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Research Article

Design of waste management area based on clustering and traveling salesman problem

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ABSTRACT

Waste management in rural Indonesia faces significant challenges as the volume of household waste increases. Waste banks are proposed as a solution to overcome this problem. This study aims to design an efficient waste management area in Gondangmanis Village by determining the optimal location of waste collection points and the shortest waste pickup route using clustering and Travelling Salesman Problem (TSP) approaches. The K-Means clustering algorithm is used to form clusters and determine the center point of each cluster, where the K value is first optimized using a genetic algorithm. Furthermore, the genetic algorithm is also applied to optimize the TSP to find the most efficient waste pickup route. The data used includes 1181 coordinate points in the study area, with household waste production of 2.5 kg/day/house and the capacity of the waste collection bin. The results showed that placing a waste collection bin with a capacity of 0.8 m^3 with 4 clusters was more effective than 3 clusters with a capacity of 1 m^3. TSP optimization resulted in the shortest waste pickup route with 19581 km, thus reducing travel distance and operational time. This approach is expected to increase waste management efficiency in rural areas, support environmental conservation, and optimize waste bank operations.

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INTRODUCTION

Urban planning and the delivery of public services heavily depend on determining where public facilities should be located. Numerous studies emphasize the importance of choosing the ideal facility sites to meet demand effectively [1]. Geographic Information Systems (GIS) technology is essential in determining appropriate places for public buildings such as parks, healthcare facilities, and disposal sites [2]. The location of public amenities is crucial to their intended function, be it easing traffic congestion, lowering pollution, or promoting public transportation use [3].

One example of a problem in the field of public facility provision that is important to consider is the location of waste banks. Waste problems are a challenge faced by many countries worldwide, including Indonesia [4]. The amount of waste generated in Indonesia has steadily increased, necessitating effective waste management strategies [5]. According to data from the National Waste Management Information System, in 2023, Indonesia produced 18 million tons of waste annually, 33.09% of which needs to be managed correctly. Household waste is the most significant contributor, with a proportion reaching 50.79% [6], which shows that waste from household activities has a dominant role in national waste generation, so waste management efforts must be focused on this sector to reduce the amount of untreated waste.

Waste management in Indonesia, particularly in rural areas, faces significant challenges. Rural communities often need help collecting waste due to limited access to collection ser-

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vices, vast geographical regions, and inadequate waste management infrastructure [6]. This results in environmentally unfriendly waste disposal practices, such as burning and littering into rivers or vacant lots. These practices have the potential to pollute the environment, cause air and water pollution, and pose health risks to the surrounding communities [7]. Research shows that waste burning in rural areas is often considered a practical solution to avoid waste accumulation [8]. However, the long-term effects of this burning can cause serious health problems, including respiratory diseases and cancer, due to exposure to toxic fumes [9].

One approach to tackling waste problems in villages is to design a waste management system with waste banks [10]. The role of community leaders in motivating waste bank management can further enhance the sustainability and effectiveness of waste bank programs [11]. Waste banks are crucial in promoting recycling, reducing waste sent to landfills, and fostering environmental sustainability [12]. Waste bank management involves activities such as customer registration, waste transactions, and waste collection from customers [12]. It provides added value to waste previously considered a burden, thus benefiting the government and society [13].

Gondangmanis Village has one waste bank, but its less strategic location makes it difficult for residents to access. In addition, the waste bank is not equipped with a waste pickup system, so residents must bring their waste to the waste bank location. This condition is one of the reasons for the residents' low participation in supporting waste management by saving waste in waste banks so that it can be processed into valuable items.

Based on data from the Gondangmanis Village government, the study area had a population of 4,894 people in 2023, spread across 1,068 households. However, only around 200 families, or 18.73% of the total, actively participate as waste bank customers. This is equivalent to about 4.09% of the total population in the study area. Residents who live far from the waste bank location tend to manage waste in a less environmentally friendly way, which can pollute the surrounding environment.

In addition to the challenge of community participation, the waste bank also faces operational constraints due to the limited number of officers. Currently, the waste bank only has four officers. With a limited number of officers, implementing a waste pickup system, such as door-to-door waste pickup, will be very difficult because it requires much time, energy, and operational resources. Therefore, an appropriate strategy is needed to minimize the distance residents travel to access the waste bank while optimizing officers' workload in collecting waste from all village areas. Investing in efficient waste collection and transportation systems is vital for managing waste in rural areas [14].

