Application of ARIMA-Decomposition in Forecasting Cocoa Exports in Indonesia

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ABSTRACT – **Cocoa is one of Indonesia's primary commodities, playing an important role in the national economy, particularly in the agricultural and export sectors. However, Indonesia's cocoa exports have shown a declining trend in recent years, caused by a reduction in cocoa production. Therefore, more accurate forecasting is needed to support effective decision-making and maintain the competitiveness of this commodity. This research aims to obtain forecasts for cocoa exports in Indonesia using the ARIMA-decomposition method. The data used is secondary data obtained from the Central Statistics Agency's publication website. The data used is monthly data from 2014-2024 using the ARIMA-decomposition method The cocoa export variable referred to in this research is the volume of cocoa exports in Indonesia per month. The research results show that there are two models obtained, namely the ARIMA (1,0,0) and ARIMA (0,0,1) models. The ARIMA model (0,0,1) is the best because it has a smaller RMSE value than the ARIMA model (1,0,0). With results of forecasting cocoa export values using the hybrid ARIMA-decomposition method, namely January 2024 is 90,756,803.63, February 2024 is 94,087,978.29, March 2024 is 100,169,842.39, April 2024 is 90,693,529.69, May 2024 is 93,809,122.09, June 2024 is 100,601,810.69, July 2024 is 99,660,519.59, August 2024 is 105,630,962.89, September 2024 is 106,286,365.49, October 2024 is 103,843,814.89, November 2024 is 111,066,384.00, and December 2024 is 100,610,577.39.**
Keywords– **ARIMA, decomposition method, cocoa export**

I. INTRODUCTION

Cocoa is one of Indonesia's primary commodities that plays an important role in the national economy, particularly in the agricultural and export sectors. Cocoa beans are one of Indonesia's main export commodities, ranking fourth in terms of foreign exchange earnings [1].Based on total cocoa exports, Indonesia ranks 12th as a global cocoa exporter, contributing 2.32% of the world's total cocoa exports in 2022, which amounted to USD 54.47 billion. As a cocoa-producing country, Indonesia faces various challenges in the global market, including international price fluctuations, climate change, and varying demand from export destination countries [2].In recent years, Indonesia's cocoa exports have shown a declining trend, both in terms of volume and ranking as a global producer. Indonesia has experienced a decline in cocoa production of 8.3 percent per year during the period from 2015 to 2023. According to [3], cocoa bean productivity in Indonesia has been on a downward trend in recent years, leading to a decrease in cocoa export value. This situation requires serious attention in policymaking to maintain the competitiveness of this commodity. To support better strategic decision-making, forecasting cocoa exports becomes very important.

Forecasting is a method that is based on past data and analyzed scientifically to predict what will happen in the future. Time series, also known as "time series" is the most commonly used and developed forecasting method to date. A time series is a collection of data collected over a certain period of time and can be weekly, monthly or yearly data. Decomposition - ARIMA is an attractive choice of time series method because of its ability to identify and model the main components in a time series. Decomposition allows the separation between trend and seasonality, while random will be predicted using the ARIMA method to increase the accuracy of forecasting results [4] . The combination of the two is expected to provide a more accurate picture of cocoa export forecasting to help stakeholders in making decisions. There is previous research that uses the ARIMA-decomposition method [5] conducted research to predict the number of international aircraft arrivals at Soekarno-Hatta Airport using the Arima-Decomposition Method. The main model obtained is (2,1,1) and there are 3 other supporting models where the best is the (1,1,0) model. From this model, forecasting was carried out for the next 12 periods, namely from January-December 2022 and it was found that the accuracy level was 91.069716 or 91.0%, meaning the forecast was accurate.

Previous research that used the ARIMA-decomposition method was [6] conducting research to predict the number of international aircraft arrivals at Soekarno-Hatta Airport using the Arima-Decomposition Method. Based on the results of the analysis carried out, the Decomposition method provides the best performance seen from the smallest error value so that it can be used to make forecasts and produces RMSE values of 5201.694, MAPE of 0.955827 and MASE of 0.0129691. The results of forecasting using the Decomposition method are that the highest forecast occurred in December, while the lowest occurred in January with amounts of 1,439,439 (tons) and 1,117,000 (tons).

