

Application of Ant Colony Optimization on CVRP for Waste Collection Route Optimization in Marga Village

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ABSTRACT

Marga Village, located in Marga District, Tabanan Regency, faces significant challenges in waste management due to the absence of a structured schedule and route for waste collection, leading to inefficiencies, high operational costs, infrastructure risks, and public health concerns. These issues are further exacerbated by population growth and spatial expansion, which continually increase waste volume. This study aims to optimize waste collection routes in Marga Village by applying the Capacitated Vehicle Routing Problem (CVRP) approach using the Ant Colony Optimization (ACO) algorithm to identify the most efficient and sustainable shortest route. The simulation considered two main constraints: a maximum vehicle capacity of 1.2 m³ and an average waste volume per point ranging from 0.04 to 0.2 m³, ensuring load feasibility. The model was tested with 10 ants over 10 iterations, with temporary disposal points located at a_1 (Banjar Lebah) and c_1 (Banjar Beng) before transportation to TPS3R. Algorithm parameters were set at $\alpha = 1.0$ for pheromone influence and $\beta = 5.0$ for visibility, while the pheromone evaporation rate (ρ) was set to 0.5 and $Q = 100$ was used to reinforce optimal paths. The results demonstrate that ACO can effectively solve CVRP in waste collection, offering a data-driven solution to improve route efficiency and support sustainable urban waste management planning.

INTRODUCTION

Marga Village, located in Marga District, Tabanan Regency, Bali, spans an area of 2.62 km² and is home to a population of 3,084 residents (Badan Pusat Statistik, 2021; Badan Pusat Statistik Kabupaten Tabanan, 2017, 2024). Despite its relatively small size, the village faces increasingly complex waste management issues, primarily due to the absence of a clearly defined schedule and route for waste collection. This inefficiency leads to heightened operational costs, the risk of infrastructure damage due to overloaded collection points, and serious threats to public health from accumulating waste. These challenges are further exacerbated by steady population growth and spatial development, which continue to escalate the volume of waste produced.

To address these challenges, this study seeks to optimize the waste collection routes in Marga Village using a computational approach based on the Capacitated Vehicle Routing Problem (CVRP). This combinatorial optimization problem is particularly suitable for modeling real-world waste collection scenarios, as it incorporates constraints related to vehicle capacity and routing. By utilizing the CVRP framework, the study aims to develop collection paths that are not only efficient in terms of distance and operational cost but also sustainable and adaptable to future demands.

To solve the CVRP, the Ant Colony Optimization (ACO) algorithm is applied. ACO is a metaheuristic inspired by the foraging behavior of real ant colonies, particularly their ability to find the shortest path between a food source and their nest through a mechanism of pheromone deposition and collective reinforcement. Initially, ants move randomly until one discovers food. On the return journey, it leaves a pheromone trail, which increases the likelihood of other ants following the same path. Over time, the shortest and most efficient path accumulates more pheromones and becomes the preferred route. Despite their limited individual intelligence, ants exhibit highly efficient collective behavior, making ACO a powerful model for decentralized optimization.

In this study, ACO is used to simulate multiple ants (agents) searching for optimal waste collection routes under CVRP constraints. Each agent constructs solutions based on probabilistic rules influenced by pheromone intensity and heuristic desirability (e.g., inverse of distance). Through iterative reinforcement and pheromone updates, the algorithm converges toward an optimal or near-optimal solution.



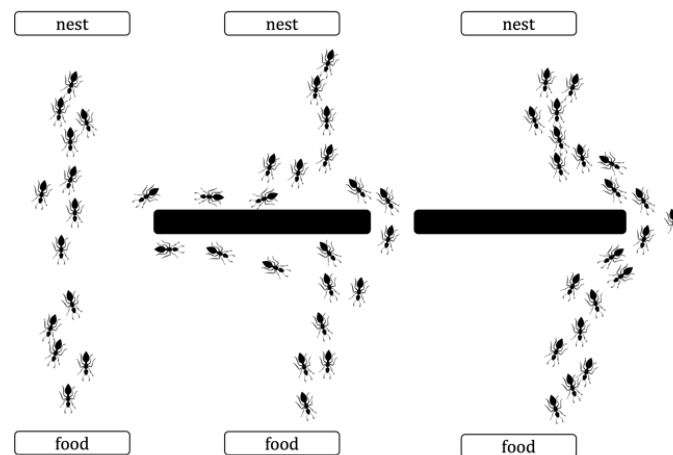


Fig. 1 Ant Illustration: From Nest to Food Source

By integrating ACO into the CVRP framework, this research aims to provide a practical and scalable solution for improving waste collection efficiency in Marga Village, with potential applications in similar rural and semi-urban areas across Indonesia.

LITERATURE REVIEW

Ant Colony Optimization (ACO) was first developed by Marco Dorigo in his doctoral dissertation in 1992 and was further formalized in a publication by Dorigo, Maniezzo, and Colnori (1996). ACO is inspired by the behavior of ant colonies in finding the shortest path to a food source, where ants use pheromones to mark and reinforce the most efficient paths. This mechanism was then modeled into an algorithm capable of solving various combinatorial optimization problems effectively. ACO has been widely applied to problems such as the Travelling Salesman Problem (TSP), the Vehicle Routing Problem (VRP), and its variants, including the Capacitated Vehicle Routing Problem (CVRP) (Dorigo et al., 1996).

