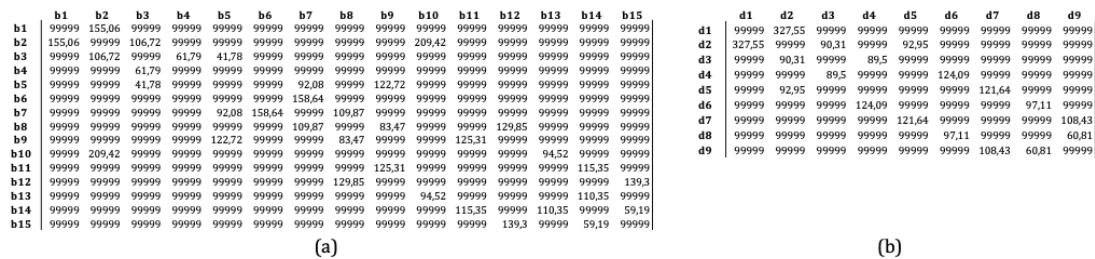


Figure 3. (a) Matrix A_B ; (b) Matrix A_D

In solving the Capacitated Vehicle Routing Problem (CVRP), it is essential to have the distance information between every pair of vertices so that optimization algorithms such as Ant Colony Optimization (ACO) can construct efficient vehicle routes without relying solely on direct connectivity. Therefore, a metric closure process is performed to transform the initial sparse graph into a complete graph[16]. The purpose of metric closure is to compute the shortest path distances between all vertex pairs. If no direct edge exists between two vertices

v_i and v_j , the shortest distance d_{ij} is determined through an intermediate vertex v_k following the principle of the triangle inequality:

$$d_{ij} \leq d_{ik} + d_{kj}, \quad \forall i, j, k. \quad (8)$$

Based on inequality (8), the metric closure process was computed using Dijkstra's Algorithm[17], resulting in the complete adjacency matrices $A_B(K)$ and $A_D(K)$.

b1		b2	b3	b4	b5	b6	b7	b8	b9	b10	b11	b12	b13	b14	b15		d1	d2	d3	d4	d5	d6	d7	d8	d9	
b2	0	155,06	261,78	323,57	303,56	554,28	395,64	505,51	426,28	364,48	551,59	635,36	459	569,35	628,54		d2	327,55	0	90,31	179,81	92,95	303,9	214,59	383,83	323,02
b3	261,78	106,72	0	61,79	41,78	292,5	133,86	243,73	164,5	316,14	289,81	373,58	410,66	405,16	464,35		d3	417,86	90,31	0	89,5	183,26	213,59	304,9	310,7	371,51
b4	323,57	168,51	61,79	0	103,57	354,29	195,65	305,52	226,29	377,93	351,6	435,37	472,45	466,95	526,14		d4	507,36	179,81	89,5	0	272,76	124,09	390,44	221,2	282,01
b5	303,56	148,5	41,78	103,57	0	250,72	92,08	201,95	122,72	357,92	248,03	331,8	452,44	363,38	422,57		d5	420,5	92,95	183,26	272,76	0	387,99	121,64	290,88	230,07
b6	554,28	399,22	292,5	354,29	250,72	0	158,64	268,51	351,98	608,64	477,29	398,36	702,99	592,64	537,66		d6	631,45	303,9	213,59	124,09	387,99	0	266,35	97,11	157,92
b7	395,64	240,58	133,86	195,65	92,08	158,64	0	109,87	193,34	450	318,65	239,72	544,35	434	379,02		d7	542,14	214,59	304,9	390,44	121,64	266,35	0	169,24	108,43
b8	505,51	350,45	243,73	305,52	201,95	268,51	109,87	0	83,47	529	208,78	129,85	434,48	324,13	269,15		d8	711,38	383,83	310,7	221,2	290,88	97,11	169,24	0	60,81
b9	426,28	271,22	164,5	226,29	122,72	351,98	193,34	83,47	0	445,53	125,31	213,32	351,01	240,66	299,85		d9	650,57	323,02	371,51	282,01	230,07	157,92	108,43	60,81	0
b10	364,48	209,42	316,14	377,93	357,92	608,64	450	529	445,53	0	320,22	403,36	94,52	204,87	264,06											
b11	551,59	396,53	289,81	351,6	248,03	477,29	318,65	208,78	125,31	320,22	0	313,84	225,7	115,35	174,54											
b12	635,36	480,3	373,58	435,37	331,8	398,36	239,72	129,85	213,32	403,36	313,84	0	308,84	198,49	139,3											
b13	459	303,94	410,66	472,45	452,44	702,99	544,35	434,48	351,01	94,52	225,7	308,84	0	110,35	169,54											
b14	569,35	414,29	405,16	466,95	363,38	592,64	434	324,13	240,66	204,87	115,35	198,49	110,35	0	59,19											
b15	628,54	473,48	464,35	526,14	422,57	537,66	379,02	269,15	299,85	264,06	174,54	139,3	169,54	59,19	0											

