

BAREKENG: Journal of Mathematics and Its Applications September 2023 Volume 17 Issue 3 Page 1533–1542 P-ISSN: 1978-7227 E-ISSN: 2615-3017

doi https://doi.org/10.30598/barekengvol17iss3pp1533-1542

# COMPARISON OF FORECASTING RICE PRODUCTION IN MAGELANG CITY USING DOUBLE EXPONENTIAL SMOOTHING AND AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA)

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#### ABSTRACT

### Article History:

Received: 14<sup>th</sup> March 2023 Revised: 5<sup>th</sup> August 2023 Accepted: 15<sup>th</sup> August 2023

#### Keywords:

Double exponential smoothing; Rice production; ARIMA; Forecasting; Time series.



Magelang City has experienced a significant decline in the rice production sector, triggering the need for forecasting research as the next crucial step. This research aims to forecast rice production in Magelang city. By applying Double Exponential Smoothing and ARIMA methods, the most suitable forecasting model is identified. Data on rice production was obtained from the Badan Pusat Statistik (BPS) of Magelang city. The results revealed that the ARIMA (0,1,1) model with MSE of 479,259 was the best choice. This model is expressed as  $Z_t = Z_{(t-1)} + \alpha_t 0.504\alpha_{(t-1)}$ . Using this model, rice production was forecast from July to December 2023, the forecasting results showed that rice paddy production is expected to fluctuate in the coming months. For July 2023, production is projected to be around 65,1762 units, followed by 51,4779 units in August, 58,2432 units in September, and so on.

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How to cite this article:

M. Imron, H. Khaulasari, D. Ayu SNM, J. Inayah and E. Eliyana S., "COMPARISON OF FORECASTING RICE PRODUCTION IN MAGELANG CITY USING DOUBLE EXPONENTIAL SMOOTHING AND AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (ARIMA)," *BAREKENG: J. Math. & App.*, vol. 17, iss. 3, pp. 1533-1542, September, 2023.

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Research Article · Open Access

### **1. INTRODUCTION**

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Indonesia is one of the developing countries where the majority of the population relies on the agricultural sector as a source of livelihood. Magelang city is one of the cities in Indonesia that has a small area of agricultural land but is able to provide 10-11 percent of its people's rice consumption needs independently. The food crop that is mostly cultivated by farmer households in Magelang city is rice. Rice is a food commodity that is processed into staple food, namely rice. The need for rice food in Indonesia, especially Magelang city, increases from year to year in accordance with population growth [1].

Based on data from the Central Bureau of Statistics (BPS) of Magelang city, rice production in Magelang city in 2021 reached 1844.17 tons, a decrease compared to rice production in 2020 whose production was 2230.4 tons. The decrease in rice production in 2021 is due to the decrease in the harvest area of rice plants. Based on the existing rice production data and considering the fact that there is a decrease in production every year, thus to make planning related to food commodities, a mathematical solution is needed, one of which utilizes time series analysis. Time series is a data series that is collected based on a time sequence with equal intervals either weekly, monthly, and quarterly and [2].

The use of time series data will produce different accuracies for each problem and depends on various factors and is not one hundred percent accurate. Double Exponential Smoothing and ARIMA methods are methods that are often used by many researchers in forecasting [3]. The ARIMA method is one of the best methods in the field of forecasting because it is flexible to data or can follow data patterns [4]. The Double Exponential Smoothing method is a linear method discovered by Brown where the advantage of this method is that there are two smoothing processes and data processing is not too complicated and can be applied in predicting data for the long and medium term [5].

Many tests of the method have been carried out, including Bitcoin Price Forecasting Using the ARIMA (Autoregressive Integrated Moving Average) Method, which produces a calculation error of MAPE 4.753% [6]. In further research it was also found that the ARIMA method is the best method in predicting as evidenced by Hartice Erkekoglu's research, which compares the evaluation of forecast accuracy in the ARIMA, Exponential Smoothing and VAR methods with the result that the accuracy value in the ARIMA method is higher [7]. While in the Double Exponential Smoothing Method, it is known that one of the studies that have been conducted is Inflation Prediction in Indonesia Using Moving Average, Single Exponential Smoothing, and Double Exponential Smoothing Methods [8].

Based on this, this research will be conducted rice production forecasting in Magelang city using Double Exponential Smoothing and ARIMA methods where the results of the research are expected to be used as a consideration by the local government in making policies related to food security in Magelang city

# 2. RESEARCH METHODS

### 2.1 Rice Production

According to Assauri and Sugeng in, Production is all activities in creating and adding utility to goods and services [1]. Production is basically an activity intended to produce goods/services to meet human needs. In relation to agriculture, production is the essence of an economy. Rice is a plant that in the process of growing requires a lot of water for good results, the fulfillment of water sources can be done through irrigation or through rain [8]. Based on the above definition, it can be seen that rice production is an activity intended to produce rice to meet human needs.

