Location Planning of Drone Charging Stations using Geographic Information System (GIS) to Maximize Service Level for on-Demand Food Delivery

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Abstrak. Layanan on-demand food delivery terus tumbuh didorong dengan pesatnya perkembangan teknologi dan internet yang memberikan kenyamanan bagi pelanggan untuk memesan makanan dari restoran dan mengirimnya sampai ke tangan mereka. Namun, peningkatan jumlah kendaraan berdampak pada terjadinya kemacetan, peningkatan biaya, dan dampak lingkungan. Penggunaa drone dapat menjadi solusi untuk mengatasi permasalahan tersebut. Akan tetapi, keterbatasan jangkauan terbang menjadi tantangan penggunaan drone. Oleh karena itu, dalam penelitian ini dikembangkan algoritma untuk menentukan lokasi drone charging station agar dapat memaksimalkan cakupan layanan. Metode optimasi yang digunakan dalam algoritma berupa ant colony optimization. Sementara itu, pengujian algoritma menggunakan studi kasus area dalam Ring Road Yogyakarta, dengan OpenStreetMap sebagai sumber data. Hasil optimasi menunjukkan cakupan demand sebesar 22357 titik atau 93,56% dari total titik potential demand yang ada. Selain itu, dalam penelitian ini juga dibangun tiga skenario untuk mengidentifikasi pengaruh jenis kendaraan terhadap rute pengiriman dan dampak lingkungan yang dihasilkan. Ketiga jenis kendaraan yang digunakan sebagai skenario berupa drone jangkauan 2 km, drone jangkauan 4 km, dan sepeda motor.

Kata kunci: On-demand food delivery; drone charging station; facility location problem; sistem informasi geografis; routing problem.

Abstract. _On-Demand Food Delivery (ODFD) services have witnessed significant growth, driven by advancements in technology and internet accessibility. This has facilitated consumer convenience by enabling food orders from restaurants to be delivered directly to their doorstep. However, this rapid expansion has contributed to an increase in vehicular traffic and associated travel routes, particularly within urban areas. This surge in vehicle usage has resulted in traffic congestion, higher costs, and environmental impacts, hindering the efficiency of the supply chain system. The utilization of drones presents a promising solution to overcome those challenges. However, their limited flight range poses a significant obstacle to widespread implementation. To address this limitation, this research focuses on developing an algorithm to optimize the location of drone charging stations, thereby maximizing service coverage. Ant Colony Optimization is used as the optimization method within the algorithm. A case study is conducted within the Yogyakarta Ring Road area, utilizing OpenStreetMap as the data source, to evaluate the algorithm's performance. The optimization results show a demand coverage of 22357 points, representing 93.56% of the total potential demand_ _points. In addition, three distinct delivery mode scenarios are established: drone with 2 km flight range, drone with 4 km flight range, and motorcycle. These scenarios are implemented to assess the influence of vehicle types on delivery routes and environmental impact._

Keywords: _On-demand food delivery; drone charging stations; facility location problem; geographic information system; routing problem._

1. Introduction

Recent technological advancements have profoundly transformed consumer behavior, particularly in the realm of food consumption. The widespread adoption of the internet and the proliferation of mobile devices have facilitated the emergence of on-demand food delivery (ODFD) services, enabling consumers to easily order meals from restaurants through mobile applications. This phenomenon has witnessed remarkable growth across Southeast Asia, with the Gross Merchandise Value (GMV), representing the total value of goods purchased through ODFD platforms, experiencing a significant surge. Between 2015 and 2019, the GMV in Southeast Asia increased by nearly fifteenfold, reaching an estimated USD 6 billion. This rapid growth is projected to continue, with forecasts suggesting that the GMV will exceed USD 20 billion by 2025 [1]. Globally, the market for ODFD services is also experiencing substantial expansion, with estimates indicating that the total sales value will reach USD 559.2 billion between 2024 and 2028 [2].

The rapid growth of the ODFD sector presents both significant opportunities and critical challenges. While offering benefits such as increased consumer convenience, the creation of new employment opportunities, and enhanced customer relationships [3]. This expansion also presents challenges, these include the need for robust technological infrastructure, concerns related to data privacy and security [4]. Most critically, the potential negative impacts on urban transportation and logistics. The surge in ODFD services has inevitably led to a significant increase in the number of vehicles and associated travel routes, particularly within urban areas [5]. This increase in vehicular traffic contributes to traffic congestion, exacerbates environmental pollution, and poses challenges to urban planning and infrastructure. Moreover, the reliance on individual delivery can lead to inefficiencies in the overall supply chain, including increased delivery times and higher operational costs [3].

Addressing these challenges requires a comprehensive approach that considers the principles of urban logistics. City logistics, also referred to as urban (freight) distribution, last mile logistics, urban logistics, or city distribution [6]. Last mile delivery, a critical component of urban logistics, specifically refers to the final stage of the delivery process, encompassing the movement of goods from a distribution center to the final customer destination [7]. In the context of ODFD services, last mile delivery has evolved significantly, driven by the increasing consumer demand for same-day delivery, often referred to as on-demand delivery [8].

Martínez-Sykora, McLeod, Cherrett, and Friday [9] and Xue, Wang, and Wang [10] conducted research on optimizing order scheduling and delivery routes within On-Demand Food Delivery (ODFD) services. Their research involved the development of models and heuristic solution algorithms to address the challenges posed by fluctuating demand across different time periods and geographical locations. These algorithms aimed to ensure equitable order distribution among couriers while minimizing workload. Whereas, Zhou, Ye, and Hu [11] developed a heuristic algorithm to enhance the efficiency of ODFD services. This algorithm leverages the potential for order consolidation by grouping multiple orders from the same restaurant for delivery by a single courier. The research demonstrated that the developed algorithm effectively improved service quality while minimizing delivery distances.

