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Last-Mile Delivery Routing Using Ant Colony Optimization and Google Maps API

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Abstract−The rapid growth of e-commerce has significantly increased the demand for efficient last-mile delivery, making route optimization an essential challenge for logistics providers. Conventional manual route planning often depends on driver experience and may fail to produce efficient delivery sequences, particularly as the number of destinations increases. This study proposes a web-based last-mile delivery routing optimization system that integrates Residential Delivery Clusters, the Google Maps Distance Matrix Application Programming Interface (API), and the Ant Colony Optimization algorithm to generate practical delivery routes based on actual road-network distances. Residential Delivery Clusters group destinations within the same residential area through representative entrance points, enabling the routing model to better reflect real-world delivery environments while reducing route complexity. The proposed system was evaluated using seven real delivery scenarios containing between 5 and 62 delivery locations obtained from an expedition service in Bekasi Regency, Indonesia. Experimental results demonstrate that the proposed approach consistently improved routing performance by reducing total travel distance by 0.07% to 23.91% compared with manually planned routes. Notably, the optimal testing scenario comprising 62 delivery points achieved a substantial travel distance saving of 60.62 km. Furthermore, route planning time was reduced by 60.2% to 89.6% relative to manual planning performed by experienced expedition drivers. These findings indicate that integrating residential delivery clustering with road-network-based optimization can improve routing efficiency and substantially reduce operational planning effort, making the proposed approach suitable for practical implementation in real-world last-mile delivery operations.

Keywords: Last-Mile Delivery; Ant Colony Optimization; Vehicle Routing Problem; Route Optimization; Google Maps Distance Matrix API; Residential Delivery Cluster

1. INTRODUCTION

Indonesia's e-commerce sector has experienced rapid expansion, creating substantial operational pressure on logistics and fulfillment networks. Early mapping from the Badan Pusat Statistik indicated that the wholesale and retail trade sector already dominated digital commerce activities in 2019, accounting for 13,425 businesses or 14.24 percent of registered e-commerce enterprises [1]. This growth continued significantly, with transaction values increasing from approximately 474 trillion rupiah in 2023 to 487 trillion rupiah in 2024. By 2025, Indonesia had become the largest digital economy in Southeast Asia, reaching a Gross Merchandise Value of 100 billion US dollars, with e-commerce contributing 71 billion US dollars following a 14 percent annual growth rate. Supported by an internet penetration rate of 80.66 percent and 229.4 million connected citizens, electronic commerce transactions reached 1.44 billion occurrences during the third quarter of 2025 alone [2]. The continuous growth of online shopping has substantially increased the demand for efficient last-mile delivery services, making the final stage of the logistics process increasingly critical for maintaining delivery efficiency, customer satisfaction, and operational sustainability [3]. Consequently, this massive influx of point-to-point product fulfillment activities places considerable pressure on distribution networks, necessitating advanced computational approaches to support efficient route planning and delivery operations.

From a computational perspective, last-mile distribution belongs to the class of Vehicle Routing Problems (VRP) and Travelling Salesperson Problems (TSP), both of which are categorized as NP-hard combinatorial optimization problems [4], [5]. As the number of delivery destinations increases, obtaining exact optimal solutions becomes computationally expensive due to exponential growth in processing time and memory requirements [6]. Traditional exact approaches, including integer linear programming, brute-force computation, and classical graph-based algorithms, become increasingly impractical for large-scale routing scenarios. Consequently, modern optimization research has shifted toward metaheuristic frameworks capable of producing near-optimal solutions within significantly shorter execution times [4], [7]. Rather than exhaustively searching for a global optimum, metaheuristic methods employ stochastic exploration strategies to efficiently approximate high-quality routing configurations suitable for large-scale practical delivery operations.

Among these metaheuristic approaches, swarm intelligence algorithms have gained significant attention for solving large-scale routing and delivery problems. Nature-inspired optimization techniques have been widely adopted because they provide computationally efficient approaches for solving NP-hard routing problems while remaining applicable to practical logistics environments and geospatial routing applications. Their flexibility enables the incorporation of realistic operational constraints and spatial information, making them well suited for real-world delivery optimization problems [8].

Ant Colony Optimization (ACO) has been extensively applied in logistics optimization due to its cooperative search mechanism inspired by pheromone-based communication behavior in biological ant colonies. Recent studies have demonstrated its effectiveness across various routing applications, including dynamic vehicle routing through pheromone

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diversity enhancement [9], complex e-logistics routing involving multiple pickups, deliveries, time windows, and heterogeneous fleets [10], and Vehicle Routing Problems with Time Windows (VRPTW) using local search and mutation mechanisms [11]. ACO has also been successfully applied to drone-assisted delivery routing [12], carbon-aware multi-compartment vehicle routing [13], and connected vehicle traffic routing systems [14]. More recently, adaptive hybrid ACO frameworks have further improved route quality and computational efficiency for last-mile delivery [15], while enhanced ACO variants have been proposed for split-delivery vehicle routing and integrated logistics optimization, demonstrating the scalability and flexibility of ACO in increasingly complex logistics environments [16], [17].

Although previous studies have demonstrated the effectiveness of ACO in addressing various routing problems, several limitations remain in the existing literature. Most studies primarily focus on algorithmic enhancements and optimization performance under experimental routing scenarios, including dynamic vehicle routing, time-window constraints, drone-assisted delivery, and multi-objective optimization. While these studies provide valuable insights into the capability of ACO for solving complex routing problems, relatively limited attention has been devoted to the development of ACO-based routing systems that employ actual road-network distance information for practical delivery operations [18]. Recent studies have emphasized that simplified distance representations may not adequately capture the complexity of real-world routing conditions, highlighting the importance of realistic spatial and transportation data [18].