### 2.2 Time Series

Time series analysis is a method that studies time series applied to make predictions or forecasting. Time series is quantitative forecasting by analyzing data patterns that aim to get patterns that can be extrapolated in predicting a value so that it can be used as a benchmark for the future [9]. Forecasting with time series can predict with various combinations of factors, be it trends, seasonal cycles in certain periods and various combinations of other factors [10]. Forecasting will be effective if the selection of methods and variables taken is appropriate so that the data collection stage becomes important [11]. There are several components in time series analysis is Trend Component (T), Seasonal Component (S), Cyclical Component (C), Irregular Component (I) [12].

#### 2.3 Forecasting

Forecasting is the activity of predicting something using previous or past data with the aim of anticipating the situation and can minimize the chance of an error occurring. One of the important fields to predict is agriculture [13]. According to Subagyo, the purpose of forecasting is to get forecasts that can minimize forecasting errors which can be measured by Mean Absolute Error (MAD) and Mean Square Error (MSE).

### 2.4 Exponential Smoothing

Exponential Smoothing or smoothing method is a weighting method that shows an exponential decrease in the value of the previous observation. The equation used in the Double Exponential Smoothing calculation process is as follows [10]:

$$S_t = \alpha X_t + (1 - \alpha)(S_{t-1} + b_{t-1})$$
(1)

$$b_t = \gamma(S_t - S_{t-1}) + (1 - \gamma)b_{t-1}$$
(2)

$$F_t = S_{t-1} + b_t \tag{3}$$

$$F_{t+m} = S_t + b_t m \tag{4}$$

Where:

 $S_t$  = Level to t stimulus ( $\alpha$  as weight)

 $X_t$  = Data period to t

 $b_t$  = trend modulator to t ( $\gamma$  as weight)

 $\alpha, \gamma$  = Parameter (0<x<1)

 $F_t$  = Predicted value of period to t

m = Number of forecasting periods

### 2.5 ARIMA (Autoregressive Integrated Moving Average)

ARIMA is one of the widely used time series forecasting methods that requires the data to fulfill the assumption of stationarity. There are several models that can be formed from ARIMA time series including autoregressive (AR) models, moving average (MA) models, autoregressive moving average (ARMA) models, autoregressive integrated moving average (ARIMA) and seasonal autoregressive integrated moving average (SARIMA) models [11].

In the ARIMA model, there is a p-coded Autoregressive (AR) process or a q-coded Moving Average (MA) process or a combination of both. D-rank differencing is performed if the time series data is not stationary. Most time series data are not stationary [14]. The following is the basic formula of ARIMA [15]:

$$Z_{t} = (1 + \phi_{1})Z_{t-1} + (\phi_{2} + \phi_{1})Z_{t-2} + \dots + (\phi_{p} + \phi_{p-1})Z_{t-p} - \phi_{p}Z_{t-p-1} + a_{t} + \theta_{1}a_{t-1} + \dots + \theta_{g}a_{t-g}$$
(5)

Where,

AR : p indicates the order/degree of autoregressive

I : d indicates the order/degree of differencing.

MA : q denotes the order/degree of moving average

The formation of the ARIMA model conjecture is seen from the lag on the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots of data that has been stationary with the following conditions [12]:

| Plot       | ACF                     | PACF                    |
|------------|-------------------------|-------------------------|
| AR (p)     | Dies Down               | Cut off after lag p     |
| MA (q)     | Cut off after lag q     | Dies Down               |
| ARMA (p,q) | Dies Down after lag q-p | Dies Down after lag p-q |

Tabel 1. ACF and PACF

# 2.6 Evaluation Of Forecasting Result

Evaluation of forecasting results is used to determine the accuracy of the forecasting results that have been carried out against actual data. There are many methods for calculating forecasting errors [16]. Mean Squared Error (MSE) is used to measure the error of the model's predicted value expressed as the average of the squared errors [17]:

$$MSE = \frac{\sum (X_t - F_t)^2}{n}$$

Where,

 $X_t$  : data actually occurred

 $F_t$  : forecast data calculated from the model to be used at time t

*n* : a lot of data

# 2.7 Data Source

The data taken as the object of this research is monthly data of rice harvest in Magelang District from January 2019 to June 2023 obtained from the Informatics and Statistics Office of Magelang City. The sample data can be seen in Table 2.

| Table 2. Data Sample |       |                        |  |
|----------------------|-------|------------------------|--|
| Year                 | month | <b>Rice Production</b> |  |
| 2019                 | 1     | 228.00                 |  |
| 2019                 | 2     | 255.36                 |  |
| 2019                 | 3     | 264.00                 |  |
| 2019                 | 4     | 182.40                 |  |
| :                    | :     | :                      |  |
| 2023                 | 4     | 79.04                  |  |
| 2023                 | 5     | 93.60                  |  |
| 2023                 | 6     | 37.44                  |  |

The forecasting algorithm can be seen in Figure 1.



