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Cayenne Pepper Price Forecast in Singkawang City Based on Rainfall using Transfer Function Model

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ABSTRACT

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Fluctuations in the price of cayenne pepper are a significant problem in Indonesia's agricultural sector, especially in Singkawang City. Weather conditions, including rainfall are often the main factor affecting the production and distribution of cayenne pepper, causing price instability. This study aims to analyze the relationship between rainfall and the price of cayenne pepper, and build a forecasting model using a transfer function approach. In this study, the input series used is rainfall, while the output series is the price of cayenne pepper. The data used is secondary data obtained from the Central Statistics Agency in Singkawang City from January 2016 to December 2023. The data is analyzed through the stationarity stage, then the identification of the ARIMA model for the input series. After that, prewhitening and cross-correlation analysis were carried out to identify the parameter values (b, r, s) and determine the noise series ARMA model. The results show that the transfer function model with parameters $(b, r, s) = (4,0,0)$ with ARMA $(3,0)$ noise series is the best model for forecasting the price of cayenne pepper. The results of forecasting the price of cayenne pepper in Singkawang City have a MAPE value of 22.27%, so it can be concluded that the transfer function model is quite good at forecasting the price of cayenne pepper in Singkawang City with the highest forecasting result of IDR 61,899 in May 2024 and the lowest is IDR 32,206 in April 2024. This study focuses solely on the transfer function model because it is specifically designed to analyze the dynamic relationship between an input variable (rainfall) and an output variable (price). Other forecasting methods such as ARIMA or exponential smoothing only capture internal patterns within a single series and cannot represent the influence of external factors. Therefore, the transfer function approach is considered more appropriate for the purpose of this study.

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1. Introduction

In Indonesia, food commodity price forecasting is a very important concern, especially for commodities whose price fluctuates high such as cayenne pepper. Cayenne pepper is one of the agricultural commodities that has an important role in the food needs of people in Indonesia, including in the city of Singkawang, West Kalimantan. The high demand for cayenne pepper makes it a commodity with significant economic value, because its price fluctuations can influence household spending and contribute to food inflation. However, the price of cayenne pepper tends to fluctuate which is influenced by various factors, including weather conditions such as rainfall [1]. Climatic and weather conditions are often external factors that affect cayenne pepper production. High rainfall can result in a decrease in the quality and quantity of production due to crop damage, while low rainfall can also limit the supply of cayenne pepper in the market [2]. Besides weather, other factors such as pest attacks, distribution costs, demand fluctuations, and government policies on food trade can also affect price movements. Therefore, the analysis of the relationship between rainfall and the price of cayenne pepper is very important to identify the impact of changes in rainfall patterns on the price of cayenne pepper in Singkawang City. Previous studies have examined the relationship between climate variability and agricultural commodity prices, particularly using statistical and time series methods. However, studies focusing specifically on cayenne pepper prices in Singkawang City are still limited, especially those that analyze the influence of rainfall patterns. Therefore, the analysis of the relationship between rainfall and the price of cayenne pepper is very important to identify the impact of changes in rainfall patterns on the price of cayenne pepper in Singkawang City.

In overcoming these problems, an analysis is needed to model and forecast the price of cayenne pepper, which is influenced by rainfall so that fluctuations in cayenne pepper prices can be anticipated. This study focuses only on weather factors, particularly rainfall, because rainfall has a direct effect on plant growth and productivity, while other factors are more complex and difficult to quantify accurately. If only the linear regression method is used, a direct relationship between dependent and independent variables can be displayed, but the method is not able to capture the lag pattern [3]. The effect of rainfall on the price of cayenne pepper does not always occur simultaneously, but can have a delayed impact due to the growth and distribution process of cayenne pepper. Therefore, a method is needed that can understand changes in cayenne pepper prices by considering the delayed effects of rainfall. A forecasting method that can be used to model and forecast the price of cayenne pepper based on rainfall is the transfer function model. The transfer function method is a method that describes the future predicted value of a time series data based on the past values of the data with one or more variables related to the output of that series [4]. The transfer function method was chosen because it can capture the relationship between rainfall and the price of cayenne pepper by considering the delayed effect (lag) that occurs [5].