Furthermore, most existing routing approaches model each customer address as an independent delivery destination without considering the spatial characteristics of residential delivery environments. In practice, multiple delivery addresses are often located within the same residential complex and share a common entrance connecting the internal road network to the public road network. Treating these addresses as completely independent routing nodes may increase route complexity and overlook opportunities to exploit the inherent spatial organization of residential areas. Although recent studies have explored delivery zoning strategies to improve operational efficiency in last-mile logistics, these approaches primarily focus on service-area allocation rather than incorporating shared residential access points into the route optimization process [19]. The growing complexity of modern last-mile delivery operations therefore continues to create demand for computationally efficient routing solutions that accurately represent practical delivery environments [20].

Therefore, there is a need for a routing optimization approach that combines the computational efficiency of ACO with realistic road-network information while explicitly considering the spatial characteristics of residential delivery areas. To address this need, this study proposes a last-mile delivery routing optimization system that introduces Residential Delivery Clusters, in which delivery destinations located within the same residential area are associated with a representative entrance point before route optimization. The proposed approach integrates this clustering strategy with actual road-network distance information obtained through the Google Maps Distance Matrix API to produce routing decisions that better reflect real transportation conditions. The primary contribution of this research is the development of a hybrid routing framework that bridges theoretical swarm intelligence with realistic operational constraints by incorporating shared residential access points and actual road-network metrics into the optimization process. The system is implemented as a web-based application and evaluated using actual delivery destination data from expedition service operations. The objective of this research is to assess the effectiveness of the proposed residential delivery cluster-based ACO model in generating efficient delivery routes while supporting practical route planning in real-world last-mile logistics environments.

2. RESEARCH METHODOLOGY

The overall stages of the proposed route optimization system consists of four major phases as illustrated in **Figure 1**.



Figure 1. Proposed Framework for Last-Mile Delivery Route Optimization

2.1 Spatial Database Construction

The proposed routing system relies on a spatial database that models the geographical characteristics of the delivery area and provides the information required for route optimization. Three datasets were constructed: the residential delivery cluster dataset, the road dataset, and the representative point dataset. Together, these datasets describe delivery locations, road accessibility, and shared access points within residential areas. After data acquisition, all datasets were stored in Google BigQuery to support subsequent preprocessing and route optimization.

Residential delivery clusters were established by grouping delivery locations based on geographical proximity and historical expedition service coverage, enabling destinations within the same residential area to be treated as a single delivery cluster. The study area comprises two administrative districts (*kecamatan*) and eight urban villages (*kelurahan*), organized into 45 residential delivery clusters and supported by a spatial database containing 1,096 road and location records. Each cluster stores administrative and geographical information, including province, city, district, subdistrict, location tags, cluster names, and latitude–longitude coordinates. The attributes of the residential delivery cluster dataset are summarized in Table 1, while Figure 2 illustrates the residential delivery clusters together with their corresponding representative points.

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Table 1. Attributes of the Residential Delivery Cluster Dataset

Attribute	Data Type	Description	Sample Value
Province	String	Province where the residential delivery cluster is located	Jawa Barat
City	String	City where the residential delivery cluster is located	Kabupaten Bekasi
District	String	Administrative district of the cluster	Serang baru
Subdistrict	String	Administrative subdistrict of the cluster	Sukasari
Location_tags	String	Additional labels associated with the cluster	Mega Regency
Location_name	String	Name of the residential delivery cluster	Mega Regency
Coordinate	String	Geographic coordinates in latitude-longitude format	-6.383522321149479, 107.10632819877314

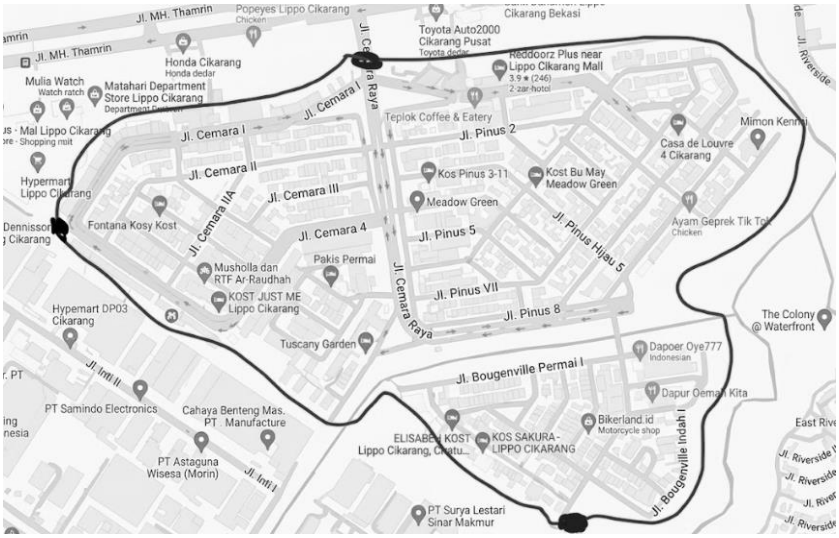


Figure 2. Example of Residential Delivery Clusters and Their Representative Points

In addition to residential delivery cluster information, a road dataset was constructed to represent the transportation infrastructure associated with each cluster. Each record contains administrative information, road names, cluster identifiers, and geographical coordinates, enabling the system to associate individual road segments with their corresponding residential delivery clusters. This dataset supports accessibility modelling and serves as the basis for determining representative points and generating candidate delivery routes. The attributes of the road dataset are presented in Table 2.