Figure 4. (a) Matrix $A_B(K)$; (b) Matrix $A_D(K)$

The following figures illustrate the complete graph models for Banjar Basa and Banjar Tembau.

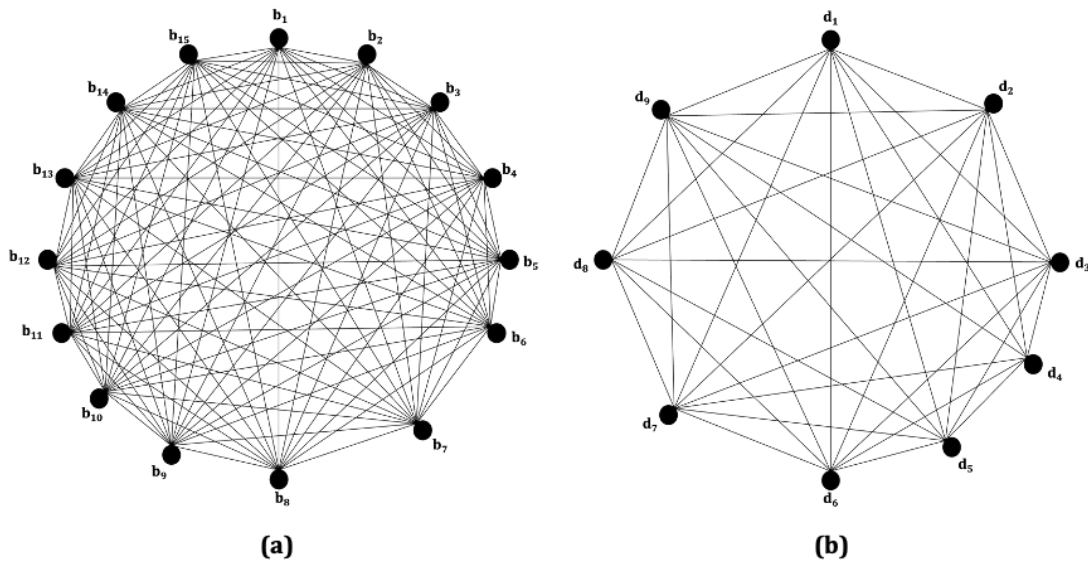


Figure 5. (a) Complete Graph Banjar Basa; (b) Complete Graph Banjar Tembau

After obtaining the shortest distances (Figure 3), the next step is to perform a mathematical simulation of the ACO algorithm. An initial single iteration using the Banjar Tembau complete adjacency matrix $A_D(K)$ is conducted to illustrate the mechanism of the algorithm in constructing a waste collection route solution. First, the initial parameters are defined as follows: vehicle capacity = 1200 m^3 ; number of ants = 10, number of iterations = 10; $\alpha = 1,0$; $\beta = 5,0$; $\rho = 0,5$ and $Q = 100$. The waste volumes (in m^3) are given by $\{0, 150, 130, 135, 125, 150, 140, 120, 160\}$ and the initial pheromone levels are set to $\tau_{ij}^{(0)} = 1$. Following Equation (2), the results are obtained as follows:

Table 2. Mathematical Simulation Steps of the ACO Algorithm

Step	Source Vertex	Chosen Destination Vertex	Distance d_{ij} (m)	Desirability $\left(\frac{1}{d_{ij}}\right)^5$	Probability P_{ij}	Remaining Capacity (m^3)
1	d_1	d_2	327.55	2.65×10^{-13}	0.54	1050
2	d_2	d_5	92.95	1.37×10^{-10}	0.45	925
3	d_5	d_7	121.64	2.80×10^{-11}	0.83	785
4	d_7	d_9	108.43	6.98×10^{-11}	0.60	625
5	d_9	d_8	60.81	1.19×10^{-9}	0.79	505
6	d_8	d_6	97.11	1.13×10^{-10}	0.93	355
7	d_6	d_4	124.09	3.42×10^{-11}	0.77	220
8	d_4	d_3	89.50	1.76×10^{-9}	1.00	90
9	d_3	d_1 (return)	416.86	—	—	—

Source: Data processed by the authors (2025)

The resulting route is $d_1 \rightarrow d_2 \rightarrow d_5 \rightarrow d_7 \rightarrow d_9 \rightarrow d_8 \rightarrow d_6 \rightarrow d_4 \rightarrow d_3 \rightarrow d_1$ with a total load $150 + 125 + 140 + 150 + 135 + 130 = 1110 \leq 1200$ which indicates that the trip is feasible as a single route within the vehicle capacity. The total travel distance is calculated as $L = 327.55 + 92.95 + 121.64 + 108.43 + 60.81 + 97.11 + 124.09 + 89.50 + 417.86 = 1439.94m$.

After all ants complete their respective routes, the pheromone values are updated according to Equations (5) and (6).

$$\Delta\tau_{ij} = \frac{Q}{L} = \frac{100}{1439.94} \approx 0.0695$$

For each traversed edge:

$$\tau_{ij}^{(1)} = (1 - \rho)\tau_{ij}^{(0)} + \Delta\tau_{ij} = 0.5(1) + 0.0695 = 0.5695$$

Edges that are not traversed experience pheromone evaporation, resulting in $\tau_{ij}^{(1)} = 0.5$. The mathematical simulation indicates that in the first iteration, the ants successfully construct a complete route without exceeding the vehicle capacity. The edges included in the route receive higher pheromone reinforcement compared to the others, thereby increasing the likelihood of these paths being selected in subsequent iterations. As the process continues, the ant colony progressively converges toward a global optimal route with the shortest total travel distance. The next iterations are computed programmatically using C++.

The flowchart in Figure 1 illustrates the main logical flow of the Ant Colony Optimization (ACO) algorithm used to solve the Capacitated Vehicle Routing Problem (CVRP). Each stage in the diagram is directly translated into the C++ program structure implemented for the waste collection case in Banjar Basa and Banjar Tembau, Marga Village.

The process begins with the initialization of parameters and pheromone trails.: `const double alpha = 1.0; const double beta_param = 5.0; const double rho = 0.5; const double Q = 100.0; const double truckCap = 1200; vector<vector<double>> tau(nCity, vector<double>(nCity, 1.0)); vector<vector<double>> eta(nCity, vector<double>(nCity, 0.0)).` The next step is the solution construction phase, where each ant builds a route. `desir[j] = pow(tau[current][j], alpha) * pow(eta [current] [j], beta_param); intnext=Select (candidates, desir, gen); route.push_back(next).` This step represents the direct implementation of the “Construct Ant Solutions” block in the flowchart. The path selection is carried out probabilistically by choosing the next vertex based on its desirability value. The outcome of this process generates an optimal route for each waste collection trip while considering vehicle capacity constraints and the shortest distances between vertices. The following results present the computational simulation for Banjar Tembau.

