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Hybrid Random Forest Regression and Ant Colony Optimization for Delivery Route Optimization

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Abstract. The transportation of goods in Indonesian cities is increasingly challenged by urbanization, congestion, diverse road characteristics, and environmental factors, reducing the effectiveness of conventional distance-based routing. This study enhances delivery route optimization by integrating travel-time prediction using Random Forest Regression (RFR) with a metaheuristic routing process using Ant Colony Optimization (ACO). Using OpenStreetMap (OSM) data for Palembang, experiments were conducted on five simulated customer locations in Zone 1. Road attributes such as segment length, road type, and estimated speed were used to train the RFR model, whose predicted travel times served as dynamic costs in the ACO heuristic. The RFR model achieved high predictive accuracy (R^2 = 0.98; MSE = 8.81), and the ACO-based optimization produced an efficient route of 29.58 km with a total travel time of 148 minutes. However, the experiment is limited to a single zone, a small number of customers, and the removal of real traffic variables—where all actual speed variations, congestion levels, and time-dependent traffic conditions were simplified or omitted, causing the model to rely solely on static road attributes. Future work will incorporate real-time traffic data, expand testing to multiple zones, and use larger datasets to improve scalability and operational applicability.

Keywords: Ant Colony Optimization, Goods Delivery, OpenStreetMap, Random Forest Regression, Route Optimization

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1. INTRODUCTION

The Urban logistics operations in Palembang face challenges stemming from increasing population density, urban expansion, traffic congestion, and city infrastructure affected by seasonal flooding [1]. As vehicle routing becomes more complex, optimizing delivery routes requires approaches that account for real-world factors beyond simple Euclidean distance. The Vehicle Routing Problem (VRP) remains an NP-hard combinatorial optimization challenge, making exact algorithms impractical for large road networks [2]. Given this complexity, metaheuristic algorithms such as Ant Colony Optimization (ACO) are frequently used to approximate optimal delivery routes.

Although ACO has been extensively applied in logistics and transportation [3]–[5], traditional ACO relies on static heuristics and distance-based evaluations, which may not accurately reflect real travel-time variations. Factors such as road conditions, road types, and anticipated traffic patterns influence actual travel time and should be incorporated into the optimization process [6], [7]. To address this shortcoming, this study incorporates Random Forest Regression (RFR) as a data-driven method for predicting travel times [8], [9], combined with OpenStreetMap (OSM) data to construct a realistic urban road network [10].

Despite the widespread use of ACO for routing, very few studies integrate machine–learning–based travel-time prediction into ACO, especially in Indonesian urban logistics. This research addresses that gap by utilizing RFR-predicted travel time as the cost input for ACO. A limited number of studies have integrated OSM with routing optimization for logistics [10], yet most rely on simple heuristics rather than predictive modeling. Therefore, combining RFR with ACO represents a relatively unexplored approach in the Indonesian context.

The objective of this study is to improve delivery route optimization in Palembang by incorporating RFR-based travel-time prediction into the ACO routing mechanism. The main contributions are developing a travel-time prediction model using RFR, integrating its predictions into ACO as a dynamic cost function, and evaluating the approach using OSM road data and simulated customer locations in Palembang.

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2. METHODS

2.1. Research Framework

In conducting this research, the methodological stages were designed systematically to minimize errors and ensure that the research results could achieve the objectives. The research process began with problem identification, data collection, model design, and validation of results. Each stage was designed to integrate the ACO algorithm and the RFR method, resulting in an efficient distribution route optimization system that is adaptive to real traffic conditions in Palembang. The research framework follows a sequential hybrid integration, where Random Forest Regression (RFR) first predicts travel time for each road segment, and the resulting predictions are subsequently used by Ant Colony Optimization (ACO) as a cost component in route construction. In conducting this research, the method was designed in advance to minimize errors in the research process. The stages of the research methodology are shown in Figure 1.