The K-Means clustering method can group homes based on waste generation patterns, thereby identifying high-density waste areas requiring more frequent collection [15, 16]. K-Means clustering can be used to analyze waste management performance in different districts, showing this method's effectiveness in optimizing waste collection strategies [15]. K-means can also map waste generation, highlighting the importance of clustering in extending landfill life by optimizing waste handling methods [16]. Clustering automatically groups data or objects with similar or similar characteristics [17]. Finding the shortest path between the centroid and the training data iteratively is how the K-Means clustering algorithm works [18]. Genetic algorithms can be integrated with K-means to improve the clustering process. This hybrid approach enables the optimization of cluster centers and the determination of the optimal number of clusters. Research by Pu et al. illustrates how an improved genetic algorithm can optimize K-Means clustering by selecting optimal features and improving segmentation accuracy [19]. The combination of genetic algorithms with K-Means has been shown to improve convergence rates and clustering accuracy, as discussed by Tiwari et al., who introduced an entropy weighting mechanism to enhance the clustering process [20].

Research by Tyler Parsons used weighted K-Means to divide the waste collection area based on the number of dwellings, then optimized it with a differential evolution algorithm to balance the workload. Route simulation was conducted using Dijkstra's and Hierholzer's algorithms, resulting in a more efficient collection route regarding travel distance and time. This method significantly improved waste collection area distribution and efficiency [21]. Research by Abdullah Izzeddin Karabulut et al. discusses a comparative study of the best route selection for municipal waste collection using genetic algorithms, ant colony systems, and GIS network analysis. These three methods are applied to solve the Traveling Salesman Problem (TSP) in waste collection route optimization. The results show that the ant colony algorithm is the most efficient, with a 40.52% improvement in route distance reduction, compared to 29.81% for the genetic algorithm and 15.16% for the GIS, making it the most effective method [22].

Research by Didem Guleryuz used a K-Means clustering algorithm to group 39 districts in Istanbul based on five waste management indicators: domestic waste, medical waste, population, budget, and cleaning area. The data was normalized and analyzed using IBM SPSS Modeler, resulting in four clusters with different characteristics to support more efficient waste management policies [15]. Research by Suhaibah Azri et al. proposed the WCPI method to place recycling bins in Malaysia optimally. Using geotagged data and K-Means clustering, the study found that strategic placement can increase recycling and reduce carbon emissions by 10,323.55 kg, supporting sustainability policies towards Agenda 2030 [23].

Based on previous research, this study focuses on improving the effectiveness and efficiency of the waste bank of Gondangmanis Village, Kudus, Indonesia, by establishing several waste collection points using a combination of K-Means clustering algorithm and genetic algorithm, as well as finding the closest route for picking up waste to be taken to the waste management point. Determining the right waste collection point is expected to make it easier for residents who save for the waste bank and officers who collect and facilitate officers in carrying out waste pickup. The results are expected to support a more integrated and organized waste management system.

MATERIALS AND METHODS

Dataset

In this study, the data used for the research phase, as shown in Figure 1, consisted of latitude and longitude coordinates representing the locations of 1181 houses in Gondangmanis Kulon and Gondangmanis Wetan hamlets, which are administrative areas of Gondangmanis Village, Kudus, Indonesia. This data was obtained through the Google Earth digital mapping platform, and the provision of high-resolution satellite photos in Google Earth allows for detailed land use vulnerability modeling, as seen in the micro-seismic zoning study [24]. Based on data from the government of Gondangmanis Village, the study area has an area of 200.9459 hectares, which can be seen in Figure 2. It has a total population of 4894 people in 2023. According to research by the ITB Environmental Center in Indonesia, the average household produces 2.5 kg of waste per day [24].

In Figure 1, there are two stages of genetic algorithm implementation. The first implementation uses a genetic algorithm to determine the optimal number of clusters (K). This algorithm aims to optimize the number of clusters based on the dataset. This optimization aims to find the K value that can minimize the distance variation within the cluster so that each cluster has a more even and efficient distribution. Once the K value is determined, the K-Means method is used to form clusters of house points based on their coordinates and determine the centroid of each cluster as the optimal location of the waste collection point.

The second implementation of the genetic algorithm is used for the Traveling Salesman Problem (TSP) in the context of waste pickup. The predetermined cluster centroids serve as the locations for waste collection, and the genetic algorithm is applied to find the shortest route so that the waste pickup process can be done more efficiently.

