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Segmentation of Waste Management of All Provinces in Indonesia Using K-Means Clustering

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ABSTRACT

The amount of waste in Indonesia continues to increase along with the increasing population and welfare. Waste data there are so many waste data throughout Indonesia that it is difficult to determine which managed waste data from provinces will be taken so a recommendation is needed to determine it. Mapping waste management based on the results of waste managed into animal feed raw materials, compost raw materials, recycled raw materials, up-cycle raw materials and energy source raw materials is expected to help the government (or local government) make more appropriate policies. Therefore, this research uses a clustering method, namely k-means clustering. Based on the results of the analysis using the elbow method, the optimal number of clusters selected in this study is k=2. Next, the process of clustering managed waste is carried out using the K-Means clustering algorithm. The clustering results on waste management data display data information with a low level of proportion of waste management volume consisting of 28 provinces and a high level of proportion of waste management volume consisting of 6 provinces. Based on the evaluation of the k-means clustering results, the maximum value of the silhouette coefficient = 0.940 and the Davies-Bouldin index value = 0.430. The concrete recommendations are to make the province with the highest proportion of waste management as a pilot project for the construction of PLTSa, develop a Public-Private Partnership scheme for investment in waste-to-energy processing technology and accelerate licensing and local regulations that support the operationalization of WtE.

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1. Introduction

The addition of power plants in the 2018-2027 electricity supply business plan (RUPTL) is planned to reach 56,024 gigawatts (GW) within 10 years. By the end of 2025, the additional generation consists of 0.4% fuel, 22.2% gas, 23% renewable energy and 54.4% coal, which is the energy mix that must be achieved (*RUPTL 2018-2027*, 2018).

Meanwhile, the achievement for new renewable energy (EBT) until the end of 2021 is 13.5% and at the end of 2025 there is still a need for around 10.1% to be achieved to meet the target of 23%. In order to achieve the 23% EBT target, comprehensive measures are needed from the aspects of energy sources, supply chains, and efficient models so that EBT can achieve the target according to the RUPTL (Yana et al., 2022). The increasing population in Indonesia has resulted in several challenges, one of them being waste management. Even with the government's initiatives to increase the number and size of landfills, waste management and recycling systems have struggled to keep up with the growing waste produced by homes and industries (Budiyarto et al., 2024).

The execution of special waste management occurs via reduction or recycling, encompassing collection, sorting, transportation, processing, and final disposal of waste (Fatimah et al., 2020). Information technology is crucial in endeavors to reach the EBT goal established by the government, particularly in handling data produced throughout the energy supply chain to create an efficient and optimal Waste to Energy (WtE) model for meeting the EBT target (Kasharjanto et al., 2023).

With this, waste becomes one of the alternatives as a power plant which can be shortened as PLTSa (Waste Power Plant). PLTSa is one of the EBT sources that is projected to make a strategic contribution to fill the shortage. Although its quantitative contribution is still small compared to other renewable energy sources such as hydropower or solar power, its potential is huge, especially in cities with high waste volume and good management systems. Through data approaches such as in this study, provinces with high waste management levels can be identified as priority locations for PLTSa development, thus helping to accelerate the achievement of national EBT targets in a more targeted and regional potential-based manner (Prasasti et al., 2021). Waste management data throughout Indonesia is so much that it is difficult to determine which data from which city to take. Therefore, a recommendation is needed to determine it. Previous research analyzed waste data using the Self Organizing Maps (SOM) method which does not require supervision in the training process. The findings of this research established a 3x3 hexagonal topology that categorized Buleleng, Jepara, Cilacap, and Brebes districts into zones with elevated waste generation relative to other districts. (Primandari et al., 2021).

This research aims to aid in improving waste policy decisions by identifying provinces with the highest levels of waste management, which can help in developing clustering models for effective and optimal WtE models to meet EBT targets. This will assist policy makers in more effectively managing waste. The identification of provinces with high performance in waste management is very important because these provinces can serve as models of best practices for other regions. Provinces with a high proportion of waste management have better infrastructure, policy, and community capacity. By reviewing the policies and technologies successfully implemented in these provinces, the central and local governments can improve the efficiency and accelerate the implementation of waste management policies in other provinces.