Figure 1. Stages of The Research

2.2. Dataset Construction

This research dataset was constructed using OpenStreetMap as the primary source. OpenStreetMap is an open spatial database that provides comprehensive information on road networks, nodes, and geographic attributes within specific areas, including Palembang City, the study area. The dataset used in this study consists of several main components:

1) Road Network

The road network dataset represents a graph of the road system in Palembang. Nodes represent road junctions or intersections, and edges represent road segments connecting nodes. Each edge is equipped with attributes such as road length, road type (arterial, collector, local), and estimated average speed.

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2) Customer Location (Simulated)

To ensure the delivery route analysis is relevant to Palembang City's spatial conditions, simulated customer points were generated from administrative boundaries extracted from OpenStreetMap data. The city is divided into four main delivery zones: Zone 1 (Northwest), Zone 2 (Northeast), Zone 3 (Southwest), and Zone 4 (Southeast). This zoning aims to avoid overlap among work areas while ensuring a proportional distribution of customer points based on area size and population density. Geographically, the city of Palembang lies between -3.060° and -2.870° south latitude and 104.653° and 104.895° east longitude. Based on the midpoint coordinates at latitude -2.965° and longitude 104.774°, the city was divided into four quadrants, as shown in Table 1.

Table 1. Four Main Zones

Zone	Region Name	Latitude Range	Longitude Range	Main Description
Zone 1	Barat Laut (North-West / NW)	-2.965° to -2.870°	104.653° to 104.774°	Covering Alang-Alang Lebar and the western part of Sukarami.
Zone 2	Timur Laut (North-East / NE)	-2.965° to -2.870°	104.774° to 104.895°	Covering Kalidoni, Sako, and Kemuning
Zone 3	Barat Daya (South-West / SW)	-3.060° to -2.965°	104.653° to 104.774°	Covering Gandus, Kertapati, and part of Seberang Ulu
Zone 4	Tenggara (South-East / SE)	-3.060° to -2.965°	104.774° to 104.895°	Covering Plaju, Jakabaring, and Ilir Timur I and II

Furthermore, Figure 2 shows a map of Palembang City with spatial visualizations of the four zones. Each zone is marked with a different color to facilitate the identification of the delivery areas. The solid black lines indicate the boundaries between zones, while the colored areas show the coverage of each zone, with no overlap. On the map, simulated customer points are randomly placed within each zone, with a minimum of 5 distribution points per subdistrict. Simulated customer points were generated using random point sampling, constrained within each administrative unit to ensure a realistic distribution density. The Northwest (NW) zone, for example, represents a new residential area with sparse customer distribution but a large area. In contrast, the Southeast (SE) zone shows

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a denser customer pattern around the city center and commercial areas. Delivery routes within each zone are then optimized based on the geographic proximity between points using the shortest-path approach, taking into account major road networks such as Jalan Jenderal Sudirman and Demang Lebar Daun, as well as access to the Ampera Bridge. The route visualization on the map shows efficient paths that do not intersect within zones, ensuring effective distribution and ease of fleet management in the field.