Based on the explanation previously described, the purpose of this study is to produce a model and the results of forecasting the price of cayenne pepper in Singkawang City from January 2024 to December 2024. The data used is cayenne pepper price data and rainfall in Singkawang City for the period January 2016 to December 2023. This research uses a methodology that begins with preparing the input series and output series data. Next, ARIMA modeling is performed on the input series data. After the ARIMA model is obtained, the next step is prewhitening the input series and output series. Then the cross-correlation between the input series and output series that has been prewhitened before. Next, find the value of (b, s, r) which will be the temporary transfer function model parameters and establish the noise series ARMA model. Furthermore, parameter estimation and model diagnosis are carried out to obtain the final transfer function model. To determine the transfer function model, it can be done by finding a temporary transfer function model obtained from the combined (b, s, r) value of each input that has been previously identified. The assign the noise series ARMA model to the transfer function. If the final multivariate transfer function model has been declared feasible, then the model can be used in forecasting.

2. Research Methods

The following are the research stages in transfer function model, starting with the research methodology as an introduction.

2.1 Time Series Analysis

Time series analysis is basically used to analyze data that considers the influence of time. Time series analysis can be done to help in planning ahead. Stationary is a very important assumption in time series analysis. If the data is not stationary in variance, then the data can be stationary using Box-Cox transformation. The Box-Cox transformation can be formulated as follows [6]:

$$T(Z_t) = \begin{cases} \dfrac{Z_t^\lambda - 1}{\lambda}, \lambda \neq 0 \\ \ln Z, \lambda = 0 \end{cases} \tag{1}$$

where, λ is the value of the transformation parameter and $T(Z_t)$ is the transformation function on Z_t.

Table 1. Value of $\boldsymbol{\lambda}$ and Transformation [7]

$\boldsymbol{\lambda}$	$\mathbf{-1}$	$\mathbf{-0.5}$	$\mathbf{0}$	$\mathbf{0.5}$	$\mathbf{1}$
Transformation	$\frac{1}{Z_t}$	$\frac{1}{\sqrt{Z_t}}$	$\ln Z_t$	$\sqrt{Z_t}$	Z_t

Then, if the data is not stationary on average, the data can be stationary by differencing with the following formula:

$$Z_t^d = (1 - B)^d Z_t \tag{2}$$

where, Z_t^d is the data at time t after differencing, $(1 - B)^d$ is the d differencing and Z_t is the t time series.

2.2 ARIMA

The Autoregressive Integrated Moving Average (ARIMA) model is a time series model popularized by Box and Jenkins in 1970 by combining the AR(p) and MA(q) models. The autoregressive (AR) model was first introduced by Yule in 1926 and developed by Walker in 1931, the autoregressive (AR) model with order p is denoted by AR(p) with the general form of the model, namely [8]:

$$\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p \tag{3}$$

then, the Moving Average (MA) model was first introduced by Slutzky in 1973, with order q denoted by MA(q) with the general form of the model, namely [8]:

$$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q \tag{4}$$

AR(p) and MA(q) models can be unified into a model known as Autoregressive Moving Average (ARMA), so it has the assumption that the data of the current period is influenced by data in the previous period. The general form of the ARMA(p, q) mode is as follows:

$$\phi_p(B) Z_t = \theta_q(B) \alpha_t \tag{5}$$

If the time series data is stationary on average after the d differencing and can be modeled using the ARMA(p, q) model, then this model is an ARIMA(p, d, q) model. The ARIMA(p, d, q) model can be expressed by the following equation [9]:

$$\phi_p(B)(1 - B)^d Z_t = \theta_q(B) \alpha_t \tag{6}$$

where, ϕ_p is the AR(p) parameter, θ_q is the MA(q) parameter, $(1 - B)^d$ is the d-order differencing, and α_t is the residual value at the t time.

2.3 Transfer Function Model

The transfer function model is a development of the Box-Jenkins model, where this model involves two variabels with each following the ARIMA model. This model explains that the prediction of the future value of a time series (output series) not only depends on the historical data of the series, but also considers one or more other time series (input series) that have a relationship with the output series. The general form of the transfer function model is also follows [10]:

$$y_t = v(B) x_t + n_t \tag{7}$$

where, $v(B)$ is the transfer function that shows how the input series affects the output series in the backshift operator,

$$v(B) = \frac{\omega_s(B) B^b}{\delta_r(B)} \tag{8}$$

then, n_t is the noise component. If the noise is modeled as an ARIMA process with AR parameter $\phi(B)$ and MA parameter $\theta(B)$, then:

$$n_t = \frac{\theta(B)}{\phi(B)} \alpha_t \tag{9}$$

the two components can be combined to form a transfer function model, as follows:

$$y_t = \frac{\omega_s(B) B^b}{\delta_r(B)} x_{t-b} + \frac{\theta_p(B)}{\phi_q(B)} \alpha_t \tag{10}$$

where, $\omega_s(B) = \omega_0 - \omega_1 B - \cdots - \omega_s B^s$ is the parameter of s value, $\delta_r(B) = 1 - \delta_1 B - \cdots - \delta_r B^r$ is the parameter of r value, b is the parameter of b value, $\phi_p = 1 - \phi_1 B - \cdots - \phi_p B^p$ is the parameter of AR, $\theta_q = 1 - \theta_1 B - \cdots - \theta_q B^q$ is the parameter of MA, and α_t is the residual value at time t.

The transfer function $v(B)$ can be derived through a few straightforward steps [11]:

1. Prewhitening of the input series

   This process aims to remove autocorrelation from the input series so as to produce a white noise series α_t which has zero mean and variance σ_α^2.

   $$\phi_x(B)x_t = \theta_x(B)\alpha_t \tag{11}$$

   so, the white noise series α_t can be obtained:

   $$\alpha_t = \frac{\phi_p(B)}{\theta_q(B)}x_t \tag{12}$$

2. Calculate the filtered output series.

   That is, transform the output series y_t using the above prewhitening model to generate the series

   $$\beta_t = \frac{\phi_p(B)}{\theta_q(B)}y_t \tag{13}$$

3. Calculate the sample CCF, $\hat{\rho}_{\alpha\beta}(k)$ between α_t and β_t to estimate v_k

   $$\hat{v}_k = \frac{\hat{\sigma}_\beta}{\hat{\sigma}_\alpha}\hat{\rho}_{\alpha\beta}(k) \tag{14}$$

   the significance of the CCF and its equivalent $\hat{v}_k$ can be tested by comparing it with its standard error $(n-k)^{-\frac{1}{2}}$.

4. Determining the value of (b, s, r)

   The value of (b, s, r) is determined based on the CCF plot between α_t and β_t. The following are the rules used to estimate (b, s, r) from a transfer function:

   a. The value of b states that y_t is not affected by x_t until period $t + b$. The amount of b can be determined from the first significant lag of the CCF plot.

   b. The value of s indicates how long x_t continues to influence y_t and is seen from the next lag after the first significant lag. the value of s is the number on the lag of the CCF plot before the downward pattern occurs.

   c. The value of r states that y_t is influenced by past values of y_t i.e. $y_{t-1}, y_{t-2}, \ldots, y_{t-r}$. The value of $r = 0$ if the cross-correlation plot does not show a certain pattern. The value of $r = 1$ if the plot of the cross-correlation shows a decreasing exponential pattern. The value of $r = 2$ if the plot on the cross-correlation shows a decreasing exponential pattern and follows a sine pattern [12].

   Once $b, r,$ and s are chosen, preliminary estimates $\hat{\omega}_j$ and $\hat{\delta}_j$ can be found from their relationships with v_k as shown in Equation below [11]:

   $$\delta(B)v(B) = \omega(B)B^b \tag{15}$$

   or

   $$[1 - \delta_1 B - \cdots - \delta_r B^r][v_0 + v_1 B + \cdots + v_j B^j] = [\omega_0 - \omega_1 B - \cdots - \omega_s B^s]B^b \tag{16}$$

   Thus, we have a preliminary estimate of the transfer function $v(B)$ as

   $$\hat{v}(B) = \frac{\hat{\omega}(B)}{\hat{\delta}(B)}B^b \tag{17}$$

5. Noise model identification

   After obtaining a preliminary transfer function, we can compute the estimated noise series using the following formula:

   $$\hat{n}_t = y_t - \frac{\hat{\omega}(B)}{\hat{\delta}(B)}B^b x_t \tag{18}$$

To identify a suitable noise model, we analyze the sample ACF and PACF of the estimated noise series, or apply other univariate time series identification methods, which leads to the model: [13]

$$\phi(B)n_t = \theta(B)\alpha_t \tag{19}$$

6. Diagnostic checking

   Once the model structure is determined and parameters are estimated, it is crucial to assess whether the model fits adequately before proceeding with forecasting, control, or other applications. The transfer function model assumes that the noise terms α_t are white noise and uncorrelated with the input series x_t, as well as with the prewhitened input series α_t. Therefore, diagnostic checking involves evaluating both the residuals $\hat{\alpha}_t$ from the noise model and the residuals α_t from the prewhitened input, to verify if these assumptions are satisfied.