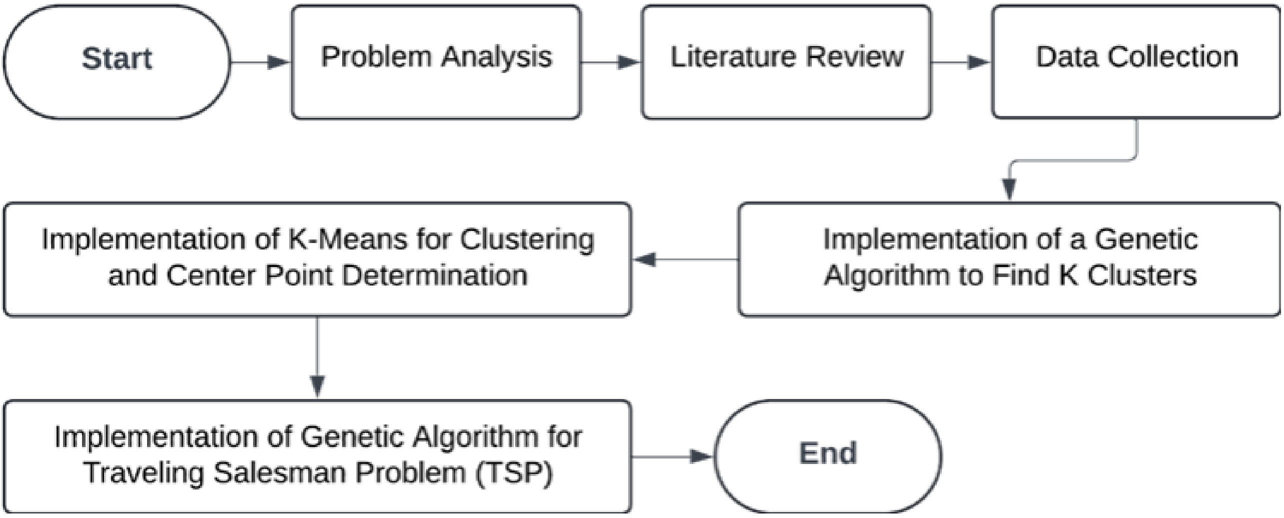

Figure 1. Stages of research

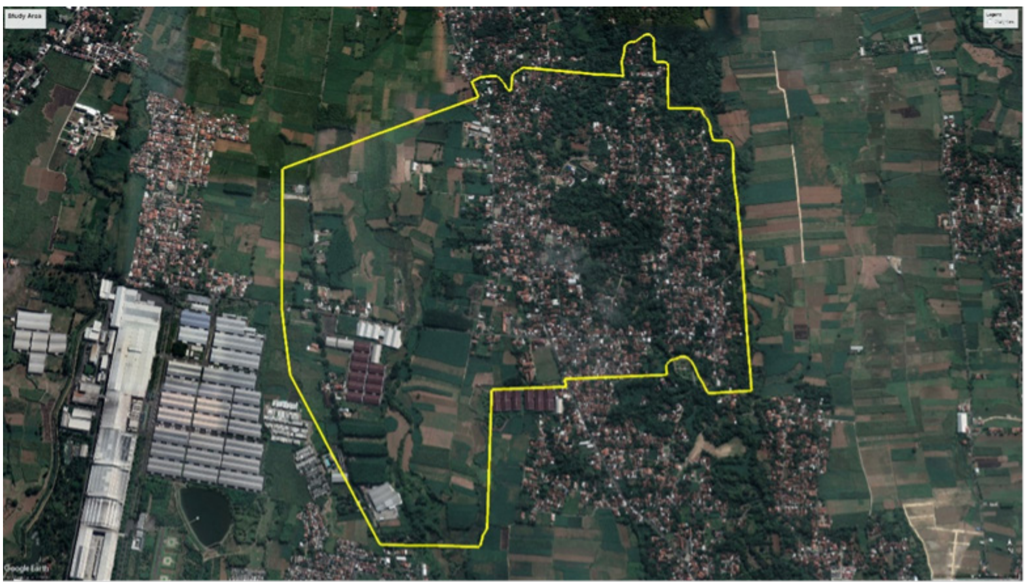

Figure 2. Map of the study area location

Genetic Algorithm (GA)

Genetic algorithms (GAs) are optimization techniques inspired by natural selection and genetic principles [25]. They are highly effective for solving complex optimization problems where traditional methods may need help. Holland introduced the basic concepts of GAs and later expanded them to Goldberg, establishing GAs as powerful tools in various fields, including engineering, computer science, and artificial intelligence [26].