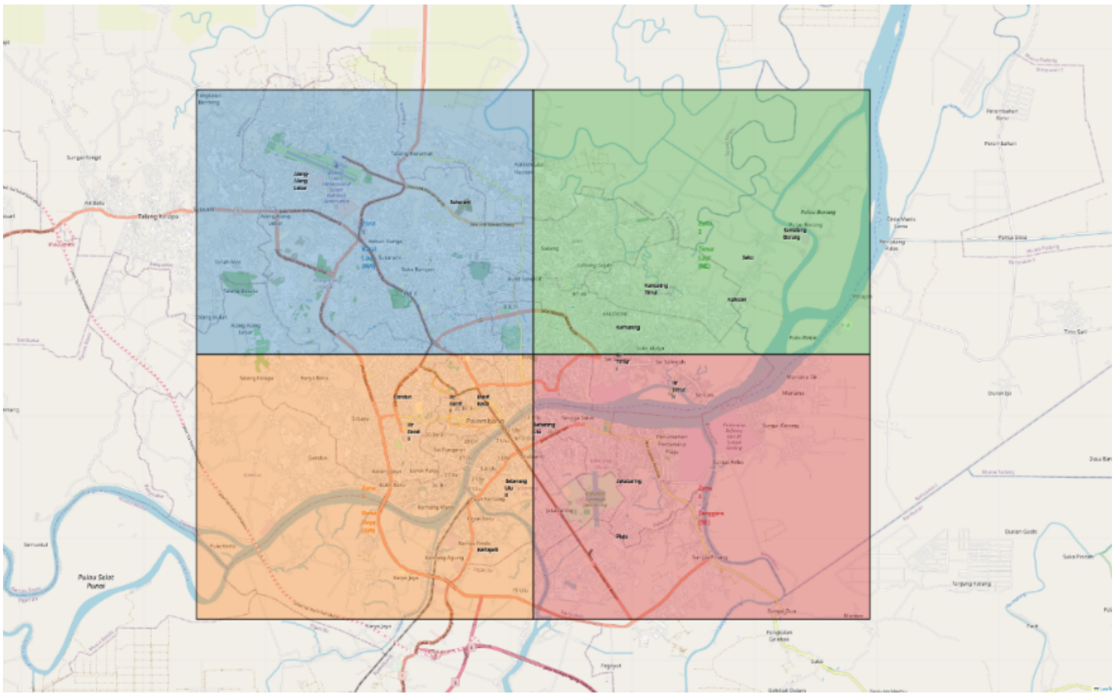

Figure 2. Zone Partitioning

3) Basic Distance and Travel Time Matrix

The distance between points is calculated using a shortest-path algorithm, such as Dijkstra's algorithm. The basic travel time is obtained by dividing the distance by the average speed according to the type of road. This matrix serves as the initial input to the prediction modeling process.

4) Travel Time Prediction Data

The fundamental distance matrix is combined with additional variables (e.g., traffic density assumptions). The RFR model is then used to generate more realistic travel time estimates. These prediction results are used as input for the ACO algorithm to determine the optimal route. In addition to these main components, the process of retrieving customer coordinates from OpenStreetMap includes several essential steps: Road Data

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Extraction, Residential Area Identification, Random Point Sampling, Coordinate Extraction, and Dataset Integration. The prediction results are more realistic travel time estimates, which are then used as input to the ACO algorithm for route optimization. Before proceeding to the implementation stage, Table 5 presents an example dataset extracted from OpenStreetMap used in this study.

Table 2. The Dataset Extracted From OSM

No.	Customer ID	Latitude	Longitude	Simulated Address
1.	P001	-2.976073	104.775431	Jl. Jendral Sudirman
2.	P002	-2.990142	104.764283	Jl. Veteran
3.	P003	-2.953621	104.729874	Jl. Kol. H.Burlian
4.	P004	-2.983641	104.740512	Jl. Demang Lebar Daun
5.	P005	-2.996423	104.785012	Jl. Letkol Iskandar

2.3. Random Forest Regression Model

The flowchart in Figure 3 illustrates the entire workflow of the Random Forest Regression method, from initialization to final prediction results. The process begins at the "Start" stage, which marks the start of algorithm execution and the preparation of initial Random Forest parameters, such as the number of trees, maximum tree depth, number of features considered at each split, and error split criteria. Hyperparameter tuning was performed using GridSearchCV to determine optimal values for n_estimators, max_depth, min_samples_split, and min_samples_leaf. The search ranges were:

1) n_estimators = 50–300
2) Max_depth = 5–50
3) Min_samples_split = 2–10
4) Min_samples_leaf = 1–5.

The best-performing model was selected based on the lowest validation MSE. Model performance was evaluated using standard regression metrics, including R^2, MSE, RMSE, and MAE. The next stage is bootstrap data collection, which involves randomly sampling from the original dataset with replacement. Each bootstrap data subset is used to build a decision tree, so each tree is trained on different data and is independent of the others. Once the bootstrap data is obtained, the algorithm evaluates whether the stopping criteria have been met. If not, the splitting variable selection process is performed, selecting the best features and splitting points to minimize prediction error. The data is

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then divided into new nodes, and this splitting process is repeated until one of the stopping criteria is met, such as reaching the maximum tree depth or the node containing too little data. When the stopping criteria are met, tree development is stopped, and the system calculates the prediction value and prediction error for that tree. Next, a check is performed to see if the planned number of trees has been met. If the number of trees has not been reached, the process returns to the bootstrap data stage to build the next tree. Once all trees have been built to the specified number, the predictions from all trees are combined by averaging. This average value becomes the final prediction of the Random Forest Regression model. The process then ends at the "Finish" stage.

