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Application of autoregressive integrated moving average and vector autoregression prediction models for stock and price stabilization at perum bulog

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Abstract: This study implements the ARIMA (Autoregressive Integrated Moving Average) method to predict rice stock levels at Perum Bulog in Lhokseumawe City. The objective of this research is to forecast rice stock levels for the upcoming year, 2024, and provide Perum Bulog Lhokseumawe with a more accurate reference for future stock planning. The benefit of this research lies in its potential to enable preventive measures to minimize rice stock shortages and support Perum Bulog in formulating policies to reduce the risk of future shortages. Error testing for rice prices with the ARIMA model shows MAPE values of ARIMA (1,0,0) = 21,256,076,432,276.10%, ARIMA (0,0,2) = 3.54%, and ARIMA (1,0,2) = 21,305,440,935,436.50%. Rice stock testing with MAPE error values yielded ARIMA (2,0,0) = 13.49%, ARIMA (0,0,1) = 13.65%, and ARIMA (2,0,1) = 10.27%. The error measurement results for prediction using MAPE are 1.5% for rice prices and 58.9% for rice stock. Based on these error measurements, the VAR model appears sufficiently accurate for predicting rice prices, as the MAPE value is at a low level.

Keywords: *ARIMA, Bulog, Forecasting, Price, Rice stock.*

1. Introduction

One of the primary commodities for daily life in Indonesia is rice, which plays a crucial role as the staple food for the population. Rice consumption has increased annually alongside Indonesia's population growth [1]. Although the government has made various efforts to reduce rice consumption by promoting local food alternatives, rice consumption levels continue to rise each year due to population growth [2].

Perum Bulog, a state-owned enterprise in Indonesia, is responsible for managing food logistics, including the distribution and provision of rice reserves for the public [3]. The growing population has led to increased rice demand to meet the needs of Indonesia's residents [4]. With a large portion of the population engaged in farming, it is expected to have a positive impact on meeting food demand and supporting Indonesia's economic sector [5].

Forecasting is the practice of estimating future events. Predictive methods are quantitative approaches used to forecast future occurrences based on relevant historical data [6]. This study utilizes predictive methods to objectively forecast future trends by analyzing historical data from Lhokseumawe City to identify the best forecasting method [7].

The national rice stock is calculated by considering population growth, based on census data from the Central Statistics Agency [8]. Analyzing rice stock availability is crucial for measuring and predicting market demand, both domestically and internationally [9] [8]. In this context, food security to achieve rice self-sufficiency is an issue that cannot be overlooked by the Local Government of Lhokseumawe. Therefore, comprehensive rice stock data collection in Lhokseumawe City is essential for

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maintaining food security stability [10]. The challenge of ensuring the availability of essential food logistics depends on the availability and demand for rice. The uncertainty of rice availability and demand poses challenges for Perum Bulog, leading to issues such as lost sales and excess stock [11]. Another issue is the lack of analysis on depleted rice stocks, which leads to shortages when consumer demand is high and new rice stock is added only at certain times [12] [13].

Price stability and rice supply are critical issues, as price fluctuations can impact the welfare of farmers and the community [14] [15] [16]. Rice is also a major contributor to national food inflation. Thus, balancing supply and demand is a shared responsibility between the central and local governments [17]. In this study, predicting demand and supply plays a vital role. By understanding trends in production and consumption, as well as supply conditions in Lhokseumawe and Aceh Utara, strategic steps can be taken to maintain price and supply stability for rice in the future [18].

Given the issues above, the challenges related to rice prices and stock are essential to address, requiring a comprehensive approach to maintain stable prices and stock. Predictive models can be used as an effective strategy to ensure the availability and stability of rice stock in each region, thereby maintaining stable rice supplies.

2. Literature Review

2.1. Forecasting

Forecasting is the act of estimating future events. In this context, forecasting refers to a predicted condition or situation expected to occur in the future [19], and can be achieved through various methods known as forecasting techniques [20]. Forecasting methods are quantitative approaches used to predict future events based on relevant historical data [21]. Therefore, forecasting methods are applied to achieve objective predictions [22]. Forecasting is the initial step in the decision-making process, with data typically categorized on a monthly basis. Additionally, time series grouping was first identified in oil price forecasting for decision-making purposes [23]. Forecasting serves as an initial phase in future decision-making processes using mathematical models [24] [25].