In the context of waste collection, numerous studies have demonstrated the effectiveness of ACO and its variants. Hu et al. (2024) developed a hybrid algorithm called the Improved Ant Colony–Shuffled Frog Leaping Algorithm (IAC-SFLA) for domestic waste collection, which successfully reduced travel distance and improved load efficiency. Rattanawai et al. (2024) applied ACO to optimize the collection of both medical and non-medical waste by considering service priorities and time constraints.

Okrah et al. (2023) adapted ACO for waste collection in Ghana by incorporating carbon emissions and social cost considerations, demonstrating high efficiency. Shen et al. (2023) compared ACO with Particle Swarm Optimization (PSO) in a multi-trip urban waste collection context, finding that ACO remained competitive. Algethami (2023) showed that ACO could deliver optimal solutions with efficient computation time when combined with appropriate initialization strategies.

Gunawan et al. (2024) successfully implemented ACO in the waste transportation system of Tegal City, generating adaptive routes based on local spatial data. Manoharan et al. (2025) integrated ACO with an IoT-based Swin Transformer model for smart solid waste management. Wouda et al. (2024) combined ACO with data-driven decision-making to support waste selection and routing in urban areas.

The fundamental concept and applications of ACO were comprehensively formulated by Dorigo and Di Caro (1999), providing the foundation for subsequent developments of ACO variants. These studies reaffirm that ACO remains relevant and flexible for local-scale waste transportation scenarios, especially those with limited vehicle capacity and variable waste volumes, as addressed in this study.

METHOD

The initial mapping and preliminary observation phase was conducted in two areas: Lebah and Beng. This stage involved creating a base map that included administrative boundaries, road networks, and topographical conditions. Field observations were then carried out to identify primary roads, narrow alleys, potential obstacles, and the condition of road surfaces. This preliminary information served as the foundation for determining temporary waste disposal points and identifying feasible routes for waste collection vehicles.

Following this, a detailed survey of road segments and topography was conducted by measuring the length of each segment connecting the temporary disposal points to the main waste transfer station (TPS). Measurements were performed using GPS devices and direct field measurements. The collected data were then used to construct a realistic route network and to determine which road segments are suitable for waste collection vehicles to traverse.

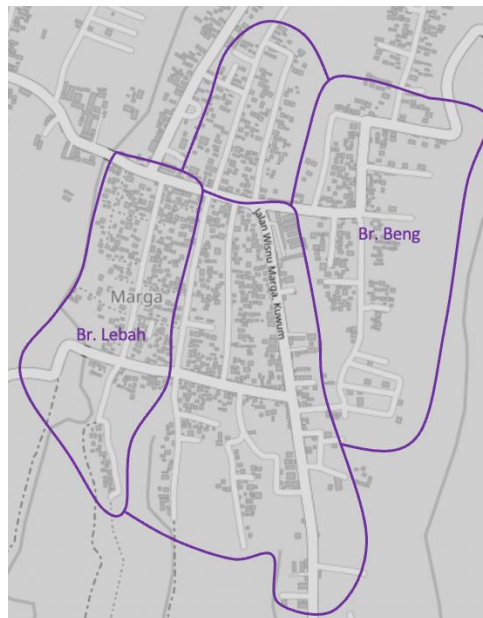


Fig. 2 Br. Lebah and Br. Beng

The data collected from mapping temporary disposal points and surveying road segments were processed into a graph, where each disposal point and the main TPS are represented as nodes, and the connecting roads as edges. Edge weights are based on road length and adjusted for topography and obstacles to reflect actual distance or travel time.

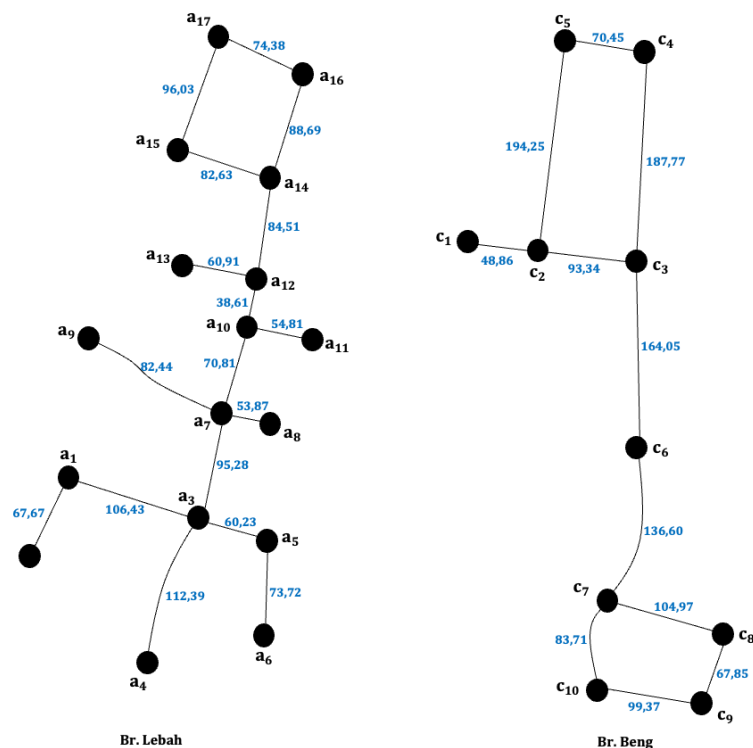


Fig. 3 Graph

After constructing the graph from the temporary disposal points and connecting road segments, the next step was to create an adjacency matrix. Each row and column in the matrix represents a node, and if two nodes are directly connected, the corresponding cell is filled with a weight representing road length or travel time from the survey. If no direct connection exists, a large value (99999) is used to indicate the absence of a link (K. et al., 2023). This matrix serves as a numerical representation of the road network in Marga Village.