This study aims to examine waste data through K-Means clustering, an unsupervised learning technique. This technique separates data into clusters (Ali et al., 2021). This strategy isolates information into groups. Information with similar characteristics is assembled into a single group, and information with diverse characteristics is aggregated into diverse groups (Assef et al., 2022). The waste management data used in this study focuses on the volume of management results and does not directly describe the technical, economic, or logistical aspects required in Waste-to-Energy (WtE) integrative modeling. Thus, the clustering results are more relevant to be used for regional prioritization and the preparation of an initial potential map, which can then be used as the basis for further studies to develop WtE integration strategies in supporting the national green energy transition.

2. Method

The dataset used in this research comes from National Waste Management Information System Ministry of Environment and Forestry (SIPSN) (*SIPSN*, 2020). The data taken is about managed waste data, namely data from waste bank centers throughout Indonesia. The data selected is data related to managed waste in 2023-2024. Figure 1 describes the overall process of the proposed method.

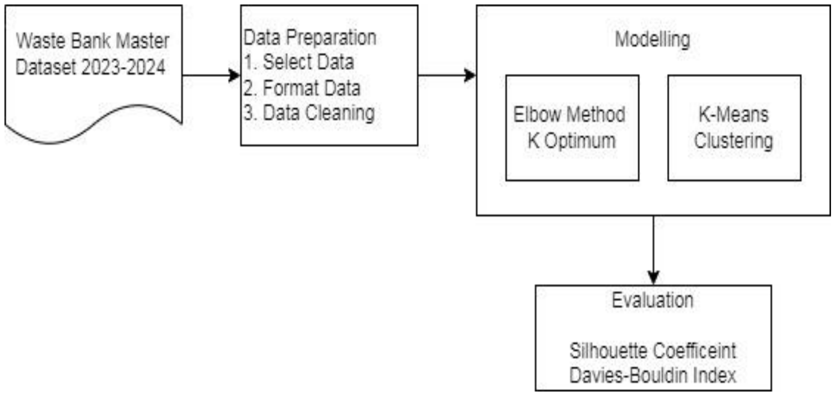

Figure 1. Proposed Method

First, researchers collected data from the SIPSN website. The dataset obtained consists of 18 variables. After that, researchers calculated the variables used, namely the results of managed waste consisting of 5 variables, namely Animal Feed raw materials, Compost raw materials, Recycled raw materials, Up-cycle raw materials and Energy Source raw materials produced in 2023 to 2024. These variables represent the final results of the waste management process that are explicitly recorded and reported by the waste bank center, and are key segments in the managed waste management chain that are relevant to be analyzed in the context of efficiency and potential waste-to-energy (WtE). The selection of the 2023–2024 period is based on the availability of the latest data that can be publicly accessed from SIPSN. Practically, this data reflects the most up-to-date conditions of national waste management activities and illustrates the impact of recent policies implemented by the government over the past few years, especially those related to the acceleration of WtE and the achievement of EBT targets, so that the data can be used as a baseline in the analysis of energy transition policies. Although the data used is limited to a two-year span, the clustering analysis is still relevant to identify provinces that have high and low waste management achievements. These results are useful as a basis for short- and medium-term policy formulation, especially for the integration of WtE management. Description is shown in Figure 2.

