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Food Security Optimization Forecasting Fertilizer Production With Method Weighted Moving Average (WMA)

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Abstract

This research focuses on optimizing food security through the application of fertilizer production forecasting method at PT Pupuk Iskandar Muda (PIM) using Weighted Moving Average (WMA). Effective food security relies heavily on stable and adequate fertilizer availability, which in turn requires accurate production predictions to ensure efficiency. In this study, historical data of urea and ammonia fertilizer production from January 2019 to December 2023 is used to build a forecasting model that can provide an overview of future production trends. The WMA method was chosen due to its adaptive nature, where greater weight is given to the most recent data, allowing the model to be more responsive to changes and emerging trends. The results showed that for urea production, WMA produced a MAPE value of 1773.8% and MAD of 13,223.2, while for ammonia production, the MAPE was recorded at 3085.5% with MAD of 7,538.5. Total production showed a MAPE of 69.7% with a MAD of 20,568.9, indicating significant fluctuations in production during the period under study. Nevertheless, the WMA method still provides a fairly good prediction and can be used as a reference in future production planning. In addition, the results of this study also provide valuable insights into the production dynamics at PIM, which is critical in supporting the national food security strategy. This research recommends further exploration of other more advanced forecasting methods, such as ARIMA or machine learning techniques, to improve prediction accuracy and better anticipate changes in production patterns. **Keywords:** Food security, Weighted Moving Average, Fertilizer Production Forecasting, MAPE, MAD.

Introduction

Ensuring the welfare of a nation is closely linked to the ability to secure sufficient food supplies for its population. Adequate and high-quality food is not only a fundamental necessity but also serves as the cornerstone for economic development and societal well-being [1]. By maintaining a stable food supply, a nation can reduce hunger rates, improve public nutrition, and foster conditions conducive to economic growth [2]. Food security also enhances a country's competitiveness on the global stage, making it crucial to continually strengthen policies that focus on food security, agricultural production, and equitable distribution.

Enhancing agricultural production is vital for achieving food security. In response to the growing population, nations must adopt policies and programs that promote the modernization of the agricultural sector. This includes investments in agricultural research and technology, the development of agricultural infrastructure, and the provision of training and education for farmers [3]. Sustainable and environmentally friendly agricultural practices must also be adopted to maintain ecosystem balance and increase crop productivity. Efficient fertilizer production, high-quality seeds, and effective irrigation systems can significantly boost agricultural yields. By fostering collaboration between the government, farmers, and the private sector, a nation can achieve self-sufficiency in food production, reduce reliance on imports, and create jobs and economic growth in the agricultural sector [4].

Fertilizers play a crucial role in enhancing agricultural productivity by supplying essential nutrients to plants, thereby increasing crop yields and improving product quality [5]. The challenges related to fertilizer availability in 2023 present significant obstacles to the agricultural sector in Indonesia. The demand for fertilizer in Indonesia is approximately 13.5 million tons, but only 3.5 million tons have been met [6]. This shortfall not only threatens national food security but also has the potential to impact global food security. The fertilizer crisis of 2023 led to a sharp increase in fertilizer prices and shortages, threatening the productivity and livelihoods of farmers.

Technological developments continue to develop in a more sophisticated direction, this development is based on human innovation and creativity [7]. With this technological development, efforts to deal with fertilizer problems require comprehensive measures, including support from appropriate regulations in the context of food security. Fertilizer production forecasting is vital for anticipating shortages, ensuring efficient distribution, and optimizing resources. The Weighted Moving Average (WMA) method, which emphasizes recent data trends while reducing the impact of outliers, is an effective and simple forecasting tool. This study applies the WMA method to forecast fertilizer production in Aceh Province using data from 2019 to 2023 provided by PT Pupuk Iskandar Muda (PIM), aiming to enhance production planning accuracy and efficiency in the region.

Related Works

1. Forecasting

Forecasting is the process of predicting what will happen in the future. The forecasting process is done by scientific and systematic methods. Qualitative properties such as feelings, experiences, and others are very important in forecasting and use scientific or organized procedures [8]. Forecasting is the process of using scientific methods and past phenomenal data to estimate or forecast what will happen in the future. Allowing the results of the forecast to be used to describe potential situations that will occur in the future, help make the right decisions, and minimize risks that may arise [9].