Genetic algorithm for determining clusters

The genetic algorithm becomes an effective tool in data clustering, especially in optimizing the initial centroid in K-Means to improve the accuracy of clustering results [27]. Genetic algorithms also have global optimization capabilities that allow them to effectively use clustering validation criteria to determine the optimal number of clusters and form the best data partition [28]. The integration of genetic algorithms with clustering techniques provides a solution to this limitation by utilizing the global optimization capabilities of genetic algorithms to determine k dynamically. Liu et al. proposed a method that leverages the principles of genetic algorithms to enhance clustering performance by evolving the cluster centers through iterative processes [29]. This method enables automatic k adjustment based on data characteristics, thus eliminating the need for prior knowledge of the number of clusters. In addition, the integration of multi-objective genetic algorithms has been shown to improve clustering results significantly.

This study uses a genetic algorithm to determine the optimal value of K, the most appropriate number of clusters, which will be applied in the k-means clustering process. The K value is determined by considering several main parameters, namely the house in the study area, the amount of household waste generated per house per day, and the capacity of the waste collection bins. This approach aims to produce efficient clustering, where the capacity of the waste collection bins in each cluster can optimally accommodate the amount of waste generated. Some of the main steps in this algorithm include:

1)Population Initialization: The initial solution is formed based on various cluster divisions, considering the waste bank's capacity.

2)Fitness Evaluation: Each solution (number of clusters and grouping of houses) is evaluated based on the efficiency of the waste collection capacity in each cluster. A better solution can optimize the use of the shelter capacity by minimizing excess or lack of capacity. Therefore, the more balanced the distribution of waste volume against the shelter capacity in each cluster, the higher the fitness value of the solution.

3)Selection: The existing solutions (ways of grouping houses into clusters) are evaluated based on their fitness value and efficiency so that each cluster can accommodate waste in a balanced way. The solution with the highest fitness (most optimized clustering) will be selected as the "parent."

4)Crossover: Combining two parent solutions to produce a new solution. In this context, the new solution will combine the clustering of houses from the two parents to create a more efficient combination, such as optimizing the number of clusters (K) and the distribution of waste within each cluster.

5)Mutation: The mutation process prevents the algorithm from getting stuck in a local solution, introducing variations in the solution.

Optimal Solution: After several iterations, the genetic algorithm produces an optimal solution, dividing households into ideal clusters.

Genetic algorithm for traveling salesman problem

Implementing a genetic algorithm for the Traveling Salesman Problem in this research aims to find the shortest route for waste pickup in the study area. Using this approach, the optimization system is designed to determine the most efficient sequence of visits to waste collection points, resulting in minimal travel distance. Reducing waste management, travel time, and operational costs are considered important. The stages of the genetic algorithm applied in this study to find the shortest route for waste pickup include the following steps:

1.Population Initialization: Create an initial population of random routes that visit all points.

2.Calculate Fitness: The fitness value is calculated based on the total distance traveled by the route. The route with the shortest total distance will have a higher fitness value, as it is more efficient in visiting all points. The best route is the one with the highest fitness value, which means the shortest distance traveled.

3.Selection: Based on the fitness value, select the best reproduction route using a selection method, such as tournament selection.

4.Crossover: The two routes selected as parents are merged to produce a new route. This process combines the order of visit points from both parents while keeping the order of points for each parent.

5.Mutation: Make small changes to the new route, such as swapping the positions of two nodes, to increase variety and prevent local solutions.

6.Population Update: Replace the sub-optimal route with a new route and repeat this process for several generations.

7.Final Result: After a certain number of generations, take the route with the shortest distance as the final solution, which indicates the optimal sequence to visit all the center points of each cluster.

K-Means Clustering

The K-Means algorithm is an extensively employed technique for identifying cluster centers owing to its iterative characteristic and efficiency in optimizing these centers [30]. This adaptability and data-driven approach solidify K-Means as a powerful tool for clustering analysis and center point determination [30]. The primary goal of K-means is to partition data into k distinct clusters, where each cluster is represented by its centroid, which is the mean of all points assigned to that cluster. This method is particularly effective in scenarios where the data is well-separated and can be grouped based on similarity [31, 32].

After implementing the genetic algorithm, a K-Means clustering process is performed to divide the houses into several clusters and determine the centroid that will serve as the waste collection location. This clustering process aims to group houses based on geographical distance so each cluster can be managed efficiently according to the available waste bank capacity.

Several essential steps must be followed to effectively carry out the K-Means clustering process. The method includes the following steps:

1.Determine the K value representing the desired number of clusters or groups. In this research, the K value has been determined using a genetic algorithm.