In contrast to these studies, which primarily focused on optimizing conventional ODFD services, recent research has explored the integration of drones as a mode of delivery. Liu [12] and Lu, Jiang, Bi, and Gao [13] conducted research on optimizing delivery routes specifically for drone-based ODFD systems. Furthermore, some recent research has incorporated environmental considerations into the analysis of on-demand delivery systems utilizing drones. Troudi, Addouche, Dellagi, and ElMhamedi [14] and Kirschstein

[15] incorporated environmental criteria, such as the energy consumption of delivery modes, into their research. While Baldisseri, Siragusa, Seghezzi, Mangiaracina, and Tumino [16] conducted a comprehensive assessment of both economic and environmental impacts within last-mile delivery systems by using a Life Cycle Assessment (LCA) methodology.

Another prominent research area within the context of on-demand delivery is the Facility Location Problem (FLP). FLP has been widely studied because of its applicability in various real-world problems [17]. Fundamentally, FLP involves the identification of optimal locations for facilities or equipment to effectively serve a group of demand points or customers distributed in planar area [18], [19]. As a well-established research domain, FLP has been actively investigated since the 1960s, with a focus on developing sophisticated models, devising effective solution techniques, and exploring real-world applications [18]. Blanco and Gázquez [20] developed a solution model for FLP within a continuous framework, allowing for the placement of facilities anywhere within the designated solution space. Similarly, Baldomero-Naranjo, Martínez-Merino, and Rodríguez-Chía [21] investigated a two-level facility location problem, specifically focusing on the placement of warehouses that serve as intermediaries, which stored the products that have been manufactured in the first level, between manufacturing facilities and customers.

Technological advancements have significantly contributed to the ongoing evolution of FLP research. Saldanha-da-Gama [18] emphasized the strong interdisciplinary nature of FLP, highlighting its significant interactions with fields such as geography, economics, transportation, and logistics. Geographic Information Systems (GIS) have emerged as a crucial tool for addressing real-world location problems, as they facilitate the integration and analysis of spatial data. Alizadeh and Nishi [22] and Medrano-Gómez, Ferreira, Toso, and Ibarra-Rojas [23] effectively utilized GIS in their respective research, utilizing GIS data to identify optimal locations for first aid centers and recycling facilities. Furthermore, GIS is also used as a source of data for determining the location of potential demand, such as research conducted by Mohamad and Sopha [24] and Wirawan [25].

Based on the literature reviewed, it is evident that research on facility location problems, particularly those leveraging Geographic Information Systems (GIS), continues to evolve. While GIS-based models and solution approaches have been developed, their capabilities remain limited, with many relying on heuristic algorithms to obtain feasible solutions [18]. Moreover, a comprehensive literature review on drone-based delivery and FLP conducted by Dukkanci, Campbell, and Kara [26] revealed that only 16% of the studies considered coverage-based objectives. Thus, this research focuses on determining the optimal locations for drone charging stations based on the coverage of potential demand within the Yogyakarta Ring Road area. This research leverages Geographic Information Systems (GIS) as the source of data. Furthermore, three distinct delivery mode scenarios are established: drone with 2 km flight range, drone with 4 km flight range, and motorcycle. These scenarios are implemented to assess the influence of vehicle types on delivery routes and environmental impact.

2. Research Method

The stages conducted in this research are outlined in the flowchart depicted in Figure 1. This flowchart illustrated the ten stages of the research process, encompassing data collection and preprocessing, road network data processing, data validation, building the covering algorithm, running the optimization process of covering problem, scenarios planning, building the routing algorithm, running the optimization process of routing problem, environmental impact assessment, and results analysis. Python is utilized as the programming language in this research.

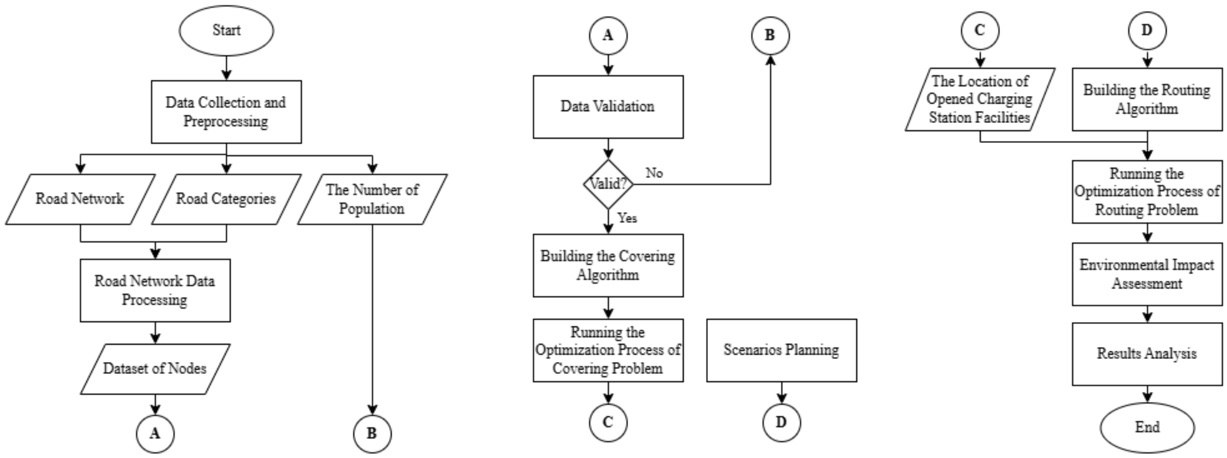

Figure 1. Flowchart of Research Stages

2.1. Data Collection and Preprocessing

OSMnx Python package was used to acquire road network data. OSMnx is a Python library that facilitates the retrieval of road networks, building footprints, and administrative boundaries directly from OpenStreetMap [27]. The obtained data underwent a series of preprocessing steps, including road network topology simplification and removal of nodes that did not represent the actual intersections by eliminating the periphery road. In addition, population data for each sub-district within the Yogyakarta city area was also collected. The data collection, preprocessing, and subsequent road network processing steps refer to the methodology outlined in the research conducted by Wirawan [25].

