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Predicting Waste Volume Using ARIMA and ARFIMA Models

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Abstract

The final waste processing facility plays a crucial role in waste management. The growing amount of waste in landfills is causing significant harm to the surrounding environment and the health of nearby residents. This study seeks to offer insights into the projected future waste volume in landfills. This research applies the mathematical models of the Autoregressive Integrated Moving Average (ARIMA) and Autoregressive Fractionally Integrated Moving Average (ARFIMA). This research method begins by determining the source of monthly waste data at the final waste disposal place. Based on monthly observation data from 11 January 2011 to 24 December 2023, identification and estimation of ARIMA and ARFIMA modelling are carried out. Based on the results of the RMSE and MAPE calculations, the ARIMA model is the best for predicting the volume of waste at the final waste processing site location, compared to the ARFIMA model. However, when comparing predictions from the two models with actual conditions for January to June 2024, the ARFIMA model yielded a MAPE value of 6%, while the ARIMA prediction model resulted in a MAPE of 8%. This research is significant in providing predictive information on the volume of waste at the final waste processing site for the government. The results of this research can be used to make policies and design more effective waste management regulations. Furthermore, the appropriate model for predicting waste volume in 2024 is ARIMA (3, 1, 3), and ARFIMA (2, -0.32, 1).

Keywords: ARFIMA, ARIMA, MAPE, RMSE, Waste Volume.

Introduction

Garbage is a global problem. The issue of waste is related to increasing population, economic growth, and changing consumption patterns (1). The solution to the waste problem in Bandung and its surrounding areas is done by disposing of it at the final disposal site. The volume of waste increases every year and at some point, it will no longer be able to accommodate the waste, prompting the government to seek new locations. Planning waste disposal sites is important in short-term and long-term waste management (2). Modern societies must prioritize intelligent waste processing strategies to enhance resource productivity and curtail landfill dependencies (3). Building relationships between factors that determine the amount of waste generated by local governments and estimating waste management needs plays a fundamental role in developing effective planning strategies (4). This research was conducted at the Sarimukti landfill site, which serves as the waste disposal location for three areas: Bandung City, Bandung Regency, West Bandung Regency, and Cimahi. The volume of waste fluctuates and increases every month. Figure 1 shows that the monthly waste volume in Sarimukti from January 2011 to December 2023 fluctuates randomly. In the period 2011-2016, it fluctuated around 36,000 tons per month, and then there was an increase from 2016 to 2018, fluctuating around 55,000 tons per month. Therefore, to predict future waste volumes, a time series model was applied. This research aims to create a model to predict waste volumes based on the daily historical data from January 2011 to December 2023. The models applied are ARIMA and ARFIMA. Using these models, the monthly waste volume at Sarimukti for the year 2024 will be predicted. Predicting future waste volumes is necessary to ensure that waste management does not create potential problems and that these issues can be anticipated as early as possible. Furthermore, predicting future waste volumes is beneficial for making better plans in managing infrastructure, selecting landfill sites, and scheduling waste collection for local governments or waste management agencies (5). Accurate modelling in predicting waste accumulation is crucial for decision-making, and it also provides certainty for better future waste

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processing (6).

Methodology

The results of our study on waste prediction modelling show that several researchers have applied time series models to predict waste volumes. For instance, the Artificial Neural Networks model has been used to predict waste accumulation, and this predictive model is more accurate than other mathematical models (2). A simpler predictive model, the Holt Trends Exponential model, was used by researchers to predict electronic waste generated from old mobile devices (7), and to predict waste accumulation (8). Most researchers utilize the ARIMA model for time series data forecasting, particularly due to its ability to handle no stationary data. Numerous studies have demonstrated the application of the ARIMA model in various contexts, including forecasting the growth of municipal solid waste in Bengaluru, India (9), forecasting the average electronic waste processing in India from 2023 to 2030 using ARIMA (10) and accurately predicting waste volume in Ghana using the ARIMA model (11). ARIMA also provided accurate rainfall predictions in the municipality of Vitória de Santo Antão (12). The ARIMA model is well-suited for short-memory data patterns (13). While the ARFIMA model is more appropriate for long-memory data patterns (14, 15). Several researchers have developed the ARFIMA model. For example, the application of the ARFIMA model to analyze and predict fluctuations in global oil prices. This model was chosen for its ability to capture long-memory characteristics in time series data (16). In another study, ARFIMA was used to predict CO2 emissions from fossil fuel combustion and cement production in Portugal, projecting emissions up to 2050 (17). Additionally, ARFIMA was applied to predict CO2 emissions globally and in regions such as China, Russia, India, Japan, and the European Union with high accuracy for the period 2018–2050 (18).