2. Food Security

Food security is an essential principle in ensuring that all individuals have adequate access to safe, nutritious and affordable food Achieving this goal requires organized collaboration between a number of sectors, including agriculture, food distribution, infrastructure, government policies, and education [10].

3. Fertizers

Fertilizers are substances introduced into the soil by humans to meet the needs of plant growth and production [5]. These substances can be chemical compounds or organisms that provide nutrients to plants either directly or indirectly. Article 1 Chapter 1 of Government Regulation No. 8/2001 explains that fertilizer is a chemical substance or organism that has a role in providing nutrients for plants, either directly or indirectly. Urea is an organic compound that has the chemical formula NH2CONH2 or CO(NH2)2 [5]. Ammonia fertilizer is a type of fertilizer that contains ammonia (NH₃) as its main nutrient. The ammonia in these fertilizers provides an essential supply of nitrogen to plants, which is essential for the growth of leaves, stems, and protein formation [11].

4. System

The system is a unit consisting of various components that are interconnected and work together to achieve the desired results optimally in accordance with the predetermined goals. Each component in this system has a complementary role and function, thus creating a harmonious and efficient mechanism. By operating synergistically, the system is able to achieve its goals effectively, optimize the use of existing resources and produce outputs that are in line with expectations. The goal of this system is not only limited to achieving the end result, but also to an efficient and sustainable work process.[12].

5. Website

A website is a set of pages used to present information in the form of text, images, video, animation, sound, or a combination of all these elements, both static and dynamic. These pages are interconnected through links or a network of pages, forming a single unit that conveys various types of information in an integrated manner [13].

6. Python

Python is a popular programming language among large companies and developers for its ability to develop desktop, web, and mobile applications. Python is considered an easy-to-learn programming language that focuses on code readability. This means that Python codes tend to be clear and easy to understand, as well as complete. Python generally supports object-oriented, imperative, and functional programming paradigms [14].

7. Waterfall

Waterfall is an approach in software development that adopts a linear and sequential sequence of steps. In this methodology, the software development process is divided into stages that are performed sequentially, without returning to the previous stage, like a flowing waterfall. The stages that generally exist in the waterfall model include requirements analysis, design, implementation, testing, and maintenance [15].

8. Streamlit

Streamlit is an open-source Python library that makes it easy for users to quickly and easily turn data scripts into interactive web applications. Developers can use Streamlit to build data-driven applications without needing to understand various complex front-end or web development frameworks. This simplifies the process of creating applications from analytical data [16].

9. Flowchart

According to (Abdullah, 2020) in his book flowchart or flow diagram is a diagram with graphical symbols that express the flow of an algorithm or process that displays the steps symbolized in certain forms, along with the sequence by connecting each of these steps using arrows. Flowchart is a visual representation of the process flow or logical

sequence of a system. Using standard symbols, flowcharts describe the activities, conditions, and logical flow of the process being described. The use of flowcharts is not limited to a particular field, but can be applied in various contexts such as software development, business planning, project management, and system design. Flowcharts are useful for clearly identifying process flows, uncovering errors or deficiencies in the system, and improving the efficiency of a process being analyzed [17].

10. Weighted Moving Average Method (WMA)

The WMA method places more weight on the most recent data, enabling the model to be more responsive to changes and emerging trends. This is crucial for accurately forecasting fertilizer production, where recent trends are more indicative of future production needs [18]. In this method, different weights will be applied to the data based on its recency, as following the weights in table 1:

Tal	ble 1. Weight
Period	Weighting Values
0,7	Last Month
0,2	Two Months Ago
0,1	Three Months Ago

The weights were derived from the study by Singgih and colleagues, which showed optimal and accurate results when applied in forecasting [19].

11. Mean Absolute Percentage Error

MAPE or Mean Absolute Percentage Error is a common evaluation metric used to assess how accurate a model or prediction is in estimating the actual value of a variable. The use of MAPE in the evaluation of forecasting results makes it possible to assess how accurate the forecasting number is compared to the actual number, and the result is multiplied by 100 to be expressed as a percentage [20].

12. Mean Absolute Deviation

The concept of Mean Absolute Deviation (MAD) is the average of the absolute values of deviations between returns and expected returns over a given period. This resulting value is referred to as the MAD for each evaluated asset. When the MAD value is greater, it indicates that the data points are spread further away from the mean value. Conversely, a lower MAD value indicates that the data points tend to be closer to the mean value[21].