2.Randomly determine the centroid for each cluster, with the number of centroids adjusted to the predetermined K value.

3.Each data will be grouped into the closest cluster based on a specific distance calculation using the Euclidean distance metric with Equation 1.

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

4.After the initial clustering, the centroid position of each cluster will be recalculated based on the average of the data belonging to that cluster.

5.The process of clustering and updating the centroid will be repeated iteratively until there is no significant change in the centroid position. In other words, the process will stop when the centroid has reached the optimal position, and there is no more data movement between clusters.

In this study, the K-Means algorithm is applied to determine the center point in each formed cluster, which will later serve as the location of the waste collection point. In this way, each cluster represents a group of houses that are geographically close to each other, thus enabling efficient and easily accessible placement of waste collection bins for the surrounding residents. As an illustration, Figure 3 is the clustering results of a sample dataset consisting of several house coordinates in the study area. In the figure, the symbol "x" marks the center point of each cluster generated by the K-Means algorithm, indicating the optimal location for placing waste collection bins based on the geographical proximity of houses within each cluster.

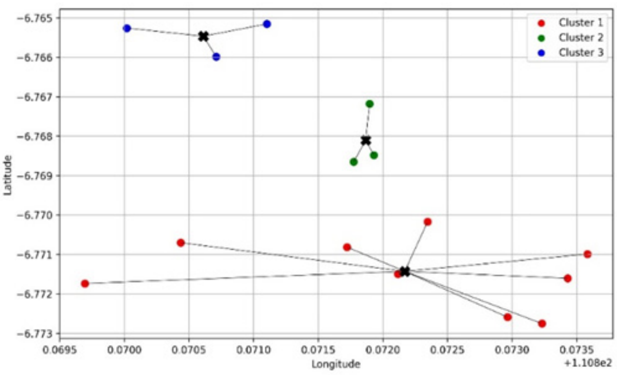

Figure 3. Illustration of K-Means clustering implementation

Euclidean distance

Euclidean distance calculation is fundamental in various fields, particularly computer science and mathematics. In computer science, the Euclidean distance is commonly employed in centroid-based clustering algorithms like K-Means [33]. This distance measure is crucial for determining the similarity between data points [34]. The Euclidean distance is vital in spatial analysis, such as evaluating spatial accessibility to urban parks and conducting spatial co-location pattern mining of facility points of interest [35]. It is also a key component in cluster analysis, where the choice of distance matrices, including Euclidean distances, influences the definition of regions [36].

Traveling Salesman Problem

The Traveling Salesman Problem (TSP) is a well-known combinatorial optimization problem that aims to find the shortest route for a salesman to visit each city in a given set exactly once before returning to the starting point. It is a key problem in operations research and computer science, often used as a benchmark to test new optimization techniques. The classification of this problem as NP-complete indicates that no existing polynomial-time algorithm can solve every problem instance efficiently [37].

The TSP has various applications across multiple domains, including logistics, manufacturing, and transportation, where optimizing routes can lead to significant cost savings and efficiency improvements [38, 39]. The problem has been extensively studied, leading to numerous algorithms, including exact methods like branch-and-cut and heuristic approaches such as genetic algorithms, ant colony optimization, and particle swarm optimization [40].

Genetic algorithms (GAs) have gained popularity as a heuristic method for solving the TSP because they can efficiently navigate large search spaces and identify solutions that are close to optimal [41, 42]. The stages of applying genetic algorithms to the Traveling Salesman Problem encompass a systematic approach that includes initialization, fitness evaluation, selection, crossover, mutation, replacement, and termination, often supplemented by post-processing techniques. Each stage plays a vital role in the overall effectiveness of the algorithm in finding optimal solutions for the TSP [41].

RESULTS AND DISCUSSIONS

This research focuses on household waste management using genetic algorithms and clustering methods. In waste management, determining the optimal number of clusters is very important so that waste collection can be done effectively and efficiently. Based on the dataset, it has been explained that there are 1181 houses in the study area, each household produces 2.5 kg of waste per day, and each waste collection site has a specific capacity to be used as a limitation in cluster grouping.

To design a waste management area in the study area based on SNI 3242- 2008 [25], the author simulates two capacities of waste collection bins that will be placed at each center point of each cluster, 0.8 m3 and 1 m3, and analyzes them to determine which scenario provides optimal results.

The calculation results show a variation in the number of clusters formed based on the waste collection bins' capacity. With a capacity of 0.8 m^3, 4 clusters were generated, while a capacity of 1 m^3 generated 3 clusters, as shown in Table 1.