ARIMA (p,d,q)

There are three components in the ARIMA model. The first is Autoregressive AR(p), which accounts for the relationship between the current value and previous values in the time series. The second is Integrated (d), indicating the number of times differencing is required to make the data stationary. The third is the Moving Average (MA (q)), which considers the relationship between the current values and previous residuals (errors) (19, 20). The general form of the ARIMA model with parameters p, d, and q is as follows.

$Z_t = u_t + \text{c}$

$\phi_p(B)(1-B)^d u_t = \theta_q(B)\varepsilon_t$ [1]

$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$

$\theta_q(B) = 1 + \theta_1 B + \theta_2 B^2 + \cdots + \theta_q B^q$

Z_t = Observed data

Where: t = 1, 2,....T, with T = being the total number of observations

B = Backshift operator,

d = Differencing parameter (integer)

μ = Mean of the observations

ε_t= Residuals (errors)

This modelling is conducted using the Box-Jenkins method. The parameter d is estimated based on the number of differencing steps applied to non-stationary time series data until it becomes stationary, while the parameters p and q are selected based on the pattern of the autocorrelation (AC) and the partial autocorrelation (PAC) on the stationary time series data. Additionally, AIC (Akaike's Information Criterion) and Bayesian Information Criterion (BIC) are applied, where p and q are estimated based on the smallest AIC and BIC values (21). Mathematically, AIC and BIC are expressed in the equations below

AIC = $ln\frac{\sum (y_t - \hat{y}_t)^2}{n} + \frac{2k}{n} + c$ [2]

The equation $\sum\ (y_t - \hat{y}_t)^2$ represents the sum of squared residuals, and k is the number of model parameters. Furthermore, the BIC criterion takes into account the number of observations, and the equation is as follows:

BIC = $ln\frac{\sum (y_t - \hat{y}_t)^2}{n} + k\frac{ln\,(n)}{n}$ [3]

Where n is the number of observation.

ARFIMA

The ARFIMA (p,d,q) model was developed by Granger and Joyeux. This model's equation is the same as ARIMA, with the difference being the fractional differencing d, which is in the form of a fraction (22), namely

$\phi_p(B)(1-B)^d(Y_t - \mu) = \theta_q(B)\varepsilon_t$ [4]

Where:

$(1-B)^d = 1 - dB - \frac{1}{2}(1\text{-d})\text{d}B^2 - \frac{1}{6}(1-d)(2-d)dB^3 + \cdots$

If $-0.5 < d < 0.5$, then the data Y_t is considered stationary (21).

Error

The performance of both models is assessed based on the prediction accuracy compared to the actual data through the calculation of the root mean squared error (RMSE) (22), with the error equation as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} (y_i - \hat{y}_i)^2} \quad [5]$$

Where $\hat{y}_i$ is the predicted value, y_i is the actual data value at time i, and n is the number of observations. Additionally, the prediction errors for both models are calculated using Absolute Percent Error (APE) and Mean Absolute Percent Error (MAPE), employing the following equations:

$$APE_i = [\frac{y_i - \hat{y}_i}{y_i}] x100\% \quad [6]$$

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n} APE_i \quad [7]$$

This error represents the percentage of deviation of the prediction from the actual data. If the MAPE is between 0% and 20%, the model used is considered to have good accuracy (23).