Tahun	P	Provinsi	Kabupaten /Kota	Nama Fasilitas	Jenis	Status	Sampah masuk (ton/thn)	Sampahterkelola (ton/thn)	Bahan baku Pakan Ternak	Bahan baku Kompos	Bahan baku Daur Ulang	Bahan baku Up-cycle	Bahan baku Sumber Energi	Alamat	Kelurahan	Kecamatan	Pengelola
2024	2	Aceh	Kab. Aceh Selatan	BANK SAMPAH INDUK E	BSI	A	0	0	0	0	0	0	0	Lorang Tengah Gampong Suak Hu			LSM
2024	2	Aceh	Kab. Aceh Selatan	BANK SAMPAH INDUK F	BSI	A	0	0	0	0	0	0	0	Gampong Pasi Rasian			LSM
2024	2	Aceh	Kab. Aceh Selatan	BANK SAMPAH INDUK K	BSI	A	0	0	0	0	0	0	0	D.I Panjait	Pasar	Tapaktuan	LSM
2024	2	Aceh	Kab. Aceh Singkil	Bank Sampah Rimo Kon	BSI	A	109.5	109.5	0	54.75	54.75	0	0	Jalan Singkil Rimo Km 5 Aceh Sin			Masyarakat
2024	2	Aceh	Kab. Bireuen	Asri	BSI	A	146	1.02	0	0	1.02	0	0	Gampong Blang Asan, Kecamatan			LSM
2024	2	Aceh	Kab. Nagan Raya	Bank Sampah Lestari Su	BSI	A	9.13	9.13	0	0	9.13	0	0	KOMPLEK PERKANTORAN SUKA			Pemda
2024	2	Aceh	Kab. Aceh Tamiang	Bank Sampah Induk	BSI	A	2438.2	2362.65	0	0	2362.65	0	0	Dusun Suk	Durian	Rantau	Pemda
2024	2	Aceh	Kota Banda Aceh	Bank Sampah Induk Sac	BSI	A	1731.98	1709.72	0	0	1709.72	0	0	Jl Tgk Dia	kampung	kuta raja	LSM
2024	2	Aceh	Kota Lhokseumawe	BANK SAMPAH YAYASAN	BSI	A	1460	1460	0	0	1460	0	0	UJONG BLANG KECAMATAN BAN			Pemda
2024	2	Aceh	Kota Langsa	Bank Sampah Induk Srik	BSI	A	23.73	20.44	0	5.48	7.67	7.3	0	Jalan Prof.	Matang Se	Langsa Bara	Masyarakat
2024	1	Sumatera	Kab. Langkat	Bank Sampah Induk Sta	BSI	A	957.03	785.02	0	0	785.02	0	0	Jl Karya Ba	sidomulyo	stabat	Masyarakat
2024	1	Sumatera	Kab. Langkat	sumatera trash bank	BSI	A	632.18	486.99	0	0	486.99	0	0	bukit lawa	bahorok	bahorok	Masyarakat
2024	2	Sumatera	Kab. Simalungun	Simpati Sait Buttu	BSI	A	277.4	124.1	0	0	118.63	5.48	0	Pamatang Sidamanik			Masyarakat
2024	2	Sumatera	Kab. Toba	Bank Sampah Ias Toba	BSI	A	69.64	69.64	0	0	69.64	0	0	jl. Somba Debata No. 7 Balige			Pemda

Figure 2. Description of the Dataset

The data preparation stage will produce a dataset that will be used in the next research process. The focus of this research is on managed waste data into 5 variables that are used, especially those reported by waste banks and official management units so that this data is more representative of the performance of the output side of waste management. The stages in the data preparation above are as follows: Select data, which is taking data that is suitable for the selected dataset fragment can be seen in Figure 2 (Rudnichenko et al., 2023). Data formatting, which is transforming the data used into a form that is more suitable for analysis purposes by sorting the data and separating it into several file, forms with the file format used, namely CSV (Comma Separated Values) or .csv so that it is easier to read when loading datasets on google colab later (Garcia-Fossa et al., 2023). Data cleaning, which removes noise and inconsistent data contained in the dateset used. In the data cleaning stage, provinces with very small data have been identified and handled by normalizing the data where the data is rescaled between 0 and 1 with the min-max scalling technique so that it only includes valid values that can be analyzed using the K-Means algorithm (Karrar, 2022).

Furthermore, at the modeling stage, researchers design designs from the results of the analysis carried out and made into a computer-based system. This system will use pyton programming language on google colab. The elbow method is used to determine the optimal number of clusters by varying the number of clusters (k) from 1-10 (Saxena et al., 2024). Then calculate the number of clusters or for each value of K. The graph will move quickly at a point so that it creates an elbow shape (Almotairy et al., 2024). Then the graph will move closer to or parallel to the x-axis. The optimal number of clusters or k value will adjust to this point (Gujski et al., 2022).