Table 2. Attributes of the Road Dataset

Attribute	Data Type	Description	Sample Value
Province	String	Province where the road is located	Jawa Barat
City	String	City where the road is located	Kabupaten Bekasi
District	String	Administrative district where the road is located	Serang baru
Subdistrict	String	Administrative subdistrict where the road is located	Sukaragam
Cluster	String	Associated residential delivery cluster	Perumahan Kota Serang Baru
Location_tags	String	Additional labels associated with the road	Nuri II
Location_name	String	Road name	Jalan Nuri 2
Coordinate	String	Latitude and longitude coordinates	-6.39576374977387, 107.1106406640788

Each residential delivery cluster is associated with one or more representative points that function as shared entrance and exit nodes during route generation. These representative points connect the internal road network of a residential area to the public road network, reducing route complexity while reflecting actual delivery operations. The representative points were determined using a combination of historical expedition records, field observations, and coordinate averaging of roads within each cluster. Historical delivery patterns and field observations were used to identify practical vehicle access locations, while Google Maps was used to verify that the selected points were located on accessible roads.

To estimate the center of activity within a residential delivery cluster, the average latitude and longitude coordinates of roads belonging to the cluster were calculated. The resulting coordinates provide an initial approximation of the cluster representative point, which was subsequently adjusted based on practical accessibility considerations. The average coordinates were computed using Equations (1) and (2).

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$$\overline{Lat} = \frac{\sum_{i=1}^{n} Lat_i}{n} \quad (1)$$

$$\overline{Lon} = \frac{\sum_{i=1}^{n} Lon_i}{n} \quad (2)$$

where $\overline{Lat}$ and $\overline{Lon}$ denote the average latitude and longitude coordinates, respectively, Lat_i and Lon_i represent the coordinates of the i-th road segment within the cluster, and n denotes the number of coordinate points considered in the calculation. The resulting representative point information was stored as a separate dataset consisting of cluster identifiers and geographical coordinates. The attributes contained in the representative point dataset are summarized in Table 3.

Table 3. Attributes of the Representative Point Dataset

Attribute	Data Type	Description	Sample Value
Location_name	String	Name of the residential delivery cluster	Meadow Green
Location_weight	String	Identifier of the representative point	Meadow Green Gate 1
Coordinate	String	Latitude and longitude coordinates of the representative point	-6.333329829457844, 107.14158469838233

2.2 Data Preparation

The data preparation stage transforms raw delivery records into a structured dataset suitable for route optimization. Delivery records collected from expedition service operations often contain inconsistent address formats, duplicate destinations, and incomplete spatial references that cannot be processed directly by the optimization model. Therefore, preprocessing was performed through three sequential stages: address standardization, spatial transformation, and route generation. The overall preprocessing workflow and an example of the transformation process are presented in Table 4.

Table 4. Example of Data Preparation Process

Stage	Example Output	Description
Raw Delivery Data	Jl. Nuri II No.18, Perum Kota Serang Baru, Sukaragam	Original delivery address.
Address Standardization	JALAN NURI 2 NO 18 PERUMAHAN KOTA SERANG BARU	Address normalized using Regex, abbreviation expansion, and Roman numeral conversion.
Spatial Matching	Cluster = *Perumahan Kota Serang Baru* Road = *Jalan Nuri 2*	Address matched against the spatial database stored in Google BigQuery.
Location Classification	Flag = Inside Cluster	Delivery location classified as Weighted, Inside Cluster, or Non-Cluster.
Representative Point Assignment	Gate = *Perumahan Kota Serang Baru Entrance*	Representative point assigned for clustered deliveries.
Duplicate Aggregation	Delivery Count = 3	Multiple deliveries to the same destination are merged while preserving item quantities.
Route Generation	Warehouse → Kota Serang Baru Entrance (Gate) → Jalan Nuri 2	Optimization origin–destination sequence generated before requesting distances from Google Maps Distance Matrix API.

Since operational addresses may differ in abbreviations, capitalization, punctuation, and numbering conventions, normalization was performed using Regular Expressions (Regex), abbreviation expansion, Roman numeral conversion, and character cleaning. Address standardization has been recognized as an essential preprocessing step for improving the reliability of geocoding and routing in last-mile delivery applications [21]. Accordingly, the proposed system applies rule-based preprocessing before matching delivery addresses to the spatial database.

After standardization, each delivery address is transformed into a spatially referenced delivery location by matching it against the residential delivery cluster and road datasets stored in Google BigQuery. The matching process utilizes regular expression patterns together with administrative location information to identify the corresponding residential delivery cluster and road segment. Once matched, each delivery record is assigned its associated geographical attributes, including the residential delivery cluster, road segment, representative point, and geographic coordinates. Delivery locations are subsequently classified into three categories: Weighted, representing representative entrance or exit points; Inside Cluster, representing destinations located within predefined residential delivery clusters; and Non-Cluster, representing destinations outside the predefined clusters.

The final stage generates candidate routes for optimization. Delivery destinations belonging to residential delivery clusters are connected through their assigned representative points, while duplicate destinations are consolidated without

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altering the corresponding delivery quantities. The system then generates all feasible origin–destination combinations, producing optimization-ready routes that are subsequently submitted to the Google Maps Distance Matrix API to obtain road-network travel distances and estimated travel times for the Ant Colony Optimization process.

2.3 Google Maps Distance Matrix API Integration

Following data preparation, road-network distances between representative points and delivery locations were obtained using the Google Maps Distance Matrix API [22]. Unlike Euclidean distance, the API computes travel distances based on the actual road network, producing routes that better reflect real-world driving conditions and accessibility constraints.

For each origin–destination pair generated during preprocessing, the API returns the travel distance and estimated travel duration. These values are subsequently stored in the system database as a distance matrix, enabling the optimization process to evaluate candidate delivery routes using actual road-network distances rather than geometric approximations. Table 5 presents an example of the generated distance matrix.