2.4 Forecast Accuracy Level

The forecast accuracy level is determined by dividing the time series data into a training set and a testing set. The training set is used to build the model, while the testing set is used to evaluate its accuracy. Forecast accuracy measures how well a model predicts actual data. One common metric for this is the Mean Absolute Percentage Error (MAPE). MAPE measures the average percentage deviation of forecasts from actual values. A lower MAPE value indicates higher forecasting accuracy. The MAPE criteria are shown in Table 2.

Table 2 MAPE Criteria

MAPE (%)	Criteria
$MAPE \leq 10$	Very Good
$10 < MAPE \leq 20$	Good
$20 < MAPE \leq 50$	Fair
$MAPE > 50$	Poor

The MAPE value is calculated using the following formula:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100$$

where Y_t is the actual value at time t, and $\hat{Y}_t$ is the predicted value.

3. Results And Discussion

The data used in this study are cayenne pepper price and rainfall data obtained from the publication of the Central Statistics Agency (BPS) of Singkawang City in the form of monthly data from January 2016 to December 2023 with a total of 96 data. Rainfall in Singkawang City has an average of 248.82 mm per month with a standard deviation of 134.92 mm, which indicates a considerable variation in the amount of rainfall from month to month. Meanwhile, the price of cayenne pepper has an average of IDR 60,704.79 per kilogram with a standard deviation of IDR 14,300.57, which indicates significant price fluctuations.

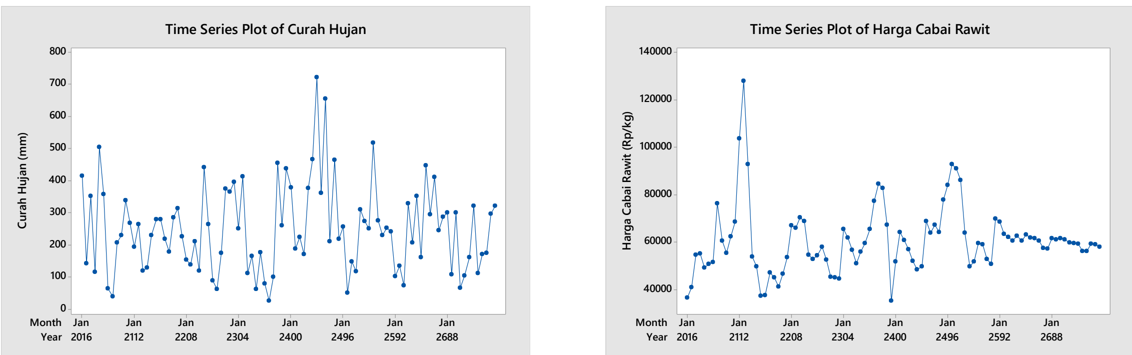

Figure 1. Time Series Plot of Rainfall and Cayenne Pepper

Based on **Figure 1**, it shows that the data has a pattern of increasing and decreasing data in each month, so it can be said that the data has a seasonal pattern. The basic assumption that must be met in time series analysis is the stationarity of the data in terms of mean and variance. Checking the stationarity of data in the average can be done using the ADF test. The ADF test results for the input series provide a $p - value < 0.05$, which is $0.01 < 0.05$, then the output series also provides a $p - value < 0.05$, which is $0.01388 < 0.05$, so it can be concluded that the input and output series are stationary on average. Furthermore, checking data stationarity in variance can be done using Box-Cox Plot.