Data

This study uses sample data on waste volume from the Sarimukti final waste processing site, recorded by the West Java Provincial Environment Agency from January 2011 to December 2023. This secondary data is obtained from the daily waste amounts transported from three locations: Bandung City, Bandung Regency, Cimahi City, and West Bandung Regency. Based on a historical monthly sample size of 156, identification was performed using logarithmic transformation to stabilize the variance, and data stationarity was tested using the Augmented Dickey-Fuller test statistic (24). If the time series data is non-stationary in terms of mean, first differencing is applied. If it remains non-stationary, a second differencing is performed. The parameter d = 1 is used for the first differencing and d = 2 for the second differencing.

Estimation

Estimation of the parameters p and q in the ARIMA (p, d, q) model is performed through AC and PAC plots. The parameter p is determined from significant lags in the PAC plot, while the parameter q is determined from significant lags in the AC plot, AIC, and BIC are calculated for various combinations of p and q, and the pair with the smallest AIC and BIC values are selected (25). Estimation of the ARFIMA (p, d, q) model is done by determining p, d, and q based on the smallest AIC and BIC values (26).

Prediction and Evaluation

At this stage, predictions from both models are compared using the RMSE and MAPE. The model with the smallest values from both calculations is considered the best forecasting model. Subsequently, the volume of waste at the Sarimukti waste processing site will be predicted for the period from January to December 2024. To assess the accuracy of the predictions, the forecasts from both models will be compared with the observed data for the first six months, from January to June 2024.

Results and Discussion

The waste volume data at the Sarimukti Final Waste Processing Site for the period from January 2011 to December 2023 is presented in Figure 1. A logarithmic transformation was applied to stabilize the data variance. If Y_t represents the waste volume at time t, the logarithmically transformed data is expressed $\ln Y_t$, subsequently, a first differencing was applied to the $\ln Y_t$ data, resulting in Dlny.

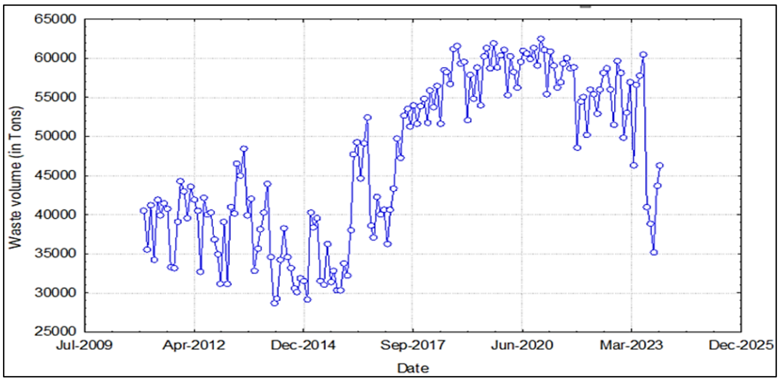

Figure 1: Monthly Waste Volume at Sarimukti Final Waste Processing Site

The results of the ADF hypothesis test on Dln(y) are shown in Table 1, where the t-statistic is substantially less than the t-distribution's critical value at the 1% significance level. A P-value of 0.0000 was obtained, indicating that Dln(y) is stationary. Therefore, estimate for d in the ARIMA (p, d, q) model is d = 1 .

Table 1: Stationarity Test on Dln(y)

t-Statistic		-16.776	
Prob		0.0000	
Test Critical Values	1%		-3.4731
		5%	-2.8802
		10%	-2.5768

