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Prediction Of Industrial Waste Using The Autoregressive Integrated Moving Average Method

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Abstract

This study presents the development of a web-based industrial waste prediction system using the Autoregressive Integrated Moving Average (ARIMA) method to forecast the volume of liquid and solid waste generated by PT Pupuk Iskandar Muda (PIM). The predictive model is built upon historical waste data collected between 2020 and 2023, serving as the foundation for the statistical analysis. The system is developed using the Flask web framework, offering an interactive and user-friendly interface, while SQLite3 is employed as a lightweight local database solution for efficient data handling. The ARIMA (1,1,1) model was selected based on stationarity testing and examining ACF and PACF patterns. The results suggest that the model can moderately capture prediction trends, although limitations in accuracy are evident. For 2024, liquid waste is projected to decrease from 30,600 tons in January to 29,400 tons in December. In contrast, solid waste displays a more stable trend, with an average monthly generation of approximately 23.2 tons. Model performance was evaluated using the Mean Absolute Percentage Error (MAPE) method, yielding high error rates—166.11% for liquid waste and 100% for solid waste, highlighting the significant impact of data quality and completeness on prediction accuracy. The system generates visual outputs through interactive graphs and tables accessible via a web browser, supporting data-driven decision-making. This research is a predictive tool for PT PIM and a reference for future development of technology-driven waste management systems to promote environmental sustainability.

Keywords: *ARIMA, Flask, Industry, Waste Prediction, SQLite3*

1. Introduction

If waste management is ineffective, industrial waste can negatively impact the environment, society, good conditions, and sustainability, including pollution of water, soil, and air. Therefore, effective industrial waste management is crucial to maintaining sustainability and minimizing its negative impact. By predicting industrial waste, companies can devise production strategies to manage waste generation more efficiently, which can help prevent uncontrolled waste accumulation. Waste prediction helps companies comply with strict environmental regulations. By knowing the type and volume of waste generated, the company can take the necessary steps to meet the applicable environmental standards. The most common waste issue at PT Pupuk Iskandar Muda is ammonia gas leaks, which greatly disturb the residents and disappoint them. Ammonia gas leaks can damage the environment, and the most dangerous thing is that they can cause diseases for residents who inhale them. Of course, this is very concerning for the residents of the Dewantara District, Aceh Utara, where the residential area and the factory owned by PT Pupuk Iskandar Muda are only separated by a road from the residents' homes. The presence of industrial waste around the community in Dewantara District, North Aceh, has caused many complaints from the residents. The residents are asking PT Pupuk Iskandar Muda to address the waste issue and manage the waste properly so that it no longer pollutes the surrounding environment. Autoregressive Integrated Moving Average (ARIMA) is a forecasting method that generates predictions based on past data patterns. Forecasting using this method is done by ignoring the independent variables because this method uses the current and past values of the dependent variable to produce accurate short-term forecasts [1]. This research aims to design and build a system that predicts industrial waste for the future using the Autoregressive Integrated Moving Average (ARIMA) method.

Waste is the leftover material or substance from human activities that is unnecessary and has no value or benefit for those who produce it. Waste is the byproduct generated from a production process, whether industrial or domestic (household), commonly known as garbage. Its presence at a particular time and place is undesirable to the environment because it has no economic value [2].

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Industry is a sector that carries out the processing/production process of all businesses or companies that process or transform a less valuable material to produce a useful product for society. Industry is an economic activity that processes raw materials, semi-finished goods, or finished goods into high-value products [3].

Waste is the residue from an effort or activity that contains hazardous or toxic materials which, due to their nature, concentration, and quantity, either directly or indirectly, can endanger the environment, health, and the survival of humans and other living beings [4].

The solid waste treatment at PT Pupuk Iskandar Muda has waste treatment facilities that control the factory's liquid, solid, and gas waste. This facility has equipment such as oil traps, mud traps, stripping towers, and acid neutralizers [5]. The treatment of liquid waste from the fertilizer industry can serve as a raw material source in other processing processes, such as construction material mixtures, or it can be used as an energy source, such as in using liquid waste as biogas fuel [6]. Data mining is an activity that utilizes statistical methods, mathematical calculations, AI, and machine learning to filter and discover valuable data and relevant insights from various large data warehouses. This data mining activity is a series of steps to uncover hidden benefits from a set of information in the form of knowledge that would previously go undetected if done conventionally [7].

