Greedy Heuristics for the Maximum Covering Location Problem: A case study of Optimal Trashcan Location in Kampung Cipare – Tenjo – West Java

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Abstract. Having a rapidly growing economy without proper waste handling system and infrastructure has made Indonesia one of the top contributors of plastic marine debris in the world: 3.22 million metric tons of mismanaged plastic waste per year. The mismanagement of waste is worse in the rural area where the number of available public trashcan is limited and the people have no idea where their trash actually ends up. In this research, a case study of waste management in Kampung Cipare - Tenjo, a small village 80 kilometers away from Jakarta, is conducted. The biggest purpose of the research is to educate people about sanitation and waste management, initiated by computing the most optimum number and locations of the public trashcans. The problem is addressed as Maximum Covering Location Problem (MCLP) to determine a set of facility locations that maximizes the total demand population served by the facilities within a prespecified maximum service distance. Two greedy heuristics algorithms: Greedy Adding Algorithm (GAA) and Greedy Adding with Substitution Algorithm (GAAS) are utilized to solve the problem. A sensitivity analysis is also done to check the result on the effect of trashcan number and maximum service distance to demand coverage. Out of the 26 location candidates, it is concluded that the final 10 locations are the most optimum in terms of demand coverage and service distance. The result of the research has been implemented in Kampung Cipare-Tenjo.

Keywords: Maximum Covering Location Problem, Greedy Heuristics, waste management, trashcan location optimization

1. Introduction
As one of the top five most populated countries with rapidly growing economy, Indonesia has become one of the biggest contributors to marine pollution with its plastic waste. The insufficient waste
handling system and infrastructure has put Indonesia as the second biggest contributors to plastic debris (Jambeck, 2015). Plastic debris in the ocean endangers the life of marine organism as well as human’s existence, since it circulates in the ocean, changes marine ecosystem, absorbs other pollutants and consistently remains in nearly all forms of marine life (McKinsey, 2017) in the food chain, with human in the top of the chain. The biggest supplier to this plastic marine debris is the uncollected plastic waste that ends up in the river and waterways, goes on to the ocean, forming the plastic gyres.

The waste generation rate in Indonesia is 0.52 kg per person per day with 11% of it is the plastic waste, resulting to 3.22 million metric tons mismanaged plastic waste which contributes up to 1.29 million metric tons of plastic marine debris to the world (Jambeck, 2015). Figure 1 displays the data of waste management in Indonesia, based on the Indonesian Statistics Bureau report of the year 2016 (Badan Pusat Statistik, 2016). It is shown that within the year of 2014, in daily basis, only 71.5% waste in major cities in Indonesia is managed correctly. Although the number is actually better compared the previous years, this data shows that the remaining 28.5% waste in major cities is not transported to the landfill. The chance is that the “untreated” waste was independently managed by the citizen. However, only a small number is treated in correct ways such as recycling and composting. Meanwhile, the rest is discarded in the river or other waterways and eventually ends up in the ocean.

Figure 1. Waste production and the volume transported to landfills in major cities of Indonesia

The situation in the city perhaps indicates that the importance of waste management is not yet understood by most Indonesians. However, the situation gets worsen in the rural area where the number of available public trashcans is limited and the incorrect waste management is practiced. Not many people care about sanitation and the effects of trash mismanagement to their health. In this study, we took the case of Kampung Cipare - Tenjo, a small village in Bogor, West Java, that is located only 80 km away from the current capital city of Indonesia: Jakarta. Tenjo consists of around 120 households with average earnings around Rp 2,500,000 or US$180 a month and surely, waste management is not in the top priority yet. The people of Tenjo has no specialized area dedicated as a landfill, no trashcans outside the houses nor on the side of the road. In the public areas of Tenjo, scattered plastic bottles are swept away during rainy days and end up in the waterways, while the household trash is regularly burned. People of Tenjo still have no idea that the plastic trash in the waterway will end up in the ocean and the burned garbage produces dangerous gases harmful to their
own health. To alleviate this situation, we are taking initiative to provide several public trashcans that optimally located in the vicinity of the houses in Tenjo. Moreover, a social engineering has been conducted to educate the importance of a proper waste management. However, due to fund limitation, the number of trashcans being donated is limited.