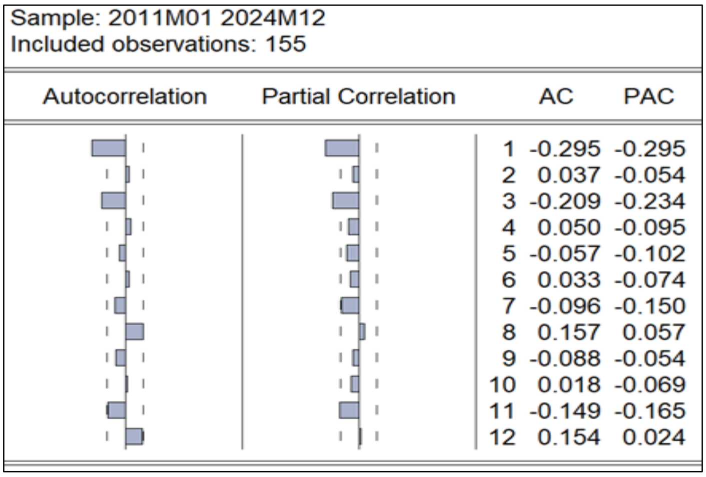

Figure 2: Correlogram of D (lny)

The next stage in the ARIMA (p, 1, q) model identification process is performed by plotting the Dlny correlogram. The analysis results show that the AC and PAC have significant values at lags 1 and 3, as illustrated in Figure 2. These findings indicate that parameters p and q potentially have values of 1, 2, and 3. Based on these indications, fifteen (p, q) combinations are viable for further analysis. Subsequently, Table 2 presents the five best combination pairs that have the lowest AIC and BIC values from all identified combinations.

Table 2: AIC and BIC for ARIMA (p, 1, q)

No	Model	AIC	BIC
1	(3,1,3)	-1.671794	-1.514714
2	(2,1,2)	-1.668623	-1.550813
3	(3,1,2)	-1.656085	-1.518640
4	(2,1,3)	-1.655981	-1.518536
5	(0,1,3)	-1.651557	-1.553382

Based on the analysis results presented in Table 2, the ARIMA (3, 1, 3) model was selected as the optimal model as it has an AIC value of -1.6717 and a BIC value of -1.5147, which are the lowest values compared to the other five ARIMA models. Parameter estimates for the ARIMA (3, 1, 3) model along with hypothesis testing results for each Autoregressive (AR) and Moving Average (MA) coefficient are detailed in Table 3. All ARIMA coefficients demonstrate high significance, as evidenced by a P-value of 0.0000.

Table 3: ARIMA (3, 1, 3) Parameter Estimation

Dependent Variable: D(LOG(Y))			
Variable	**Coefficient**	**t-Statistic**	**Prob.**
C	0.000573	0.1243	0.9012

	1	0.581415	5.5670	0.0000
AR	2	0.941853	20.0522	0.0000
	3	-0.62839	-6.6798	0.0000
	1	-0.933166	-11.534	0.0000
MA	2	-0.911244	-15.3564	0.0000
	3	0.899618	12.3523	0.0000

Define Z_t = $Dln(Y_t)$ with $Dln(Y_t)$ =$ln\ ln\ Y_t - ln\ (Y_{t-1})$ where Y_t is the waste volume in month t. Based on the parameter estimates for Z_t from Table 3, we obtain:

Z_t = 0.00057+ u_t

(1 + 0.58B + 0.94B^2 - 0.63B^3) u_t = (1 – 0.93B - 0.63B^2 + 0.068B^3) ε_t

The equation is equivalent to:

Z_t = 0,001 – 0,58Z_{t-1} – 0,94 Z_{t-2} + 0,63Z_{t-3} + ε_t - 0.93ε_{t-1} + 0.630ε_{t-2} + 0.068ε_{t-3}

In Figure 3, the graph of the equation is compared with the graph of the actual data. The predicted monthly waste volume fluctuations from 2011 to 2023 closely match the data. Meanwhile, the ARIMA model forecast for waste from January to December 2024 shows fluctuations of around 48,000 tons per month, gradually decreasing to approximately 44,000 tons by December. The ARIMA model forecast for waste from January to December 2024 shows fluctuations of around 48,000 tons per month, gradually decreasing to approximately 44,000 tons by December.