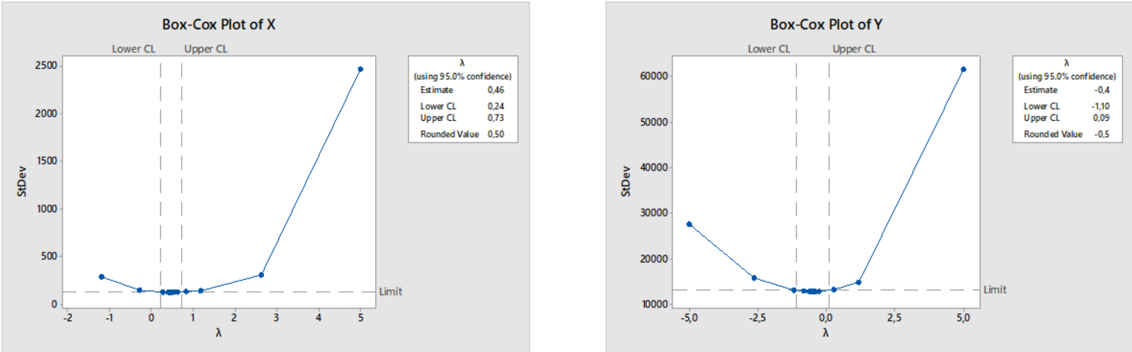

Figure 2. Box-Cox Plot of Rainfall and Price of Cayenne Pepper Data

Based on **Figure 2**, it can be seen that the data is not yet stationary in variance, because the value of λ in the input series is 0.50 so it must be transformed using $\sqrt{Z_t}$ and the value of λ in the output series is -0.50 so it must be transformed using $\frac{1}{\sqrt{Z_t}}$.

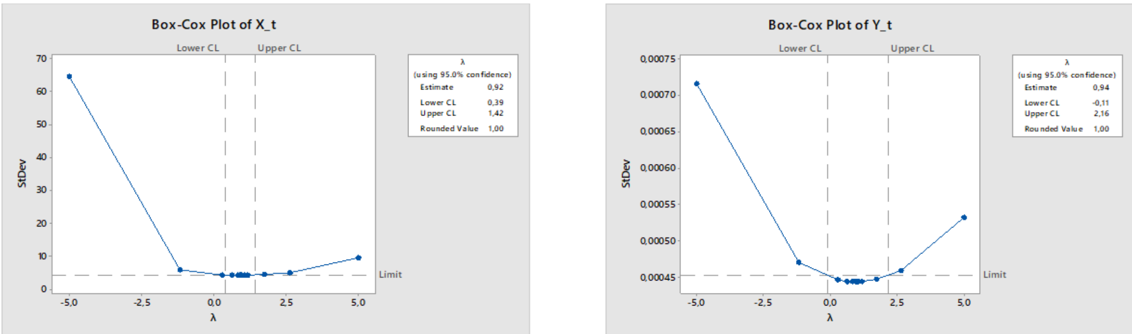

Figure 3. Box-Cox Plot of Rainfall and Cayenne Pepper Price Data After Transformation

After Box-Cox transformation, the value of λ is 1 so that no further Box-Cox transformation is required. This means that the x_t and y_t series is stationary in variance after the second Box-Cox transformation.

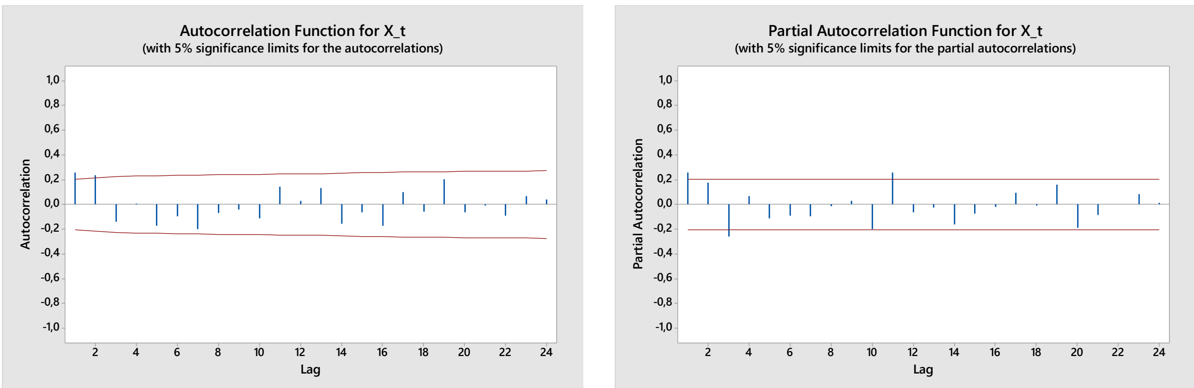

Figure 4. ACF and PACF Plots of x_t

in **Figure 4**, it can be seen that the ACF plot has a cut off at lags 1 and 2, while the PACF plot has a cut off at lags 1 and 3, so the alleged ARIMA rainfall models are ARIMA (1,0,1), ARIMA (1,0,2), ARIMA (3,0,1), ARIMA (3,0,2), ARIMA (3,0,0), and ARIMA (0,0,2).

