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Research Original Article

Prediction of Trash in Aceh Province Using the Autoregressive Integrated Moving Average (ARIMA) Method

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Abstract

The increase in trash production in Aceh Province presents challenges for trash management, particularly in planning adequate infrastructure. This study applies the Autoregressive Integrated Moving Average (ARIMA) model to predict trash volume in Aceh. The data utilized originates from the National Trash Management Information System (SIPSN) and the Central Bureau of Statistics (BPS) from 2020 to 2023. The prediction results indicate that ARIMA can capture the primary trends in trash volume but has limitations in accounting for seasonal fluctuations in certain trash categories. Accuracy evaluation using the Mean Absolute Percentage Error (MAPE) shows varying accuracy levels across trash types, with some categories requiring additional models to enhance accuracy. These findings are expected to support planning and policy for trash management in Aceh.

Keywords: Trash Prediction; ARIMA; Aceh; Trash Management; Time Series Analysis

INTRODUCTION

Trash is a byproduct of various human activities, which, if not managed properly, can negatively impact the environment and public health. Law No. 32 of 2009 on Environmental Protection and Management defines trash as residual material from human activities that could pollute the environment. In Aceh Province, the volume of trash continues to rise with population growth and increased consumption activities. The primary sources of trash in Aceh include households, industries, and the agricultural sector, which produce various types of trash, from organic to inorganic trash like plastic and chemicals. This diversity in trash types and characteristics requires appropriate management to minimize negative impacts on the environment[1].

The trash management challenges in Aceh mirror those in other urban areas experiencing population and economic activity growth. For example, research in Yogyakarta has shown that increased trash has become a significant issue, particularly with tourism and urbanization activities. In this context, trash volume prediction plays a crucial role in assisting stakeholders in planning appropriate trash management infrastructure and anticipating future management needs [2].

One method that can be used for trash prediction is the ARIMA model, which has proven effective in forecasting time series for various types of data, including infectious diseases and biogas production [3]. The application of ARIMA in urban trash prediction, as implemented in Bengaluru, demonstrates that this model is not only accurate for short-term projections but is also valuable for long-term analysis necessary for trash planning [4]. Given these advantages, ARIMA is an ideal choice for predicting trash volume in Aceh, particularly under conditions of limited supporting data.

This study aims to predict trash volume in Aceh Province using the ARIMA model. The model is expected to provide an accurate forecast of future trash volumes in Aceh, supporting better planning. By using the MAPE method, this research will also measure the prediction model's accuracy level, ensuring that the predictions are reliable for planning. The study's results are expected to support more effective and sustainable trash management policies in Aceh and assist the government in planning infrastructure and strategies that promote environmental sustainability [5].

RELATED WORKS

1. Environmental Trash

Environmental trash is a major issue that pollutes the air, water, and soil, endangering both humans and wildlife. Trash types, whether solid, liquid, or hazardous, as well as air and noise pollution, can lead to environmental

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degradation, climate change, habitat destruction, and health risks [6]. This problem is exacerbated by trash from community activities, particularly in densely populated areas, which continues to increase in line with population growth and economic development. Efforts such as reducing, reusing, recycling, composting, and participating in cleanup programs are essential steps in mitigating the negative impact of trash on the environment.

Environmental trash can originate from various sources, including industry, agriculture, households, and other activities, and it can negatively impact the environment if not managed or disposed of properly. Some types of environmental trash include:

- 1. Solid Trash: This includes household trash, industrial solid trash, and agricultural trash, such as plastic, metal, paper, and organic trash.
- 2. Liquid Trash: This refers to trashwater from businesses, agriculture, and households, potentially containing pollutants and hazardous chemicals that can contaminate rivers and groundwater.
- 3. Gaseous Trash: Produced by industries, motor vehicles, and the burning of fossil fuels, these gases can cause pollution and worsen air quality.
- 4. Hazardous Trash: This category includes chemical, medical, and electronic trash, which can contain toxic or hazardous materials harmful to the environment and human health.