Materials & Methods

1. Research Stages

The following is a flow of research stages that will be used during research based on the waterfall flow:

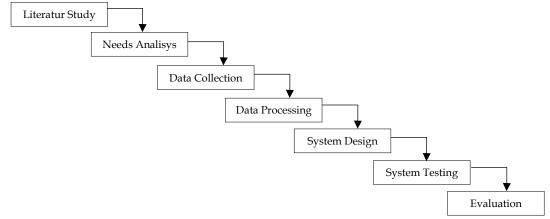


Figure 1. Research Stages

The waterfall diagram explains the stages of system development starting from literature study, needs analysis, data collection, data processing, system design, testing, to evaluation, following a structured and sequential flow.

2. Data Collection

Data for this study was collected from PT Pupuk Iskandar Muda (PIM) covering the period January 2019 to December 2023. The data includes monthly production figures for urea fertilizer, ammonia and total production. The following graphs are for urea, ammonia and total fertilizer production data. The following graphs are for urea, ammonia and total fertilizer production data.

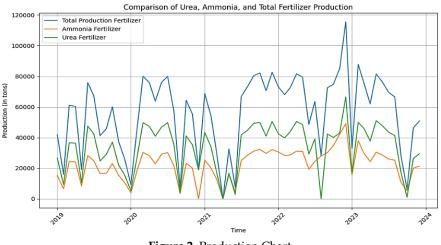


Figure 2. Production Chart

This chart compares total fertilizer, ammonia and urea production from 2019 to 2023. The data shows significant fluctuations in total production, while ammonia and urea production are more stable but also experience variations.

3. Data Preprocessing

- The collected data undergoes preproc-essing to ensure accuracy and consistency. Steps include:
- Handling Missing Data, Any missing values in the dataset are identified and addressed, either by removing incomp-lete records or imputing missing values using statistical methods.
- Outlier Detection, Extreme values are identified using statistical techniques such as z-score analysis or box plots to ensure they do not skew the forecasting model.
- Division of Data into Training and Test Data, Splitting the data into training and test data is the last step in preprocessing. This is usually done with a certain ratio, such as 80% for training data and 20% for test data.

4. Method

The first step in this research is data collection from PT Pupuk Iskandar Muda (PIM). This dataset includes Urea, Ammonia, and Total Production fertilizer production data from January 2019 to December 2023. This historical data is the basis of the analysis and predictions that will be carried out in this study. The scheme of the Fertilizer production forecasting system using the WMA method is as follows.

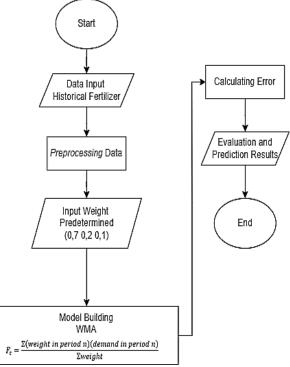


Figure 3. System Schematics

Data calculation using the WMA method was implemented using Python and integrated into a website with the Streamlit framework. Libraries such as NumPy, Pandas, Matplotlib (pyplot), Scikit-learn, and Streamlit are used in the

process of data manipulation and visualization of prediction results. This WMA model applies certain weights to historical production data to produce more accurate value estimates. the following is the formula for the WMA method:

$$F_t = \frac{\Sigma(weight in period n)(demand in period n)}{\Sigma weight}$$
(1)

Where:

Ft = Experience the following period demand

5. Evaluation

The performance of the Weighted Moving Average (WMA) model is assessed by employing two key evaluation metrics, Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD). MAPE measures the average percentage error between predicted and actual values, providing insight into the relative accuracy of the model across different scales. Meanwhile, MAD quantifies the average absolute error in the predictions, giving a direct assessment of forecast accuracy in absolute terms. Together, these metrics offer a comprehensive understanding of the WMA model's predictive capabilities. Here is the formula for MAPE:

$$MAPE = \Sigma |xt - yt| xt nt = 1 n \times 100\%$$
(2)

Description: xt = actual value yt = predicted value n = number of data

And here is the formulation of the MAD:

 $MAD = \mathbb{E}[|R_i - \mathbb{E}(R_i)|] \tag{3}$

Description: R_i: i-th security return E(R_i): expected return of i-th security

Results and Discussion

The identification of the Weighted Moving Average (WMA) forecasting model aims to estimate future data based on historical trends. This model's responsiveness to recent changes makes it particularly effective for capturing emerging patterns. In this research, data normalization or transformation is carried out to ensure accuracy and consistency by addressing missing values and outliers. Data scaling techniques, such as z-score analysis, are applied to standardize the dataset. After preprocessing, the data is divided into training and test sets for model validation, utilizing metrics like Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) to measure the accuracy of the predictions. The WMA method is chosen for its simplicity and ability to assign greater weight to recent data, enhancing its effectiveness in forecasting within agricultural production.