Table 3. Parameter Estimation of the Input Series ARIMA Model

Model	Parameters	Coefficient	$p-value$	μ	MAPE
ARIMA (1,0,1)	ϕ_1	0.4774	0.1918	15.2072	27.96%
	θ_1	−0.2205	0.2931		
ARIMA (1,0,2)	ϕ_1	−0.8031	0.0000	15.1871	27.84%
	θ_1	1.0894	0.0000		
	θ_2	0.4313	0.0000		
ARIMA (3,0,1)	ϕ_1	−0.1175	0.6635	15.1907	27.85%
	ϕ_2	0.3234	0.0030		
	ϕ_3	−0.1985	0.1159		
	θ_1	0.4096	0.1278		
ARIMA (3,0,2)	ϕ_1	0.6141	0.0000	15.2865	27.99%
	ϕ_2	0.6913	0.0000		
	ϕ_3	−0.4296	0.0000		
	θ_1	−0.4092	0.0055		
	θ_2	−0.5908	0.0000		
ARIMA (3,0,0)	ϕ_1	0.2597	0.0097	15.1883	27.90%
	ϕ_2	0.2422	0.0172		
	ϕ_3	0.0988	0.0081		
ARIMA (0,0,2)	θ_1	0.3115	0.0035	15.2109	27.96%
	θ_2	0.3194	0.0017		

After parameter estimation and model diagnosis, the best ARIMA model for the input series is ARIMA (1,0,2) with the equation:

$$x_t = 27.3839 - 0.8031x_{t-1} + e_t - 1.0894e_{t-1} - 0.4313e_{t-2}$$

The initial stage in 59odelling the input series transfer function is prewhitening the x_t, with the equation $\alpha_t = x_t - 27.3839 + 0.8031x_{t-1} - 1.0894\alpha_{t-1} - 0.4313\alpha_{t-2}$ and prewhitening the y_t, namely $\beta_t = y_t - 27.3839 + 0.8031y_{t-1} - 1.0894\beta_{t-1} - 0.4313\beta_{t-2}$. Next is to find the cross correlation that will be used to find the value of (b, s, r).

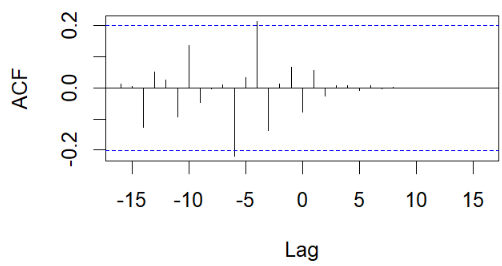

Figure 5. CCF Plot of $\boldsymbol{x_t}$ and $\boldsymbol{y_t}$

Based on **Figure 5**, a temporary transfer function model that can be used for the relationship between rainfall and cayenne pepper prices is $(b, s, r) = (4,0,0)$. So that the temporary transfer function model is,

$$y_t = \delta_0 x_{t-4} + n_t$$

Next, the noise series ARMA model obtained from the output of the temporary transfer function model is sought. The noise series ARMA model that has met the requirements in forming the transfer function model is the ARMA (3,0) model.

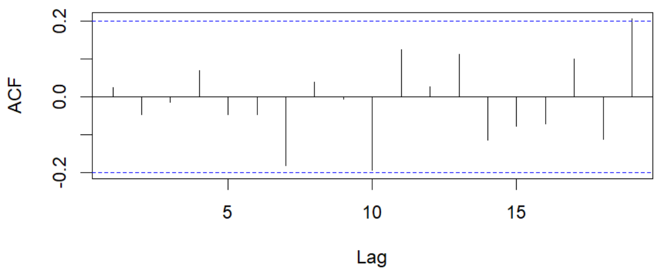

Figure 6. ACF Plot of Noise Series Residuals

Based on **Figure 6**, the ACF value of the ARMA (3,0) residuals is within significant limits, indicating that there is no residual correlation between time lags, so it can be concluded that the assumption of residual freedom can be fulfilled.