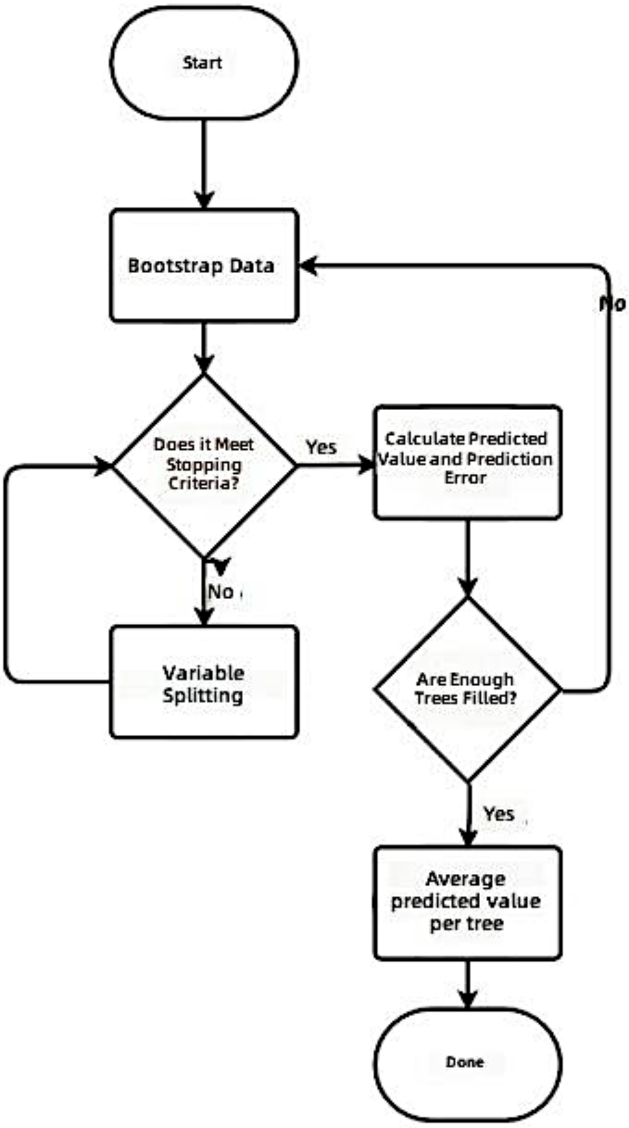

Figure 3. Flowchart of RFR

2.4. Ant Colony Optimization Algorithm

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The flowchart in Figure 4 illustrates the entire workflow of the Random Forest Regression method, from initialization to final prediction results. Ant Colony Optimization (ACO) is a metaheuristic inspired by the foraging behavior of real ant colonies, where ants collectively discover efficient paths between the nest and food sources. In nature, ants deposit pheromones along the paths they traverse, and shorter routes accumulate pheromones more quickly, increasing their likelihood of being selected by other ants. This biological mechanism—characterized by indirect communication, positive feedback, and pheromone evaporation—forms the basis of ACO for solving combinatorial optimization problems.