2.2. Rice Stock Availability

Inventory refers to the quantity of resources required by a company, including raw materials, semi-finished goods, and finished products ready for use by the company to meet market demand [26]. Rice, as a staple food, holds strategic value, and ensuring a secure rice stock is crucial for achieving stable food security or for maintaining a readily available supply of raw materials for the production process [27]. However, inventory control involves two main factors: determining the quantity or volume of inventory orders and establishing the timing of inventory order deliveries [28]. Relevant inventory costs in most inventory systems include (1) Purchase costs and (2) Ordering costs [29] [30].

2.3. Demand and Supply

Demand is the quantity of goods and services that consumers are willing to purchase over a specific period and under certain conditions. The quantity of goods consumers will buy (demand for goods) depends on all the factors mentioned above. Demand represents the quantity of goods desired by consumers in a given market. Meanwhile, a market is a place where transactions occur between producers and consumers for economic goods [31] [32]. In analyzing demand, it is essential to distinguish between the term's "demand" and "quantity demanded." Quantity demanded refers to the amount of goods requested at a particular price level. Conversely, the lower the price of a good, the more consumers will buy it [33] [34].

2.4. ARIMA (Autoregressive Integrated Moving Average)

ARIMA (Autoregressive Integrated Moving Average) is considered an essential part of time series analysis used to forecast future data [35]. The ARIMA model is based on the idea that data from the most recent period influences the data and residual values from previous periods [36] [37] [38]. ARIMA combines moving average and autoregressive methods. The ARIMA method is used for time series forecasting by utilizing historical and current data to generate accurate short-term predictions [39]. The forecasting stages using the ARIMA method [36] are as follows:

1. Model Identification: This model is constructed using statistical significance, variance, and mean.

$$Y_t{}^{\lambda} = \frac{Y_t{}^{\lambda} - 1}{\lambda} \quad (1)$$

Where:
Y_t= data at time t
λ = transformation parameter value

2. Diagnostic Checking: The next stage involves normality testing and parameter estimation.

$$at = Yt - \phi 1Yt - 1 - \theta pYt - 1 - \theta pYt - p \quad (2)$$

Where:
at = the form of the observation Y
ϕ = parameter
θ = parameter

This stage tests whether the overall estimated data obtained is suitable for forecasting by examining the residual correlation across lags.

a. Residual Independence Test: This test is performed to identify the independence of the remaining lags. The residual independence test is conducted by observing the ACF and PACF plot pairs.
b. Normality Test: The Kolmogorov-Smirnov technique generates a p-value. If the sample size is larger than 30 (n > 30), it can be considered to have a normal distribution.

$$t_i = \frac{\phi_2}{se\phi_2} \; or \; t_i \frac{\theta_1}{se\theta_1} \quad (3)$$

Where:
H_0 is rejected if $t_i > t_{table}$, or by using the p-value, where H0 is rejected if the p-value < α.

3. Selection of the Best ARIMA Model:

The next step is to choose the best ARIMA model. The model used is ARIMA (p, d, q) with the general equation as follows:

$$Y_t = \alpha + A_1 Y_{t-1} + A_2 Y_{t-2} + A_P Y_{t-P} + e_t \quad (4)$$

The equation can be written with backshift operators, namely:

$$\left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots \emptyset_p B^p\right)(1 - B) z_t = \emptyset_0 + \left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots \emptyset_q B^q\right)\alpha_t \quad (5)$$

Where:
Zt = data at time t, t = 1,2,3, ... , n; B = operator backshift
(1 − B) d Zt = stationary time series at the differentiation to − d
at = error in period t, t = 1,2,3, ... , n
p = order (AR); d = order of distinction; q = order (MA)

4. Vector Autoregressive (VAR) Method

The Vector Autoregressive (VAR) method is a modeling approach that includes one or more independent variables simultaneously. Then, each independent variable is explained by the lag of its own values and the lags of other independent variables in the model.