The WMA model is developed using Python, with libraries like Numpy and Pandas, and implemented on the Google Colab platform. This approach applies specific weights to historical production data, prioritizing recent trends, making the model more sensitive to changes in the data. As a result, it produces more accurate forecasts by emphasizing the most current information. The WMA model is also successfully integrated into a web application using the Streamlit framework. This integration allows users to interactively input data, view real-time calculations, and analyze forecasting results. The web interface facilitates easy visualization of urea, ammonia, and total fertilizer production, providing valuable insights for production planning and fertilizer distribution decisions.

In addition to the automated model, manual calculations of the WMA model are performed using ammonia fertilizer production data for 2023 as an example. This ensures that the manual calculations align with the automated Python model, and the same methodology can be applied to urea and total fertilizer production. Below are the manual calculations for ammonia production in 2023:

- Apr-2023 = $((15766 \times 0.1) + (37899 \times 0.2) + (29672 \times 0.7)) / 1 = 29926.8$
- May-2023 = $((37899 \times 0.1) + (29672 \times 0.2) + (24313 \times 0.7)) / 1 = 26743.4$
- Jun-2023 = $((29672 \times 0.1) + (24313 \times 0.2) + (30435 \times 0.7)) / 1 = 29134.3$
- Jul-2023 = $((24313 \times 0.1) + (30435 \times 0.2) + (24551 \times 0.7)) / 1 = 28504$
- Aug-2023 = $((30435 \times 0,1) + (24551 \times 0,2) + (25887 \times 0,7)) / 1 = 26951,6$
- Sep-2023 = ((24551 × 0,1) + (25887 × 0,2) + (25244 × 0,7)) / 1 = 25725,3
- Oct-2023 = $((25887 \times 0.1) + (25244 \times 0.2) + (10711 \times 0.7)) / 1 = 11146.2$
- Nov-2023 = $((25244 \times 0,1) + (10711 \times 0,2) + (5205 \times 0,7)) / 1 = 8310,1$
- Dec-2023 = $((10711 \times 0.1) + (5205 \times 0.2) + (20039 \times 0.7)) / 1 = 16139.4$

The accuracy of the WMA model is tested using two key metrics: Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD). These metrics are applied to evaluate the forecast performance for ammonia, urea, and total fertilizer production. MAPE measures the average percentage error between the predicted and actual values, providing insight into the model's relative accuracy across different scales. Meanwhile, MAD quantifies the average absolute deviation between the forecasted and actual values, offering a straightforward assessment of forecast accuracy in absolute terms.

The following table presents the accuracy test results for urea, ammonia, and total fertilizer production:

_	Table 2. Manual A	ccuracy rest Amonia	rertilizer
_	Fertilizer Type	MAPE (%)	MAD
_	Urea	1773.8	13,223.2
	Ammonia	3085.5	7,538.5
	Total Production	69.7	20,568.9

These results indicate that the WMA model's predictive performance varies significantly across different types of fertilizer. The relatively high MAPE values for urea and ammonia reflect significant fluctuations in their production data, which the WMA model struggled to capture accurately. However, the model performs better for total fertilizer production, as reflected by the lower MAPE and MAD values. This suggests that the WMA method is more effective in forecasting broader production trends rather than highly fluctuating data.

The forecasting of urea, ammonia, and total fertilizer production is projected for the next 12 months using the WMA model. This forecast aims to provide an overview of future production trends to assist in decision-making for production planning and distribution.