2.2. Road Network Data Processing

Road network information utilized in this study comprises node coordinates, edges, and road categories. Road categories served as the basis for determining the weight assigned to each node within the dataset for the optimization process. The demand weight of a node represents the priority of the associated road. Areas characterized by high population density tend to be reflected by a higher concentration of nodes located along the main road. The weighting for each node was assigned according to Table 1.

Table 1. Weighting Reference according to Road Categories in OpenStreetMap

Road Categories	Explanation	Weight
motorway, motorway_link	A restricted access major divided highway, normally with two or more running lanes plus emergency hard shoulder	7
trunk, trunk_link	The most important roads in a country's system that are not motorways (Need not necessarily be a divided highway)	6
primary, primary_link	The next most important roads in a country's system (Often link larger towns)	5
secondary, secondary_link	The next most important roads in a country's system (Often link towns)	4
tertiary, tertiary_link	The next most important roads in a country's system (Often link smaller towns and villages)	3
unclassified	The least important through roads in a country's system, but which serve a purpose other than access to properties (Often link villages and hamlets)	2
residential, living_street	Roads which serve as an access to housing, without function of connecting settlements. Often lined with housing.	1

2.3. Data Validation

Data validation of the road network aims to assess the extent to which the nodes accurately represent the population distribution within the study area. Pearson correlation was used as the statistical method for this validation. Pearson correlation is a statistical test used to measure the strength and direction of the linear relationship between two numerical variables, which can be measured on an interval or ratio scale [28].

2.4. Building the Covering Algorithm

The algorithm development was based on the basic model of Maximal Covering Location Problem (MCLP), with additional constraint which requires interconnectivity between all the charging station facilities that is decided to be opened. This constraint was added to accommodate the flight range limitations of drones, ensuring that drones can move from one facility to another. The proposed model is shown in equations (1) to (8). In addition, the Ant Colony Optimization (ACO) was utilized as the optimization method within the algorithm.

$$Max \sum_{i \in I} a_i x_i, \tag{1}$$

$$d_{ij} \leq S \ (\forall i \in I, \forall j \in J, i \neq j), \tag{2}$$

$$\sum_{j \in J} y_j = p, \tag{3}$$

$$x_i \leq \sum_{j \in \{J | d_{ij} \leq S\}} y_j \ \ (\forall i \in I), \tag{4}$$

$$x_i \in \{0,1\} \ (\ \forall i \in I), \tag{5}$$

$$y_j \in \{0,1\} \ (\forall j \in J), \tag{6}$$

$$d_{jk} \leq 2S \ (\forall j, k \in J, j \neq k), \tag{7}$$

$$\sum_{j \in \{J | d_{jk} \leq 2S\}} y_j \geq 1, \tag{8}$$

Equation (1) represents the objective function, which aims to maximize the demand coverage. Equations (2) to (8) represent the constraints of the model. Equation (2) defines the distance constraint between demand point i and facility j, ensuring that it must be less than or equal to the coverage radius of the facility. Equation (3) limits the number of facilities that can be opened. Equation (4) ensures that each demand point i is served by at least one facility. Equations (5) and (6) indicate that the variables x (demand) and y (facility) are binary, assuming values of either zero or one. Equations (7) and (8) enforce the constraint that a facility can only be opened if at least one other facility exists within less than twice its coverage radius.

2.5. Running the Optimization Process of Covering Problem

The optimization process commenced with inputting necessary parameters, including the facility coverage radius and the maximum number of facilities to be established. Subsequently, the dataset that was generated before was also inputted. The optimization process was then executed by running the algorithm, yielding results such as the number of demand coverage and the optimal locations of the drone charging stations.

2.6. Scenarios Planning

Three scenarios were defined based on the type of delivery mode, drone with 2 km flight range, drone with 4 km flight range, and motorcycle. The aim of establishing these scenarios is to compare the resulting delivery routes and environmental impact.

2.7. Building the Routing Algorithm

The algorithm development was based on the basic model of Vehicle Routing Problem (VRP), with additional constraint to limit the distance between nodes (charging stations, customers, and food sellers) to accommodate the maximum flight range of drones [29], [30]. The proposed model is shown in equations (9) to (15).

$$Min\ z = \sum_{i=1}^{N_a} \sum_{j=1}^{N_a} x_{ij} c_{ij}, \tag{9}$$

$$c_{ij} \leq S\ (\forall i, j \in N_a, i \neq j), \tag{10}$$

$$\sum_{j \in \{N_a | c_{ij} \leq S,\ i \neq j\}} x_{0j} = 1, \tag{11}$$

$$\sum_{j \in \{N_a | c_{ij} \leq S,\ i \neq j\}} x_{in+1} = 1, \tag{12}$$

$$\sum_{j \in \{N_a | c_{ij} \leq S,\ i \neq j\}} x_{ij} = 1\ (\forall i \in N_r), \tag{13}$$

$$\sum_{i \in N_a} x_{ij} = \sum_{k \in N_a} x_{jk}\ (\forall j \in N_a, i \neq j \neq k), \tag{14}$$

$$x_{ij} \in \{0,1\}\ (\forall i, j \in N_a, i \neq j), \tag{15}$$

Equation (9) represents the objective function, which aims to minimize the total travel distance of the drone. The distance between nodes is calculated using the Euclidean Distance method. Equations (10) to (15) represent the constraints of the model. Equation (10) defines the distance constraint, ensuring that the distance between node i and node j must be less than or equal to the maximum flight range of the drone. Equations (11) and (12) ensure that the route originates from the food-seller node and terminates at the customer node. Equation (13) ensures that the drone can only travel from node i to exactly one other node. Equation (14) ensures that if the drone visits node j, then node j becomes the starting point for the next flight of the drone. Equation (15) indicates that the variable x (route from i to j) is binary, assuming a value of either zero or one.