To improve computational and cost efficiency, the distance matrix is precomputed during preprocessing and reused throughout the optimization process, eliminating repeated API requests. While real-time traffic conditions are not considered, the proposed approach provides a practical routing solution based on actual road-network distances for daily expedition operations.

Table 5. Example of Distance Matrix Generated Using the Google Maps Distance Matrix API

Origin	Destination	Origin Coordinate (Latitude, Longitude)	Destination Coordinate (Latitude, Longitude)	Travel Distance (m)	Estimated Travel Time (s)
Warehouse	Kota Serang Baru (Cluster)	-	(-6.394959569321667, 107.10498654099429)	5.823	691
Kota Serang Baru (Cluster)	Jalan Nuri 2	(-6.394959569321667, 107.10498654099429)	(-6.39576374977387, 107.1106406640788)	148	39

2.4 Ant Colony Optimization Model

The final stage applies the ACO algorithm to optimize the delivery sequence using the precomputed distance matrix [23]. The proposed model integrates representative points into the optimization process, enabling residential delivery clusters to be considered while preserving actual road-network distances. The overall workflow is illustrated in **Figure 3**.

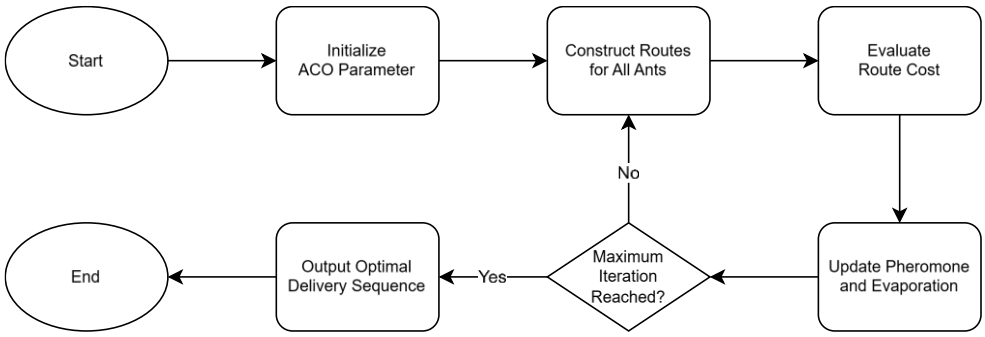


Figure 3. Workflow of the Proposed Ant Colony Optimization Algorithm

2.4.1 Initialize ACO Parameter

Before the optimization process begins, several parameters are initialized to control the search behavior of the ACO algorithm. Unlike conventional implementations that employ fixed parameter values, this study adaptively determines the numbers of ants and optimization iterations according to the number of delivery locations. Let n denote the total number of delivery locations. The iteration bias and ant bias are first calculated using Equations (3) and (4), followed by the adaptive numbers of iterations and ants as defined in Equations (5) and (6).

$$Iteration\ Bias = ceil\left(\frac{n}{1.5}\right) \tag{3}$$

$$Ant\ Bias = ceil\left(Iteration\frac{Bias}{2}\right) \tag{4}$$

$$Number\ of\ Iterations = 20 + Iteration\ Bias \tag{5}$$

$$Number\ of\ Ants = 10 + Ant\ Bias \tag{6}$$

This adaptive strategy scales the search effort according to problem size by increasing both the number of ants and optimization iterations as the number of delivery locations grows, thereby improving solution exploration while

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maintaining reasonable computational cost. The remaining ACO parameters were determined empirically during system development and are summarized in Table 6.

Table 6. ACO Parameters

Parameter	Value	Description
Number of Ants	$10 + Ant\ Bias$	Determines the number of candidate routes constructed during each optimization iteration.
Number of Iterations	$20 + Iteration\ Bias$	Specifies the maximum number of optimization cycles performed before termination.
Number of Best Routes ($n_\{best\}$)	2	Number of best routes used for pheromone reinforcement
Pheromone Evaporation Rate (ρ)	0.70	Controls pheromone decay
Pheromone Influence (α)	3	Controls the influence of pheromone trails
Heuristic Influence (β)	4	Controls the influence of distance heuristic

2.4.2 Construct Routes for All Ants

The transition probability from location i to location j for ant k is determined according to the standard ACO transition rule, as expressed in Equation (7) [23].

$$P_{ij}^{k} = \frac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}{\sum_{l \in N_i}(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}} \tag{7}$$

where P_{ij}^{k} denotes the probability of selecting location j from the current location i, τ_{ij} represents the pheromone level on the connection between the two locations, η_{ij} is the heuristic visibility, while α and β control the relative influence of pheromone information and heuristic information, respectively. The heuristic visibility is calculated as the inverse of the travel distance.

Unlike the conventional TSP formulation, route construction in the proposed model incorporates operational constraints introduced during the data preparation stage. When a delivery route enters or exits a residential delivery cluster, the corresponding representative point is automatically included to ensure that vehicles access the cluster through predefined entrance and exit locations. Previously visited destinations are excluded from subsequent selections to prevent duplicate visits, while representative points are inserted only when necessary to preserve feasible transitions between clustered and non-clustered delivery locations. As a result, every ant produces a complete and operationally feasible delivery route that satisfies the spatial organization of residential delivery clusters before the optimization proceeds to the route evaluation stage.