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	a13	a14	a15	a16	a17
a1	99999	67,67	106,43	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999
a2	67,67	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999
a3	106,43	99999	99999	112,39	60,23	99999	95,28	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999
a4	99999	99999	112,39	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999
a5	99999	99999	60,23	99999	99999	73,72	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999
a6	99999	99999	99999	99999	73,72	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999
a7	99999	99999	95,28	99999	99999	99999	99999	53,87	82,44	70,81	99999	99999	99999	99999	99999	99999	99999
a8	99999	99999	99999	99999	99999	99999	53,87	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999
a9	99999	99999	99999	99999	99999	82,44	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999
a10	99999	99999	99999	99999	99999	70,81	99999	99999	99999	99999	54,81	38,81	99999	99999	99999	99999	99999
a11	99999	99999	99999	99999	99999	99999	99999	99999	99999	54,81	99999	99999	99999	99999	99999	99999	99999
a12	99999	99999	99999	99999	99999	99999	99999	99999	99999	38,81	99999	99999	60,91	84,51	99999	99999	99999
a13	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	60,91	99999	99999	99999	99999	99999	99999
a14	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	84,51	99999	99999	99999	82,63	88,69	99999
a15	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	82,63	99999	99999	96,03
a16	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	88,69	99999	99999	74,38
a17	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	99999	96,03	74,38	99999	99999

Br. Lebah

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
c1	99999	48,86	99999	99999	99999	99999	99999	99999	99999	99999
c2	48,86	99999	93,34	99999	194,25	99999	99999	99999	99999	99999
c3	99999	93,34	99999	187,77	99999	164,05	99999	99999	99999	99999
c4	99999	99999	187,77	99999	70,45	99999	99999	99999	99999	99999
c5	99999	194,25	99999	70,45	99999	99999	99999	99999	99999	99999
c6	99999	99999	164,05	99999	99999	99999	136,6	99999	99999	99999
c7	99999	99999	99999	99999	99999	136,6	99999	104,97	99999	83,71
c8	99999	99999	99999	99999	99999	99999	104,97	99999	67,85	99999
c9	99999	99999	99999	99999	99999	99999	67,85	99999	99999	99,37
c10	99999	99999	99999	99999	99999	99999	83,71	99999	99,37	99999

Br. Beng

Fig. 4 Adjacency matrix

This condition implicitly forms a weighted sparse graph, where only a small portion of all possible node connections actually exists. Therefore, this study assumes that a node may be visited more than once, as long as doing so enables the determination of a minimum-length route. In this context, a complete graph is constructed to ensure that every node is connected to every other node. The shortest path is then calculated using Dijkstra's algorithm, which has been widely applied in similar studies, such as for determining evacuation routes in disaster-prone areas (Arimbawa K, 2024). From this process, a new adjacency matrix is obtained and illustrated as a complete graph, as shown below.

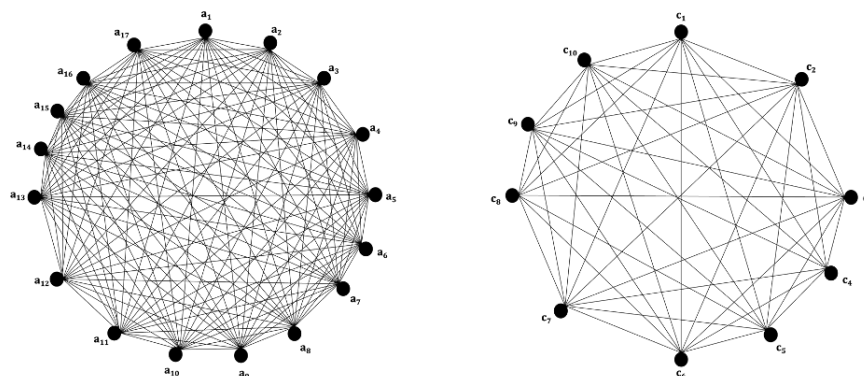


Fig. 5 Complete Graph

The complete graph described above is then represented as an adjacency matrix, which serves as the input data for the C++ programming implementation. The adjacency matrix is constructed based on the connectivity and weights between all nodes in the complete graph. The resulting matrix is presented as follows.