Prediction is the process of forecasting the occurrence of a scientific event in the future. A prediction is merely an estimate (guess), but using specific techniques makes predictions more than just estimates. Predictions can be considered educated guesses [8]. George Box and Gwilym Jenkins created the ARIMA method, often called the Box-Jenkins technique or the ARIMA process. ARIMA modeling uses an iterative approach to identify an existing model. The selected model is re-tested using historical data to measure its accuracy. A model is considered accurate if the residuals between the model and historical data have small values, are randomly distributed, and are independent or white noise [9]. Mean Absolute Percentage Error (MAPE) is a metric used to evaluate the accuracy level of a forecasting model in percentage form. MAPE is calculated by calculating the absolute difference between the predicted value and the actual value for each data point, converting that difference into a percentage of the actual value, and then taking the average of all the error percentages. MAPE is often used in various fields, such as sales forecasting, weather analysis, and finance, due to its simple and easy-to-understand interpretation [10].

The prediction of waste can help companies monitor and control environmental quality in line with their production activities. By understanding the patterns and trends of industrial waste over time, companies can program more economical production activities to maximize the optimal use of raw materials, avoid waste, and improve resource efficiency [11].

2. Research Methods

The research conducted by the author focuses on the stages involved in predicting industrial waste at PT Pupuk Iskandar Muda. The author uses the research stages as a guide to ensure that the results remain aligned with the established objectives and do not deviate from the intended goals.

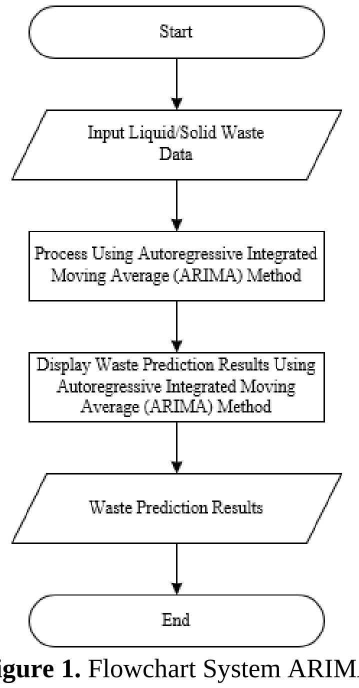

Figure 1. Flowchart System ARIMA

Each stage will be explained as follows based on the system framework above.
a. The System Process begins.
b. The user inputs solid and liquid waste data.
c. Next, the user clicks on the data processing process, and then the system calculates using the Autoregressive Integrated Moving Average (ARIMA) method.
d. After that, the data processing results for the industrial waste prediction appear, depending on the data shown.
e. The system's work process is complete.

Scheme of the Autoregressive Integrated Moving Average (ARIMA) method. This can be seen in the image below:

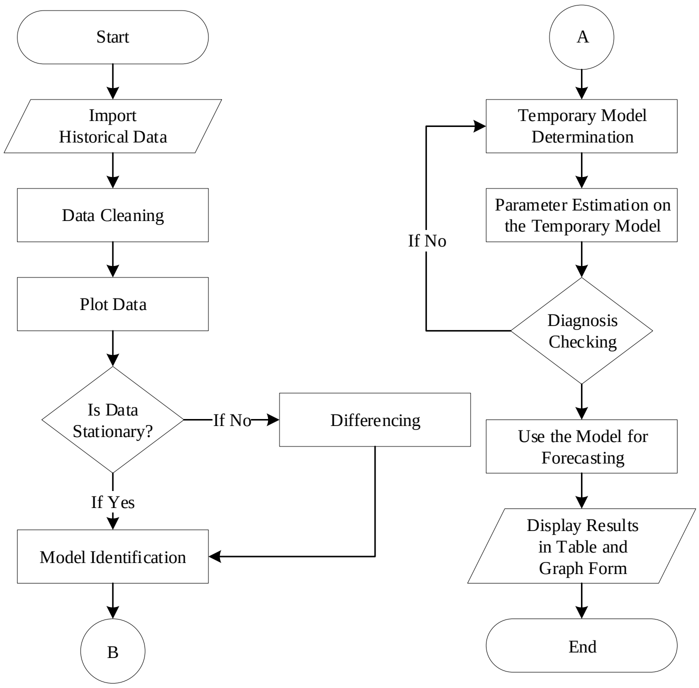

Figure 2. Scheme of the ARIMA Method

Each stage will be explained as follows based on the system framework above.
a. Performing the import of historical data that will be used
b. Conduct Data Cleaning.
c. Plot Data, displaying the movement of the data to determine if it is stationary.
d. If the data is non-stationary, differencing will be performed.
e. Identifying the model. At this stage, the type of model deemed most suitable and appropriate is identified. Next, a provisional model will be established, and the parameters within that model will be estimated.
f. Diagnosis checking. A check is conducted at this stage to determine whether the model can be used.
g. Suppose the model is deemed usable. Next, forecasting is carried out.
h. Finally, the results are presented in the form of tables and graphs.

The industrial waste prediction application system is designed to illustrate the structure, flow, and interactions between components in the system using UML (Unified Modeling Language).

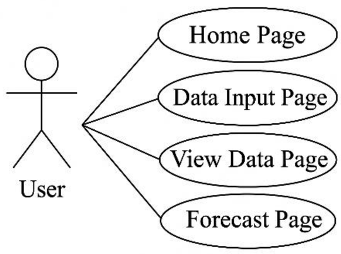

Figure 3. Use Case Diagram

3. Result and Discussion

3.1. Dataset

The dataset is historical data of monthly waste amounts. The liquid and solid waste data of PT PIM is presented in the table below to provide a clearer picture of the movement of waste generated during the analysis period. This data illustrates the amount of waste generated each month from 2020 to 2023, which will be further analyzed to predict future waste trends. Table 1 presents the monthly custom waste data with 48 data entries from January 2020 to December 2023. Table 2 presents liquid waste data with 48 entries from January 2020 to December 2023 with monthly frequency. Here are Table 1 and Table 2.

Table 1. Solid Waste Data

No	Date	Amount (Ton)	No	Date	Amount (Ton)
1	2020-01	13.6	25	2022-01	0
2	2020-02	0	26	2022-02	0
3	2020-03	0	27	2022-03	115.2
4	2020-04	0	28	2022-04	3.45
5	2020-05	0	29	2022-05	0
6	2020-06	0.03	30	2022-06	0.09
7	2020-07	0	31	2022-07	0
8	2020-08	0	32	2022-08	0
9	2020-09	0	33	2022-09	0
10	2020-10	0	34	2022-10	0
11	2020-11	0	35	2022-11	0
12	2020-12	0	36	2022-12	0
13	2021-01	0	37	2023-01	35.2
14	2021-02	0.05	38	2023-02	0
15	2021-03	13.27	39	2023-03	0
16	2021-04	0	40	2023-04	0
17	2021-05	0	41	2023-05	0
18	2021-06	0	42	2023-06	0
19	2021-07	0	43	2023-07	0
20	2021-08	0	44	2023-08	0
21	2021-09	113	45	2023-09	0
22	2021-10	0	46	2023-10	0
23	2021-11	0	47	2023-11	0
24	2021-12	0	48	2023-12	22.665

Table 2. Liquid Waste Data

No	Date	Amount (Ton)	No	Date	Amount (Ton)
1	2020-01	6139.92	25	2022-01	42967.8
2	2020-02	29920.8	26	2022-02	34454.4
3	2020-03	49664.88	27	2022-03	44307.25
4	2020-04	44869.2	28	2022-04	51131.65
5	2020-05	41126.16	29	2022-05	49175.85
6	2020-06	43010.16	30	2022-06	29225.69
7	2020-07	49664.88	31	2022-07	38995.8
8	2020-08	36416.76	32	2022-08	41009.2
9	2020-09	4452.72	33	2022-09	42312.32
10	2020-10	46533.36	34	2022-10	40677.95