2.4.3 Evaluate Route Cost

After all ants have completed the construction of their candidate delivery routes, each route is evaluated to determine its overall quality. In this study, route quality is measured by the total travel distance required to visit all delivery destinations in the generated delivery sequence. Since the proposed optimization model aims to minimize travel distance, routes with shorter total distances are considered better solutions. The travel distances used during this evaluation are obtained from the precomputed distance matrix generated using the Google Maps Distance Matrix API, ensuring that the evaluation reflects actual road-network conditions rather than straight-line distances.

The total travel cost of the route generated by ant $k$is computed as the cumulative distance between consecutive delivery locations, as expressed in Equation (8).

$$L_k = \sum_{i=1}^{N-1} d_{i,i+1} \tag{8}$$

where L_k denotes the total travel distance of the route generated by ant k, N represents the total number of locations in the delivery route, and $d_{i,i+1}$ is the road-network distance between two consecutive locations obtained from the distance matrix.

Once all candidate routes have been evaluated, they are ranked according to their total travel distances. The routes with the lowest travel costs are selected as the best-performing candidate solutions and forwarded to the pheromone update stage, where they influence the search process in subsequent iterations.

2.4.4 Update Pheromone and Evaporation

The selected best routes are subsequently used to update the pheromone matrix, allowing information from high-quality solutions to influence the search process in subsequent iterations. In the proposed implementation, pheromone is deposited on every edge belonging to the selected routes. The amount of pheromone deposited is inversely proportional to the total

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travel distance of the corresponding route, so shorter routes receive a greater pheromone reinforcement than longer routes. The pheromone deposited by ant k on edge (i, j) is calculated as **Equation (9)**:

$$\Delta\tau_{ij}^{k} = \begin{cases} \frac{1}{L_k}, & if\ edge\ (i,j) belongs\ to\ the\ route\ of\ ant\ k, \\ 0, & otherwise. \end{cases} \quad (9)$$

where $\Delta\tau_{ij}^{k}$ represents the pheromone deposited by ant k on edge (i, j) , and L_k denotes the total travel distance of the route generated by ant k. The total pheromone deposited on each edge is obtained by accumulating the contributions from all selected best routes.

Following pheromone deposition, a decay factor is applied to the entire pheromone matrix to prevent unlimited pheromone accumulation and preserve the balance between exploration and exploitation. The pheromone update is performed according to **Equation (10)**:

$$\tau_{ij} \leftarrow \rho(\tau_{ij} + \Delta\tau_{ij}) \quad (10)$$

where τ_{ij} denotes the current pheromone intensity on edge (i, j), $\Delta\tau_{ij}$ is the accumulated pheromone deposited on the edge, and ρ is the pheromone decay factor. In this study, ρ was set to 0.7, meaning that 70% of the updated pheromone intensity is retained after each iteration. The updated pheromone matrix is then used in the next iteration, allowing the search process to progressively converge toward shorter delivery routes while maintaining exploration of alternative solutions.

2.4.5 Output Optimal Delivery Sequence

The optimization cycle of route construction, evaluation, and pheromone updating continues until the maximum number of iterations is reached. Throughout the optimization process, the algorithm maintains the best-performing delivery sequence obtained so far. Upon termination, the route with the minimum total travel distance is selected as the final solution. The resulting delivery sequence, including the representative points required for residential delivery clusters, is subsequently visualized through the developed routing application.

3. RESULT AND DISCUSSION

3.1 Experimental Configuration

The proposed residential delivery cluster-based Ant Colony Optimization (ACO) model was evaluated using actual delivery data obtained from an expedition service operating in Bekasi Regency, Indonesia. The objective of the experiment was to assess the effectiveness of the proposed routing model in improving last-mile delivery planning through reductions in travel distance and route planning time. The evaluation utilized the preprocessed delivery dataset together with the road-network distance matrix generated using the Google Maps Distance Matrix API.

The experimental dataset consisted of 45 residential delivery clusters distributed across two administrative districts (*kecamatan*) and eight urban villages (*kelurahan*). The underlying spatial database contained 1,096 location and road-segment records, including representative entrance points, residential roads, and cluster information. Seven independent delivery scenarios were selected from actual expedition operations to evaluate the proposed model under different routing complexities. These scenarios contained between 5 and 62 delivery locations, representing both small-scale and large-scale delivery operations. For each scenario, the optimized route generated by the proposed ACO model was compared with the original delivery route prepared manually by experienced expedition drivers.

To evaluate the operational benefit of the proposed approach, five experienced expedition drivers who routinely served the study area participated in the route planning experiment. Each driver was provided with the same delivery destinations for every scenario and asked to determine the delivery sequence manually. The planning time was measured from the moment the destination list was provided until the driver finalized the proposed delivery route. The average planning time of the five drivers was then compared with the time required by the proposed ACO model to generate an optimized delivery sequence for the same delivery scenario.

The performance of the proposed model was evaluated using four complementary metrics: (1) total travel distance of the generated route, (2) estimated travel duration based on the Google Maps Distance Matrix API, (3) route planning time required to produce the delivery sequence, and (4) percentage improvement compared with manual route planning. These metrics were selected to evaluate both the quality of the optimized routes and the practical efficiency of the proposed approach in supporting daily expedition operations. The quantitative results are presented in **Section 3.2**, followed by a case study illustrating the optimized delivery route and a discussion of the implications of the proposed residential delivery cluster-based routing strategy.

3.2 Performance Evaluation of the Proposed Routing Model

The effectiveness of the proposed residential delivery cluster-based Ant Colony Optimization model was evaluated using seven delivery scenarios with varying numbers of delivery locations. The optimized routes generated by the proposed model were compared with the original delivery routes manually prepared by expedition drivers. The evaluation

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considered two complementary perspectives. First, the quality of the optimized routes was assessed based on travel distance and estimated travel duration. Second, the operational efficiency of the proposed system was evaluated by comparing the time required to prepare delivery routes against manual planning performed by experienced drivers.