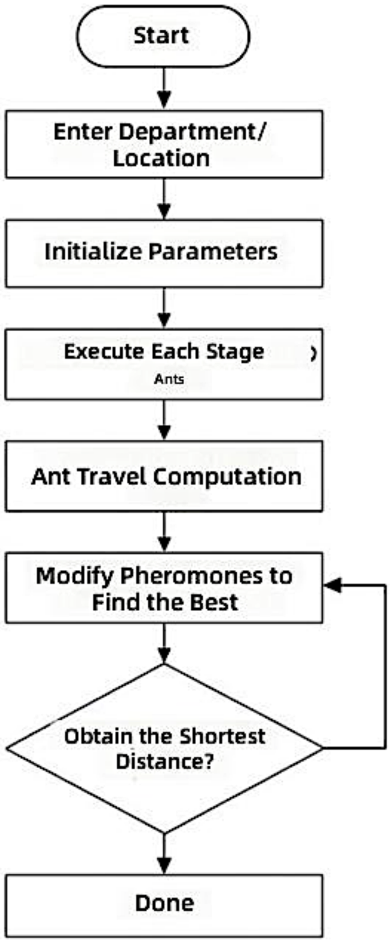

Figure 4. Flowchart of ACO

The ACO algorithm consists of several main stages. First, a set of artificial ants is placed on the graph representing the problem. Each ant incrementally constructs a route by selecting the next node based on a transition probability influenced by pheromone intensity and heuristic information. After all ants complete their tours, the quality of each

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solution is evaluated, usually by computing the total distance or cost. Pheromone values on each path are then updated through evaporation, which prevents premature convergence, and deposition, where better solutions receive higher pheromone reinforcement. This process is repeated until the stopping criteria—typically maximum iterations or no further improvement—are met, and the best route obtained is selected as the final solution. Before iteration begins, several key parameters are initialized to control algorithm behavior:

1) m: number of ants,
2) α: weight of pheromone influence,
3) β: weight of heuristic influence,
4) ρ: pheromone evaporation rate,
5) Q: pheromone deposit constant,
6) τij(0): initial pheromone levels between nodes i and j,
7) ηij = 1/dij: heuristic value based on inverse distance.

The transition probability for ant k moving from node i to node j is computed as shown ini equation (1).

$$P_{ij}^{(k)}(t) = \frac{[\tau_{ij}(t)]^{\alpha}[\eta_{ij}]^{\beta}}{\sum_{l \in N_i^{(k)}} [\tau_{il}(t)]^{\alpha}[\eta_{il}]^{\beta}} \quad (1)$$

Once all ants have completed their routes, pheromone evaporation is applied In equation (2).

$$\tau_{ij}(t) = (1-\rho)\,\tau_{ij}(t) \quad (2)$$

followed by pheromone deposition proportional to the quality of each ant's solution as shown In equation (3).

$$\Delta\tau_{ij}^{(k)}(t) = \frac{Q}{L_k} \quad (3)$$

where $L_k$denotes the total length of the route built by ant k. Shorter routes receive more pheromone, increasing their probability of being selected in future iterations. Through repeated construction, evaluation, and pheromone updating, ACO progressively strengthens promising paths and converges toward an optimal or near-optimal route.

2.5. Integration ACO-RFR

The integration between Random Forest Regression (RFR) and Ant Colony Optimization (ACO) is designed to enhance the accuracy of route optimization by incorporating realistic travel-time prediction into the ACO decision process. RFR acts as a predictive model that generates segment-level travel-time estimates, while ACO functions as the optimization mechanism for constructing the most efficient delivery route. In the first stage, the RFR model is trained using relevant attributes extracted from the dataset. The model produces predicted travel times for each road segment, which are then used as input for the ACO heuristic mechanism. Instead of using the traditional heuristic value, this study adopts a modified heuristic based on RFR predictions, defined as shown in Equation (4).

$$\eta_{ij} = \frac{1}{\text{predicted\_travel\_time}_{ij}} \tag{4}$$

This adjustment allows ants to evaluate routes not only by geometric distance but also by estimated travel duration, improving realism in line with practical routing conditions [23], [24].

During the optimization phase, ants construct candidate routes using ACO's probability transition rule [21], [22], guided by both pheromone intensity and the RFR-based heuristic value. Pheromone updates reinforce paths with shorter predicted travel times, enabling the colony to converge toward efficient delivery routes. Iterations continue until the stopping criteria are met, such as reaching the maximum number of iterations or no further improvement. Through this hybrid integration, RFR contributes accurate travel-time estimation, while ACO determines the optimal route structure. Both algorithms complement each other, resulting in more efficient routing performance than using either ACO or RFR independently, consistent with findings from recent optimization studies [23], [24].