2.5. *Vector Autoregression (VAR)*

The Vector Autoregressive (VAR) method is a modeling approach that includes one or more independent variables simultaneously, where each of these independent variables is explained by the lag of its own values as well as the lags of other independent variables in the model. The VAR model is used when the data is stationary at the level. [40]. The general form of the Vector Autoregressive (VAR) model is written as follows:

$$X_t = \alpha + A_1 Y_{t-1} + A_2 Y_{t-2} + A_P Y_{t-P} + e_t \quad (6)$$

Where :

X_t : a vector of size n x l that contains n variables in the VAR model
A_0 : an intercept vector of size n x l
A_1 : a coefficient matrix of size n x n
E_t : a residual vector of size n x l

2.6. Determining the Lag Length

The determination of the lag is focused on finding the optimal lag length to be used in the analysis. The best model is the one with the smallest Akaike Information Criterion (AIC) value. Here is the formula for calculating AIC:

$$AIC(p) = log[\sum e^p] + \frac{2pK^2}{n} \quad (7)$$

Where :
n : number of observations
p : lag length
k : number of variables

3. Methods

3.1. Research Steps

3.1.1. Problem Identification

The first step in this research is to identify the issues in data collection, which includes rice stock data and rice price data. This can affect either a shortage or excess of rice stock, as well as the rice price distribution by Perum Bulog.

3.1.2. Data Collection Techniques

This step involves direct observation and data collection at BULOG Regional Office in Lhokseumawe City, as well as conducting interviews with BULOG employees in the same region. The collected data will then undergo a preprocessing phase to clean, organize, and prepare it for the forecasting process.

3.1.3. Forecasting Model Analysis

The initial stage of model identification is to determine whether the time series data is stationary (i.e., the mean remains unchanged over time). If the data is not stationary, it needs to be converted into stationary form through differencing methods. The analysis will include Autocorrelation and Partial Autocorrelation values, followed by estimation of ARIMA and Vector Autoregression model parameters.

3.1.4. Model Diagnosis Testing

Model testing is performed to assess the effectiveness of forecasting rice stock and rice prices using MAPE and MSE metrics.

3.1.5. System Implementation

System implementation is carried out to evaluate the accuracy of the methods used, applying metrics such as Mean Squared Error (MSE) and MAPE to assess how well the model fits the test data.

3.2. Overall System Scheme

The stages of the methodology for implementing the ARIMA prediction model for rice stock to stabilize supply in support of the Government Program include:

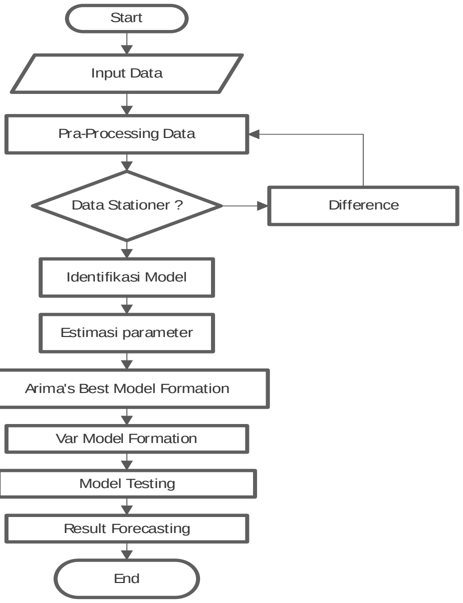

Figure 1.
Research method.

The data used includes demand and supply of rice stock from 2019 to 2023. To minimize redundancy, normalization is applied. To assess stationarity, mean and variance tests are performed using the Augmented Dickey-Fuller (ADF) test. For data that is non-stationary in variance, differencing is conducted using the Box-Cox test. For data non-stationary in mean, the ACF and PACF tests are applied. Model identification is then done by analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) graphs. The ARIMA model is estimated on the time series data using maximum likelihood estimation and pre-estimators. The demand and supply forecasts are then evaluated using Mean Absolute Percentage Error (MAPE) and Root Mean Square Error of Prediction (RMSEP). The Vector Autoregression (VAR) method checks stationarity to align data. If data does not exhibit growth or decline, and is non-stationary, differencing is applied until stationarity is achieved. Stationary data is then analyzed using Akaike's Information Criterion to determine the optimal lag for data testing. Next, potential VAR models are estimated, and MAPE is calculated to evaluate forecasting effectiveness.

4. Result and Discussion

4.1. Autoregressive Integrated Moving Average (ARIMA) Prediction Model

The analysis of rice stock data applies the ARIMA prediction model to stabilize supply in support of government programs as follows:

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Table 1.
Table Rice stock data from 2019 to 2022.