3.2.1 Route Optimization Performance

The effectiveness of the proposed routing model was evaluated by comparing the original delivery routes with the optimized routes generated for each experimental scenario. The comparison results are summarized in **Table 7**.

The results demonstrate that the proposed optimization model consistently generated shorter delivery routes across all seven experimental scenarios. Although the magnitude of improvement varied according to the complexity of each routing problem, every scenario exhibited a reduction in the total travel distance after optimization. This consistency indicates that the proposed residential delivery cluster-based ACO model was able to identify delivery sequences that were at least as efficient as manually planned routes while maintaining practical accessibility within residential areas.

Table 7. Comparison of Original and Optimized Delivery Routes

Route	Delivery Location	Original Distance (km)	Otimized Distance (km)	Distance Reduction (km)	Improvement (%)
1	5	15.00	14.60	0.40	2.67
2	8	28.72	28.70	0.02	0.07
3	10	46.34	42.72	3.62	7.82
4	8	19.16	17.50	1.66	8.67
5	8	33.38	31.26	2.12	6.35
6	39	168.32	145.18	23.14	13.73
7	62	253.62	193.00	60.62	23.91

For relatively small delivery scenarios containing between five and ten destinations, the improvements ranged from 0.07% to 8.67%. The modest gains observed in these scenarios are expected because the number of feasible delivery sequences remains relatively limited. Experienced expedition drivers, particularly those familiar with the operational area, are generally capable of constructing routes that are already close to optimal. Consequently, the opportunity for further improvement through optimization is relatively small.

In contrast, substantially greater improvements were achieved for larger delivery scenarios. Route 6, consisting of 39 delivery locations, achieved a travel distance reduction of 23.14 km (13.73%), while Route 7, containing 62 delivery locations, produced the largest improvement with a reduction of 60.62 km (23.91%). These findings indicate that the proposed optimization model becomes increasingly beneficial as the number of delivery destinations grows. Since the number of possible delivery sequences increases combinatorially with the number of destinations, manually identifying an efficient route becomes significantly more difficult. The ACO algorithm systematically explores a much larger solution space and is therefore better positioned to discover high-quality routing solutions for large-scale delivery operations.

Beyond the reduction in travel distance, the optimized routes also produced corresponding reductions in estimated travel duration because the routing process relied on actual road-network distances and travel times obtained through the Google Maps Distance Matrix API. By minimizing unnecessary travel between residential delivery clusters and reducing repeated traversal of road segments, the proposed model generates delivery sequences that are not only shorter but also operationally more efficient. These findings demonstrate that integrating representative entrance points into the routing process enables the optimization algorithm to better reflect the characteristics of residential road networks encountered in real-world last-mile delivery operations.

Overall, the experimental results confirm that the proposed routing strategy consistently improves delivery efficiency while preserving feasible vehicle movements. The increasing percentage improvement observed in larger routing scenarios further suggests that the proposed approach is particularly suitable for expedition companies managing large numbers of daily deliveries, where manual route planning becomes increasingly difficult and time-consuming.

3.3.3 Route Planning Efficiency

Besides improving route quality, the proposed model was also evaluated based on the time required to prepare delivery routes. Unlike previous studies that primarily measured algorithm execution time, this study assessed the operational time required to generate a delivery plan by comparing manual route planning performed by experienced expedition drivers with the proposed ACO-based optimization model. This evaluation provides a more practical measure of the benefits that can be achieved in daily delivery operations.

The manual planning time reported in Table 8 represents the average time obtained from five experienced expedition drivers who independently determined the delivery sequence for each experimental scenario. The ACO planning time represents the time required by the proposed system to generate an optimized delivery sequence for the same delivery locations.

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Table 8. Comparison of Route Planning Time

Route	Delivery Location	Average Manual Route Planning Time (s)	ACO Route Planning Time (s)	Planning Time Reduction (%)
1	5	81.40	32.40	60.20
2	8	151.00	39.00	74.20
3	10	327.60	70.40	78.50
4	8	153.20	37.80	75.30
5	8	105.50	38.00	64.00
6	39	2,525.40	377.80	85.00
7	62	3,641.60	379.60	89.60

Across all seven experimental scenarios, the proposed optimization model substantially reduced the time required to prepare delivery routes. The planning time reduction ranged from 60.20% for Route 1 to 89.60% for Route 7. Even for relatively small routing problems, the proposed system consistently generated delivery sequences more rapidly than manual planning. As the number of delivery locations increased, however, the advantage of the proposed approach became considerably more pronounced.

For the largest delivery scenario consisting of 62 delivery locations, the average manual planning process required approximately 3,641 seconds (60.7 minutes), whereas the proposed optimization model generated the delivery sequence in only 380 seconds (6.3 minutes). Similar improvements were observed for Route 6, where planning time decreased from 2,525 seconds to 378 seconds, representing an 85% reduction. These results demonstrate that the proposed model substantially decreases the operational effort required before delivery vehicles are dispatched.

The reduction in planning time can largely be attributed to the systematic search mechanism of the ACO algorithm and the use of residential delivery clusters. During manual planning, drivers must mentally evaluate numerous alternative delivery sequences while considering road accessibility and their familiarity with the service area. As the number of delivery destinations increases, this process becomes increasingly complex and time-consuming. In contrast, the proposed optimization model automatically evaluates candidate delivery sequences using road-network distances and representative entrance points, thereby reducing the amount of manual decision-making required before dispatch.

From an operational perspective, these findings indicate that the proposed routing model provides benefits beyond distance optimization alone. By producing an optimized delivery sequence that can be directly visualized using Google Maps, the system allows dispatch personnel and drivers to obtain a practical navigation route without manually rearranging delivery destinations. This capability can improve dispatch efficiency, reduce dependence on individual driver experience, and support more consistent route planning across different delivery scenarios.