The following table presents the forecasted production data for the year 2024, broken down by month: **Table 3** Forecasting results for 2024 (12 months ahead)

Month	Urea	,	Total Production
Monun	Urea	Ammonia	
Jan	25,953.2	19,482.4	45,435.6
Feb	26,680.8	19,914.2	46,595.0
Mar	26,809.2	19,972.7	46,782.0
Apr	26,697.9	19,912.0	46,610.0
May	26,718.5	19,924.3	46,642.9
Jun	26,723.5	19,926.7	46,650.2
Jul	26,719.9	19,924.8	46,644.7
Aug	26,720.5	19,925.1	46,645.6
Sep	26,720.7	19,925.2	46,645.9
Oct	26,720.6	19,925.1	46,645.7
Nov	26,720.7	19,925.1	46,645.7
Dec	26,720.6	19,925.1	46,645.7

The forecast results show relatively stable production estimates, especially for ammonia and total production. These stable predictions indicate that the WMA model may not capture significant short-term fluctuations but provides a reasonable baseline for broader production trends.

Below is a graphical comparison of the actual production data and the forecasted values for urea, ammonia, and total production over the next 12 months:

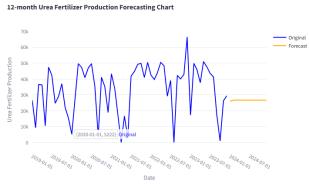


Figure 4. Forecasting Results Of Urea Fertilizer



Figure 5. Forecasting Results of Ammonia Fertilizer 12-month Total Fertilizer Production Forecasting Chart

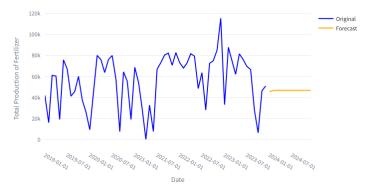


Figure 6. Forecasting Results of Total Fertilizer Production

These graphs compare the actual data with the forecasted data for 2024. The predictions remain relatively stable, highlighting that the WMA model is more suited for capturing longer-term trends rather than accounting for short-term production fluctuations. Despite the variations, the forecast can serve as a useful tool for strategic planning in fertilizer production and distribution.

The implementation of the WMA model is integrated into a web application using the Streamlit framework, which allows for an interactive and user-friendly interface. Users can easily input data, visualize real-time results, and analyze forecasts for future production. The web application is designed to support decision-making by providing accessible insights into fertilizer production trends. On the homepage, users are introduced to the main purpose of the application, which is to optimize food security through effective fertilizer production forecasting. This page offers an overview of the features and functionalities available within the system.



Figure 7. Home Page

In the forecasting page, users can input production data and view detailed results of the WMA model calculations. The interface also provides a graphical representation of forecast results, helping users to better understand future production trends and plan accordingly. This page is essential for real-time data processing and model evaluation.

nonia Production	Forecasting Ammonia	Fertilizer
tal Production	Production	
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	Upload CSV File	
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	NO Water produktion 0 1 2019-01-01.000.00 15.228 1 2 2013-02-01.000.000 6.558	
	MO Winkin perdoksi 0 1 2094-93-01.4000.000 15,228 1 2 2 2094-93-01.4000.000 6,558 2 3 2025-93-01.0000.000 2,4448	

These features make the WMA model easily accessible for practical use, allowing stakeholders to interact with forecasting data and adjust production and distribution strategies more effectively. The image above shows the forecasting page for ammonia fertilizer, which also uses the same format for forecasting urea and total fertilizer production, ensuring consistency and ease in data analysis.

Conclusions

The implementation of the Weighted Moving Average (WMA) method in forecasting urea, ammonia, and total fertilizer production has provided valuable insights into future production trends. The accuracy test results, with MAPE values of 1773.8% for urea and 3085.5% for ammonia, indicate that the model struggled to handle the fluctuations present in the production data for these fertilizers. However, the WMA method performed better for total fertilizer production, with a MAPE of 69.7%, demonstrating its utility in predicting broader trends with less variability.

Despite the high MAPE values for urea and ammonia, the WMA model still provides reasonably stable predictions, especially for total fertilizer production. The forecasted data for 2024 showed consistent production estimates across all months, with minimal variations. For example, the forecasted total production ranged from 45,435.6 tons in January to 46,645.7 tons in December, demonstrating the model's ability to project stable output despite inherent data fluctuations. This suggests that while WMA may not be optimal for volatile datasets, it can still serve as a reliable tool for long-term production planning.

In conclusion, the WMA model is a suitable forecasting method for scenarios where the data exhibits less volatility, such as total fertilizer production. However, for more dynamic datasets like urea and ammonia production, more sophisticated methods such as ARIMA or machine learning models may be required to capture short-term fluctuations more accurately. Future research could explore these advanced techniques to enhance prediction accuracy and better support decision-making in fertilizer production and distribution strategies.

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