Date	Stok	Date	Stok	Date	Stok	Date	Stok	Date	Stok
2019-1	133	2020-1	2.272	2021-1	34.485	2022-1	4.195	2023-1	1.601
2019-2	8.545	2020-2	6.615	2021-2	33.821	2022-2	2.982	2023-2	36
2019-3	3.193	2020-3	6.194	2021-3	43.085	2022-3	6.803	2023-3	25
2019-4	9.560	2020-4	6.360	2021-4	57.313	2022-4	1.050	2023-4	770
2019-5	19.264	2020-5	11.833	2021-5	42.886	2022-5	394	2023-5	25
2019-6	15.209	2020-6	4.843	2021-6	66.844	2022-6	1.788	2023-6	680
2019-7	17.779	2020-7	8.428	2021-7	33.156	2022-7	1.057	2023-7	464
2019-8	8.638	2020-8	18.691	2021-8	52.349	2022-8	1.706	2023-8	361
2019-9	2.836	2020-9	16.230	2021-9	71.541	2022-9	1.156	2023-9	4.111
2019-10	12.164	2020-10	20.208	2021-10	28.459	2022-10	4.189	2023-10	4.090
2019-11	13.806	2020-11	7.207	2021-11	38.004	2022-11	1.464	2023-11	1.602
2019-12	4.511	2020-12	2.888	2021-12	1.996	2022-12	2.126	2023-12	413

Based on the obtained data, several processes were conducted, including normalization, differencing, Pre ACF, PACF, and residual analysis. The results of these processes are displayed in the following table:

Table 2.
Rice stock ACF, PACF, predicted Y, and residuals.

Date	Stock norm	Devi asi	Praacf	acf	pacf	Pred Y	Residual
2019-1	4.890	11.871	-24.789	2.848	3.401	7.805	0.263
2019-2	9.053	0.515	9.997	2.968	0.723	8.352	0.813
2019-3	8.069	0.071	9.408	2.920	0.754	8.706	1.160
2019-4	9.165	0.688	3.110	2.874	0.751	9.387	0.242
2019-5	9.866	2.342	2.005	2.859	0.744	9.440	0.346
2019-6	9.630	1.674	2.433	2.850	0.742	9.465	-0.401
2019-10	9.406	1.146	4.702	2.735	0.740	9.264	-0.850
2019-11	9.533	1.433	7.015	2.713	0.736	8.672	-0.944
2019-12	8.414	0.006	10.693	2.679	0.736	7.993	0.804
2020-1	7.728	0.369	10.053	2.627	0.737	8.410	0.321
2020-2	8.797	0.213	10.744	2.579	0.733	8.655	0.102
2020-3	8.731	0.156	10.859	2.527	0.730	8.653	0.726
2021-12	7.599	0.543	10.109	2.066	0.666	8.121	-0.121
…	….	….	….	….	….	….	….
…	….	….	….	….	….	….	….
2023-3	3.219	26.183	-13.823	-0.133	1.400	6.018	-2.799
2023-4	6.646	2.854	-13.823	-0.067	-0.086	5.004	1.518
2023-5	3.219	26.183	-3.930	0.000	-0.004	5.949	0.191
2023-6	6.522	3.290	-0.235	0.019	0.019	6.606	-0.717
2023-7	6.140	4.822	3.433	0.020	0.020	6.365	1.957
2023-8	5.889	5.988	-8.742	0.004	0.003	7.659	0.657
2023-9	8.321	0.000	11.987	0.046	0.046	8.298	-0.919
2023-10	8.316	0.000	8.818	-0.012	-0.014	7.772	-1.749
2023-11	7.379	0.916	-4.800	-0.055	-0.055	7.805	0.263

Furthermore, by calculating the φ value using the LINEST function, the following results are obtained:

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φ2	φ1	φ0
0.263664	0.559442	1.451193
0.120711	0.124262	0.807973
0.584556	1.214383	
38.69429	55	
z114.127	81.10996	

The ARIMA models used in this study are (2, 0, 0), (0, 0, 1), and (2, 0, 1). The results of the forecasting and error measurements for these three models are presented as follows:

Table 3.
Rice stock data table (After normalization).