K-means clustering is a non-hierarchical data clustering method that classifies data in the form of one or more clusters/groups (Vatresia et al., 2022). The K-Means clustering algorithm helps improve waste management policy decisions by identifying the most managed waste generated in a particular province (Michael & Utama, 2020). The first step is to determine the number of clusters using the Elbow Method to obtain the optimal cluster value, then input the data into Google Colab from the database, then model the data used with the K-Means clustering method. by grouping the proportion of waste into two clusters that have an index value used to label each type of waste composition using the results of K-Means clustering and the next step is to create an empty cell array to store the clustering results.

Finally, the evaluation stage is carried out to analyze the value of the Silhouette Coefficient results and the Davies-Bouldin index value of each cluster formed from the K-Means clustering process. The Silhouette Coefficient is a measure utilized to determine the clustering effectiveness of the technique. Its range of values spans from -1 to 1. 1: Indicates that the clusters are distinctly separated and differentiated from one another. 0: Indicates that the clusters are neutral, or we can see that the distance between clusters lacks significance. 1: Suggests that the clusters have been wrongly assigned (Rochman et al., 2022). The silhouette value assesses the degree to which an object is similar to its cluster (cohesion) compared to objects in other clusters (separation) (Jahanian et al., 2021). The Davies-Bouldin index (DBI) is an evaluation tool that can be used as one of the factors to select the best model or configuration in a clustering algorithm. The lower the DBI value, or closer to 0, the better the quality of the resulting cluster (Setiyawati et al., 2023). By applying this technique, a cohesion matrix (closeness between groups) and a separation matrix (differences between groups) will be obtained (Firman Ashari et al., 2022).

3. Results and Discussions

One of the most popular methods to determine the optimal number (k) is using the Elbow Method (Haider et al., 2020). This method works by plotting the Within-Cluster Sum of Squares (WCSS) value against various values of k (Ordenshiya & Revathi, 2025). WCSS measures the total squared distance between each data point and its cluster center. The “elbow” point marks when the decline in WCSS starts to slow down, indicating that adding further clusters does not significantly improve the representation of the data (Gratsos et al., 2023). This point was chosen as the optimal k. The graph of the Elbow method can be found in Figure 3.

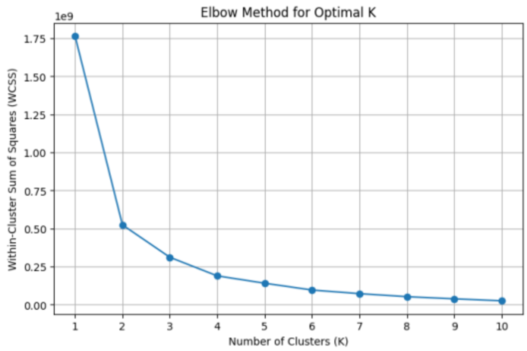

Figure 3. Graphics of the Elbow Method

Based on the results of the analysis using the Elbow Method, it can be seen in Figure 3 that the optimal number of clusters in this study is k = 2. Elbow Method shows a significant change point from k=1 to k=2, then the slope starts to occur from k=2 to k=3 and so on where after this point the decrease in Within Cluster Sum of Squares (WCSS) value starts to slope. This indicates that increasing the number of clusters after k=2 no longer provides a significant reduction in variance within each cluster, so this number of clusters is considered the optimal point in the balance between intra cluster variation and model complexity.

After determining the optimal number of clusters with the Elbow method, the grouping of managed waste is done using the K-Means clustering algorithm. The results of this process are visualized in Figure 4, which shows the distribution of Low Waste Management Level Volume and High Waste Management Level Volume by province in Indonesia. The values of Low Waste Management Volume Level and High Waste Management Volume Level were chosen to be visualized because they directly represent important dimensions in grouping waste management results into Animal Feed raw materials, Compost raw materials, Recycled raw materials, Up-cycle raw materials and Energy Source raw materials.