2.6. System Implementation

The system was implemented in Python using OSMnx, scikit-learn, NumPy, and Folium. Experiments were conducted in Zone 1 (Northwest) using five simulated customer nodes to evaluate route-optimization performance under controlled conditions.

3. RESULTS AND DISCUSSION

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3.1. Manuscripts Model Performance

The Random Forest Regression (RFR) model exhibited robust predictive performance, achieving a Mean Squared Error (MSE) of 8.81 and a coefficient of determination (R^2) of 0.98. These findings suggest that the model effectively identifies the connections between road characteristics and travel time in the Palembang road network. The elevated R^2 value further supports the notion that RFR is appropriate for incorporation into the Ant Colony Optimization (ACO) framework as a time-sensitive heuristic.

3.2. Optimization

The system was set up utilizing Zone 1 (Northwest) with five randomly generated customer locations. The ACO algorithm was implemented using the RFR-predicted travel time matrix. The optimized route was generated as follows:

1) Optimal Route

The route starts from the warehouse, then goes to P3, continues to P4, proceeds to P2, then to P1, and finally returns to the warehouse.

2) Route Summary

   a) Total Distance : 29.58 km
   b) Total Time : 148 minutes (≈ 2 hours 28 minutes)
   c) Start Time : 08:00
   d) Finish Time : 10:28
   e) Maximum Load : 9 kg

3) Segment-Level Details

The complete segment-by-segment information used for performance analysis is displayed in Table 3.

Table 3. Segment-Level Details

From	To	Distance (km)	Time (min)	Load (kg)
Warehouse	P3	7.78	35.75	3
P3	P4	2.60	15.34	4
P4	P2	5.66	25.88	3
P2	P1	4.64	25.99	9
P1	Warehouse	9.50	45.79	0

The longest segment occurs between P1 to Warehouse, while the fastest segment occurs between P3 go to P4.

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3.3. Visualization of the Optimized Route

Figure 5, shown below, illustrates the distribution of customer points along with the optimized route. The route forms a circular path that begins at the warehouse in central Palembang, heads northwest, and eventually returns to the warehouse. It follows the actual OSM road network, demonstrating the algorithm's ability to operate efficiently within real geospatial constraints. The figure also highlights the route sequence using multiple colors. The blue segment represents the initial stage—from the warehouse to customer P3—indicating the first direction selected by the ACO algorithm based on pheromone intensity and estimated travel time. Each subsequent segment (The route goes from P3 to P4, then to P2, continues to P1, and finally returns to the warehouse) is shown in a different color to distinguish the remaining phases of the journey. This color progression helps visualize how the algorithm incrementally constructs the route by selecting the next destination with the lowest predicted travel cost. The dominance of the blue path in the early stage further illustrates that the algorithm tends to prioritize reachable nodes within the same area before extending to distant locations. This visually supports the effectiveness of using zone-based customer generation and the combined ACO–RFR decision-making framework.