II. LITERATURE REVIEW

Decomposition Method

The decomposition method is one of the oldest predictive approaches. This method was used by economists in the early 20th century to identify and control economic cycles and business cycles. The basis of the modern decomposition method was born in the 1920s when the concept of ratio (trend) was introduced [7]. The decomposition method is a prediction method that mainly uses four components in predicting future values. These four factors include trend, seasonality, cycle, and error. The decomposition method is based on the assumption that existing data is a combination of several components, which are briefly described as follows [8].

Data = Pattern + Error

= f (trend, Cycle, seasonal)

The above assumption means that there are four components that influence a time series: three components that can be identified because they have certain patterns: trend, cycle, and seasonality. The general mathematical equation for the decomposition approach is:

$$X_1 = f(T_t, S_t, C_t, I_t) \quad (1)$$

where:

X_1 : periodic series value (actual data) in period t;
T_t : trend component in period t;
S_t : seasonal component in period t;
C_t : Cyclic component in period t;
I_t : Irregular error component in period t;
t : Period (time).

Decomposition methods include additive decomposition models and multiplicative decomposition models. Additive and multiplicative decomposition models can be used to predict trends, seasonal factors, and cyclical factors. The simple average decomposition method assumes an additive model that can be described mathematically.

$$Y_t = T_t + S_t + C_t + I_t \quad (2)$$

In contrast, the moving data decomposition method (classical decomposition) assumes that the multiplicative model can be described mathematically.

$$Y_t = T_t - S_t - C_t - I_t \quad (3)$$

The error component is assumed to be the difference from a combination of trend, periodic, and confidence components and actual data. This assumption is based on the assumption that there are four factors that influence the time series, three factors that can be identified because they have a certain pattern: trend, periodicity, and seasonality, while the error component is not systematic so it has a pattern. unpredictable. and shows irregular movements. The steps for using the Decomposition method for forecasting are [9]:

a. Compile daily/weekly/monthly/quarterly and yearly data.
b. Create a linear trendline scatter diagram.
c. Calculate the magnitude of the trend value.

ARIMA Method

Time series analysis and forecasting is an active area of research. This means that research regarding the accuracy of the time series forecasting process in the decision making is still being carried out. Several studies have used statistical methods, neural networks, wavelets, or fuzzy systems to investigate time series. Prediction models are based on statistical mathematics such as moving average, exponential smoothing, regression (parametric and non-parametric), and the most frequently used is ARIMA (Box Jenkins) [10].

The ARIMA or Autoregressive Integrated Moving Average method is used to obtain a prediction model based on existing time series data. The ARIMA model is different from most other predictive models because it does not require specific past data patterns. In the ARIMA process there is a very important and useful operation, namely the operator running backwards (backward shift) B which can be defined as follows [11].

$$BZ_t = Z_{t-1} \quad (4)$$

Where Z_t t is the time series data at time t and Z_{t-1} is the time series data at time (t-1) which will be used to present the models contained in the ARIMA process. These models can be explained in more detail as follows:

AR (Autoregressive) Model

In general, the autoregressive model with order p can be formulated as follows

$$Z_t = \mu + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + a_t \quad (5)$$

Where:

μ : constant value
ϕ_k : autoregressive parameter to-k ; for $k = 1.2 \ldots., p$
ε_t : residual value at time t

MA (Moving Average) Model

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In general, the moving average model with order q can be formulated as follows:

$Z_t = \mu + \varepsilon_t - \theta_1\varepsilon_{t-1} - \theta_2\varepsilon_{t-2} - \cdots - \theta_p a_{t-q}$ (6)

where θ_j: *moving average* parameter to-j ; for $j = 1.2 \ldots, q$

ARMA (Autoregressive Moving Average) Model

This model is a combined model of the AR (p) model and the MA (q) model, which can be formulated as follows:

$$Z_t = \mu + \phi_1 Z_{t-1} + \phi_2 Z_{t-2} + \cdots + \phi_p Z_{t-p} + a_t - \theta_1 a_{t-1} - \theta_2 a_{t-2} - \cdots - \theta_p a_{t-q} \quad (7)$$

C. ARIMA Model Selection Procedure

The Box-Jenkins procedure used to select the ARIMA model includes:

Identification of Temporary Prediction Model

The ARIMA model introduced by Box and Jenkins with orders p and q is used for time series data that has undergone processing (differentiating) or is stationary on average. The ARIMA model introduced by Box and Jenkins with orders p and q is used for time series data that has undergone processing (differentiating) or is stationary on average. Form for ARIMA model (*p, d, q*):

$$\phi_p(B)(1-B)^d Y_t = \theta_0 + \theta_q(B)a_t \quad (8)$$

With

$\phi_p(B) = (1 - \phi_1 B - \cdots - \phi_1 B^p)$ dan $\theta_q(B) = (1 - \theta_1 B - \cdots - \theta_1 B^q)$

If the data follows a seasonal pattern, the ARIMA model is denoted as ARIMA $(P, D, Q)^s$. In general, the ARIMA model ARIMA $(p, d, q)(P, D, Q)^s$ is a Box-Jenkins seasonal multiplicative ARIMA model and can be written as [10]:

$$\phi_p(B)\phi_p(B^s)(1-B)^d(1-B)^D Y_t = \theta_0 + \theta_q(B)$$
$$\theta_Q(B^s)a_t \quad (9)$$

where:

(p, d, q) : regular AR, differencing, and MA orders

(P, D, Q) : seasonal AR, differencing, and MA orders

$(1-B)^d$: regular differencing order

$(1-B)^D$: seasonal differencing order

Parameter Estimation

The Least Square Method is a method of finding parameter values by minimizing the sum of squared errors (the difference between the actual value and the predicted value), and is expressed in the form of the following equation [11].

$$\hat{\infty} = \frac{\sum_t^n Z_t - \phi \sum_t^n Z_{t-1}}{(n-1)(1-\phi)} \quad (10)$$

$$\phi = \frac{\sum_t^n (Z_t - \bar{Z})(Z_{t-1} - \bar{Z})}{\sum_t^n (Z_t - \bar{Z})^2} \quad (11)$$

$$\theta = \frac{\sum_t^n (Z_t - \bar{Z})(a_t - \overline{Z})}{\sum_t^n (Z a_t - 1)^2} \quad (12)$$

3. Diagnostic Examination

a) Residual Independence Test

The residual independence test is carried out by examining the pair of ACF and PACF residual diagrams. Autocorrelation Function, abbreviated as ACF, is a function that shows the magnitude of the correlation (linear relationship) between observations at time t (notated by Z_t) and observations at previous times. Meanwhile, PACF is a function that shows the magnitude of the partial correlation between observations at time t. t (notated as Z_t) with observations at previous times [12]. To test the independence of the residuals, namely by comparing the Ljung Box test with the Chi-Square Distribution:

H_0 : residual meets white noise requirements ($\rho_1 = \rho_2 = \cdots = \rho_k = 0$)

H_1 : residual is not yet white noise ($\rho_1 \neq 0, j = 0,1, \ldots, K$)

Test statistics:

$$Q^* = n(n+2)\sum_{k=1}^{K}\left(\frac{\hat{\rho}_k^2}{n-k}\right) \quad (13)$$

with:

$\hat{\rho}_k^2$: residual lag k autocorrelation. with $k = 0,1,2, \ldots$,

K : maximum lag

n : number of data

k : lag ke-k

Test criteria:

Reject H_0 if $Q < \chi^2_{(a:k-p-q)}$ (value $a = 0{,}05$) atau jika $p - value < a$.