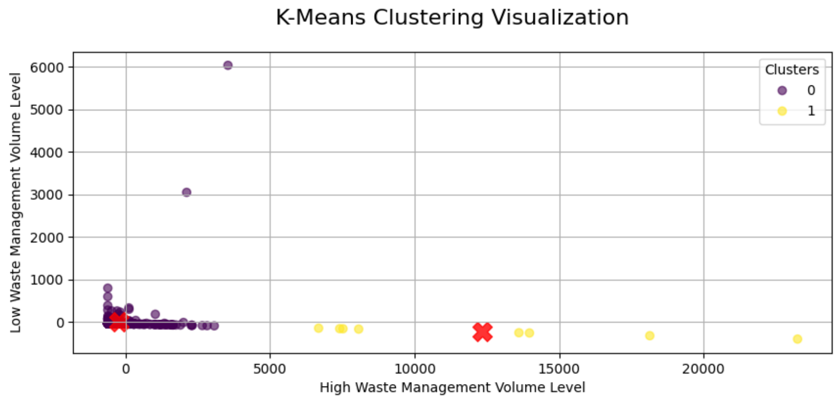

Figure 4. K-Means Clustering Visualization chart

The dataset consists of 2 clusters, 5 attributes, and 437 samples. Figure 4 displays data information with purple color is the membership of cluster 1 which has 429 members with the category of waste management volume level in certain provinces, namely low and cluster 2 membership displays data in yellow color which has 8 members with the category of waste management volume level in certain provinces, namely high. Furthermore, the clustering results were tested using the silhouette coefficient and Davies-Bouldin index for all clusters tested in this study.

Testing the clustering results in this study was carried out using the silhouette coefficient method with the number of clusters k = 2 to k = 10. Based on the silhouette coefficient calculation on waste management data throughout Indonesia, the highest silhouette coefficient value is obtained when k = 2 with a value of 0.940. The average silhouette coefficient for all clusters is shown in Figure 5. The greater the value of k, the lower the silhouette value tends to be compared to the previous number of clusters.

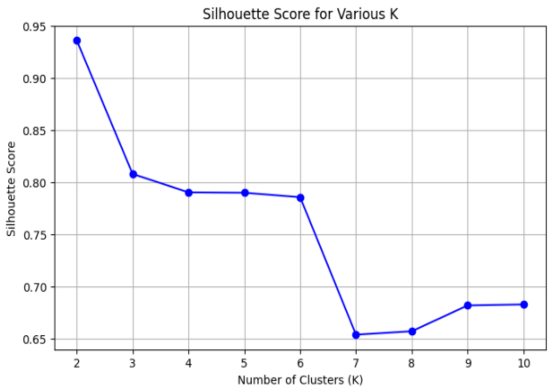

Figure 5. Graph of Silhouette Score Values

To strengthen the results of this evaluation, this research also uses the Davies-Bouldin index (DBI) method.

```
import matplotlib.pyplot as plt
from sklearn.cluster import KMeans
from sklearn.metrics import davies_bouldin_score

# List to store Davies-Bouldin Index values
db_scores = []
# Range of k values to be tested
k_values = range(2, 11)

# Calculate the Davies-Bouldin Index for each k
for k in k_values:
    # Create a KMeans model with k clusters
    kmeans = KMeans(n_clusters=k, random_state=42)

    # Perform clustering on x data
    y_kmeans = kmeans.fit_predict(x)

    # Calculating the Davies-Bouldin Index
    dbi = davies_bouldin_score(x, y_kmeans)
    db_scores.append(dbi)

    dbi = davies_bouldin_score(x, y_kmeans)
print(f"Davies-Bouldine Index : {dbi}")

Davies-Bouldine Index : 0.42992943110891946
```

Figure 6. Davies-Bouldin index value calculation

From the DBI calculation in Figure 6, the value obtained at k = 2 is 0.430. In the DBI rule, the closer the DBI value is to 0 or the lower the value, the better the resulting cluster. Table 1 shows the information that can be concluded from the k-means clustering results regarding managed waste data from which provinces will be taken because they have the most abundant proportion of waste management results in Indonesia in 2023 to 2024.