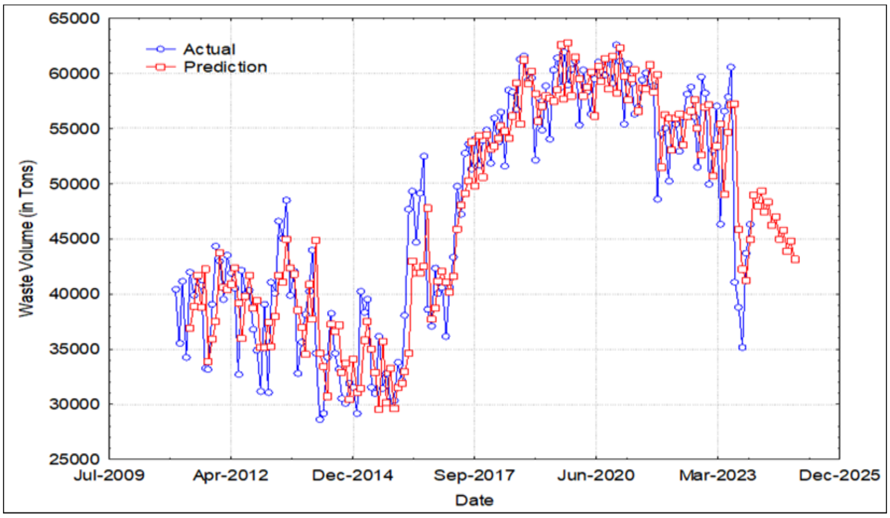

Figure 3: ARIMA Predictions against Actual Data

The identification of the ARFIMA model followed procedures similar to ARIMA modelling, applied to the ln(y) data. The fractional integration parameter d was estimated through an evaluation of various possible combinations of autoregressive (p) and moving average (q) orders within the ARFIMA (p,d,q) framework. Table 4 presents the top five parameter combinations that yielded the lowest values for both AIC and BIC, along with their corresponding estimated d values. After comprehensive analysis of the empirical data and model selection criteria AIC and BIC, the ARFIMA (2,-0.3, 1) specification emerged as the optimal model choice.

Table 4: AIC and BIC for ARFIMA (p, d, q)

ARFIMA	d	AIC	BIC
(2, d, 1)	-0.3191	-1.6555	-1.5382
(3, d, 2)	0.07277	-1.6456	-1.4892
(2, d, 2)	-0.3497	-1.6436	-1.5068
(3, d, 3)	0.06146	-1.6329	-1.457
(1, d, 3)	-0.0054	-1.6283	-1.4914

The parameter estimation results are presented in Table 5, where the fractional integration parameter (d), autoregressive coefficient of order 2, and moving average coefficient of order 1 show statistically significant values.

Table 5: Parameter Estimates for ARFIMA (2, -0.32, 1) Model

Dependent Variable: LOG(Y)

Variable	**Coefficient**	**t-Statistic**	**Prob.**
C	10.7128	91.7706	0.0000
D	-0.3191	-4.8981	0.0000
AR(1)	-0.0104	-0.7042	0.4824
AR(2)	0.9849	61.2175	0.0000
MA(1)	0.9777	34.1508	0.0000

The equation in Table 5 is expressed as follows:

Z_t = 10,7 + u_t

(1 + 0,01B - 0,98B^2)$(1 - B)^{-0,32}u_t$ = (1 – 0,98B) ε_t

Thus, the equation is equivalent to:

(1 + 0,01B - 0,98B^2) (1 + 0,32B + 0,66B^2 – 0,16 B^3 + ...)u_t = (1 – 0,98B) ε_t

(1 + 0,33B -0,3168B^2-0,467B^3 – 0,6484B^4 + 0,1568B^5 + ⋯)u_t = (1 – 0,98B) ε_t

z_t = -10,09 - 0,33z_{t-1} + 0,3168 z_{t-2} + 0,467z_{t-3} + 0,6484 z_{t-4} - 0,1568 z_{t-5} + ⋯ + ε_t – 0,98 ε_{t-1}