In this problem, there are candidates of trashcan locations that provide coverage to the nearby houses. A demand area is considered covered if it is within a predefined service distance. Thus, the basic nature of the considered problem is that of the maximum covering location problem (MCLP). The objective of MCLP is to determine a set of facilities locations that maximize the total demand population serviced by the facilities within a prespecified maximum service distance. The maximum covering location problem is a relaxation of set covering problem (SCP) when it is not feasible to cover all customers thus it needs to predefined the number of facilities being allocated. The application of MCLP application can be found in several topics such as emergency and military services, locating police stations, schools, plants, bus stops, and fire stations. However, as far as our knowledge, the application of MCLP for trashcan locations optimization is not yet being considered. The situation motivates this study to propose the use of MCLP for trashcan location optimization with a study case of Kampung Cipare – Tenjo. Moreover, due to the nature of the problem complexity is NP-Complete. For an NP-Complete problem, a heuristics or metaheuristics is perhaps the most feasible way to generate a solution. Thus, we proposed two greedy heuristics called Greedy Adding Algorithm (GAA) and Greedy Adding with Substitution Algorithm (GAAS) to solve the problem in a reasonable computational time.

The remaining content of this paper is organized as follows: In Section 2, we describe the methods of research that include the formulation of the maximum covering location problem for the trashcan location optimization and the proposed greedy heuristics for solving the problem. Section 3 is about the computational experiments result and discussion, while section 4 is the conclusion and future research. Section 5 is the Acknowledgement and the References can be found in section 6.

2. Methods

2.1 Maximum Covering Location Problem for Trashcan Location Optimization

In this study, the formulation of the MCLP is based on the model proposed by Church and ReVelle (1974). First, there is known demand node and candidate facility location denoted as set $I$ and $J$, respectively. Demand node $i \in I$ associated with demand $h_i$. A binary coefficient $a_{ij}$ takes value of 1 if a facility at candidate $j \in J$ can cover demands at node $i \in I$, otherwise it is 0. The decision variable is a binary decision $X_j$ equal to 1 if we locate a facility at $j \in J$, otherwise 0. Based on this decision variable, the node being covered can be decided and it is noted as $Z_i$. The node being covered shown by the value of $Z_i$ equals to one, otherwise 0. The number of facilities opened is restricted to a number of $P$. The MCLP formulation then adopted with the problem context which is optimally locating trashcan to maximize the demand coverage. The model is formulated as follows.

$$\text{Maximize } \sum_{i \in I} h_i Z_i$$

$$Z_i \leq \sum_{j \in J} a_{ij} X_j$$

$$\forall i \in I$$

$$\sum_{j \in J} X_j \leq P$$
The objectives (1) is to maximize the number of demands covered based on the decision variable. Constraints (2) state the demand \( i \in I \) cannot be covered unless at least one facility that covered the demand note is selected. Constraints (3) restricts the number of facilities being used is no more than \( P \).

2.2 Greedy Heuristics Algorithms

Basically, the greedy adding algorithm with substitution procedure (GAAS) is trying to select the best facility being located at each step of the algorithm. The algorithm basically consists of four steps. The first step is to find the candidate site that covers the most uncovered demand, then locating the facility at that site. A substitution procedure is conducted only if more than one facility has been located. After that, the covered demands are being updated. The algorithm terminates after a number of predefined sites have been located or all demands have been covered. A more detail about the substitution algorithm is that it is basically considers removing every selected candidate site and replacing it with every non-selected candidate site. The algorithm then selects the best selected site after the swap procedure. The variants without the substitution procedure is called Greedy Adding Algorithm (GAA). The implementation of these algorithms is based on Daskin and Maass (2019). The flowchart of the algorithm can be seen in Figure 2.

3. Computational Experiments Result and Discussion

The proposed greedy algorithm is implemented in C++ programming language using Microsoft Visual Studio 2019 on a PC with specification Intel Core i7 3.6Ghz – 16GB RAM. The following subsection described the dataset and the numerical results.

3.1. Dataset

The proposed greedy adding with substitution algorithm was evaluated using a real-case dataset based on the condition of Kampung Cipare – Tenjo. Demands nodes are assumed from the 120 households, with 4-5 people in every house the total demand is 569 people. It is assumed that the service distance coverage is 60 meters. The trashcans can be selected among 26 location candidates that approved by the community. Due to the budget limitation, only 10 trashcans can be donated.

3.2. Computational Results

Figure 3 shows the illustration of the trashcan locations optimization result in Kampung Cipare – Tenjo. The results showed that there are at least ten trashcans needed to fully cover the demand. Moreover, a more detailed experiments are conducted to compare the computational results between Greedy Adding Algorithm with Substitution procedure (GAAS) and Greedy Adding Algorithm without substitution procedure (GAA). It is known that the number of facilities being used have impact on the final results. Thus, a sensitivity analysis regarding a different number on parameter \( P \) is conducted.