	a1	a2	a3	a4	a5	a6	a7	a8	a9	a10	a11	a12	a13	a14	a15	a16	a17
a1	0	67,67	106,43	218,82	166,66	240,38	201,71	255,58	284,15	272,52	327,33	311,33	372,24	395,84	478,47	484,53	558,91
a2	67,67	0	174,1	286,49	234,33	308,05	269,38	323,25	351,82	340,19	395	379	439,91	463,51	546,14	552,2	626,58
a3	106,43	174,1	0	112,39	60,23	133,95	95,28	149,15	177,72	166,09	220,9	204,9	265,81	289,41	372,04	378,1	452,48
a4	218,82	286,49	112,39	0	172,62	246,34	207,67	261,54	290,11	278,48	333,29	317,29	378,2	401,8	484,43	490,49	564,87
a5	166,66	234,33	60,23	172,62	0	73,72	155,51	209,38	237,95	226,32	281,13	265,13	326,04	349,64	432,27	438,33	512,71
a6	240,38	308,05	133,95	246,34	73,72	0	229,23	283,1	311,67	300,04	354,85	338,85	399,76	423,36	505,99	512,05	586,43
a7	201,71	269,38	95,28	207,67	155,51	229,23	0	53,87	82,44	70,81	125,62	109,62	170,53	194,13	276,76	282,82	357,2
a8	255,58	323,25	149,15	261,54	209,38	283,1	53,87	0	136,31	124,68	179,49	163,49	224,4	248	330,63	336,69	411,07
a9	284,15	351,82	177,72	290,11	237,95	311,67	82,44	136,31	0	153,25	208,06	192,06	252,97	276,57	359,2	365,26	439,64
a10	272,52	340,19	166,09	278,48	226,32	300,04	70,81	124,68	153,25	0	54,81	38,81	99,72	123,32	205,95	212,01	286,39
a11	327,33	395	220,9	333,29	281,13	354,85	125,62	179,49	208,06	54,81	0	93,62	154,53	178,13	260,76	266,82	341,2
a12	311,33	379	204,9	317,29	265,13	338,85	109,62	163,49	192,06	38,81	93,62	0	60,91	84,51	167,14	173,2	247,58
a13	372,24	439,91	265,81	378,2	326,04	399,76	170,53	224,4	252,97	99,72	154,53	60,91	0	145,42	228,05	234,11	308,49
a14	395,84	463,51	289,41	401,8	349,64	423,36	194,13	248	276,57	123,32	178,13	84,51	145,42	0	82,63	88,69	163,07
a15	478,47	546,14	372,04	484,43	432,27	505,99	276,76	330,63	359,2	205,95	260,76	167,14	228,05	82,63	0	170,41	96,03
a16	484,53	552,2	378,1	490,49	438,33	512,05	282,82	336,69	365,26	212,01	266,82	173,2	234,11	88,69	170,41	0	74,38
a17	558,91	626,58	452,48	564,87	512,71	586,43	357,2	411,07	439,64	286,39	341,2	247,58	308,49	163,07	96,03	74,38	0

Br. Lebah

	c1	c2	c3	c4	c5	c6	c7	c8	c9	c10
c1	0	48,86	142,2	313,56	243,11	306,25	442,85	547,82	615,67	526,56
c2	48,86	0	93,34	264,7	194,25	257,39	393,99	498,96	566,81	477,7
c3	142,2	93,34	0	187,77	258,22	164,05	300,65	405,62	473,47	384,36
c4	313,56	264,7	187,77	0	70,45	351,82	488,42	593,39	661,24	572,13
c5	243,11	194,25	258,22	70,45	0	422,27	558,87	663,84	731,69	642,58
c6	306,25	257,39	164,05	351,82	422,27	0	136,6	241,57	309,42	220,31
c7	442,85	393,99	300,65	488,42	558,87	136,6	0	104,97	172,82	83,71
c8	547,82	498,96	405,62	593,39	663,84	241,57	104,97	0	67,85	167,22
c9	615,67	566,81	473,47	661,24	731,69	309,42	172,82	67,85	0	99,37
c10	526,56	477,7	384,36	572,13	642,58	220,31	83,71	167,22	99,37	0

Br. Beng

Fig. 6 Representation of the Adjacency Matrix of the Complete Graph

The Ant Colony Optimization (ACO) algorithm was implemented in C++ due to its efficiency in handling large-scale iterations and complex computations. The process including parameter initialization, solution construction, transition probability calculation, and pheromone updating was executed systematically. Data such as distance matrices, node visits, and waste volumes were managed using arrays and vectors. Each simulation used 10 ants over 10 iterations, with the best solution from each iteration recorded for analysis.

RESULT

During route construction, two key constraints were considered: the maximum vehicle capacity of 1.2 m³ and the average waste volume per point (0.04–0.2 m³), ensuring the load stayed within capacity. The ACO simulation involved 10 ants over 10 iterations, with temporary disposal points defined as a_i (Lebah) and c_i (Beng) before transport to TPS3R. Parameters were set as $\alpha = 1.0$ (pheromone influence) and $\beta = 5.0$ (visibility), balancing past experience with route length preference. The pheromone evaporation rate (ρ) was 0.5 to avoid early convergence, and $Q = 100$ strengthened optimal paths. Initial pheromones were uniformly distributed, and visibility $\eta_{ij} = \frac{1}{d_{ij}}$ was used, except when d_{ij} was extremely large (∞), where visibility was set to zero.

The ACO algorithm in this study was implemented using the C++ programming language due to its efficiency in handling iterative computations and multidimensional array processing. The program structure was divided into several main components that collectively support the construction of ACO solutions (Arimbawa, 2025).

During the simulation process, the algorithm was executed for 10 iterations involving 10 ants in each iteration. Each ant progressively constructed a route while considering two main constraints: the maximum capacity of the waste collection vehicle and the average waste volume at each collection point (Marselina et al., 2024; Siti Nur Amida et al., 2024). When the vehicle's capacity was reached, the ant was directed back to the depot to start a new sub-route. However, under the current configuration, all collection points could be served in a single trip without requiring additional sub-routes. The simulation results for each iteration are presented as follows:

Ant	Route Iteration 1	Distance (m)
1	a1 -> a8 -> a7 -> a5 -> a11 -> a10 -> a12 -> a13 -> a14 -> a9 -> a6 -> a1 -> a2 -> a3 -> a4 -> a15 -> a17 -> a16 -> a1	3368.19
2	a1 -> a2 -> a3 -> a7 -> a9 -> a10 -> a12 -> a13 -> a14 -> a16 -> a1 -> a6 -> a5 -> a4 -> a8 -> a11 -> a15 -> a17 -> a1	3234.55
3	a1 -> a2 -> a3 -> a5 -> a6 -> a10 -> a12 -> a7 -> a8 -> a9 -> a11 -> a1 -> a4 -> a13 -> a14 -> a15 -> a17 -> a16 -> a1	3029.77
4	a1 -> a2 -> a3 -> a5 -> a6 -> a12 -> a10 -> a11 -> a8 -> a7 -> a9 -> a1 -> a4 -> a13 -> a14 -> a16 -> a17 -> a15 -> a1	2888.15
5	a1 -> a2 -> a3 -> a5 -> a6 -> a4 -> a12 -> a10 -> a11 -> a14 -> a1 -> a7 -> a8 -> a9 -> a13 -> a16 -> a17 -> a15 -> a1	3134.79
6	a1 -> a2 -> a4 -> a3 -> a5 -> a6 -> a10 -> a12 -> a7 -> a8 -> a9 -> a1 -> a14 -> a15 -> a17 -> a16 -> a13 -> a11 -> a1	2888.15
7	a1 -> a2 -> a3 -> a5 -> a6 -> a8 -> a7 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a11 -> a9 -> a15 -> a17 -> a16 -> a1	3198.79
8	a1 -> a2 -> a3 -> a5 -> a6 -> a4 -> a7 -> a8 -> a9 -> a10 -> a12 -> a1 -> a13 -> a11 -> a14 -> a15 -> a17 -> a16 -> a1	2965.77
9	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a10 -> a12 -> a13 -> a14 -> a8 -> a1 -> a9 -> a11 -> a15 -> a17 -> a16 -> a4 -> a1	3057.17
10	a1 -> a3 -> a5 -> a6 -> a2 -> a8 -> a7 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a9 -> a16 -> a17 -> a15 -> a11 -> a1	3270.03

Ant	Route Iteration 2	Distance (m)
1	a1 -> a2 -> a3 -> a7 -> a10 -> a12 -> a13 -> a8 -> a11 -> a9 -> a6 -> a1 -> a5 -> a4 -> a14 -> a15 -> a17 -> a16 -> a1	3150.23
2	a1 -> a2 -> a3 -> a5 -> a6 -> a4 -> a7 -> a8 -> a10 -> a11 -> a1 -> a9 -> a14 -> a15 -> a17 -> a16 -> a12 -> a13 -> a1	2810.53
3	a1 -> a2 -> a5 -> a3 -> a7 -> a8 -> a10 -> a12 -> a13 -> a16 -> a6 -> a1 -> a4 -> a14 -> a15 -> a17 -> a9 -> a11 -> a1	3496.63
4	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a11 -> a12 -> a9 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
5	a1 -> a2 -> a3 -> a5 -> a6 -> a4 -> a14 -> a15 -> a17 -> a16 -> a8 -> a1 -> a12 -> a10 -> a11 -> a7 -> a9 -> a13 -> a1	3107.39
6	a1 -> a2 -> a5 -> a3 -> a4 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a11 -> a15 -> a14 -> a16 -> a17 -> a6 -> a1	3158.28
7	a1 -> a2 -> a3 -> a5 -> a6 -> a4 -> a7 -> a9 -> a12 -> a10 -> a8 -> a1 -> a13 -> a14 -> a15 -> a16 -> a17 -> a11 -> a1	3036.91
8	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a11 -> a14 -> a15 -> a17 -> a16 -> a1	2888.15
9	a1 -> a2 -> a3 -> a5 -> a6 -> a4 -> a10 -> a12 -> a13 -> a14 -> a17 -> a1 -> a7 -> a8 -> a11 -> a9 -> a16 -> a15 -> a1	3524.93
10	a1 -> a2 -> a7 -> a8 -> a11 -> a10 -> a12 -> a13 -> a14 -> a17 -> a1 -> a3 -> a5 -> a6 -> a4 -> a9 -> a16 -> a15 -> a1	3383.31

Ant	Route Iteration 3	Distance (m)
1	a1 -> a2 -> a3 -> a5 -> a6 -> a9 -> a7 -> a8 -> a10 -> a12 -> a13 -> a1 -> a16 -> a14 -> a15 -> a17 -> a11 -> a4 -> a1	3065.53
2	a1 -> a2 -> a3 -> a5 -> a4 -> a8 -> a7 -> a10 -> a12 -> a13 -> a9 -> a1 -> a11 -> a14 -> a16 -> a17 -> a15 -> a6 -> a1	3008.61
3	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a11 -> a16 -> a14 -> a17 -> a15 -> a1	3065.53
4	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a10 -> a12 -> a13 -> a14 -> a8 -> a1 -> a4 -> a11 -> a9 -> a15 -> a17 -> a16 -> a1	3198.79
5	a1 -> a2 -> a3 -> a5 -> a6 -> a10 -> a12 -> a13 -> a11 -> a7 -> a1 -> a4 -> a8 -> a9 -> a14 -> a16 -> a17 -> a15 -> a1	2888.15
6	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a9 -> a4 -> a11 -> a15 -> a17 -> a16 -> a1	3247.73
7	a1 -> a2 -> a5 -> a3 -> a4 -> a9 -> a7 -> a8 -> a10 -> a12 -> a13 -> a1 -> a15 -> a17 -> a16 -> a14 -> a11 -> a6 -> a1	3008.61
8	a1 -> a2 -> a3 -> a8 -> a7 -> a13 -> a12 -> a10 -> a11 -> a9 -> a6 -> a1 -> a4 -> a5 -> a16 -> a17 -> a15 -> a14 -> a1	3008.61
9	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a9 -> a10 -> a12 -> a17 -> a13 -> a1 -> a4 -> a8 -> a14 -> a16 -> a15 -> a11 -> a1	3383.31
10	a1 -> a2 -> a3 -> a8 -> a7 -> a10 -> a12 -> a13 -> a15 -> a14 -> a1 -> a4 -> a6 -> a5 -> a9 -> a11 -> a16 -> a17 -> a1	3206.84