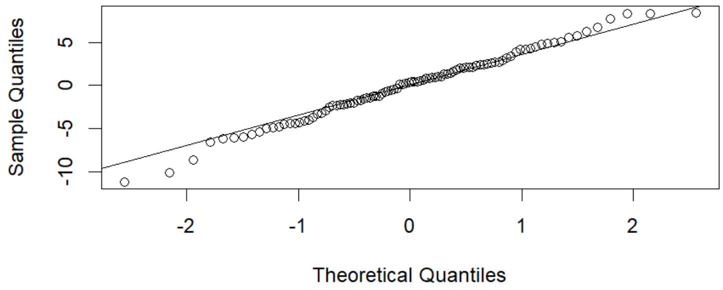

Figure 7. Normality Plot of Noise Series Residuals

Based on **Figure 7**, the points of the ARMA model formed spread quite close to the diagonal line, it can be concluded that the normality assumption is met or it can also be said that the six models formed are normally distributed. Thus, the ARMA (3,0) model can be expressed in the following equation:

$$(1 - \phi_1 B - \phi_2 B^2 - \phi_3 B^3) n_t = \alpha_t$$

The final model of the cayenne pepper price transfer function influenced by rainfall is as follows:

$$\hat{Y}_t = 0.00003156 x_{t-4} + 0.2472 n_{t-1} + 0.2451 n_{t-2} - 0.2617 n_{t-3} + \alpha_t$$

The results of the cayenne pepper price forecast in Singkawang City in 2024 can be seen in **Figure 6**.

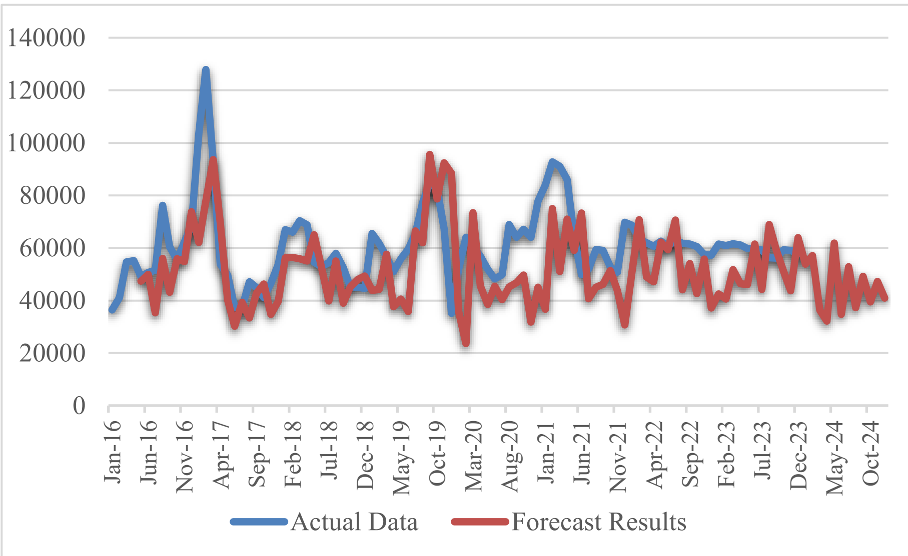

Figure 8. Plot of Actual Data and Forecast Data

In **Figure 6**, it shows that the forecast model can follow the price pattern of cayenne pepper in Singkawang City, but there are still deviations in certain periods. The results of forecasting the highest price of cayenne pepper in Singkawang City in 2024, namely in May 2024, amounting to IDR 61,899, while the lowest price of cayenne pepper in Singkawang City is in April, amounting to IDR 32,206.

4. Conclusions

The best transfer function model to forecast the price of cayenne pepper in Singkawang City is the transfer function model $(b, r, s) = (4,0,0)$ with ARMA (3,0) noise series based on the influence of rainfall. The results of this forecasting produce a MAPE value of 22.27%, indicating that the model's forecasting error is around 22% on average, which is considered acceptable for agricultural price forecasting. MAPE is used because it expresses the prediction error in percentage form, making it easy to interpret and compare model performance. These findings suggest that rainfall significantly influences the price dynamics of cayenne pepper in Singkawang City, implying that weather-related factors play an important role in market fluctuations. The model can therefore serve as a useful tool for local policymakers, traders, and farmers to anticipate price changes and plan better inventory and marketing strategies.

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