#### **Figure 1.** Flowchart of forecasting

Based on **Figure 1.** The input data is rice production data from January 2019 to June 2023. To start forecasting, analyze the data model that has been obtained and identify the data plot, then in the single exponential smoothing method, trial and error is carried out on  $\alpha$  and calculate the single exponential value and perform forecasting calculations. In the ARIMA method, after identifying the model, the alleged model that has been identified is determined and parameter estimation calculations are carried out on each model, then test the model diagnostics, then calculate the forecasting results. After both methods are completed, the best method is compared by calculating the accuracy value of the model and selecting the model to get the best model.

(6)

### 3. RESULTS AND DISCUSSION

### 3.1 Description of Magelang City Rice Production Data

In this research, the data processed is rice production data of Magelang city from January 2019 to June 2023, where the data is obtained from the official website of the Magelang City Informatics and Statistics Office. The data description is shown in the **Figure 2**.



Figure 2. Time Series Plot of Rice Production

Based on Figure 2. it can be seen that the data has a downward trend, besides that the data also has seasonal or seasonal properties so that the double exponential smoothing and ARIMA method can be applied to the data to perform forecasting.

# 3.2 Forecasting Using Double Exponential Smoothing

Using the Double Exponential Smoothing method, trial and error will be conducted to obtain the  $\alpha$  and  $\gamma$  parameters that produce the smallest error from the model. The scale used is between 0.1 to 0.9. In the process of getting the best combination of  $\alpha$  and  $\gamma$  parameters, 9801 combinations were tested. The best  $\alpha$  and  $\gamma$  parameters can be observed in the table below.

| Tabel 5. | The dest parameter $\alpha$ and $\gamma$ |        |         |
|----------|--|--------|---------|
| α        | γ  | MAPE   | MSE     |
| 0.49     | 0.23                                     | 17.346 | 532.146 |

The best second or and or

Seen in **Table 3**. where when testing the parameters  $\alpha$  and  $\gamma$  whose values are taken from the interval 0.1 to 0.9, the smallest error results are obtained when the value of the parameter  $\alpha = 0.49$  and the value of the parameter  $\gamma = 0.23$  so it is decided that this value is feasible to use for forecasting on rice production data in Magelang city.

# 3.3 Forecasting Using ARIMA

The next step is to do forecasting using the ARIMA method with the first step is to check the stationarity of Magelang city rice production data. Checking the stationarity of the data is done on variance and average, where it is said to be stationary in variance if the rounded value ( $\lambda$ ) = 1.



Figure 3. Box-Cox Plot of Rice Production data of Magelang City 2019-2021

**Figure 3.** above shows that the data is not stationary in variance due to the rounded value  $(\lambda) = 1$  so that the Box-Cox transformation will be performed. Here are the results of rice production data that has been Box-Cox transformed:



Figure 4. Box-transformed data

In **Figure 4**. It can be seen that the value of the rounded value ( $\lambda$ ) = 1 which indicates that the data has been stationary in Variance, so it can be continued by looking at the stationarity of the data against the average through the ADF test, ACF and PACF plots. The following is the ADF Augmented Dickey-Fuller Test (ADF) value after differencing 1.

| Tabel 4. | Value | e of ADF test | t |
|----------|-------|---------------|---|
| ADF      | Test  | p-value       |   |

| -5.1198 | 0.01 |
|---------|------|
|         |      |

The value of the p-value in Table 4. is 0.01 where this value is smaller than the confidence level  $\alpha = 0.05$  which indicates that the data is stationary in average. Furthermore, the formation of the alleged model through the following ACF and PACF plots.



Figure 5. a) ACF plot of data after differencing, b) PACF plot of data after differencing.

After differencing, the data has been stationary in average. It can be seen in **Figure 5.** where there is 1 lag in the ACF plot and there is 1 lag in the PACF plot that crosses the Significance limit, thus indicating that Autoregressive (AR) = 1 and Moving Average (MA) = 1. Then an ARIMA (p,d,q) model is formed, namely ARIMA (1,1,0), ARIMA (0,1,1) and ARIMA (1,1,1).