2.8. Running the Optimization Process of Routing Problem

The optimization process commenced with inputting necessary parameters, including the maximum flight range of the drone. For drone-based scenarios, the locations of charging stations obtained from the previous optimization process were also inputted as a dataset. The optimization process was then executed by running the algorithm, yielding results such as the total travel distance and the projection of delivery routes for each scenario. The optimization process for drone-based scenarios used the previously developed VRP algorithm. Whereas the optimization process for motorcycle-based scenario utilized the routing module within the OSMnx Python package.

2.9. Environmental Impact Assessment

Environmental impact analysis was conducted by evaluating three indicators, Global Warming Potential (GWP), Acidification Potential (AP), and Abiotic Depletion Potential (ADP). These indicators were assessed based on the results of existing Life Cycle Assessment (LCA) studies, with adjustments made to align with the specific problem of this research. Furthermore, the environmental impact analysis was limited to only two phases, fuel production and operational, for both drones and motorcycle scenarios. The functional unit used in this analysis is defined as the environmental impact per food order per meter.

2.10. Results Analysis

The analysis would involve identifying patterns in drone charging station placement across different predefined numbers of facilities. Furthermore, the analysis would also investigate the influence of delivery mode on the resulting routes and environmental impacts.

3. Results and Discussion

3.1. Road Network Data Processing

Figure 2 (a) presents the projection of the road network within the Yogyakarta Ring Road area obtained from OpenStreetMap using the OSMnx Python package. In this figure, nodes represent intersections, while edges represent road segments. The acquired road network data was subsequently processed based on road categories, which were used to determine the priority of each road segment. This process resulted in a dataset of nodes that are assumed to represent potential demand locations. The distribution of potential demand locations within the Yogyakarta Ring Road area can be seen in Figure 2 (b), represented by orange dots.

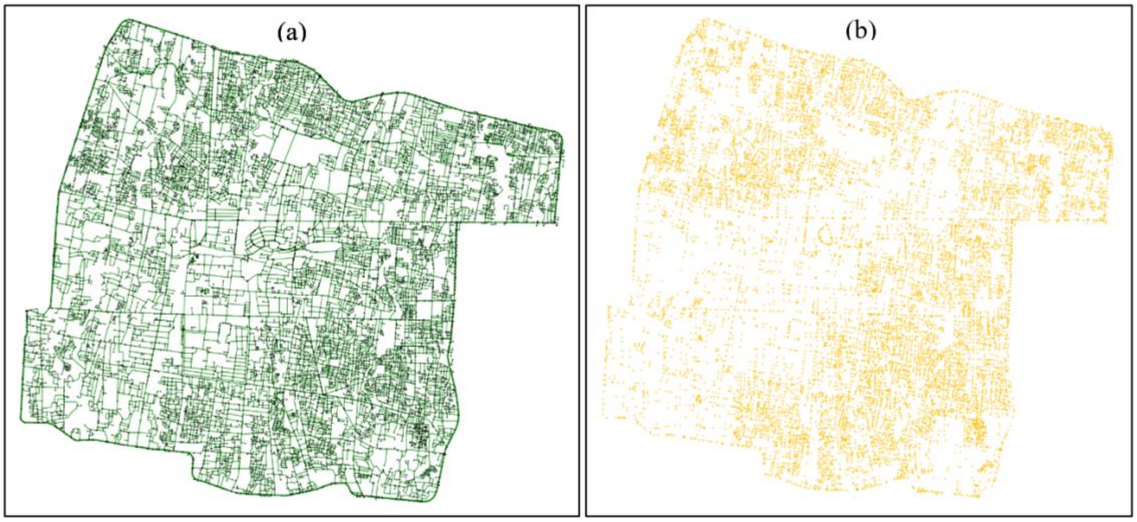

Figure 2. Road Network Projection (a) The Projection of Potential Demand Distribution Based on Road Network Data Processing (b)

3.2. Data Validation

Validation of the road network dataset was conducted using pearson correlation analysis. The analyzed variables are population and the number of potential demand nodes within each sub-district of Yogyakarta City.

Pearson correlation analysis revealed a correlation coefficient of 0.958, indicating a strong positive correlation between the two variables. This high value, approaching +1 (perfect positive correlation), signifies a strong linear relationship between the number of nodes and population. Furthermore, the p-value was found to be 0.000, as depicted in Table 2. This p-value was significantly lower than the significance level of 0.05, confirming a statistically significant correlation between the two variables.

Table 2. The Result of Road Network Data Validation using Pearson Correlation Method

Pearson Correlation	P-value
0,958	0,000

3.3. Validation of the Covering Algorithm

Validation of the MCLP algorithm was conducted by incrementally increasing the number of facilities that can be opened. As illustrated in Figure 3, the increasing margin in demand coverage diminishes as the number of charging stations increases. This result indicated that the proposed algorithm effectively prioritizes selecting facility locations with higher potential demand densities before selecting locations with lower densities.