No	Date	Amount (Ton)	No	Date	Amount (Ton)
11	2020-11	35010	35	2022-11	41674.8
12	2020-12	32685.6	36	2022-12	61152.65
13	2021-01	46875.84	37	2023-01	47756.4
14	2021-02	36208.56	38	2023-02	40955.04
15	2021-03	16170.96	39	2023-03	35422.32
16	2021-04	0.001	40	2023-04	37136.4
17	2021-05	18128.88	41	2023-05	48147.84
18	2021-06	0.001	42	2023-06	46533.12
19	2021-07	41199.84	43	2023-07	44233.44
20	2021-08	42423.12	44	2023-08	41444.64
21	2021-09	47659.72	45	2023-09	16048.8
22	2021-10	49322.16	46	2023-10	1223.28
23	2021-11	41835.84	47	2023-11	31363.2
24	2021-12	48050.16	48	2023-12	31363.2

3.2. Training and Testing Data Split

In this example, the sample data will be divided into training data and testing data, with the data from 2020–2022 as the training data and 2023 as the test data. This data division aims to evaluate the extent to which the model can generalize the patterns learned from the training data, which will be implemented on previously unseen data, namely the test data.

a. Solid Waste Training Data

Table 3. Solid Waste Training Data

No	Date	Amount (Ton)	No	Date	Amount (Ton)
1	2020-01	13.6	19	2021-07	0
2	2020-02	0	20	2021-08	0
3	2020-03	0	21	2021-09	113
4	2020-04	0	22	2021-10	0
5	2020-05	0	23	2021-11	0
6	2020-06	0.03	24	2021-12	0
7	2020-07	0	25	2022-01	0
8	2020-08	0	26	2022-02	0
9	2020-09	0	27	2022-03	115.2
10	2020-10	0	28	2022-04	3.45
11	2020-11	0	29	2022-05	0
12	2020-12	0	30	2022-06	0.09
13	2021-01	0	31	2022-07	0
14	2021-02	0.05	32	2022-08	0
15	2021-03	13.27	33	2022-09	0
16	2021-04	0	34	2022-10	0
17	2021-05	0	35	2022-11	0
18	2021-06	0	36	2022-12	0

b. Solid Waste Testing Data

Table 4. Solid Waste Testing Data

No	Date	Amount (Ton)	No	Date	Amount (Ton)
1	2023-01	35.2	7	2023-07	0

No	Date	Amount (Ton)	No	Date	Amount (Ton)
2	2023-02	0	8	2023-08	0
3	2023-03	0	9	2023-09	0
4	2023-04	0	10	2023-10	0
5	2023-05	0	11	2023-11	0
6	2023-06	0	12	2023-12	22.665

c. Liquid Waste Training Data

Table 5. Liquid Waste Training Data

No	Date	Amount (Ton)	No	Date	Amount (Ton)
1	2020-01	6139.92	19	2021-07	41199.84
2	2020-02	29920.8	20	2021-08	42423.12
3	2020-03	49664.88	21	2021-09	47659.72
4	2020-04	44869.2	22	2021-10	49322.16
5	2020-05	41126.16	23	2021-11	41835.84
6	2020-06	43010.16	24	2021-12	48050.16
7	2020-07	49664.88	25	2022-01	42967.8
8	2020-08	36416.76	26	2022-02	34454.4
9	2020-09	4452.72	27	2022-03	44307.25
10	2020-10	46533.36	28	2022-04	51131.65
11	2020-11	35010	29	2022-05	49175.85
12	2020-12	32685.6	30	2022-06	29225.69
13	2021-01	46875.84	31	2022-07	38995.8
14	2021-02	36208.56	32	2022-08	41009.2
15	2021-03	16170.96	33	2022-09	42312.32
16	2021-04	0.001	34	2022-10	40677.95
17	2021-05	18128.88	35	2022-11	41674.8
18	2021-06	0.001	36	2022-12	61152.65

d. Liquid Waste Testing Data

Table 6. Liquid Waste Testing Data

No	Date	Amount (Ton)	No	Date	Amount (Ton)
1	2023-01	47756.4	7	2023-07	44233.44
2	2023-02	40955.04	8	2023-08	41444.64
3	2023-03	35422.32	9	2023-09	16048.8
4	2023-04	37136.4	10	2023-10	1223.28
5	2023-05	48147.84	11	2023-11	31363.2
6	2023-06	46533.12	12	2023-12	31363.2

3.3. ARIMA Prediction

This process will include data stationarity tests, ARIMA order identification with ACF and PACF, parameter estimation, model diagnosis, and forecasting results. The final results will show the forecast from January 2024 to December 2024.

a. Solid Waste

Here is the graph of solid waste prediction data for 2024.