Ant	Route Iteration 1	Distance (m)
1	d ₁ → d ₉ → d ₆ → d ₄ → d ₇ → d ₅ → d ₂ → d ₃ → d ₄ → d ₁	1976.60
2	d ₁ → d ₇ → d ₆ → d ₈ → d ₆ → d ₄ → d ₃ → d ₂ → d ₅ → d ₁	1625.84
3	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
4	d ₁ → d ₅ → d ₇ → d ₉ → d ₈ → d ₆ → d ₄ → d ₃ → d ₂ → d ₁	1439.94
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₃ → d ₂ → d ₅ → d ₇ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1742.18
7	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
8	d ₁ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₂ → d ₁	1439.94
9	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1625.84
10	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1625.84

Ant	Route Iteration 2	Distance (m)
1	d ₁ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₂ → d ₁	1439.94
2	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
3	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1625.84
4	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1625.84
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
7	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
8	d ₁ → d ₃ → d ₂ → d ₅ → d ₇ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1620.56
9	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1439.94
10	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94

Ant	Route Iteration 3	Distance (m)
1	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
2	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1625.84
3	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
4	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1625.84
7	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1625.84
8	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
9	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
10	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94

Ant	Route Iteration 4	Distance (m)
1	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
2	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
3	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
4	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
7	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
8	d ₁ → d ₃ → d ₂ → d ₅ → d ₇ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1620.56
9	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
10	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94

Ant	Route Iteration 5	Distance (m)
1	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
2	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
3	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1799.56
4	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1625.84
7	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1625.84
8	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₁	1625.84
9	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
10	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94

Ant	Route Iteration 6	Distance (m)
1	d ₁ → d ₃ → d ₂ → d ₅ → d ₇ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1620.56
2	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
3	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
4	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
7	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
8	d ₁ → d ₉ → d ₈ → d ₆ → d ₄ → d ₃ → d ₂ → d ₅ → d ₇ → d ₁	1869.12
9	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
10	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94

Ant	Route Iteration 7	Distance (m)
1	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
2	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
3	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
4	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
7	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1625.84
8	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
9	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
10	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94

Ant	Route Iteration 8	Distance (m)
1	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
2	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1625.84
3	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
4	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
7	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
8	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
9	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
10	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94

Ant	Route Iteration 9	Distance (m)
1	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
2	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
3	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
4	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₃ → d ₂ → d ₅ → d ₇ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
7	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
8	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1625.84
9	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
10	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94

Ant	Route Iteration 10	Distance (m)
1	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
2	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
3	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
4	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
5	d ₁ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
6	d ₁ → d ₅ → d ₂ → d ₃ → d ₄ → d ₆ → d ₈ → d ₉ → d ₇ → d ₅ → d ₁	1439.94
7	d ₁ → d ₂ → d ₃ → d<	

Table 4. Shortest Waste Collection Route in Banjar Tembau

Trip	Route	Distance (m)	Load (m ³)
1	TPS $d_1 \rightarrow$ TPS $d_3 \rightarrow$ TPS $d_7 \rightarrow$ TPS $d_9 \rightarrow$ TPS $d_{10} \rightarrow$ TPS $d_6 \rightarrow$ TPS $d_4 \rightarrow$ TPS $d_3 \rightarrow$ TPS $d_2 \rightarrow$ TPS d_1	1439.94	1110

Source: Data processed by the authors (2025)

The visualization of the optimal routes shows that Banjar Basa and Banjar Tembau exhibit different routing patterns based on their respective geographical characteristics. The graph of Banjar Basa contains a larger number of vertices and covers a wider area, thereby requiring two trips to reach all temporary waste disposal points (TPS) while adhering to the vehicle capacity limit of $1200m^3$ per trip. In contrast, Banjar Tembau, which has fewer vertices and shorter distances between points, only requires a single trip. The visualized graph illustrates the optimal path from the depot to each TPS and returning to the depot, where edges with higher pheromone intensity represent the most efficient routes. Overall, the ACO algorithm successfully adapts its route-searching strategy based on the number of vertices and vehicle capacity constraints, producing efficient waste collection routes for both regions with varying topographical characteristics and population densities.