To maintain ecosystem balance and prevent adverse effects on human health and the environment, environmental trash management involves safe and sustainable handling, reduction, recycling, and disposal.

2. Forecasting

Forecasting is the process of estimating future events or values based on an analysis of historical data. With the primary goal of projecting trends and patterns, forecasting supports more strategic decision-making across various sectors. Quantitative approaches such as time series analysis are often used in forecasting, with mathematical models like ARIMA, Weighted Moving Average, and Neural Networks applied to analyze seasonal or long-term trends from past data [7].

When applied effectively, forecasting becomes an essential tool that helps government and industry sectors plan adaptive and responsive operational needs. In the public sector, forecasting is used to design policies more responsive to community needs, such as in energy and healthcare, so that decisions can adapt more flexibly to changes that arise [8].

3. Python

Python is one of the most widely used programming languages by developers and large companies to create various desktop, web, and mobile applications. Python was created by Guido van Rossum in the Netherlands in 1991 as a hobby and later became a programming language widely used in industry and education due to its simplicity, brevity, intuitive syntax, and extensive libraries. Python has become a popular language learned by various groups, especially students in Information Technology-based universities, to complete coursework, final projects, and research tasks [9].

4. Autoregressive Integrated Moving Average (ARIMA)

ARIMA, also known as the Box-Jenkins method, is a predictive technique used for time series data projection. This method has proven effective in analyzing data with consistent historical patterns and has been widely applied across various sectors, including economics, energy, and healthcare. Although the projections produced by ARIMA are acknowledged for their high accuracy, its implementation poses certain challenges. One major challenge is the complexity of determining the appropriate parameters, namely the Autoregressive (AR), Differencing (I), and Moving Average (MA) components, which often become obstacles for researchers who lack experience with ARIMA modeling [10].

However, with technological advancements and methodological improvements, ARIMA has become increasingly accessible. Numerous studies and experiments have focused on developing methods to automate the ARIMA modeling process, enabling automatic parameter determination without the need for complex manual adjustments. Additionally, recent research has concentrated on data stationarity identification techniques and the application of ARIMA to both seasonal and non-seasonal data in various sectors. This flexibility allows ARIMA to predict diverse data patterns, ultimately supporting data-driven strategic decision-making across multiple fields.

| Table 1 ARIMA model components and parameters | | | | | |
|-----------------------------------------------|------------|-----------------------------------------|--|--|--|
| Components | Parameters | Description | | | |
| Autoregressive (AR) | р | The number of previous data values used | | | |
| | | for forecasting. | | | |
| Integration (I) | d q | The number of differencing processes | | | |
| | | performed to make the data stationary. | | | |
| Moving Average (MA) | | The number of error terms used for | | | |
| | | forecasting. | | | |

Table 1 outlines the components and parameters used in the ARIMA model. The ARIMA model consists of three components: Autoregressive (AR) with parameter p, Integration (I) with parameter d, and Moving Average (MA) with parameter q

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MATERIALS & METHODS

Data Collection

In the data collection stage, information on trash was obtained from two main sources: the National Trash Management Information System (SIPSN) and the Central Bureau of Statistics (BPS). SIPSN data provides details on the volume, types, and distribution of trash across various regions in Indonesia. Meanwhile, data from BPS complements this information with statistics on population, socioeconomic conditions, and other indicators influencing trash production. By utilizing both sources, a more comprehensive and accurate understanding of trash issues in Indonesia can be achieved, which will then be used for data analysis and modeling.