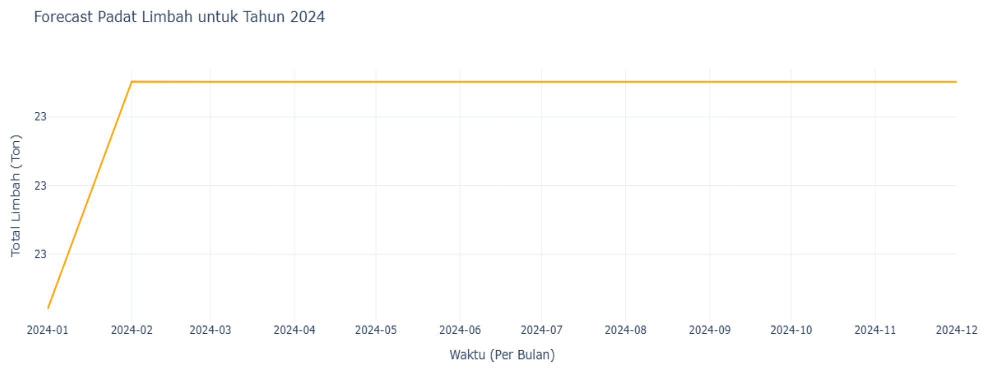

Figure 4. Graph of Solid Waste Prediction for 2024

The solid waste prediction results for 2024 show a stable trend with a slight increase at the beginning of the year and a value that tends to remain constant at 23.2 tons. However, these results are considered less representative of providing a more dynamic picture of solid waste production. This is due to the characteristics of the historical data used in the model, where many values are zero. The graphical data visualization can be seen in the table below:

Table 7. 2024 Prediction Results (Solid Waste)

No	Date	Prediction (Ton)
1	2024-01	22.64
2	2024-02	22.64
3	2024-03	22.64
4	2024-04	22.64
5	2024-05	22.64
6	2024-06	22.64
7	2024-07	22.64
8	2024-08	22.64
9	2024-09	22.64
10	2024-10	22.64
11	2024-11	22.64
12	2024-12	22.64

b. Liquid Waste

Here is the graph of liquid waste prediction data for 2024.

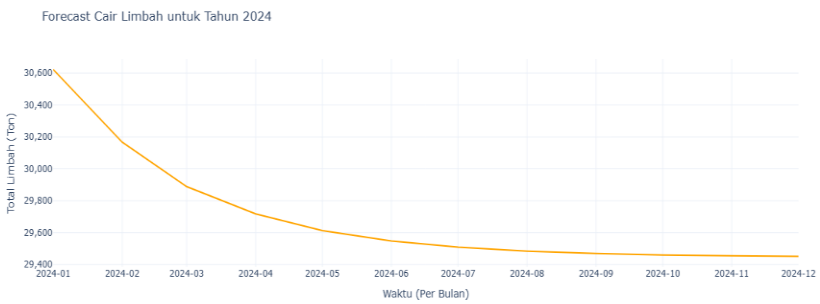

Figure 5. Graph of Liquid Waste Prediction for 2024

Based on the graph above, the forecast results for total liquid waste in 2024 show a consistently declining trend from January to December. At the beginning of 2024, the predicted value of liquid waste is around 30,600 tons, which gradually decreases to around 29,400 tons by the end of the year. This decline reflects the potential for changes in the management or reduction of liquid waste during that period. The graphical data visualization can be seen in the table below:

Table 8. 2024 Prediction Results (Liquid Waste)

No	Date	Prediction (Ton)
1	2024-01	30622.19
2	2024-02	30167.62
3	2024-03	29888.78
4	2024-04	29717.72
5	2024-05	29612.79
6	2024-06	29548.42
7	2024-07	29508.94
8	2024-08	29484.72
9	2024-09	29469.86
10	2024-10	29460.74
11	2024-11	29455.15
12	2024-12	29451.72

3.4. Evaluation Prediction Result

After obtaining the prediction results, an accuracy analysis of the predictions will be conducted using the Mean Absolute Percentage Error (MAPE) method. MAPE is an evaluation method that measures the prediction error rate by comparing the forecast results against actual data in percentage form. The smaller the MAPE value, the better the accuracy level of the forecasting model used. The results of this method's accuracy calculations are presented in the table below.