The Table shows that the smaller the waste collection site's capacity, the more clusters are generated to keep the waste distribution even and remain below the maximum capacity.

Figure 4 shows the distribution of cluster centers at K=3 and K =4, where all clusters are within an easily accessible radius of the nearest waste bank. Table 2 shows the details of the center point of each cluster at K=3 and K =4. With the results of this study, K=4 was used because of the more even distribution of clusters, making it easier to collect waste from houses in each cluster. The distance of waste collection can be minimized, reducing travel time and facilitating residents' access to waste collection points. With more clusters and an even distribution, waste management becomes more efficient, reduces the risk of overcapacity in waste banks, and ensures that waste in each cluster can be handled optimally. This approach is also expected to increase residents' participation in more responsible waste management.

Table 1. Calculation results using genetic algorithm and K-Means clustering

Cluster	Capacity 0.8 m^3 (K=4)		Capacity 1 m^3 (K=3)	
	Number of House	Total Waste (kg)	Number of House	Total Waste (kg)
Cluster 1	294	735	410	1025
Cluster 2	314	785	423	1057,5
Cluster 3	278	695	348	870
Cluster 4	295	735,5		

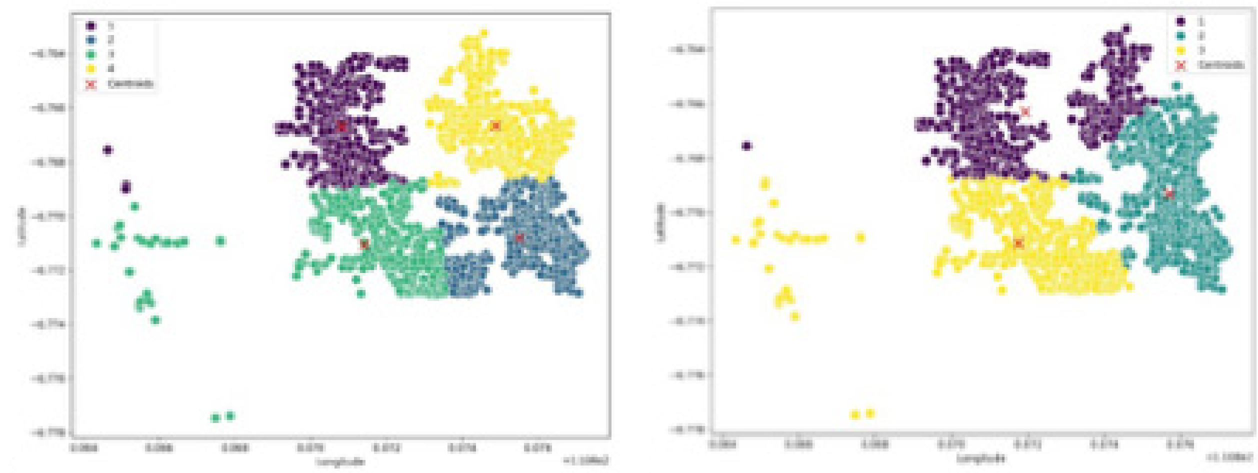

Figure 4. (a) Clustering result K=4 (b) Clustering result K=3

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Table 2. The center point of each cluster

Cluster	Center Point K=4 (Latitude, Longitude)	Center Point K=3 (Latitude, Longitude)
1	-6.7666920514324325, 110.87082578716216	-6.766305913776156, 110.87192768296838
2	-6.770811458101587, 110.87551799746032	-6.769322736718676, 110.87570026312056
3	-6.771074634380435, 110.87141084963768	-6.771145802694525, 110.87175651585014
4	-6.766665939163265, 110.8749013717687	

After getting four clusters and the center point of each cluster, the next step is to find the best route for the waste pickup process using the Traveling Salesman Problem (TSP) method with a genetic algorithm. The process of picking up and transporting waste starts at point A, the village office, and ends at point F, which is the location of the waste processing plant. The points on this transportation route can be seen in Figure 5. The distance calculation process uses Euclidean distance, as stated in Equation 1, and the search for the best route is done using Python programming, the results of which can be seen in Table 3.

Figure 6 is a visualization of the table above. The optimal route with the shortest distance is route A-C-D-E-F-B, shown in Figure 6 (d). This route has a total distance of 1.9581 km. This is consistent across populations, starting from the 3rd population to the 100th population, and shows the stability of the optimization results. The genetic algorithm showed convergence from the third population, producing stable values despite the increase in population.