Ant	Route Iteration 4	Distance (m)
1	a1 -> a2 -> a5 -> a3 -> a6 -> a10 -> a12 -> a13 -> a14 -> a15 -> a9 -> a8 -> a1 -> a7 -> a11 -> a17 -> a16 -> a4 -> a1	3327.30
2	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a12 -> a10 -> a11 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
3	a1 -> a2 -> a3 -> a5 -> a6 -> a4 -> a8 -> a7 -> a9 -> a10 -> a12 -> a1 -> a11 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
4	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a11 -> a12 -> a1 -> a15 -> a17 -> a16 -> a14 -> a13 -> a4 -> a1	2888.15
5	a1 -> a2 -> a3 -> a5 -> a7 -> a8 -> a10 -> a12 -> a11 -> a9 -> a6 -> a1 -> a4 -> a13 -> a14 -> a16 -> a17 -> a15 -> a1	3008.61
6	a1 -> a2 -> a6 -> a5 -> a3 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a9 -> a11 -> a15 -> a17 -> a16 -> a1	3057.17
7	a1 -> a2 -> a3 -> a5 -> a6 -> a4 -> a7 -> a8 -> a10 -> a12 -> a13 -> a1 -> a9 -> a11 -> a15 -> a14 -> a17 -> a16 -> a1	3037.82
8	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a12 -> a10 -> a11 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
9	a1 -> a2 -> a3 -> a5 -> a6 -> a4 -> a7 -> a8 -> a10 -> a12 -> a13 -> a1 -> a11 -> a14 -> a15 -> a17 -> a16 -> a9 -> a1	2888.15
10	a1 -> a2 -> a5 -> a6 -> a9 -> a7 -> a10 -> a11 -> a12 -> a13 -> a8 -> a1 -> a3 -> a4 -> a15 -> a14 -> a16 -> a17 -> a1	3037.82

Ant	Route Iteration 5	Distance (m)
1	a1 -> a2 -> a5 -> a3 -> a7 -> a8 -> a9 -> a11 -> a10 -> a12 -> a6 -> a1 -> a4 -> a16 -> a17 -> a15 -> a14 -> a13 -> a1	3008.61
2	a1 -> a2 -> a5 -> a3 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a6 -> a1 -> a9 -> a11 -> a17 -> a16 -> a15 -> a4 -> a1	3326.39
3	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a11 -> a1	2888.15
4	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a11 -> a14 -> a15 -> a17 -> a16 -> a1	2888.15
5	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a12 -> a10 -> a11 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
6	a1 -> a2 -> a3 -> a5 -> a6 -> a11 -> a10 -> a12 -> a13 -> a14 -> a9 -> a1 -> a4 -> a7 -> a8 -> a17 -> a16 -> a15 -> a1	3205.93
7	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a12 -> a10 -> a11 -> a1 -> a4 -> a14 -> a16 -> a17 -> a15 -> a13 -> a1	2888.15
8	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a11 -> a1	2888.15
9	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a16 -> a1 -> a11 -> a14 -> a15 -> a17 -> a4 -> a9 -> a1	3425.11
10	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a11 -> a12 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15

Ant	Route Iteration 6	Distance (m)
1	a1 -> a2 -> a5 -> a3 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a4 -> a1 -> a6 -> a11 -> a14 -> a15 -> a17 -> a16 -> a1	3008.61
2	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a11 -> a14 -> a15 -> a17 -> a16 -> a1	2888.15
3	a1 -> a2 -> a3 -> a5 -> a6 -> a12 -> a13 -> a10 -> a11 -> a14 -> a9 -> a1 -> a7 -> a8 -> a4 -> a16 -> a17 -> a15 -> a1	3325.35
4	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a14 -> a15 -> a10 -> a1 -> a4 -> a12 -> a13 -> a16 -> a17 -> a11 -> a1	3206.84
5	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a12 -> a10 -> a11 -> a1 -> a4 -> a16 -> a17 -> a15 -> a14 -> a13 -> a1	2888.15
6	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a11 -> a12 -> a1 -> a4 -> a16 -> a17 -> a15 -> a14 -> a13 -> a1	2888.15
7	a1 -> a2 -> a4 -> a3 -> a5 -> a6 -> a7 -> a10 -> a11 -> a8 -> a1 -> a13 -> a12 -> a14 -> a15 -> a17 -> a16 -> a9 -> a1	2810.53
8	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a11 -> a14 -> a15 -> a17 -> a16 -> a1	2888.15
9	a1 -> a2 -> a3 -> a5 -> a6 -> a8 -> a7 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a11 -> a17 -> a16 -> a15 -> a9 -> a1	3205.93
10	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a11 -> a10 -> a12 -> a9 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15