Table 9. MAPE Evaluation Results

No	Type of Waste	Forecast Accuracy Percentage
1	Solid Waste	100.0%
2	Liquid Waste	166.11%

Based on the table above, solid waste forecasting yields a MAPE value of 100%, which falls into the poor forecasting model performance (>50%). The high MAPE value is influenced by the sporadic nature of the solid waste data, where many months record a value of zero. This happens because PT PIM does not produce solid waste every month. This inconsistent data pattern makes it difficult for the ARIMA model to capture relevant patterns or trends, affecting prediction accuracy. Meanwhile, the forecast for liquid waste shows a MAPE value of 159.76%, which also falls into the category of poor forecasting ability (>50%). This value indicates that the ARIMA model cannot predict liquid waste data well. This may be because the wastewater data pattern has high fluctuations and a complex seasonal pattern, making it difficult for the model to identify.

3.5. System Implementation

The system implementation process in this research was carried out using the Google Colaboratory IDE to develop an application that applies the previously trained Autoregressive Integrated Moving Average (ARIMA) model to predict the amount of industrial waste. This application is designed to facilitate users in conducting analysis and viewing prediction results through an intuitive visualization interface.

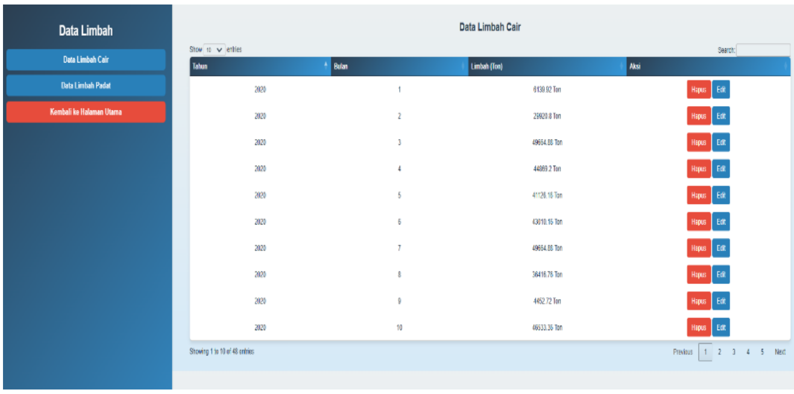

Figure 6. Waste Data Page

This page has a simple yet functional interface to ensure users can easily manage waste data. This system provides flexibility to manage historical data efficiently, which is the basis for waste analysis and prediction using the ARIMA method.

Figure 7. ARIMA Forecasting Page

The Waste Forecasting Page is designed to make it easier for users to select the type of waste they want to predict.

4. Conclusion

Based on the research conducted, the author concludes the following:
1. This research successfully applied the ARIMA method to predict industrial waste. The results show that the ARIMA (1,1,1) model can capture historical data patterns with reasonably good accuracy for liquid waste. However, its performance for solid waste is less optimal due to the sporadic nature of the data.
2. The prediction for liquid waste in 2024 shows a downward trend, decreasing the waste from 30,600 tons in January to 29,400 tons in December. On the other hand, the prediction for solid waste shows a stable pattern at an average of 23.2 tons per month throughout the year.
3. Implementing a web-based system using the Flask framework and SQLite3 database has been successful. This system allows users to manage data, make predictions, and visualize prediction results in table and graph formats.
4. Model evaluation using Mean Absolute Percentage Error (MAPE) shows that the performance of the ARIMA model for both types of waste falls into the poor category, with a MAPE of 166.11% for liquid waste and 100% for solid waste. This indicates the need for model improvement or adjustment of historical data.

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