If H_0 reject, then the ARIMA model $(p.d.q)$ is not suitable for use.

b) Normality Test

This test helps to determine whether the data collected is normally distributed or taken from a normal population. The P value resulting from the output of the Kolmogorov-Smirnov process. Based on the experience of several statisticians, it can be assumed that data containing more than 30 numbers (n > 30) is normally distributed. If the sample size (n) is large enough, then the entire population is large enough. Regardless of the probability value, the sample is most likely normally distributed[13].

Selection of the Best Model

There are many ways to get more than one ARIMA model. Therefore, it requires the best model to be selected. There are several calculations that are commonly used to calculate forecasting errors, one of which is RMSE. RMSE is a calculation of the error from the value of the average error in an observation, so RMSE is usually used to determine the size of the error in the data from the model. RMSE can be calculated using the following formula [14]:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\bar{\bar{X}} - X_i)^2} \tag{14}$$

Where:

n : the number of residuals

$\bar{\bar{X}}$: value of forecasting results

X_i : value of the observation object.

D. Cocoa Exports in Indonesia

Cocoa plays an important role as a plantation commodity subsector agriculture in economic activities Indonesia. Apart from oil and gas, cocoa is also an important commodity Indonesia's export country's foreign exchange earner. As an agricultural commodity subsector the country's third foreign exchange earning plantation after palm oil and rubber, Cocoa collection of state foreign exchange of US$ 1.24 billion. That matter shows the important role of cocoa in economic improvement [15]. As cocoa production increases from year to year, exports Indonesian cocoa is also experiencing an increasing trend. Obtained cocoa export data Indonesia from data alerts from the Directorate General of Plantations that in In 1995, Indonesian cocoa exports reached 233,593 tons with a value of USD 309,328,000.00 and increased so that in 2015 exports Indonesian cocoa amounted to 355,321 tons with a value of USD 1,307,771,000.00 (Plantation 2016) accessed July 2017. The increase in Indonesian cocoa exports is good in volume and even its value from year to year shows that potential Cocoa market is still high in the international market. As cocoa production increases from year to year, exports Indonesian cocoa is also experiencing an increasing trend. Obtained cocoa export data Indonesia from data alerts from the Directorate General of Plantations that in In 1995, Indonesian cocoa exports reached 233,593 tons with a value of USD 309,328,000.00 and increased so that in 2015 exports Indonesian cocoa amounted to 355,321 tons with a value of USD 1,307,771,000.00 (Plantation 2016) accessed July 2017. The increase in Indonesian cocoa exports is good in volume and even its value from year to year shows that potential Cocoa market is still high in the international market [16]

Cocoa is also one of Indonesia's export commodities which has an important role in increasing Indonesian national income. This can be seen from the large increase in the average value Indonesian cocoa exports were around 6.52% and the average increase in cocoa export volume was 0.93% in 2005-2019Indonesia's cocoa export market is now reaching all market areas in the world, such as Asia, America, Europe, Africa, and so on Australia. The countries that are Indonesia's main destination for exporting cocoa Among them are Malaysia, the United States, China, India, the Netherlands and the Philippines. There are differences in demand for Indonesian cocoa export volumes from the export destination country [17].

III. METHODOLOGY

A. Type of Research

This research is applied research with a quantitative approach, namely collecting data and carrying out analysis using the ARIMA-decomposition method.

B. Data Source

The data used is secondary data obtained from the Central Statistics Agency's publication website. The data used is monthly data from 2014-2024.

C. Research Variables

The variable used in this research is cocoa exports in Indonesia. The cocoa export variable referred to in this research is the volume of cocoa exports in Indonesia per month from the 2014-2024 period.