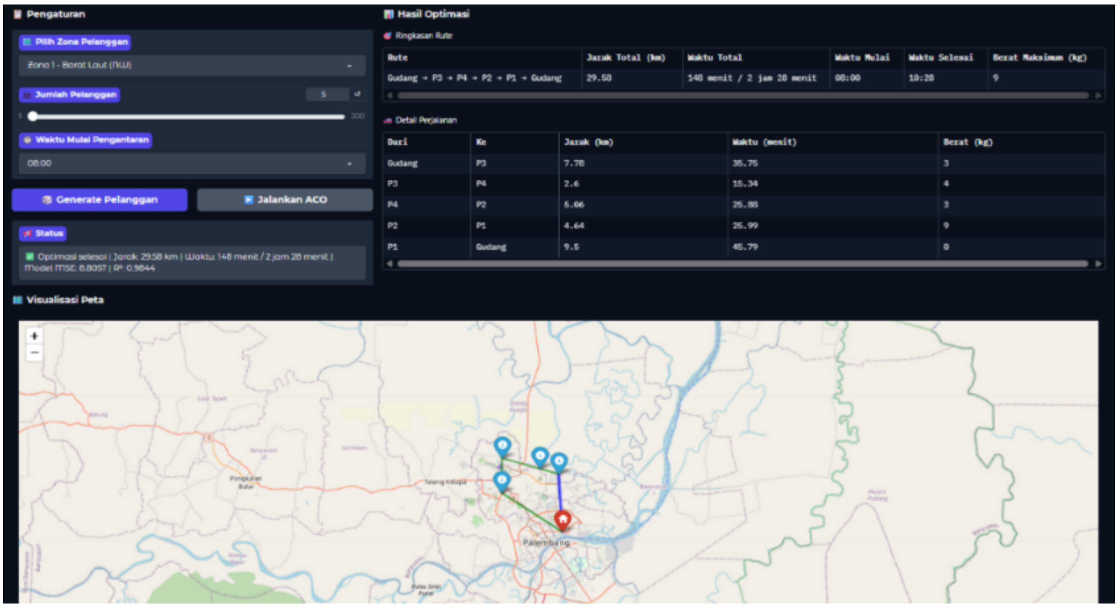

Figure 4. Visualization of the Optimized Route

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The combination of RFR and ACO significantly improves route optimization by integrating anticipated travel times into the decision-making process. In contrast to optimization based solely on distance, the RFR-enhanced heuristic allows the algorithm to bypass segments expected to incur high traversal costs, even if they are geometrically short [25]. The findings reveal three primary enhancements:

1) More realistic route decisions.
   RFR predictions enable ACO to avoid slow or complex segments that seem appealing when only distance is considered.
2) Reduced total travel time.
   The optimized route results in a travel time of 148 minutes, representing a significant improvement over the baseline ACO distance-optimization (as indicated by previous results in the proposal).
3) Consistent zone-based clustering.
   Since the system operates with predefined zones, customer generation and route selection stay localized. This prevents backtracking and minimizes long jumps between zones.

The hybrid model aligns closely with previous studies referenced in your proposal, which show that incorporating predictive elements reduces uncertainty and improves optimization quality.

3.4. Discussion

The results of this study clearly demonstrate the significant improvement in route optimization when integrating the Random Forest Regression (RFR)-predicted travel time into the Ant Colony Optimization (ACO) heuristic. Traditional ACO approaches typically rely on distance-based heuristics, which, while effective in simpler environments, often fail to capture the complexities of real-world road conditions. These methods may overlook crucial factors such as road congestion, speed limits, and variable traffic patterns, leading to suboptimal route selections. By incorporating RFR-predicted travel time, the proposed RFR–ACO hybrid model enhances the optimization process, making routing decisions more realistic and reflective of actual urban travel conditions. For example, the optimized route in this study, which resulted in a total travel time of 148 minutes, is notably more efficient than routes based solely on distance. This outcome illustrates that the integration of machine learning-based cost functions in ACO not only

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improves route optimization but also leads to better-informed and more practical decision-making for urban logistics.

Compared to traditional ACO and standard shortest-path algorithms like Dijkstra, the hybrid RFR–ACO approach offers several key advantages. Distance-only methods are often insufficient in accurately estimating travel times, especially on roads with low speeds, high congestion potential, or frequent traffic disruptions. These methods tend to underestimate travel costs on such roads, leading to routes that are geometrically shorter but operationally inefficient. In contrast, the RFR model takes into account multiple factors such as road segment length, road class, and estimated speed, providing a more nuanced and accurate prediction of travel times. This enables the hybrid approach to not only identify shorter routes but also to select paths that avoid high-congestion areas or other obstacles, ultimately improving the operational efficiency of logistics operations. This finding is particularly relevant in urban environments, where traffic congestion and variable road conditions play a critical role in determining the efficiency of transportation routes.