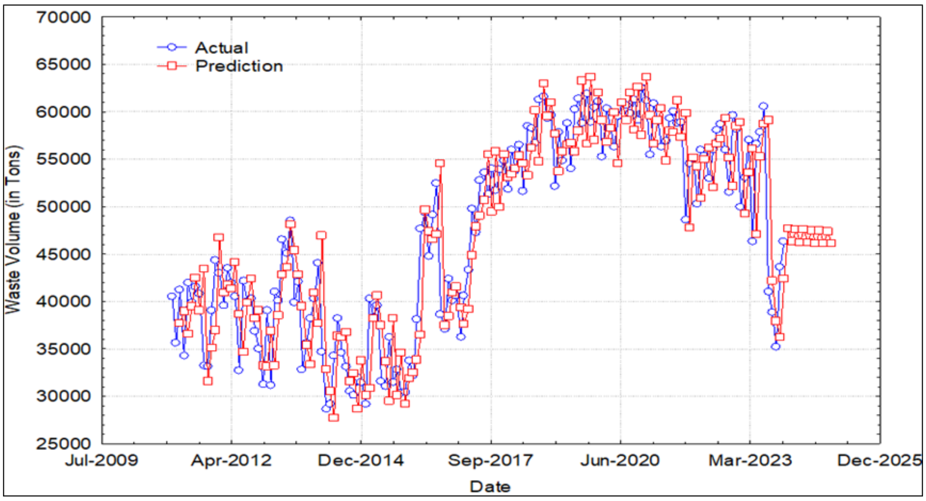

Figure 4: Actual Data versus ARFIMA Prediction

Figure 4 displays the graph of the ARFIMA (2, -0.32, 1) model equation compared to actual conditions, highlighting the comparison between the model's predictions and the observed waste data. The forecast from January to December 2024 using the ARFIMA model predicts waste fluctuations of around 46,000 tons per month. Table 6 presents the RMSE and MAPE calculations for the ARIMA (3, 1, 3) and ARFIMA (2, -0.32, 1) models over the period from 2011 to 2023. The results indicate that the ARIMA model outperforms the ARFIMA model. However, as illustrated in Table 7, from January to June 2024, the monthly APE values for the ARFIMA model are generally smaller than those for the ARIMA model. Additionally, based on the MAPE, the ARFIMA model demonstrates better prediction accuracy compared to the ARIMA model.

Table 6: Error ARIMA-ARFIMA

	ARIMA (3, 1, 3)	**ARFIMA (2, -0.32, 1)**
RMSE	4280,86	4647,39
MAPE	7,64 %	8,14 %

Table 7: ARIMA-ARFIMA Predictions and Errors (Jun-Jul 2024)

Month	Waste Volume (Ton)	Prediction of Waste Volume (Ton)		APE	
		ARIMA	ARFIMA	ARIMA	ARFIMA
Jan-24	39675.55	48993.41	47664.27	23%	20%
Feb-24	44401.76	47912.53	46295.99	8%	4%
Mar-24	48173.10	49304.57	47606.97	2%	1%
Apr-24	45860.70	47409.02	46247.14	3%	1%
May-24	45737.41	48282.62	47551.12	6%	4%
Jun-24	43325.52	46192.92	46199.65	7%	7%
			MAPE	8%	6%

Figure 5 shows the predicted waste volume at the Sarimukti Final Waste Processing Site from January to December 2024 using the ARIMA and ARFIMA models, as well as the actual data graph from January to June 2024. Visually, both models' predictions nearly match the actual data, nevertheless, the ARFIMA model shows a better fit than the ARIMA model. Furthermore, the ARIMA model's prediction exhibits a steeper decrease in the graph than the ARFIMA model. Both models can be utilized interchangeably to achieve optimal forecasts. By comparing these models, forecasts of future waste generation can become more accurate and reliable.