Optimality aims to find the most efficient route that minimizes travel distance, reducing travel time and resource consumption, such as fuel [43] or energy. With this shortest route, the collection or distribution process can be carried out more quickly and cost-effectively [44], supporting operational efficiency and improving service [45]. In addition, this resource-saving also contributes to reducing carbon emissions from vehicle operations, thus supporting environmental efficiency [46]. This is expected to improve access and quality of service, which in turn will increase citizen participation in more responsible and sustainable waste management.

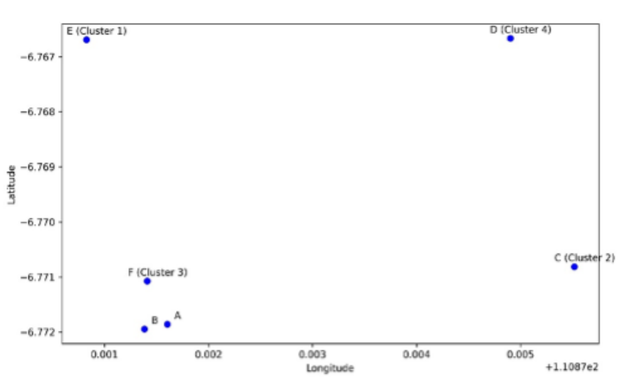

Figure 5. Points for transportation routes

Table 3. The best distance values

Population	Route	Distance (km)
0	A – D – F – E – C – B	2.9717
1	A – E – D – C – F – B	2.0543
2	A – F – E – D – C – B	1.9770
3	A – C – D – E – F – B	1.9581
10	A – C – D – E – F – B	1.9581
100	A – C – D – E – F – B	1.9581