The computational results in Table 1 show the comparison between GAAS and GAA in terms of objective function value (demand coverage) and computational time. The results shown that with the given dataset, GAAS result is able to select the facilities that cover all the demands by using only 10 facilities, on the other hand, GAA was not able to show the similar performance. The average percentage difference between demand coverage obtained by GAAS and GAA is 1.6% that shows GAAS perform better than GAA. However, the computational time of GAA is 0.06s in average, considered smaller compared to GAAS that having average computational time of 0.5s.
Figure 2. (a) Greedy adding with substitute algorithm (b) substitute algorithm

Table 1. Results comparison between Greedy Adding Algorithm with Substitution procedure (GAAS) and Greedy Adding Algorithm (GAA)

| Facility | GAAS Demand Covered | GAAS Percent (%) | GAAS Time (s) | GAA Demand Covered | GAA Percent (%) | GAA Time (s) | Diff. (%) |
|----------|---------------------|------------------|--------------|--------------------|----------------|--------------|----------|
| 1        | 156                 | 27.42            | 0.01         | 156                | 27.42          | 0.01         | 0.00     |
| 2        | 303                 | 53.25            | 0.29         | 303                | 53.25          | 0.09         | 0.00     |
| 3        | 388                 | 68.19            | 0.33         | 388                | 68.19          | 0.03         | 0.00     |
| 4        | 438                 | 76.98            | 0.38         | 438                | 76.98          | 0.08         | 0.00     |
| 5        | 481                 | 84.53            | 0.43         | 456                | 80.14          | 0.03         | 4.48     |
| 6        | 511                 | 89.81            | 0.49         | 500                | 87.87          | 0.09         | 2.20     |
| 7        | 534                 | 93.85            | 0.53         | 522                | 91.74          | 0.03         | 2.30     |
| 8        | 554                 | 97.36            | 0.76         | 535                | 94.02          | 0.06         | 3.55     |
| 9        | 565                 | 99.30            | 0.83         | 560                | 98.42          | 0.09         | 0.89     |
| 10       | 569                 | 100.00           | 0.92         | 560                | 98.42          | 0.09         | 1.61     |

Average 0.50 0.06 1.60
A further analysis regarding the number of selected facilities and coverage service distance is conducted. This sensitivity checking is done by generating the illustrations in Figure 4 and Figure 5 based on the result in Table 1. The figures show that along with the increasing number of demand facility being selected, the percentage of coverage demand is steadily increasing. Meanwhile, with increasing number of facilities, the additional demand being covered is reduced. It shows that there is a possibility of one demand location that might be covered by more than one facility. Furthermore, the effect of increasing coverage service distance to the number of demands covered is shown in Table 2. The results show that increasing coverage distance by twice of the original distance will result to smaller number of facilities that should be provided, only four trashcans are needed to fulfil all demands. This shows that there is a trade-off between the increasing service level of providing more facilities and using efficient budget by reducing the service level of coverage distance.

**Figure 3.** Illustration of the trashcan location optimization result in Kampung Cipare – Tenjo

**Figure 4** Analysis on the effect of increasing number of selected facility to the percentage demand coverage
Figure 5. Analysis on the effect of increasing number of selected facilities to the incremental demand coverage

Table 2. The effect of increasing coverage service distance to the number demand covered in the solution of GAAS with $p=4$.

| Coverage Distance | Demand Covered | Percentage (%) |
|-------------------|----------------|----------------|
| 60                | 438            | 76.98          |
| 80                | 497            | 87.35          |
| 100               | 539            | 94.73          |
| 120               | 569            | 100.00         |

4. Conclusions and Future Research

This study proposes the use of maximal covering location problem for optimizing the trashcan locations, with a case study in Kampung Cipare – Tenjo, West Java, Indonesia. Due to its complexities, two greedy heuristics have been proposed, namely Greedy Adding Algorithm (GAA) and Greedy Adding with Substitution Algorithm (GAAS). Numerical experiments are conducted to show the effectiveness of those two algorithms in solving the problem. It is shown that the use of GAAS is able to obtain better demand coverage compared to GAA with the average percentage difference of 1.46%. However, GAA can perform faster with the average of computational time of GAAS and GAA of 0.5s and 0.06s respectively. The result also shown that all ten provided trashcans can cover all the demand locations. Moreover, the analysis on number of selected facilities and coverage service distance shows the increasing number of facilities has impact on the demand coverage. It is also shown that there is a condition where one demand can be coverage by more than one facility. The analysis also shows that increasing distance service coverage can lead to a smaller number of facilities being used. Finally, the application of this result has been successfully implemented in Kampung Cipare – Tenjo.

Further research direction might consider the optimization of the waste collection to the landfill. Moreover, a more complex real-life situation can also be considered such as different cost of locating the facility, forecasting number of demands from the attribute of the family, and constraint of the minimum distance location of trashcans from the houses.

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