Rice stock data (After normalization)	Forecasting			Mape		
	ARIMA (2, 0, 0)	ARIMA (0, 0, 1)	ARIMA (2, 0, 1)	ARIMA (2, 0, 0)	ARIMA (0, 0, 1)	ARIMA (2, 0, 1)
4.8903						
9.0531						
8.0687	7.0175	8.5540	7.1649	0.1303	0.0601	0.1120
9.7858	8.7346	9.5537	8.8456	0.1074	0.0237	0.0961
9.0639	8.0127	9.6574	8.4527	0.1160	0.0655	0.0674
7.9501	6.8990	9.0792	7.6699	0.1322	0.1420	0.0353
9.4062	8.3550	8.0856	8.1261	0.1118	0.1404	0.1361
9.5329	8.4817	9.1676	8.4265	0.1103	0.0383	0.1161
8.4143	7.3631	9.4255	8.0010	0.1249	0.1202	0.0491
7.7284	6.6772	8.5173	7.3563	0.1360	0.1021	0.0481
…	…	…	…	….	….	….
3.5835	2.5323	7.4667	4.5649	0.2933	1.0836	0.2739
3.2189	2.1677	4.3107	3.3926	0.3266	0.3392	0.0540
6.6464	5.5952	3.6101	4.7794	0.1582	0.4568	0.2809
3.2189	2.1677	6.3951	3.6644	0.3266	0.9867	0.1384
6.5221	5.4709	3.9331	5.0657	0.1612	0.3970	0.2233
6.1399	5.0887	6.2927	5.2679	0.1712	0.0249	0.1420
5.8889	4.8377	6.3262	5.4169	0.1785	0.0743	0.0801
8.3163	7.2651	8.0565	7.2391	0.1264	0.0312	0.1295
7.3790	6.3278	8.3089	6.9960	0.1425	0.1260	0.0519
6.0234	4.9723	7.5362	6.0060	0.1745	0.2511	0.0029

The following shows the overall MAPE results for each of the best models:

Table 4.
Best results of ARIMA model.

Best Model	Percentase
ARIMA (2, 0, 0)	13,49%
ARIMA (0, 0, 1)	13,65%
ARIMA (2, 0, 1)	10,27%

Next, the results of the ARIMA Rice Stock Prediction Model for Supply Stabilization in Support of Government Programs are as follows:

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Table 5.
Rice stock forecast results.

Date	Rice stock forecast results
2023-01	4,737117648
2023-02	4,638308657
2023-03	4,243872327
2023-04	3,997155559
2023-05	3,75513322
2023-06	3,554685414
2023-07	3,378733918
2023-08	3,227448389
2023-09	3,096420834
2023-10	2,983229969
2023-11	2,885358995
2023-12	2,800761505

The analysis results indicate that Perum BULOG's rice stock data shows significant fluctuations throughout the year. Descriptive analysis reveals that rice stocks tend to surge during certain months (such as prior to religious holidays and major harvest periods) but decrease in the months that follow. After conducting the ADF test, it was found that the data is non-stationary at the level but becomes stationary after differencing.

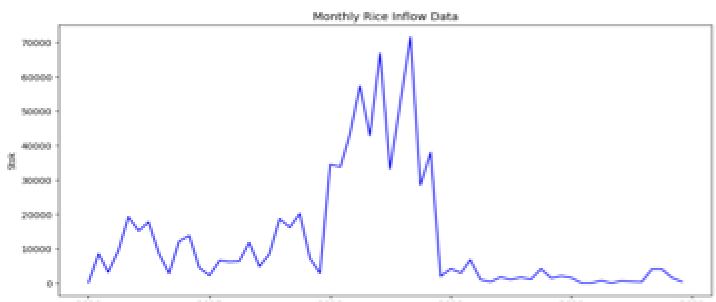
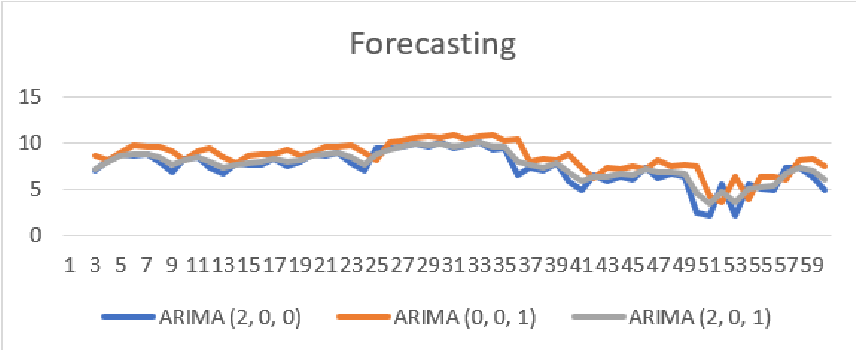


Figure 2.
Before differencing.