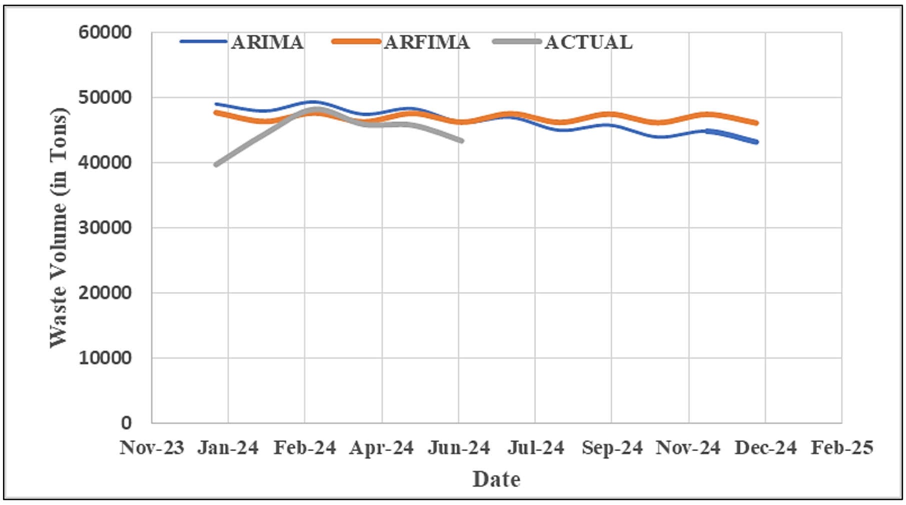

Figure 5: Monthly Waste Volume Forecast: Sarimukti Landfill 2024

The application of ARIMA and ARFIMA models in predicting waste generation offers opportunities for more sustainable and cost-effective waste management practices. By accurately forecasting future waste levels, governments and organizations can optimize waste collection schedules, recycling programs, and the capacity of waste processing facilities. This proactive approach benefits the environment by reducing waste output and helps save time and resources through more efficient waste disposal operations. Integrating these two models into waste management strategies can significantly minimize unnecessary waste accumulation while enhancing the efficiency and sustainability of disposal processes. The adoption of these predictive models in waste management can contribute to a greener and more cost-effective future for businesses and society. For instance, manufacturing companies could use these models to anticipate fluctuations in production levels and adjust their waste management processes accordingly. This approach reduces the amount of excess material ending up in landfills, optimizes disposal methods, lowers disposal costs, and minimizes environmental impact.

Conclusion

This study successfully compared the performance of the ARIMA and ARFIMA models in predicting waste volume. The analysis results show that: The ARIMA model performs well in predicting short-term waste volume patterns. This model is effective when the data becomes stationary after applying regular differencing. The ARFIMA model demonstrates an advantage in handling long memory data, where waste volume exhibits long-term dependencies that are not entirely removed by simple differencing. This model provides more accurate predictions in such conditions. Based on the MAPE evaluation criteria for predictions for the next six months, the ARFIMA model tends to deliver more accurate predictions compared to ARIMA. From this study, it can be concluded that for the waste volume data at Sarimukti Landfill, which has long memory characteristics, the ARFIMA model is more recommended than ARIMA. Therefore, ARFIMA can be the preferred choice for forecasting waste volume, especially in datasets with significant long-term patterns.

Abbreviations

ARIMA: Autoregressive Integrated Moving Average, ARFIMA: Autoregressive Fractionally Integrated Moving Average, AIC: Akaike's Information Criterion, BIC: Bayesian Information Criterion, APE: Absolute Per cent Error, MAPE: Mean Absolute Percent Error, RMSE: root mean squared error.

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Author Contributions

The authors created the research concept, study design, and paper. They also read and approved the final draft, participated in data analysis, and improved the text.

Conflict of Interest

The authors affirm that this research is free of conflicts.

Ethics Approval

This study has been approved by the Regional Waste Management Unit of the Sarimukti Landfill under the Environmental Agency of West Java Province.

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