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| Table 2 Amount of Trash and Types of Trash in Aceh Province Per Month 2020-2023 | | | | | |
|---------------------------------------------------------------------------------|----------|--------------------------------|---------------|-------------------------------------|--|
| Date | Province | Total Trash Per Month (Ton) | Type of Trash | Total Trash Type Per Month (Ton) | |
| 01-2020 | Aceh | 21.031,02 | Food Trash | 4.816,10 | |
| 02-2020 | Aceh | 19.674,18 | Food Trash | 4.505,39 | |
| | | | | | |
| | | | | | |
| 11-2020 | Aceh | 20.352,60 | Other | 1.652,63 | |
| 12-2020 | Aceh | 21.031,02 | Other | 1.707,72 | |
| | | | | | |
| 01-2023 | Aceh | 78.173,94 | Food Trash | 25.007,84 | |
| 02-2023 | Aceh | 70.608,72 | Food Trash | 22.587,73 | |
| | | | | | |
| | | | | | |
| 11-2023 | Aceh | 75.652,20 | Other | 4.463,48 | |
| 12-2023 | Aceh | 78.173,94 | Other | 4.612,26 | |

The table above presents data on the monthly amount and types of trash in Aceh Province from 2020 to 2023. This information includes the total monthly trash tonnage along with specific categories such as food trash, wood/branches, paper/cardboard, plastic, metal, fabric, rubber/leather, glass, and other categories. The data is organized by date (month and year) and lists various trash types for each recorded month, showing the contribution of each type to the total trash accumulation in the Aceh region. This information is useful for analyzing trash composition and trends over time, thereby supporting more effective trash management and reduction efforts in Aceh Province.

Methods

Data collection is the first step in this research, forming the foundation for subsequent analysis. The two primary sources of monthly trash volume data in Aceh Province are the National Trash Management Information System (SIPSN) and official publications from the Central Bureau of Statistics (BPS). SIPSN provides detailed data on trash management at the national level, including the volume of trash generated in each province, while BPS offers verified statistical data covering various social and environmental indicators. Combining these two sources offers a complete picture of the trash situation in Aceh.

The collected data spans a sufficient period to analyze seasonal patterns and trends in monthly trash production in Aceh Province. By using this historical data, the research can identify consistent patterns and variations in trash volume from month to month and year to year. This data is also crucial for understanding past conditions and forecasting future trash volumes.

The next step is data processing, which includes cleaning and adjusting the data format to meet the analysis model requirements. This process is essential to ensure that the data used does not contain errors that could impact the analysis results. Subsequently, the data is analyzed to find seasonal patterns and trends that may affect the trash volume in Aceh Province.

This study uses the Autoregressive Integrated Moving Average (ARIMA) model, one of the most common time series analysis methods, to predict upcoming trash volumes. The ARIMA model is chosen because it can identify patterns in past data, both from trends and recurring seasonal changes. The following diagram shows the forecasting scheme using the ARIMA model, illustrating the workflow from the data collection stage to the final stage, which is interpreting the forecasting results.

This research aims to provide an accurate projection of trash volume in Aceh Province using the ARIMA model. It is hoped that these predictions will assist policymakers and related parties in designing a more sustainable and efficient trash management strategy for the future.

The schematic of the trash volume prediction system in Aceh Province using the ARIMA method is shown below.

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Figure 1 Design System

The data then goes through several stages, including cleaning, transformation, and normalization, to be suitable for use in the model's prediction process. These stages aim to improve data quality, address potential issues, and prepare the data for accurate interpretation by the predictive model. During the ARIMA model development stage, steps are taken such as determining the autoregressive parameter (p), differencing (d) to achieve stationarity, and moving average (q). The ARIMA model equation is as follows:

$$(1 - \phi_{1}B - \phi_{2}B^{2} - \dots - \phi_{p}B^{p})Z_{t} = (1 + \theta_{1}B + \theta_{2}B^{2} + \dots + \theta_{s}B^{\phi})a_{t}$$
(1)

Where ϕ represents the Autoregressive (AR) parameter, *B* is the lag operator, (1 - B)^d is the differencing operator to ensure the data is stationary, θ is the Moving Average (MA) parameter, and a_t is the error at time *t*. After training, the ARIMA model is evaluated using test data. Evaluation is conducted by calculating the Mean Absolute Percentage Error (MAPE) metric, which helps assess the model's accuracy in predicting data. The result is a prediction of the monthly trash volume in Aceh Province calculated by the ARIMA model. This prediction is then renormalized to match the original data scale, making the results interpretable in real-world context.