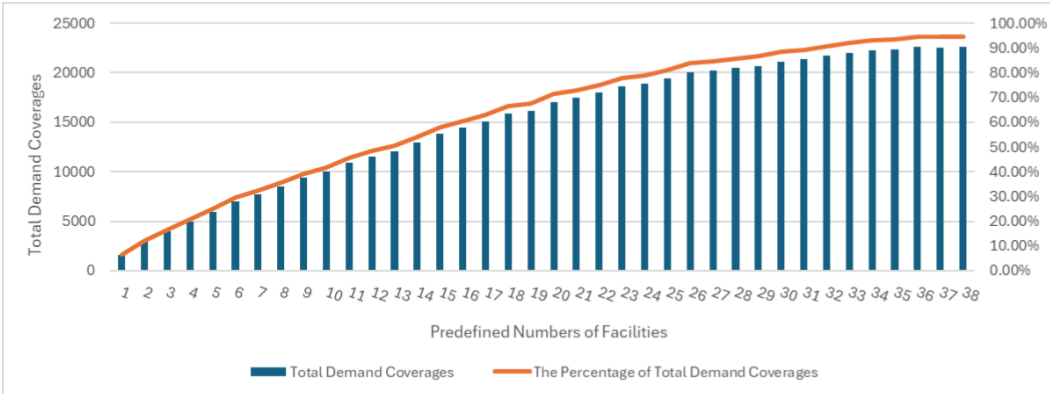

Figure 3. Graph of Total Demand Coverages against Predefined Numbers of Facilities

In addition, it also can be seen in Figure 3 that there is a slight decrease in demand coverage when the number of facilities increases from 36 to 37. This phenomenon can be attributed to the heuristic nature of the ACO algorithm, which does not guarantee the identification of the global optimum solution. When the percentage of demand coverage reaches a sufficiently high value (exceeding 94% in this case), and only a small portion of the potential demand remains unserved, the use of a heuristic approach, such as the ACO algorithm, may result in minor fluctuations in the solution quality.

3.4. Validation of the Routing Algorithm

Validation of the VRP algorithm was conducted by running the model on a small scenario and subsequently comparing the results with those obtained through enumeration method. This validation process was executed using a scenario with only six charging stations that were opened, with the projected location of each facility as depicted in Figure 4.

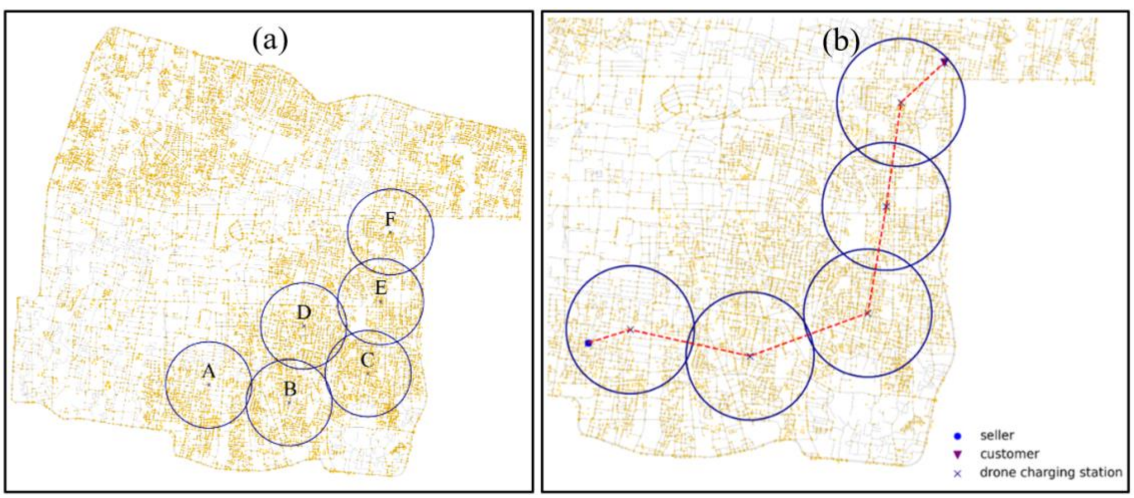

Figure 4. Projection of Drone Charging Station Locations for the Routing Algorithm Validation Process (a) Route Projection of the Routing Algorithm Validation Process (b)

By considering the interconnectivity between all six facilities, the enumeration method revealed a total of four possible routes from the seller to the customer, as stated in Table 3. Based on the enumeration results, the shortest total distance achieved was 8753 meters, corresponding to route A-B-C-E-F. This result aligns perfectly with the optimal solution obtained through the proposed VRP algorithm, as indicated in Figure 4.

Table 3. The Result of Total Distance for Each Possible Route using Enumeration Method

Possible Routes	Total Distance (meters)
A-B-C-E-F	8753
A-B-C-D-E-F	10782
A-B-D-E-F	8787
A-B-D-C-E-F	10456

3.5. Optimization Results of Drone Charging Station Locations

The optimization process was initiated by defining the number of drone charging stations that can be opened at 35 units. This number of facilities was determined based on the previous algorithm validation results, which indicated that at 35 units, the algorithm exhibited stable performance without fluctuations arising from the heuristic nature. Furthermore, the optimization process was executed with five repetitions. This approach aims to observe variations in demand coverage and obtain an average result across the five repetitions.