D. Data Analysis Techniques

The stages in forecasting using the ARIMA-decomposition method are as follows:

1. Enter data.
2. Separate the data into several components, namely trend, seasonal, and random components using the decomposition method.
3. Forecasting trends and seasonal components using the decomposition method.
4. Carry out random component forecasting using the ARIMA method with the following stages:

Perform stationary checks in variance and mean on random components.
If stationarity in the variance is not fulfilled then transformation is carried out, whereas if stationarity in the mean is not fulfilled then differencing is carried out.
Create Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots.
Identify the initial guess form of the ARIMA model by looking at the ACF and PACF plots.
Estimating parameters for each initial estimate of the ARIMA model and conducting parameter significance tests.
Perform diagnostic checks for white noise and normal distribution on the residuals of each initial estimate of the ARIMA model
If more than one ARIMA model is obtained, then the best model is selected by looking at the smallest RMSE value.
Perform forecasting on random components.
5. Combine forecasting results in trend, seasonal, and random components.

IV. RESULTS AND DISCUSSIONS

Descriptive Analysis

The data used in this research is cocoa export value (USD) data from January 2014 to December 2023. The cocoa export value data plot is shown in Figure 1 below.

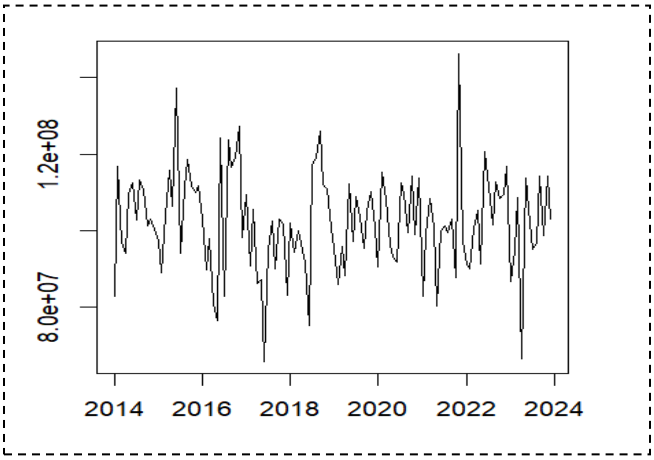

Figure 1 Data Plot of Cocoa Export Value

Based on Figure 1, it can be seen that data on the value of cocoa exports has increased and decreased from year to year. Descriptive results of cocoa export data are shown in Table 1 below.

Table 1 Descriptive Analysis of Cocoa Export Value (USD) Data

Data	Minimum	*Mean*	Maximum
Cocoa Exports	65,934,838	102,213,169	146,292,008

Based on Table 1, it is known that the minimum value in June 2017 was 65,934,838 and the maximum value in November 2021 was 146,292,008, with an average value of 102,213,169.

B. Decomposition Method

The initial stage in the decomposition method is to break down the data into 3 main components, namely trend, seasonal, and random components. The decomposition results plot is shown in Figure 2.

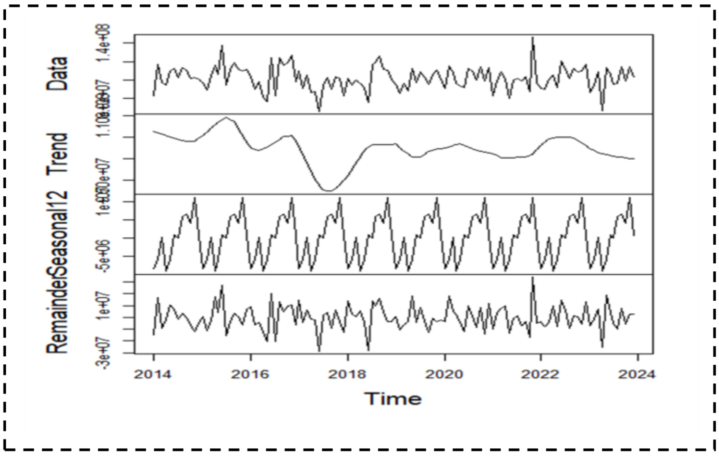

Figure 2 Plot of Decomposition Results

Figure 2 shows a plot of baseline, trend, seasonal, and random data. The next stage is to forecast each component of the decomposition results. The trend and seasonal components are predicted using the decomposition method, while the random component is predicted using the ARIMA method. The results of forecasting trends and seasonal components using the decomposition method are shown in Table 2 below.