Evaluation

Mean Absolute Percentage Error (MAPE) is the average absolute difference between the forecasted value and the actual value, expressed as a percentage of the actual value. MAPE is calculated as the average of the absolute percentage difference between the actual value and the predicted value divided by the actual value, then multiplied by 100 to obtain the percentage [11].

$$MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{A_t - F_t}{A_t} \right| \times 100$$
 (2)

Where A_t is the actual demand at time t, F_t s the forecasted result at time t, and n is the number of forecasted data points used.

| Table 3 MAPE Range Value | | | |
|--------------------------|----------------------------------------|--|--|
| Jenis Sampah | Jenis Sampah MAPE (%) | | |
| <10% | Excellent forecasting model capability | | |
| 10-20% | Good forecasting model capability | | |
| 20-50% | Fair forecasting model capability | | |
| >50% | Poor forecasting model capability | | |
| <10% | Excellent forecasting model capability | | |

RESULTS AND DISCUSSION

This study aims to predict trash volume based on nine types of trash generated by the community in Aceh Province, namely food trash, wood/branches, paper/cardboard, plastic, metal, fabric, rubber/leather, glass, and other categories.

Using the ARIMA model, each type of trash is analyzed separately to predict the future volume produced. This approach by trash type provides more detailed insights into each category's contribution to the total trash volume in Aceh, which can be used as a reference for planning more effective and specific trash management. These predictions are expected to assist the government and related parties in developing trash management strategies targeted according to each trash type's unique characteristics.



Figure 2 Rolling Mean and Rolling Standard Deviation for Trash in Aceh Province (2020-2023)

This chart shows the Rolling Mean (red line) and Rolling Standard Deviation (green line) for trash data in Aceh from January 2020 to January 2024, with a 12-month window. The blue line represents the original data, which shows a significant spike in early 2022 and a relatively stable pattern afterward. The Rolling Mean indicates a consistently increasing trend following this spike, while the Rolling Standard Deviation also experiences a change in pattern but begins to stabilize toward the end of 2023. This pattern suggests a shift in trash volume, which may be influenced by changes in external factors.



Figure 3 Autocorrelation Function (ACF) for Trash in Aceh Province

The ACF (Autocorrelation Function) chart is used to analyze the correlation between data and different lags. In this chart, a significant correlation is observed at lag 1, followed by weaker correlations at subsequent lags that fall within the confidence interval (blue area). This indicates that the relationship between observations in this trash data is only strong in the initial period and tends to weaken in later lags. The ACF helps determine the Moving Average (MA) parameter in the ARIMA model.



Figure 4 Partial Autocorrelation Function (PACF) for Trash in Aceh Province

The PACF (Partial Autocorrelation Function) chart shows the partial correlation between the data and its lags after removing the effects of the intermediate lags. From this chart, it can be seen that partial correlation is only significant at lag 1, with correlations weakening at subsequent lags. This indicates that only lag 1 provides a significant contribution, while higher lags have minimal impact. The PACF is useful in determining the Autoregressive (AR) parameter for the ARIMA model.

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The monthly trash volume predictions for Aceh Province in 2024 show variations in volume across each trash type. Based on the forecast results, food trash is expected to have the highest volume throughout the year, followed by paper/cardboard and plastic trash. On the other hand, trash types such as metal, fabric, rubber/leather, and glass are predicted to have lower and relatively stable volumes. A gradual upward trend is observed across nearly all trash types, indicating a potential increase in cumulative trash volume in Aceh during 2024. These findings provide valuable information for authorities in planning effective trash management strategies, prioritizing the trash types expected to contribute the most to the total trash volume. Such strategies will be beneficial in supporting trash reduction efforts and developing trash management facilities that align with the needs of Aceh Province.