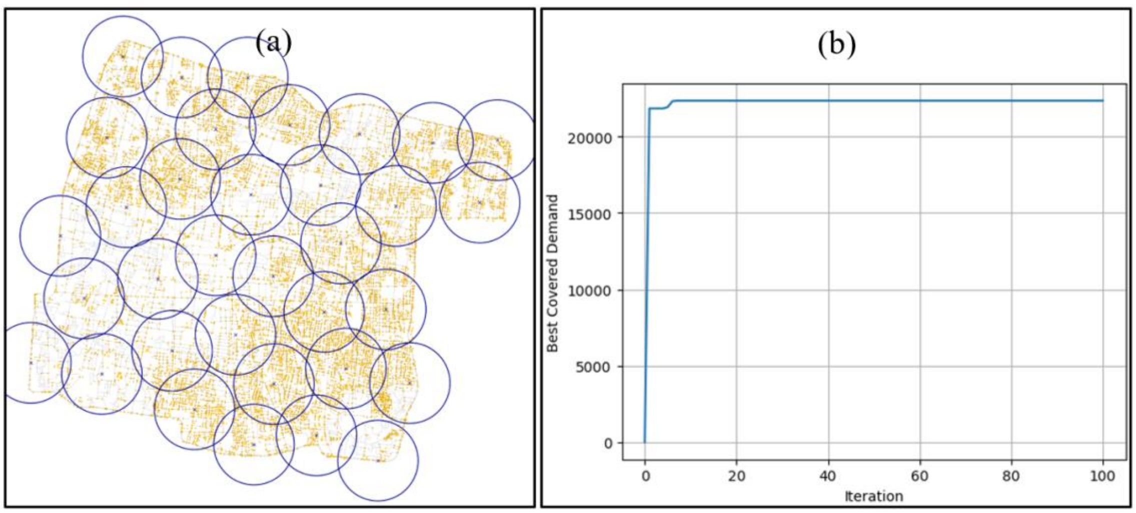

Figure 5. Projection of Drone Charging Station Locations Resulting from Optimization Process (a) Graph of Total Demand Coverages along Iterations in the Optimization Process (b)

The projection of drone charging station locations from one of those repetitions result is depicted in Figure 5 (a). While Figure 5 (b) shows the search orders for the optimal demand coverage within defined number of iterations in the optimization process. The result achieved a total demand coverage of 22,357 nodes with a computational time of 2486 seconds. The result of this repetition was selected to represent all the repetitions that were conducted because the demand coverage was the closest to the average of all five repetitions, as summarized in Table 4.

Table 4. Optimization Results for Each Repetition that is Conducted

Repetition	Computational Time (seconds)	Total Demand Coverages (nodes)
1	2486	22357
2	2367	22309
3	2277	22319
4	2401	22372
5	2307	22374
Average		22346.2 nodes

3.6. Optimization Results of Delivery Routes

The locations of drone charging stations obtained through the MCLP optimization process were subsequently utilized as input data for the route optimization process. Other necessary data that is also needed are the starting point and endpoint of delivery. In this study, the starting point, referred to as "sellers," was defined as the location of a restaurant, fast-food outlet, or cafe. Those locations were also obtained from OpenStreetMap using the OSMnx Python package. Whereas the endpoint, referred to as "customers," was randomly selected from the set of potential demand nodes that previously identified during the MCLP optimization process.

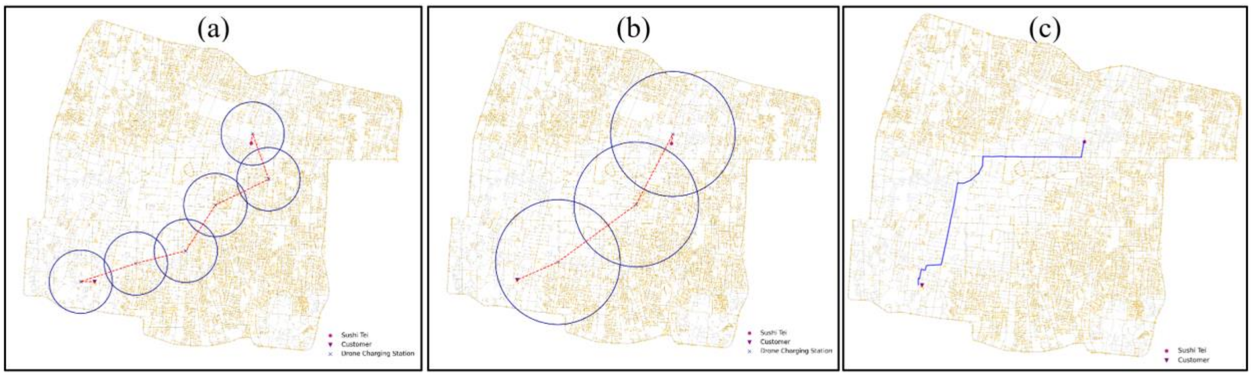

Figure 6. Route Projection of the Optimization Results for Each Scenario:
Drone with 2 km Flight Range (a), Drone with 4 km Flight Range (b), and Motorcycle (c)

The optimization process was conducted for two drone flight range scenarios: 2 km and 4 km. The scenario with a 2 km drone flight range resulted in a total delivery distance of 9269 meters. In contrast, the scenario with a 4 km drone flight range yielded a shorter delivery distance of 7347 meters. These results are visually represented in Figure 6 (a) and (b), which depict the flight routes for each scenario. In both optimization processes, the starting point (Sushi Tei restaurant) was randomly selected, denoted by a small pink circle. The ending point (customer) was also randomly selected, denoted by an inverted purple triangle.

This study also investigated the optimal route for ground delivery, assuming the use of motorcycle, mirroring current conventional food delivery practices. This comparison aims to evaluate the performance of drone-based delivery against ground-based delivery. The route optimization process for ground-based delivery utilized the routing module within the OSMnx Python package. This optimization process generated the shortest route based, with a total distance of 8684 meters, as depicted in Figure 6 (c) as a blue line.

3.7. Results of Environmental Impact Assessment

3.7.1. Environmental Impact for Drone-Based Delivery

The research conducted by Stolaroff, Samaras, O'Neill, Lubers, Mitchell, and Ceperly [31] investigated the relationship between battery weight, flight range, and energy consumption in drones. Two types of drones were utilized in their study: the 3D Robotics' Iris quadcopter and the Turbo Ace's Infinity 9 octocopter. These two drone models would serve as a reference for this study.

Meanwhile, the research conducted by Nugroho, Hanafi, Shobatake, Chun, Tahara, and Purwanto [32] would be used as a reference for determining the environmental impact of electricity production per kWh. This research was selected as it focuses on electricity production in Indonesia, specifically in Java, Madura, and Bali (Jamali).