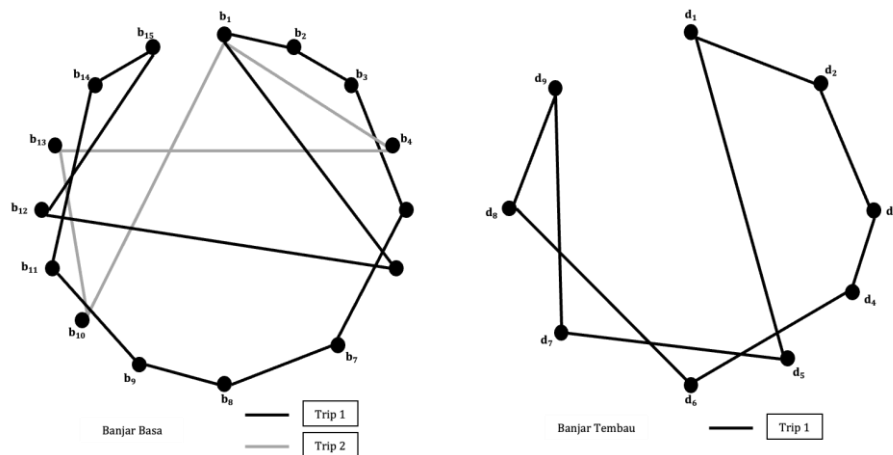


Figure 8. Visualization of the Optimal Waste Collection Route Graph

The subsequent discussion focuses on the analysis of solution convergence achieved by the Ant Colony Optimization (ACO) algorithm within the framework of the Capacitated Vehicle Routing Problem (CVRP). In this study, convergence refers to the stabilization of the minimum travel distance as the number of iterations increases. Each iteration represents a cycle of route exploration by the colony of ants, during which pheromone intensities on graph edges are adaptively updated based on the quality of the solutions obtained. Key parameters including α which controls the influence of pheromone; β which regulates the impact of distance or heuristic information; and ρ which denotes the pheromone evaporation rate play a significant role in determining the speed and direction of convergence. A well-balanced parameter configuration enables the system to effectively explore new paths while retaining the ability to exploit the best routes previously identified. Accordingly, this analysis highlights the relationship between the number of iterations, algorithmic parameter combinations, and

the stability of the shortest route solution, all of which collectively influence the effectiveness of ACO in converging toward a globally optimal solution.

IV. Conclusion

Based on the implementation and simulation results of the Ant Colony Optimization (ACO) algorithm applied to the Capacitated Vehicle Routing Problem (CVRP) in Banjar Basa and Banjar Tembau, it can be concluded that ACO is capable of generating efficient waste collection routes that adapt effectively to variations in the number of vertices and vehicle capacity constraints. The simulation results reveal that Banjar Basa, which has a larger number of vertices and a wider coverage area, requires two trips to serve all waste collection points, whereas Banjar Tembau only requires a single trip due to its simpler graph topology and shorter inter-vertex distances. Convergence toward the best route occurs progressively through pheromone updates in each iteration, where pheromone intensity increases significantly along routes with shorter total distances. The parameter combination of $\alpha = 1.0$, $\beta = 5.0$, $\rho = 0.5$, and $Q = 100$ is proven to maintain a balanced trade-off between exploration of new paths and exploitation of the best-discovered routes, thus accelerating convergence toward the global optimal solution. Therefore, the ACO algorithm is demonstrated to be an effective approach for optimizing waste collection systems based on shortest-route planning, particularly in areas with complex topographical characteristics and heterogeneous point distributions such as Banjar Basa and Banjar Tembau.

Acknowledgment

The authors would like to express their deepest gratitude to the Direktorat Riset, Teknologi, dan Pengabdian kepada Masyarakat (DRTPM) for providing the financial support that made this research possible. The authors extend their gratitude to the Perbekel of Marga Village for the facilities and logistical assistance provided during fieldwork, including the use of waste collection vehicles. The authors also wish to thank the LPPM of Bali Dwipa University for their consistent guidance and institutional support throughout the research process.