To gain a more detailed understanding of the accuracy of the ARIMA model predictions, a separate analysis was conducted for each trash type. The following presents a comparison between the model's forecast results and actual data for each trash category in Aceh Province, aiming to identify how well the model captures monthly patterns and fluctuations for each trash category. This analysis is expected to provide specific insights to enhance the model's accuracy and support the planning of more effective trash management strategies in the future. Below are the graphs for each trash type:



Figure 6 Comparison of ARIMA Predictions with Actual Data for Food Trash in Aceh Province for 2023

The forecast of food trash volume in Aceh Province shows a significant difference between actual data and the ARIMA model predictions. The actual food trash data fluctuates monthly between approximately 22,000 and 25,000 tons, while the ARIMA model only displays a linear upward trend without capturing these variations. This indicates that while the ARIMA model performs well in identifying long-term trends, it lacks sensitivity to the seasonal changes observed in food trash.



Figure 7 Comparison of ARIMA Predictions with Actual Data for Wood/Branch Trash in Aceh Province for 2023 The actual data for wood/branch trash shows a fluctuating pattern, ranging between 10,500 and 11,500 tons each month. However, the ARIMA model's predictions display a stable upward trend without accounting for monthly

variations. This indicates that while the ARIMA model can capture the general trend, it lacks accuracy in predicting the seasonal changes observed in wood/branch trash.



Figure 8 Comparison of ARIMA Predictions with Actual Data for Paper/Cardboard Trash in Aceh Province for 2023 For paper/cardboard trash, the actual data shows significant monthly fluctuations, with volumes ranging between 7,000 and 7,500 tons. The ARIMA model, however, forecasts a steady upward trend that does not reflect these monthly variations. This outcome indicates that, although the ARIMA model captures the long-term trend, it lacks sensitivity to monthly changes in paper/cardboard trash.



Figure 9 Comparison of ARIMA Predictions with Actual Data for Plastic Trash in Aceh Province for 2023

Plastic trash in Aceh Province displays a fluctuating pattern in the actual data, while the ARIMA model forecasts a stable linear increase throughout the year. The actual plastic trash data ranges between 16,000 and 18,000 tons, whereas the predictions do not show significant seasonal variation. This indicates that the ARIMA model is less responsive to monthly changes in plastic trash, even though it captures the overall upward trend.



Figure 10 Comparison of ARIMA Predictions with Actual Data for Metal Trash in Aceh Province for 2023

The volume of metal trash shows monthly fluctuations in the actual data, ranging from 3,400 to 3,800 tons. However, the ARIMA model predicts a linear upward trend without these fluctuations. This indicates that the model lacks sensitivity in capturing the monthly patterns present in metal trash, though it does provide a stable long-term trend estimate.

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Figure 11 Comparison of ARIMA Predictions with Actual Data for Fabric Trash in Aceh Province for 2023 For fabric trash, the actual data shows a fluctuating pattern, ranging between 2,600 and 2,800 tons each month. However, the ARIMA model forecasts a stable upward trend without accounting for seasonal variations. This result indicates that the model lacks sensitivity to the fluctuations present in fabric trash.



Figure 12 Comparison of ARIMA Predictions with Actual Data for Rubber/Leather Trash in Aceh Province for 2023

Rubber/leather trash shows monthly variation in the actual data, but the ARIMA model prediction only displays a stable linear upward trend. The actual trash data for this category ranges between 2,200 and 2,800 tons, while the predictions do not reflect the monthly changes. This indicates that the model tends to overlook seasonal variations for the rubber/leather category.



Figure 13 Comparison of ARIMA Predictions with Actual Data for Glass Trash in Aceh Province for 2023 The predictions and actual data for glass trash show a similar discrepancy as seen in other categories. The actual data displays monthly fluctuations around 2,400 to 2,700 tons, while the ARIMA model predicts a linear upward trend. This indicates that the ARIMA model lacks sensitivity to the monthly variations occurring in glass trash.