Figure 3.
After differencing.

The ARIMA (2,0,1) model was selected as the best model based on the lowest AIC and BIC values. The selection of this model indicates that there is a relationship between past stock values and the current values, as well as the presence of random components that influence the stock.



MAPE:
ARIMA (2, 0, 0) = 13.49%
ARIMA (0, 0, 1) = 13.65%
ARIMA (2, 0, 1) = 10.27%

Figure 4.
Trend and evaluation of the ARIMA model.

The forecasting results for the next six months indicate a stable increase in rice stock, with projections showing a significant rise in stock levels by the end of the forecast period. This increase suggests that Perum BULOG needs to make more comprehensive preparations to enhance storage capacity and rice distribution. The observed fluctuations also emphasize the importance of flexible management strategies, which are crucial for handling unexpected surges in demand. Additionally, it is important to note that while the ARIMA model yields good results, there are limitations in this method, particularly due to its assumptions of stationarity and linearity. However, to gain a more comprehensive understanding of rice market dynamics, it is recommended to consider external variables that may influence rice demand and supply, such as economic factors, climate change, and government policies.

4.2. ARIMA Model for Rice Price Prediction

The dataset used in this study includes monthly rice prices from August 2019 to December 2022.. Dataset Application of Autoregressive Integrated Moving Average and Vector Autoregression Prediction Models for Stock and Price Stabilization at Perum Bulog.

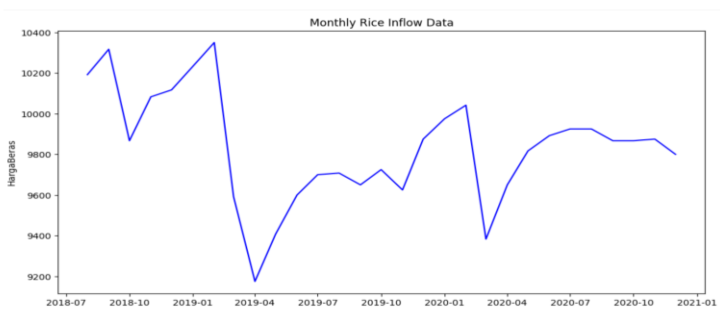


Figure 5.
Rice prices.

There are 29 rice price data points with noticeable variations, reflecting price fluctuations that can be influenced by factors such as harvest seasons, market demand, and government policies. Before applying the ARIMA model, a descriptive analysis was conducted to understand the trends and patterns in the data. From the initial observations, rice prices showed fluctuations, with some months experiencing significant drops, particularly between March 2020 and May 2020. The average rice price during this period was around 9,775, with the highest value reaching 10,350 in February 2019 and the lowest at 9,175 in April 2019.

To apply the ARIMA model, the data must be stationary. The Augmented Dickey-Fuller (ADF) test was performed to test the stationarity of the data. The results indicated that the data is stationary at level, as evidenced by the p-value being smaller than the significance level set (α = 0.05). After confirming stationarity, the ARIMA model was selected. The ARIMA(p,d,q) model was chosen based on the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) analysis, as well as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). From the analysis results, the ARIMA (0,0,2) model was selected as the best model for this data, indicating significant autoregressive and moving average components.

4.3. Vector Autoregression Prediction Model

4.3.1. ADF Test Results

p-value = 0.0455, which is slightly below 0.05. This means we can reject the null hypothesis at the 5% significance level. The ADF Test Statistic (-2.8984) is smaller than the critical value at the 5% significance level (-2.9128), but greater than the critical value at the 10% significance level (-2.5941). Based on these results, rice prices can be considered close to stationary at the 5% significance level, although it is not entirely conclusive. This suggests that the variable may tend toward stationarity, though there is some uncertainty.

p-value = 0.2943, which is much larger than 0.05. This means we cannot reject the null hypothesis that the data has a unit root. The ADF Test Statistic (-1.9824) is larger than all critical values at the 1%, 5%, and 10% significance levels. Based on these results, it is concluded that rice stock is not stationary. Therefore, differencing was applied to meet the stationarity assumption.