Furthermore, a significance test will be carried out on the model that has been obtained where if the p - value of the model is less than 0.05, the model is said to be significant. The significance test results are as follows:

| Model        | Parameter  | Estimate | p-value | Description   |
|--------------|------------|----------|---------|---------------|
| ARIMA(1,1,0) | $\phi_1$   | -0.494   | 0.000   | significant   |
| ARIMA(0,1,1) | $\theta_1$ | 0.504    | 0.000   | significant   |
| ARIMA(1,1,1) | $\phi_1$   | -0.250   | 0.359   | incignificant |
|              | $\theta_1$ | 0.323    | 0.216   | msignificant  |

 Table 5. Significance Value of the Estimated ARIMA Model

In **Table 5**. the results show that the ARIMA (1,1,0), ARIMA (0,1,1) models are significant because the p-value of the model is less than 0.05, while and ARIMA (1,1,1) is not significant because the p-value of the model is more than 0.05. Then the ARIMA (1,1,0), ARIMA (0,1,1) models are evaluated for model goodness by looking at the MSE value.

| Tabel 6. MSE Value ARIMA Model |          |  |
|--------------------------------|----------|--|
| Model                          | MSE      |  |
| ARIMA(1,1,0)                   | 483.3958 |  |
| ARIMA(0,1,1)                   | 479.2596 |  |

It can be seen in **Table 6.** that the smallest MSE value is the ARIMA (0,1,1) model with a value of 479.2596 so that the model can be assumed to be the best model. The next step the ARIMA (0,1,1) model must fulfill the white noise residual test using Ljung-Box, following the following Ljung-Box results table:

 Table 7. ARIMA (1,2,1) white noise test value using Ljung-Box

| Lag | p-value | Description |
|-----|---------|-------------|
| 12  | 0.919   | White Noise |
| 24  | 0.976   | White Noise |
| 36  | 0.997   | White Noise |

Looking at the results in Table 7. where the value of the p-value intended for the ARIMA (0,1,1) model is above the significance level  $\alpha = 5\%$ , which means that the model is white noise and deserves to be chosen as the best model for forecasting using the ARIMA method.

### **3.4 Evaluation of The Best Model**

After the calculation process using the Double Exponential Smoothing Method and the ARIMA method, then the best model evaluation will be carried out based on the smallest error value (MSE) with the aim of getting the best model that will be used in forecasting rice production in Magelang City in the future. The following table compares the MSE of the models that have been obtained:

# Tabel 8. MSE Model ARIMA (0,1,1) And Double Exponential Smoothing

| Method                             | MSE     |
|------------------------------------|---------|
| ARIMA (0,1,1)                      | 479.259 |
| Double Exponential Smoothing (DES) | 532.146 |

Looking at the error rate obtained between the ARIMA (0,1,1) and Double Exponential Smoothing models, the best model chosen is the ARIMA (0,1,1) model with an error rate of 479.259 which is smaller than the Double Exponential Smoothing model. The model on rice production in Magelang city is ARIMA (0,1,1) as follows:

$$(1 - B)Z_t = (1 - \theta_1 B)a_t$$
  

$$Z_t = Z_{t-1} + a_t - \theta_1 a_{t-1}$$
  

$$Z_t = Z_{t-1} + a_t - 0.504a_{t-1}$$

Furthermore, this model is used for forecasting rice production in Magelang city for the next 6 months, July 2023 to December 2023.

| Month          | Rice<br>Production |  |
|----------------|--------------------|--|
| July 2023      | 65.1762            |  |
| August 2023    | 51.4779            |  |
| September 2023 | 58.2432            |  |
| October 2023   | 54.9019            |  |
| November 2023  | 56.5521            |  |
| December 2023  | 55.7371            |  |
|                |                    |  |

#### **Tabel 9. Forecasting Result**

#### 4. CONCLUSIONS

In this study, data analysis of rice paddy production in Magelang city from January 2019 to June 2023 was conducted with the results showing a downward trend and seasonal nature in the data. Two forecasting methods, namely Double Exponential Smoothing and ARIMA, were tested. The ARIMA(0,1,1) model proved to be the best model with the lowest MSE of 479.259, so it was used to forecast rice production for the next six months. Based on the ARIMA (0,1,1) model, rice paddy production is expected to fluctuate in the coming months. For July 2023, production is projected to be around 65.1762 units, followed by 51.4779 units in August, 58.2432 units in September, and so on.

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