3.3 Case Study of the Optimized Delivery Route

To further illustrate the practical application of the proposed routing model, the largest delivery scenario containing 62 delivery locations was selected as a representative case study. This scenario achieved the greatest improvement in travel distance among all experimental scenarios, with a reduction of 23.91%, making it suitable for demonstrating the routing behavior produced by the proposed optimization model. Figure 8 presents the optimized delivery route generated by the system and visualized using Google Maps.

As shown in Figure 4, the optimized route begins at the warehouse and follows the delivery sequence generated by the proposed ACO model. The numbered destinations displayed on Google Maps represent the recommended visiting order, enabling drivers to execute deliveries directly using a familiar navigation platform. Unlike conventional navigation systems that only compute routes after the destination sequence has been manually determined, the proposed model automatically optimizes the delivery order before generating the navigation route. Consequently, drivers receive a complete delivery sequence that is already optimized with respect to the road-network distances.

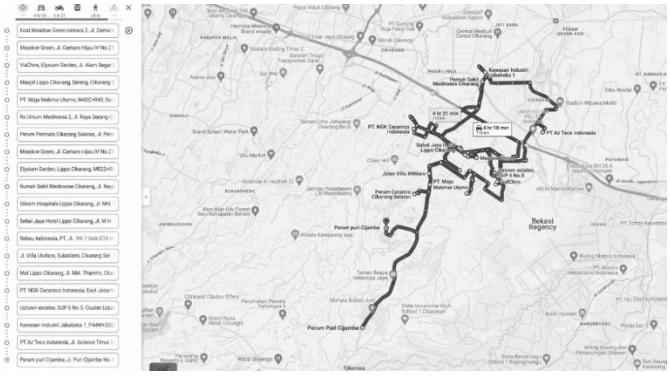


Figure 4. Optimized Delivery Route for the Largest Delivery Scenario (62 Delivery Locations) Generated Using the Proposed Routing Model

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The optimized route also reflects the integration of residential delivery clusters into the routing process. Rather than considering each customer destination independently, deliveries located within the same residential area are naturally grouped through representative entrance points. This organization reduces unnecessary transitions between residential clusters and minimizes repeated traversal of the same road segments. As a result, the generated route exhibits a more continuous travel pattern while maintaining accessibility to every delivery destination.

From an operational perspective, presenting the optimization result directly through Google Maps provides a practical advantage for expedition services. Dispatch personnel are no longer required to manually translate the optimized sequence into a navigation system, while drivers can immediately follow the recommended route using a widely available mapping application. This reduces the preparation effort before dispatch and minimizes the possibility of human errors when determining the delivery order.

The observations from the case study are consistent with the quantitative evaluation presented in **Section 3.2**. The smoother transitions between residential delivery clusters and the systematic ordering of destinations contribute to the reductions in travel distance and planning time achieved by the proposed routing model. These results demonstrate that the integration of residential delivery clusters with the ACO algorithm not only improves optimization performance but also produces delivery routes that can be directly applied in real-world expedition operations.

3.4 Discussion

This section provides a comprehensive evaluation of the proposed routing model by contextualizing the experimental results within the broader landscape of last-mile delivery research. Specifically, it compares the achieved routing improvements with existing literature, analyzes the sensitivity of the ACO parameters on algorithm convergence, and addresses the operational limitations of utilizing a precomputed distance matrix.

3.4.1 Comparison with Previous Routing Optimization Studies

The experimental results demonstrating travel distance reductions of 0.07% to 23.91% highlight the distinct advantage of the proposed residential delivery cluster-based Ant Colony Optimization (ACO) model over conventional routing methods. When comparing these findings with existing literature on last-mile delivery optimization, several key differentiators emerge. Previous studies leveraging standard ACO algorithms for Vehicle Routing Problems (VRP) frequently rely on simplified Euclidean distance representations [18]. While Euclidean-based metaheuristics often report theoretical distance reductions of 10% to 15% in simulated environments, they frequently fail to translate these savings into real-world operations due to physical road constraints, one-way streets, and residential barriers. By integrating the Google Maps Distance Matrix API, the proposed model guarantees that the 23.91% reduction achieved in the 62-point scenario (Route 7) represents actual, drivable road-network savings rather than theoretical approximations.

Furthermore, recent advancements in adaptive hybrid ACO frameworks (such as MCAH-ACO) have focused heavily on computational enhancements and multi-criteria routing [15]. However, these approaches still largely treat each delivery node as an independent destination. The proposed clustering strategy bridges a critical gap identified in recent spatial logistics research [19], which emphasizes the need for delivery zoning. By introducing representative entrance points for residential clusters, the proposed model aggressively prunes the search space. Instead of the algorithm wastefully exploring impossible paths through residential walls or dead-ends, it restricts entry and exit to practical gates. This spatial pruning is the primary driver behind the significant 89.6% reduction in route planning time (from 60.7 minutes manually to 6.3 minutes algorithmically) for large-scale operations. Compared to drone-assisted routing [12] or multi-compartment routing [13], which require specialized hardware, this software-side clustering approach offers a highly accessible operational upgrade for traditional expedition fleets.

3.4.2 Sensitivity Analysis of ACO Parameters

The performance and convergence speed of the proposed ACO algorithm are highly sensitive to its controlling parameters: pheromone influence (α), heuristic influence (β), and the pheromone evaporation rate (ρ). During the development phase, a sensitivity analysis was conducted to determine the optimal configuration for last-mile delivery scenarios.