Subsequently, the environmental impact of drone usage for delivery per meter can be calculated by multiplying the energy consumption of each drone by the environmental impact value. The calculated environmental impacts for both drone types are presented in Table 5 and Table 6.

Table 5. Environmental Impact Per Meters with the Usage of 2 km Flight Range Drone

Environmental Impact Indicators	Environmental Impact Value	
	Fuel Production Phase	Operational Phase
GWP (kg CO_2 eq.)	7,420 x 10^{-6}	0
AP (kg SO_2 eq.)	4,123 x 10^{-8}	0
ADP (kg Sb eq.)	1,610 x 10^{-8}	0

Table 6. Environmental Impact Per Meters with the Usage of 4 km Flight Range Drone

Environmental Impact Indicators	Environmental Impact Value	
	Fuel Production Phase	Operational Phase
GWP (kg CO_2 eq.)	7,219 x 10^{-5}	0
AP (kg SO_2 eq.)	4,011 x 10^{-7}	0
ADP (kg Sb eq.)	1,566 x 10^{-7}	0

3.7.2. Environmental Impact for Motorcycle-Based Delivery

The environmental impact assessment of motorcycle delivery is based on the findings of Sopha, Setiowati, and Ma'mun [33]. This research was selected as the reference due to the use of a similar functional unit (per kilometer) and the utilization of Indonesian case study data. The data obtained from this research are the total environmental impact value and its corresponding percentage only for the operational phase.

For the fuel production phase, the research conducted by Restianti and Gheewala [34] was used as a reference. Like the rationale for selecting the research by Nugroho, Hanafi, Shobatake, Chun, Tahara, and Purwanto [32] as electricity production reference, the study by Restianti and Gheewala was chosen due to its focus on gasoline production that also particularly for Indonesia.

Subsequently, the environmental impact of motorcycle delivery during the operational phase was calculated by multiplying the total environmental impact by its corresponding percentage and then converting the functional unit to per meter. For the fuel production phase, the environmental impact was calculated by multiplying the total environmental impact by the fuel efficiency of the motorcycle (Supra X 125), which is 26.71 km/L. This fuel efficiency value was obtained from the research conducted by Sopha, Setiowati, and Ma'mun [33]. The environmental impacts for motorcycle delivery per meter are presented in Table 7.

Table 7. Environmental Impact Per Meter with the Usage of Motorcycle

Environmental Impact Indicators	Environmental Impact Value	
	Fuel Production Phase	Operational Phase
GWP (kg CO_2 eq.)	7,980 x 10^{-6}	1,003 x 10^{-4}
AP (kg SO_2 eq.)	4,191 x 10^{-8}	2,176 x 10^{-7}
ADP (kg Sb eq.)	8,012 x 10^{-10}	0

3.8. Discussion

3.8.1. Drone Charging Station Locations

The optimization results for the scenario with five facilities that can be opened, as depicted in Figure 7 (a), show that the optimal locations are situated in the eastern region of the study area, characterized by the highest density of potential demand nodes. This observation indicated that the implemented algorithm effectively identifies optimal locations. However, in optimization scenarios with a higher number of facilities, some facilities were observed to be in areas with relatively low potential demand density. For instance, in the optimization results with 11 facilities that were opened, a facility was observed to be located in the center of the study area as can be seen in Figure 7 (b), where the density of potential demand points is visibly low. This phenomenon can be attributed to the interconnectivity constraint imposed on the algorithm. This constraint, implemented to accommodate the battery capacity limitations of real-world drones, may sometimes compel the algorithm to select locations that are suboptimal from the perspective of maximizing demand coverage.

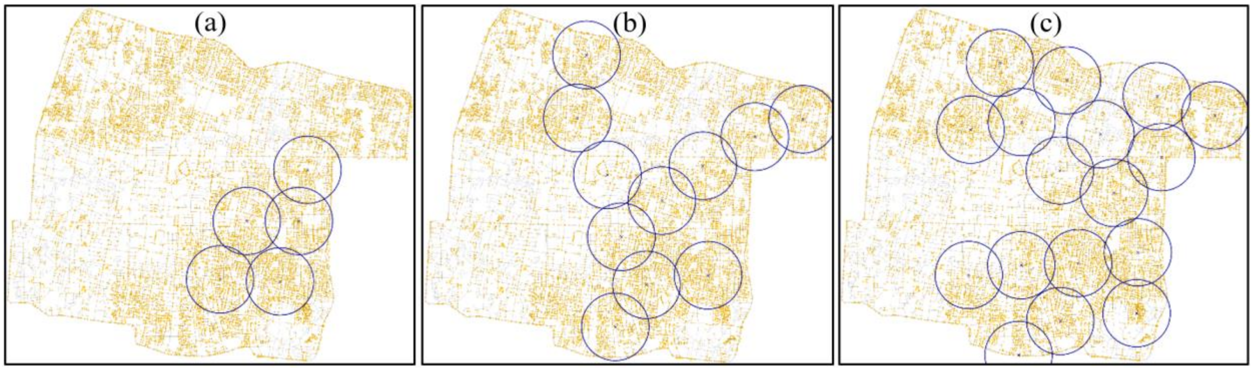

Figure 7. Optimization Results of Covering Problem with Predefined Numbers of Facilities: 5 (a), 11 (b), 17 (c)

The analysis revealed that there were areas with significant potential demand that were not selected as facility locations, or the selected location of the facilities slightly shifted from those areas. For instance, in the optimization scenario with seventeen facilities that were opened, a facility was observed to be located at the southern boundary of the study area, resulting in a portion of its coverage area encompassing no potential demand points. Conversely, areas with high potential demand that were close to the selected facility location remained unserved. This phenomenon can be attributed to the heuristic nature of the ACO algorithm, which may not always converge to the global optimum solution.