Table 1. Cluster Members

Cluster	Members	Total	Criteria
Cluster 1	Aceh, Sumatra Selatan, Riau, Sumatra Utara, Jambi, Bengkulu, Kepulauan Bangka Belitung, Lampung, Kepulauan Riau, Jawa Timur, DKI Jakarta, Nusa Tenggara Timur, Nusa Tenggara Barat, Kalimantan Tengah, Kalimantan Barat,	28	Low

	Kalimantan Timur, Kalimantan Selatan, Kalimantan Utara, Sulawesi Tenggara, Sulawesi Tengah, Sulawesi Utara, Sulawesi Selatan, Gorontalo, Maluku Utara, Maluku, Papua Barat, Papua, Papua Tengah.		
Cluster 2	Sumatra Barat, Jawa Tengah, Jawa Barat, Daerah Istimewah Yogyakarta, Bali, Banten.	6	High

Table 1 is a table containing provincial data with a total of 28 provinces that are included in cluster 1 grouping, namely those with the lowest proportion of waste management volume and 6 provinces that are included in cluster 2 grouping, namely those with the highest proportion of waste management volume. It is hoped that by mapping waste data based on the results of waste managed into Animal Feed raw materials, Compost raw materials, Recycled raw materials, Up-cycle raw materials and Energy Source raw materials throughout the provinces in Indonesia can help the government (or local government) make more appropriate policies by knowing the provinces that carry out high waste processing so that they can make policies that can be applied regarding waste management better for other provinces in Indonesia.

The policy recommendations that can be applied by the government (or local government) from the results of this clustering are that the provinces in Cluster 1 need more attention from the government, both in the form of support for strengthening basic waste management infrastructure such as landfills, TPS 3R, and sorting systems, providing special funding for provinces in Cluster 1 to start adopting energy processing technology from small-scale waste (for example village incinerators), as well as technical assistance to increase waste management capacity so that provinces in Cluster 1 can shift towards WtE technology readiness in the next 5-10 years. Then the Government can conduct comparative studies or knowledge transfer from provinces in Cluster 2 to provinces in Cluster 1, to find out what policies, strategies, and technologies are successful in increasing the proportion of managed waste so that these results can be the basis for formulating more targeted and targeted waste management policies, including in budget allocation and community training and education programs. As provinces in Cluster 2 already have a high level of waste management, provinces in this cluster have the initial potential to be more operationally and logistically ready to integrate WtE technologies. The concrete recommendations are to make provinces in Cluster 2 as pilot projects for the construction of PLTSa (Waste Power Plant), develop Public-Private Partnership (PPP) schemes for investment in waste-to-energy technology and finally accelerate local permits and regulations that support WtE operations.

4. Conclusions

The clustering results on waste management data display data information with membership from cluster 1 which has 28 provinces with a low level of proportion of waste management volume in certain provinces and membership from cluster 2 which has 6 provinces with a high level of proportion of waste management volume in certain provinces. After the process of working from design, trials, and implementation that has been done using k-means clustering to find out the highest proportion of managed waste management in certain provinces throughout Indonesia, the results of the k-means clustering method research with k = 2, is the optimal number of clusters in grouping waste management and followed by clustering validation using the Silhouette coefficient and Davies-Bouldin index resulting in a Silhouette value of 0.940 and a Davies-Bouldin index value of 0.430. The policy recommendations that can be implemented by the government (or local government) from the results of this clustering are that the provinces in Cluster 1 need more attention from the government, both in the form of infrastructure support, funding, and technical assistance to increase waste management capacity. Since provinces in Cluster 2 already have a high level of waste management, provinces in this cluster have the initial potential to be more operationally and logistically ready to integrate WtE technology. The concrete recommendations are to make provinces in Cluster 2 as pilot projects for the construction of

PLTSa (Waste Power Plant), develop Public-Private Partnership (PPP) schemes for investment in waste-to-energy technology and finally accelerate local permits and regulations that support WtE operations.
It is expected to develop and explore clustering methods other than k-means clustering in future research using types of clustering methods in Partition-based clustering including K-Medoids, K-Median, or Fuzzy c-Means.

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