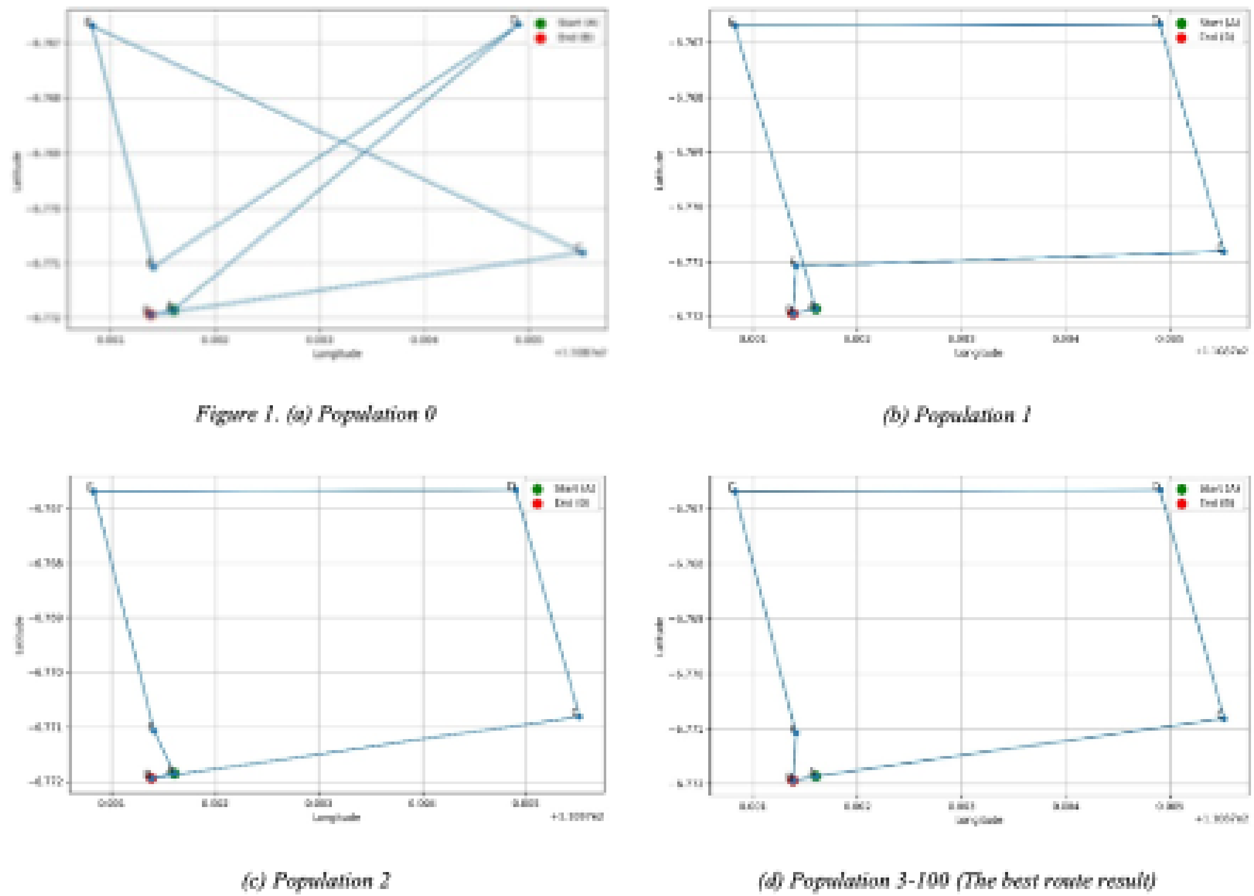

Figure 6. Optimization process of the waste pickup route using the TSP method with a Genetic Algorithm
a) Population 0, b) Population 1, c) Population 2, d) Population 3-100 (the best route result)

The garbage pickup route starts from point A (-6.771856, 110.871603) namely the village office then goes to point C or cluster 2 (-6.770811458101587, 110.87551799746032), then to point D or cluster 4 (-6.766665939163265, 110.8749013717687), then to point E or cluster 1 (-6.7666920514324325, 110.87082578716216), then to point F or cluster 3 (-6.771074634380435, 110.87141084963768), the last destination is point B or waste processing site (-6.771944444, 110.8713833). The route ends at the waste processing site, where all waste is placed in the waste processing site, and then the fleet returns to the village office.

Referring to the Governor Regulation of the Special Capital Region of Jakarta Number 102 of 2021 concerning Waste Management Obligations [47], the fleet used in the waste transportation process is an Arm Roll truck with a load capacity of 6 m^3. This fleet was chosen because it has sufficient capacity to transport the total waste generated, which is 2,950.5 kg. With this capacity, the waste pickup process can be completed in one trip. This not only increases the efficiency of transportation but also reduces the frequency of trips required, thus optimizing the use of the fleet and reducing operational costs and the environmental impact of vehicle emissions [48].

With the proposed solution, residents no longer need to travel long distances to save at the waste bank, as waste can be collected at designated collection points according to their respective clusters. In addition, the waste pickup officers, with a current number of four officers, can work more efficiently by only picking up waste at the collection points without going to each resident's house. The transportation process can be completed in one trip, so there is no need for additional officers, even if there are several collection points.

CONCLUSIONS

This research aims to design a waste management area in Gondangmanis Village, Kudus, Indonesia, by assigning multiple waste collection points to facilitate residents' access to waste bank services and increase their participation in waste management. This research uses a k-means clustering algorithm and genetic algorithm to determine waste clusters' optimal number and location. In addition, the shortest route for waste pickup is optimized using the Traveling Salesman Problem (TSP) method to make it easier for officers to collect and transport waste to waste management locations.

A genetic algorithm was used as an optimization method to find the most efficient number of clusters, ensuring that the grouping of households was done optimally without exceeding the capacity of the waste bin. With a bin capacity of 0.8 m^3, 4 clusters are formed, which results in a more even distribution compared to the 1 m^3 capacity, which only forms 3 clusters. This makes waste management more accessible, avoids the risk of overcapacity at collection points, and ensures that each cluster can be managed efficiently.

Once the optimal number of clusters was identified, the K-Means algorithm grouped the houses in the study area and found the center point of each cluster. K-Means helps map houses into smaller clusters to place waste collection points efficiently.

After the clusters are formed and the center point of each cluster is found, the traveling salesman problem using a genetic algorithm is used to find the shortest waste pickup route from the village office to the waste processing site. By considering several routes, the best route is obtained. This method can reduce distance and travel time, improve operational efficiency, and reduce logistics costs and vehicle emissions.

The results of this study show how the proposed waste management solution can improve residents' accessibility to waste banks and officers' efficiency in conducting waste pick-ups at the waste collection points in each cluster. By optimizing the waste collection points and routes, the number of officers required can remain efficient, resulting in more effective waste management.

The results of this study can serve as a reference for local governments or policymakers in designing more integrated and effective waste management areas, especially in rural Indonesia. By applying this method in other villages, community participation in waste management will increase, as will the creation of more integrated and efficient household waste management.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

USE OF AI FOR WRITING ASSISTANCE

Not declared.

ETHICS

There are no ethical issues with the publication of this manuscript.

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