Ant	Route Iteration 7	Distance (m)
1	a1 -> a2 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a15 -> a1 -> a3 -> a4 -> a9 -> a11 -> a16 -> a17 -> a1	3206.84
2	a1 -> a2 -> a3 -> a5 -> a6 -> a13 -> a12 -> a10 -> a11 -> a7 -> a1 -> a4 -> a9 -> a8 -> a14 -> a15 -> a17 -> a16 -> a1	2888.15
3	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a11 -> a10 -> a12 -> a9 -> a1 -> a4 -> a13 -> a14 -> a15 -> a17 -> a16 -> a1	2888.15
4	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a11 -> a12 -> a9 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
5	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a11 -> a12 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
6	a1 -> a2 -> a3 -> a5 -> a6 -> a12 -> a13 -> a14 -> a15 -> a17 -> a9 -> a8 -> a1 -> a4 -> a7 -> a10 -> a11 -> a16 -> a1	3234.55
7	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a15 -> a17 -> a16 -> a11 -> a9 -> a1	3057.17
8	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a11 -> a1	2888.15
9	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a9 -> a11 -> a16 -> a17 -> a15 -> a1	3057.17
10	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a11 -> a12 -> a9 -> a1 -> a4 -> a16 -> a17 -> a15 -> a14 -> a13 -> a1	2888.15

Ant	Route Iteration 8	Distance (m)
1	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a9 -> a11 -> a4 -> a17 -> a15 -> a16 -> a1	3565.82
2	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a11 -> a9 -> a17 -> a15 -> a16 -> a1	3375.26
3	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a11 -> a12 -> a1 -> a13 -> a14 -> a15 -> a17 -> a16 -> a4 -> a1	2888.15
4	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a11 -> a9 -> a17 -> a16 -> a15 -> a1	3347.55
5	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a9 -> a11 -> a15 -> a17 -> a16 -> a1	3057.17
6	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a9 -> a11 -> a16 -> a17 -> a15 -> a1	3057.17
7	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a11 -> a9 -> a17 -> a16 -> a15 -> a1	3347.55
8	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a11 -> a16 -> a17 -> a15 -> a14 -> a1	2888.15
9	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a11 -> a14 -> a15 -> a17 -> a16 -> a1	2888.15
10	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a10 -> a12 -> a13 -> a14 -> a9 -> a1 -> a4 -> a8 -> a11 -> a16 -> a15 -> a17 -> a1	3233.64

Ant	Route Iteration 9	Distance (m)
1	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a11 -> a12 -> a9 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
2	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a9 -> a11 -> a16 -> a17 -> a15 -> a4 -> a1	3057.17
3	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a9 -> a11 -> a16 -> a17 -> a15 -> a4 -> a1	3057.17
4	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a11 -> a12 -> a9 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
5	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a13 -> a1 -> a4 -> a11 -> a16 -> a17 -> a15 -> a14 -> a1	2888.15
6	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a9 -> a11 -> a16 -> a17 -> a15 -> a1	3057.17
7	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a9 -> a10 -> a12 -> a11 -> a1 -> a4 -> a14 -> a15 -> a17 -> a16 -> a13 -> a1	2888.15
8	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a9 -> a11 -> a16 -> a17 -> a15 -> a1	3057.17
9	a1 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a9 -> a1 -> a2 -> a4 -> a15 -> a17 -> a16 -> a11 -> a1	3057.17
10	a1 -> a2 -> a3 -> a5 -> a6 -> a7 -> a8 -> a10 -> a12 -> a13 -> a14 -> a1 -> a4 -> a15 -> a17 -> a16 -> a11 -> a9 -> a1	3057.17

Ant	Route Iteration 9	Distance (m)	Ant	Route Iteration 10	Distance (m)
1	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95	1	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95
2	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95	2	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95
3	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95	3	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95
4	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95	4	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95
5	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95	5	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95
6	c1 -> c2 -> c3 -> c4 -> c5 -> c6 -> c7 -> c10 -> c9 -> c1 -> c8 -> c1	2853.68	6	c1 -> c2 -> c3 -> c4 -> c5 -> c6 -> c7 -> c10 -> c9 -> c1 -> c8 -> c1	2853.68
7	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95	7	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95
8	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95	8	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95
9	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95	9	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95
10	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95	10	c1 -> c2 -> c3 -> c6 -> c7 -> c10 -> c9 -> c8 -> c4 -> c1 -> c5 -> c1	2086.95

Fig. 8 10 Iterations with 10 Ants : Br. Beng

The optimal waste collection route is determined based on the shortest distance that the collection vehicle must travel. Identifying the shortest route is crucial because it directly affects time efficiency and operational costs in the waste transportation process. However, due to the limited capacity of the collection vehicle, it is not possible to transport all the waste in a single trip. Therefore, multiple trips are required to ensure that all waste is collected efficiently. Based on distance calculations and capacity considerations, the shortest route was identified as the most efficient path, ensuring that all waste can be collected with minimal time and effort.

Trip	Route	Distance (m)	Load (m ³)
1	TPS a1 -> TPS a2 -> TPS a3 -> TPS a5 -> TPS a6 -> TPS a4 -> TPS a7 -> TPS a8 -> TPS a10 -> TPS a11 -> TPS a1	1390.42	1160
2	TPS a1 -> TPS a9 -> TPS a14 -> TPS a15 -> TPS a17 -> TPS a16 -> TPS a12 -> TPS a13 -> TPS a1	1420.11	840

Trip	Route	Distance (m)	Load (m ³)
1	TPS c1 -> TPS c3 -> TPS c4 -> TPS c5 -> TPS c10 -> TPS c7 -> TPS c8 -> TPS c9 -> TPS c6 -> TPS c1	1915.20	1070
2	TPS c1 -> TPS c2 -> TPS c1	97.72	200

Fig. 9 Shortest Waste Collection Route

To evaluate the performance of the Ant Colony Optimization (ACO) algorithm, a series of experiments was conducted by testing different combinations of its key parameters: α , β , and ρ . The objective was to identify the parameter settings that yield the most efficient waste collection route in terms of total travel distance and number of trips. In these experiments, the number of ants was fixed at 10 and the maximum number of iterations at 10, while the parameters were systematically varied. The pheromone influence parameter (α) was adjusted between 0.5 and 3.0 to observe its effect on ant decision-making. The visibility parameter (β) was varied from 2.0 to 15 to analyze how the distance heuristic influences route selection. Additionally, the pheromone evaporation rate (ρ) was tested at 0.1, 0.5, and 0.8 to assess the stability of pheromone trails over time.