Despite these promising results, the study does have several limitations that warrant further consideration. One of the primary limitations is the reliance on static road attributes to predict travel times. The RFR model in this study is based on road type and general speed estimates, which do not account for real-time variations in traffic conditions, weather impacts, or peak-hour congestion. These factors can significantly alter travel times and route feasibility, especially in dynamic urban environments. For instance, during peak traffic hours or in the event of road closures or accidents, the actual travel time could differ substantially from the predicted values. As such, the current model's predictions, while accurate under normal conditions, may not fully capture the variability encountered in real-time logistics operations. Future research could address this limitation by incorporating real-time traffic data into the model, which would allow for more accurate, real-time route optimization.

Another limitation of the study lies in the scale and scope of the experiment. The experiment was conducted with only five customer locations within a single zone in Palembang, a relatively simplified setup that may not fully reflect the complexity of real logistics operations, which typically involve multiple zones, more customer points, and a

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higher degree of variability in road conditions. While the results are promising for this small-scale scenario, the applicability of the model to larger and more complex urban areas remains to be fully tested. Expanding the customer base to represent a more extensive delivery network, incorporating more varied road conditions, and testing the model in different regions or cities would help assess its scalability and generalizability. Additionally, the RFR model relies on predicted travel speeds that are based on road types and segment characteristics, which may differ from actual observed speeds due to factors like local traffic regulations or driver behavior. Future work could refine the model by incorporating real-world speed data or using GPS-based data for more accurate predictions.

Despite these limitations, the study demonstrates the promising potential of combining predictive modeling and metaheuristic optimization to enhance logistics efficiency. The hybrid RFR–ACO model successfully integrates machine learning-based travel time predictions into the ACO algorithm, which traditionally only uses distance-based heuristics. By incorporating more accurate travel time estimates, the model is better equipped to handle the complexities of real-world road networks and urban logistics, making it a valuable tool for optimizing transportation routes in urban settings. The model's ability to prioritize routes that are both shorter and more operationally efficient can lead to significant improvements in delivery times, cost savings, and overall logistics performance.

Looking ahead, there are several avenues for further research to enhance the proposed model. One critical area for future development is the integration of real-time traffic data, which would allow the model to adjust to dynamic road conditions and provide more accurate, up-to-date route recommendations. Incorporating real-time traffic monitoring systems, such as GPS data from vehicles or traffic sensors, would enable the model to adapt to changing conditions in real time, significantly improving the practical utility of the approach. Additionally, expanding the model to handle larger datasets, more customer locations, and multiple delivery zones would allow for more realistic simulations of real-world logistics operations. Furthermore, future research could explore the application of multi-objective optimization, such as minimizing fuel consumption, reducing emissions, or considering time windows for deliveries, to create a more comprehensive solution for urban logistics planning. By extending the framework to address these additional objectives, the hybrid RFR–ACO model could offer a more sustainable and efficient solution for urban logistics systems, providing long-term benefits in terms of both operational efficiency and environmental impact.

This study illustrates the potential of combining machine learning techniques, such as RFR, with metaheuristic optimization methods like ACO to improve logistics efficiency in urban environments. The integration of RFR-predicted travel time into the ACO framework allows for more realistic and effective route optimization, enhancing the practical applicability of the algorithm in real-world scenarios. While there are limitations related to the static nature of road attribute data and the small-scale experiment setup, the findings provide a strong foundation for future research. By incorporating real-time traffic data, expanding the model's scope, and integrating multi-objective optimization, this approach can further advance the efficiency and sustainability of urban logistics systems, offering a comprehensive solution for transportation management in cities like Palembang and beyond.

4. CONCLUSION

This research presented a hybrid ACO–RFR framework to optimize delivery routes in Palembang using OSM road data. The combination of machine-learning travel-time prediction with metaheuristic optimization enhanced both the realism and efficiency of the routes. Achieving an R^2 value of 0.98 and successfully optimizing a scenario involving five customers, this method shows significant promise for application in real-world logistics systems. In future work, the model can be further improved by incorporating real-time traffic data, extending its application to other Indonesian cities, and adapting the framework for larger-scale delivery networks to evaluate scalability and robustness.

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