References

- [1] Badan Pusat Statistik, Statistik Lingkungan Hidup Indonesia 2021: Energi dan Lingkungan, Katalog 3305001. Jakarta: Badan Pusat Statistik, 2021.
- [2] Badan Pusat Statistik Kabupaten Tabanan, Kecamatan Marga dalam Angka 2017, Katalog BPS 11020015102050. Tabanan: Badan Pusat Statistik Kabupaten Tabanan, 2017.
- [3] Badan Pusat Statistik Kabupaten Tabanan, Kabupaten Tabanan dalam Angka 2024, Katalog 51021102001. Tabanan: Badan Pusat Statistik Kabupaten Tabanan, 2024.
- [4] S. K. Okrah, E. N. Wiah, H. Otoo, and J. A. Addor, "A velocity-based ACO algorithm for optimizing routes and social cost," *Scientific African*, vol. 23, p. e02031, 2024.
- [5] M. Li, B. Li, Z. Qi, J. Li, and J. Wu, "Optimized APF-ACO algorithm for ship collision avoidance and path planning," *Journal of Marine Science and Engineering*, vol. 11, no. 6, 2023.
- [6] M. L. Mutar, M. A. Burhanuddin, A. S. Hameed, N. Yusof, and H. J. Mutashar, "An efficient improvement of ant colony system algorithm for handling capacity vehicle routing problem," *Int. J. Ind. Eng. Comput.*, vol. 11, pp. 549–564, 2020.
- [7] Z. H. Ahmed, A. S. Hameed, M. L. Mutar, and H. Haron, "An enhanced Ant Colony System algorithm based on subpaths for solving the Capacitated Vehicle Routing Problem," *Symmetry*, vol. 15, no. 11, Nov. 2023.

- [8] M. Teguh, W. Fuadi, and Z. Fitri, "Application of Ant Colony Algorithm to Determine the Shortest Route for Nature and Culinary Tourism in North Aceh," *International Journal of Engineering, Science and Information Technology*, vol. 5, no. 2, pp. 413–423, Apr. 2025
- [9] F. Suryana, Nurdin, and D. Hamdhana, "Implementation of Ant Colony Optimization (ACO) Algorithm for Route Optimization of Tourist Paths in Takengon," *Journal of Applied Informatics and Computing (JAIC)*, vol. 9, no. 4, pp. 1886–1896, Aug. 2025.
- [10] K. Tomitagawa, A. Anuntachai, S. Chotipant, O. Wongwirat, and S. Kuchii, "Performance Measurement of Energy Optimal Path Finding for Waste Collection Robot Using ACO Algorithm," *IEEE Access*, vol. 10, pp. 117261–117272, Nov. 2022
- [11] S. K. Okrah, E. N. Wiah, H. Otoo, and J. Kangah, "Application of a modified ACO algorithm for optimizing routes and externality effect of solid waste management," *American Academic Scientific Research Journal for Engineering, Technology, and Sciences (ASRJETS)*, vol. 93, no. 1, pp. 140–155, Jun. 2023.
- [12] I. B. K. P. Arimbawa K, "Ant Colony Optimization for Waste Collection Routing: A Case Study in Sekar Tunjung Residential," *Brilliance: Research of Artificial Intelligence*, vol. 5, no. 1, pp. 175–186, May 2025.
- [13] M. Dorigo, V. Maniezzo, and A. Colorni, "Ant system: Optimization by a colony of cooperating agents," *IEEE Transactions on Systems, Man, and Cybernetics – Part B: Cybernetics*, vol. 26, no. 1, pp. 29–41, Feb. 1996.
- [14] M. Dorigo and G. Di Caro, "The ant colony optimization meta-heuristic," *New Ideas in Optimization*, pp. 11–32, 1999.
- [15] M. Dorigo, T. Stützle, G. Di Caro, and L. M. Gambardella, "The ant colony optimization metaheuristic: Algorithms, applications, and advances," *Handbook of Metaheuristics*, pp. 250–285, 2003.
- [16] I. B. K. P. Arimbawa K, I. G. A. Novitasari, and P. N. A. Permana, "Application of Ant Colony Optimization on CVRP for Waste Collection Route Optimization in Marga Village," *Brilliance: Research of Artificial Intelligence*, vol. 5, no. 2, pp. 940–951, 2025.
- [17] I. B. K. P. Arimbawa K, "Algoritma Djikstra: Rute pengungsian terpendek daerah rawan bencana di Desa Cunggu," *Jurnal Matematika*, vol. 14, no. 1, pp. 52–60, 2024.