The results of the waste collection route analysis are visualized using a graph representation. This graph illustrates the overall structure of the road network and highlights the selected shortest route. Through this visualization, the vehicle's travel path can be understood more intuitively, including the sequence of visits to each collection point and the connections between locations that form the optimal route.

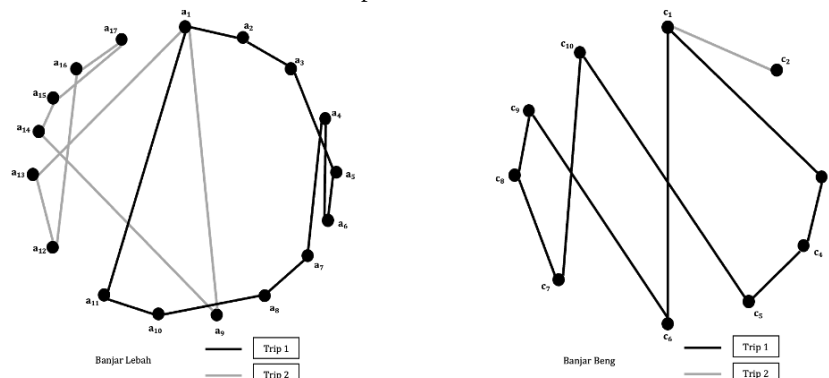


Fig. 10 Visualization of the Shortest Route in a Graph

DISCUSSION

This study confirms the effectiveness of the Ant Colony Optimization (ACO) algorithm in designing efficient waste collection routes within a controlled simulation environment. The current implementation, however, was conducted using only a limited number of waste collection points, which serves as a simplified representation of the actual field conditions in Marga Village. In reality, the number of collection points is expected to increase significantly in line with population growth and residential expansion, resulting in a far more complex waste collection network than the one modeled in this study. Such conditions would require more sophisticated strategies, including advanced graph modeling, segmentation of service areas, and dynamic adjustments to vehicle capacity and waste generation patterns.

Moreover, the algorithm's operational parameters were intentionally kept modest, involving 15 ants and 5 to 50 iterations. While this configuration proved sufficient for exploring route solutions in a small-scale scenario, larger and more complex networks would benefit from scaling up these parameters to enhance solution diversity and improve convergence toward optimal routes. A higher number of ants and iterations would enable deeper exploration of the solution space and potentially yield more efficient routing strategies, albeit at the cost of increased computational effort.

Given these limitations, this research should be regarded as an exploratory study that demonstrates the feasibility of using ACO for waste collection optimization under constrained conditions. Future work could expand the scope by applying the algorithm to a larger number of collection points, integrating real-time spatial and environmental data, and incorporating IoT-based waste prediction models to anticipate fluctuations in daily waste volume. Additionally, the development of adaptive decision-support systems could enhance the scalability and sustainability of waste management strategies, ultimately enabling local governments to plan more effective collection schedules and resource allocations in rapidly growing residential areas.

CONCLUSION

This study demonstrates that the Ant Colony Optimization (ACO) algorithm is highly capable of producing efficient solutions for waste collection route planning on a local scale. A simulation involving two areas, Br. Lebah and Br. Beng in Marga Village, showed that ACO can generate optimal waste collection routes by considering several critical factors, including total travel distance, vehicle capacity, and waste volume at each collection point. The results confirm that ACO is an adaptive, flexible, and effective approach for designing data-driven waste management logistics systems, capable of adapting to field conditions and providing optimal solutions within a relatively efficient computational time.

The benefits of this research include improved waste collection efficiency, both in terms of time and operational costs, reduced fuel consumption, and support for more structured and sustainable urban logistics planning. Furthermore, the proposed method has significant potential to be applied to a broader range of route-based transportation systems, such as logistics distribution, goods delivery, and public transportation services especially in scenarios involving capacity limitations and spatial constraints. In addition, ACO has proven to be effective in solving the Capacitated Vehicle Routing Problem (CVRP) an optimization problem focused on determining distribution routes under vehicle capacity constraints which is highly relevant to the context of waste collection in residential areas.

Despite these promising outcomes, several limitations should be noted. One major limitation is that the number of waste collection points used in the simulation remains relatively small, which does not fully reflect real-world conditions. Moreover, the study has not yet incorporated various real-time factors such as traffic congestion, daily fluctuations in waste volume, and service time constraints, all of which could significantly affect route performance. Therefore, future studies are recommended to integrate real-time spatial and temporal data, expand the number of waste collection points to better represent actual conditions, and increase the number of ants and iterations in the simulation to improve solution exploration.

Furthermore, future research could explore the development of hybrid optimization approaches that combine ACO with other algorithms to enhance convergence speed and solution quality, particularly in more complex scenarios. With such advancements, ACO has the potential to become a leading method for solving CVRP and planning efficient, adaptive, and sustainable waste collection systems, not only in rural areas like Marga Village but also in large-scale urban environments.

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