3.8.2. Delivery Routes

The analysis of the total delivery distance, as summarized in Table 8, revealed significant variations among the three delivery modes. The 2 km range drone exhibited longer delivery routes compared to motorcycle-based delivery. Conversely, the 4 km range drone showed shorter delivery routes than motorcycle-based delivery.

Table 8. Total Delivery Distance of the Optimization Results for Each Scenarios

Delivery Modes	Total Delivery Distance (meters)
Drone with 2 km flight range	9269
Drone with 4 km flight range	7347
Motorcycle	8684

This disparity can be attributed to the strong dependence of drone delivery routes on the location of charging stations. While drones can fly in a straight line without adhering to road networks, as is the case with motorcycle deliveries, this advantage is contingent upon the alignment of all charging station locations along a straight line between the seller and the customer. Furthermore, the significant difference in total distance between the two drone types can be attributed to the greater flexibility afforded to drones with longer flight ranges in selecting appropriate charging stations.

3.8.3. Environmental Impacts

The total environmental impact was calculated by multiplying the total delivery distance by the environmental impact per meter, as calculated previously in sub-section 3.7. The total environmental impact results are presented in three separate graphs corresponding to each environmental impact indicator, as shown in Figure 8.

The results indicate that for the operational phase, the GWP and AP indicators had zero values. This is because electric-powered drones do not generate emissions during operation [35]. Conversely, the result for the motorcycle-based scenario showed that most of its environmental impact comes up from the operational phase. This is because a combustion engine used in motorcycles generates substantial amounts of greenhouse gas emissions and other pollutants, which contribute to climate change and air pollution. Meanwhile, the ADP indicator for the operational phase in all scenarios was zero as no non-renewable raw materials were used during this stage.

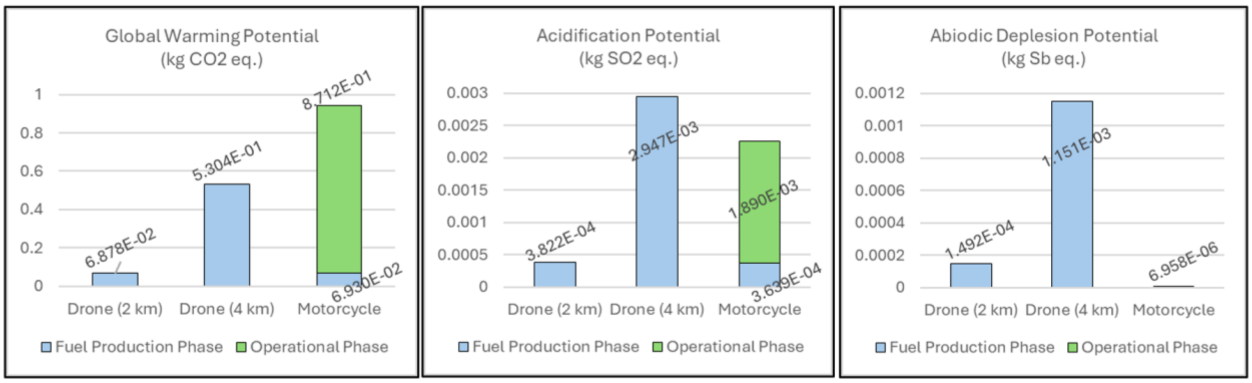

Figure 8. Graphs of Total Environmental Impact for Each Indicators

Furthermore, based on the three environmental impact graphs, it is evident that, considering the fuel production phase, the 4 km range drone exhibited the highest emissions across all environmental impact indicators compared to the other two modes. This can be attributed to the dominance of non-renewable energy sources in the electricity generation mix used to power the drones [32].

4. Conclusion

The optimization results for the location of drone charging stations within the area of Yogyakarta Ring Road revealed a demand coverage of 22,357 nodes, representing 93.56% of the total potential demand nodes. The optimization results also indicate that some areas with relatively low potential demand density were selected as facility locations. This phenomenon can be attributed to the constraint within the algorithm that compels interconnectivities for all facilities that were opened, this requirement necessary to accommodate the battery capacity limitations of real-world drones. Furthermore, the optimization results exhibit that some areas with significant potential demand were not selected as facility locations, or the selected location of the facilities slightly shifted from those areas. This can be attributed to the heuristic nature of the algorithm, which does not always guarantee to obtain global optimum results.

The optimized routes for each delivery scenario, drone with 2 km flight range, drone with 4 km flight range, and motorcycle, were determined to be 9,269 meters, 7,347 meters, and 8,684 meters, respectively. Meanwhile, the results of environmental impact assessments with the same scenarios were divided based on three indicators, Global Warming Potential (GWP), Acidification Potential (AP), and Abiotic Depletion Potential (ADP). The total environmental impact associated with GWP was calculated to be 6.88×10^{-2}, 5.30×10^{-1}, and 9.40×10^{-1} for each scenario, respectively. Similarly, the total environmental impact associated with AP was determined to be 3.82×10^{-4}, 2.95×10^{-3}, and 2.25×10^{-3}, respectively. Finally, the total environmental impact associated with ADP was found to be 1.49×10^{-4}, 1.15×10^{-3}, and 6.96×10^{-6}, respectively.

Future research could consider using exact optimization methods to ensure the solution is global optimum. Moreover, incorporating other parameters such as land availability, investment costs, and charging station capacity could help identify not only the optimal location of the charging station but also the allocation of drones for each facility. For the routing problem, the Euclidean shortest path method could be considered as it can accommodate real-world conditions, such as obstacles or restricted areas [36]. Regarding the environmental impact assessment, a more comprehensive and systematical life cycle assessment (LCA) could be conducted.

5. References

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