4.3.2. Determining the Optimal Lag

The optimal lag was determined using the Akaike Information Criterion (AIC). The optimal lag value (AIC) obtained was 3. Based on this optimal lag value, the VAR model training process was carried out. The following correlation matrix was obtained:

	rizeStocks	rice stocks
rice stocks	1.000000	0,290734
Rizestocks	0,290734	1.000000

The diagonal value of 1.000 indicates that each variable has a perfect correlation with itself, which is standard in a correlation matrix. The correlation between Rice Price and Rice Stock is 0.2907. This is a positive but weak correlation, meaning that when Rice Prices rise, Rice Stock tends to increase as well, although this relationship is not strong enough to be considered significant. The residual correlation of 0.2907 is still within the tolerance limits. This residual correlation suggests that the VAR model is effective in removing the dynamic relationship between Rice Price and Rice Stock.

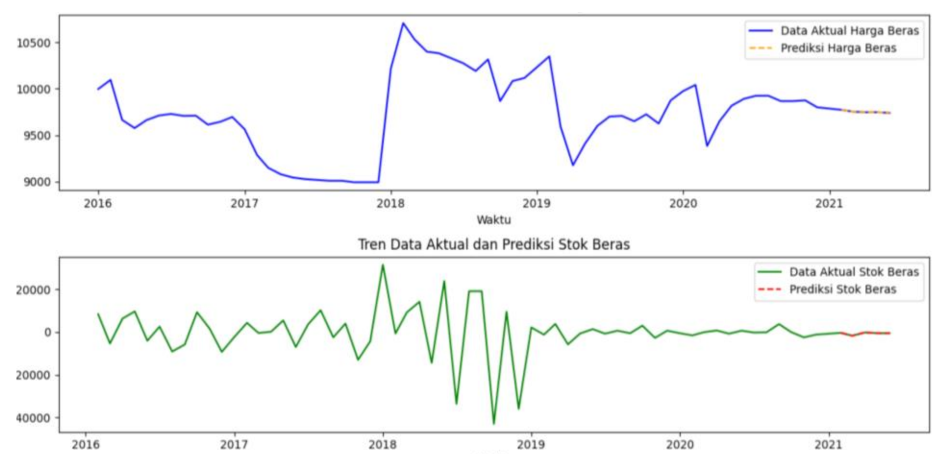


Figure 6.
Actual and predicted rice stock and price data.

The prediction error measurement using MAPE resulted in 1.5% for rice prices and 58.9% for rice stock. Based on these error measurements, the VAR model appears to be quite accurate in predicting rice prices, as the MAPE value is low. However, for rice stock, the model shows a high MAPE value of 58.9%.

5. Conclusion

Based on the predictions made using the Autoregressive Integrated Moving Average (ARIMA) and Vector Autoregression (VAR) models for rice stock and price stabilization at Perum BULOG, the following conclusions can be drawn:

1. This study successfully forecasts rice stock at Perum BULOG using ARIMA and VAR, which can assist in decision-making related to rice stock and pricing. The forecasts indicate that rice stocks will increase in the coming months, signaling the need for better stock management strategies. Therefore, Perum BULOG must prepare adequate storage capacity and strengthen its distribution network to prevent rice shortages or surpluses that could affect prices. In the future, Perum BULOG can take more effective steps to ensure rice availability and maintain price stability, thus supporting food security.
2. The ARIMA (2, 0, 1) model was selected as the best model based on the lowest AIC and BIC values. This model suggests a relationship between past stock values and current values, along with the presence of random components affecting stock levels. The best MAPE value was achieved with ARIMA (2, 0, 1) = 10.27%, followed by ARIMA (2, 0, 0) = 13.49% and ARIMA (0, 0, 1) = 13.65%.
3. The VAR model proved to be accurate in predicting rice prices, with a prediction error measurement of 1.5% for rice prices and 58.9% for rice stock. The correlation between rice prices and stock levels was found to be 0.2907, indicating a positive correlation. As rice prices increase, rice stock tends to rise as well. The residual correlation of 0.2907 remains within acceptable tolerance. Both models demonstrate the ability to predict rice stock and price stabilization at Perum BULOG and can provide recommendations to leadership. These findings highlight the effectiveness of both models in forecasting and their potential to support informed decision-making at Perum BULOG.

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