Increasing the heuristic influence ($\beta > 5$) heavily prioritized the Google Maps road-network distance, causing the algorithm to act similarly to a greedy search. While this led to highly rapid early convergence, the artificial ants quickly stagnated in local optima, particularly in scenarios with multiple adjacent residential clusters (e.g., Routes 6 and 7). Conversely, heavily weighting the pheromone trails ($\alpha > 4$) caused the algorithm to over-commit to initial route discoveries, severely limiting exploration and resulting in suboptimal routing distances. The chosen balance ($\alpha = 3, \beta = 4$) provided the optimal trade-off, allowing the heuristic distance to guide the initial search while maintaining enough pheromone influence to discover complex, non-obvious shortcuts between clusters over successive iterations.

Furthermore, the pheromone evaporation rate (ρ) played a critical role in preventing premature convergence. Testing with a high retention rate ($\rho > 0.85$) resulted in "pheromone stagnation," where all ants blindly followed the same suboptimal path after the first 10 iterations. Lowering the rate to ($\rho = 0.70$) ensured that older, less efficient paths evaporated quickly, forcing the swarm to continuously explore alternative entry points to the residential clusters. This configuration, paired with the adaptive ant and iteration sizing (Equations 3-6), ensured that the algorithm scaled efficiently from 5-point to 62-point delivery scenarios without requiring manual parameter tuning for each execution.

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3.4.3 Limitations of Precomputed Distance Matrices Under Dynamic Traffic Conditions

While the proposed model successfully bridges metaheuristic optimization with actual road-network infrastructure, its reliance on a precomputed distance matrix presents a notable operational limitation. To ensure computational efficiency and minimize expensive, repetitive queries to the Google Maps Distance Matrix API during the optimization loops, all distances and travel times are extracted and stored locally prior to the ACO execution. Consequently, the optimization process operates on a static snaphot of the road network. Under heavy traffic congestion, unexpected road closures, or peak operational hours, the precomputed estimated travel times may deviate significantly from actual driving conditions. A route optimized for minimal distance might direct a driver through a residential bottleneck that is physically shorter but temporally highly inefficient during rush hour. Real-time traffic integration would require dynamically updating the heuristic visibility η_{ij} matrix at each iteration of the algorithm. However, repeatedly querying the Google Maps API for a 62-point matrix update every few seconds is financially prohibitive and computationally heavy, conflicting with the goal of rapid dispatch planning. Future iterations of this system must explore predictive traffic modeling or time-dependent speed heuristics to approximate traffic delays without incurring excessive API costs.

4. CONCLUSION

This study proposed a residential delivery cluster-based Ant Colony Optimization (ACO) model to improve last-mile delivery route planning for expedition services operating in residential areas. Unlike conventional routing approaches that treat every delivery destination independently, the proposed model incorporates representative entrance points for residential delivery clusters and utilizes road-network distances obtained from the Google Maps Distance Matrix API to generate practical delivery routes. By integrating spatial clustering with ACO, the proposed approach better represents the accessibility characteristics of residential road networks while producing optimized delivery sequences that can be directly applied through Google Maps navigation. The experimental evaluation using seven real-world delivery scenarios demonstrated that the proposed model consistently outperformed the original manually planned delivery routes, reducing total travel distance by 0.07% to 23.91%, with greater improvements observed as the number of delivery locations increased. Notably, the optimal testing scenario comprising 62 delivery points achieved a substantial travel distance saving of 60.62 km. In addition, the proposed model significantly reduced route planning time compared with manual planning performed by five experienced expedition drivers, achieving planning time reductions ranging from 60.2% to 89.6%. The direct impact of such fuel-related operational cost efficiency is highly significant for the shipping and logistics industry; minimizing total route mileage translates to substantially lower fuel consumption, reduced carbon emissions, and enhanced overall profit margins. From an operational perspective, the proposed routing model enables dispatch personnel to automatically generate optimized delivery sequences, reducing dependence on individual driver experience and improving the consistency of route planning. Nevertheless, this study has several limitations, primarily that the road-network distance matrix was generated prior to the optimization process and stored in the system database instead of being retrieved dynamically. Although real-time distance retrieval could better reflect current traffic conditions, repeatedly querying the Google Maps Distance Matrix API for every optimization would incur substantial API costs and reduce the practicality of large-scale deployment. Future research may extend the proposed model by incorporating real-time traffic information, dynamic delivery requests, multi-depot routing, and adaptive distance matrix updates to further improve routing performance under changing operational conditions.

5. DECLARATIONS

5.1 Author Contributions

Conceptualization: Y.P., H.C.C., H.M., R.M.;
Methodology: Y.P., H.C.C., H.M., R.M.;
Software: Y.P., H.C.C., H.M.;
Validation: Y.P.;
Formal Analysis: H.C.C., H.M., R.M.;
Investigation: H.C.C., H.M., R.M.;
Resources: H.C.C., H.M., R.M.;
Data Curation: H.C.C., H.M., R.M.;
Writing Original Draft Preparation: Y.P.;
Writing Review and Editing: Y.P.;
Visualization: Y.P., H.C.C., H.M., R.M.;
All authors have read and agreed to the published version of the manuscript.

5.2 Data Availability

The data presented in this study are available on request from the corresponding author.

5.3 Funding

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5.4 Institutional Review Board Statement

Not applicable.

5.5 Informed Consent Statement

Not applicable.

5.6 Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

5.7 Generative AI and AI-assisted Technologies in The Writing Process

During the preparation of this manuscript, the authors used generative AI tools (ChatGPT and Gemini) to assist with language refinement, grammar checking, and improving readability. The authors reviewed and edited all AI-assisted content and take full responsibility for the final content of the manuscript.

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