Figure 14 Comparison of ARIMA Predictions with Actual Data for Other Trash in Aceh Province for 2023 For the other trash category, actual data shows monthly variations around 4,200 to 4,600 tons, while the ARIMA model predicts a linear upward trend. The model appears unable to capture the seasonal fluctuation patterns present in

| Trash TypeMAPE (%)Food Trash27.93%Wood/Branches21.73%Paper/Cardboard20.14%Plastic30.08%Metal24.11%Fabric26.64%Rubber/Leather18.39%Glass39.31%Other18.69% | Table 4 MAPE Percentage by Trash Type | | | | |
|----------------------------------------------------------------------------------------------------------------------------------------------------------|---------------------------------------|----------|--|--|--|
| Food Trash27.93%Wood/Branches21.73%Paper/Cardboard20.14%Plastic30.08%Metal24.11%Fabric26.64%Rubber/Leather18.39%Glass39.31%Other18.69% | Trash Type | MAPE (%) | | | |
| Wood/Branches21.73%Paper/Cardboard20.14%Plastic30.08%Metal24.11%Fabric26.64%Rubber/Leather18.39%Glass39.31%Other18.69% | Food Trash | 27.93% | | | |
| Paper/Cardboard20.14%Plastic30.08%Metal24.11%Fabric26.64%Rubber/Leather18.39%Glass39.31%Other18.69% | Wood/Branches | 21.73% | | | |
| Plastic 30.08% Metal 24.11% Fabric 26.64% Rubber/Leather 18.39% Glass 39.31% Other 18.69% | Paper/Cardboard | 20.14% | | | |
| Metal 24.11% Fabric 26.64% Rubber/Leather 18.39% Glass 39.31% Other 18.69% | Plastic | 30.08% | | | |
| Fabric 26.64% Rubber/Leather 18.39% Glass 39.31% Other 18.69% | Metal | 24.11% | | | |
| Rubber/Leather18.39%Glass39.31%Other18.69% | Fabric | 26.64% | | | |
| Glass 39.31% Other 18.69% | Rubber/Leather | 18.39% | | | |
| Other 18.69% | Glass | 39.31% | | | |
| | Other | 18.69% | | | |

the actual data, resulting in less accurate forecasts for this category.

The accuracy of ARIMA model predictions heavily depends on the quality and completeness of the data used. Consistent historical data covering a sufficiently long period can help the model capture relevant trends and patterns, thereby improving prediction accuracy. Conversely, incomplete or inaccurate data can negatively impact the quality of predictions, making them less representative and harder to rely on. In this study, the quality of data obtained from relevant sources may influence the ARIMA model's ability to predict seasonal fluctuations in certain trash categories, such as the "other" category. The model's inability to track these variations could be due to seasonal patterns not being adequately represented in the available historical data.

Therefore, improving prediction accuracy is not only determined by selecting the right model but also by the quality of data used as input. Moving forward, enhancing the accuracy of trash volume predictions in Aceh can be achieved through more detailed and continuous data collection processes. Additionally, applying a hybrid model that combines ARIMA with other methods could be more effective in handling complex and dynamic data patterns. With these steps, it is hoped that prediction results will become more reliable and useful in supporting strategic decision-making for trash management in Aceh Province.

CONCLUSIONS

This study has evaluated the ability of the ARIMA model to predict trash volume in Aceh Province. The prediction results show that ARIMA is effective in capturing long-term trends in trash volume; however, the model is less sensitive to seasonal variations, especially for trash types such as glass and plastic, which exhibit significant monthly fluctuations. This indicates that, although ARIMA can provide an overview of general trends, it has limitations in capturing the variable patterns of certain trash types. Therefore, to achieve more accurate predictions, it is recommended to combine the ARIMA model with other approaches, such as hybrid models or machine learning, which can accommodate higher data complexity.

Moreover, prediction accuracy is highly dependent on the quality of the data used. More complete and detailed data will enhance the accuracy and relevance of the results. Thus, efforts to improve structured data collection processes are essential in supporting effective decision-making for trash management in Aceh. The findings of this study are expected to serve as a reference for the government and relevant stakeholders in designing trash management strategies that are more sustainable and adaptive to future changes in trash volume.

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