Table 2 Trend and Seasonal Component Forecasting Results

Month-Year	Forecasting Trends	Seasonal Forecasting
January 2024	99,962,872	-8,289,892.3
February 2024	99,899,278	-5,821,082.2
March 2024	99,835,683	324,376.9
April 2024	99,808,223	-9,124,475.8
May 2024	99,793,278	-5,993,938.4
June 2024	99,775,185	816,843.2
July 2024	99,757,092	-106,354.9
August 2024	99,772,253	5,848,927.4
September 2024	99,787,415	6,489,168.0
October 2024	99,821,532	4,012,500.4
November 2024	99,861,687	11,194,914.6
December 2024	99,951,780	649,014.9

C. ARIMA Method

After obtaining forecasts on the trend and seasonal components, then forecasting is carried out on the random components using the ARIMA method. The initial stage in the ARIMA method is to check the stationarity of the data.

1. Data Stationarity Test

The stationarity test carried out is the stationarity test in variance and the stationarity test in average. The stationary test results in variance are shown in Table 3 below.

Table 3 Trend and Seasonal Component Forecasting Results

Box-Cox Lambda	Λ
	1.058946

Based on Table 3, it is known that the value of $\lambda = 1.058946$, so it can be concluded that the data is stationary in terms of variance. Next, a stationarity test was carried out on the average. The stationary test results in variance are shown in Table 4 below.

Table 4 Stationarity Test in Means

Uji *Augmented Dickey-Fuller* (ADF)	*p-value*
	0.01

Based on Table 4, it is known that the p-value in the ADF test is 0.01, where this value is smaller than $\alpha = 0.05$. So it can be concluded that the data is stationary on average.

2. Model Identification

After testing the stationarity of the data, the next step is to identify the model by looking at the ACF and PACF plots. The ACF and PACF plots are shown in Figure 3 below.

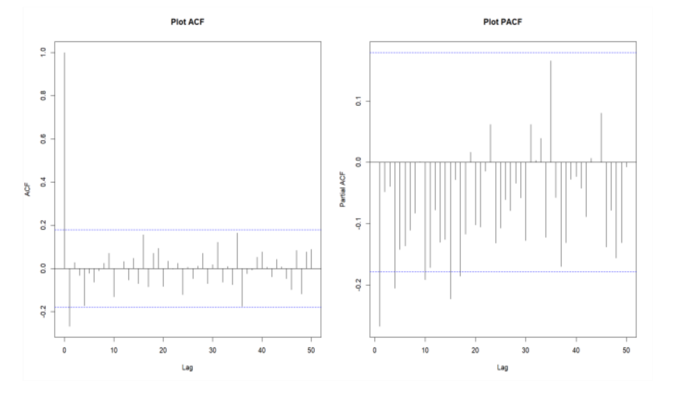

Figure 3 ACF Plot and PACF Plot

Based on Figure 3, it can be seen that the ACF and PACF plots show the same pattern, namely the cut-off after lag 1. So the temporary estimation models used are ARIMA (1,0,0) and ARIMA (0,0,1).

3. Parameter Estimation

After obtaining the estimated temporary model, the next step is to test the significance of the parameters on the estimated model. The results of the parameter significance test in the ARIMA (1,0,0) and ARIMA (0,0,1) models are shown in Table 5 below.

Table 5 Parameter Significance Test

Model	Parameter	*p-value*
ARIMA (1,0,0)	$\emptyset_1 = -0.270100$	0.002209
ARIMA (0,0,1)	$\theta_1 = -0.304975$	0.002145

Based on Table 5, it can be seen that the parameters of all models are significant. This can be seen from the p-value < $\alpha = 0.05$.

4. Residual White Noise Test

A model is said to be feasible if the residuals in the model are uncorrelated and follow a random process (white noise). The results of the white noise residual test on the ARIMA (1,0,0) and ARIMA (0,0,1) models are shown in

Table 6 Residual White Noise Test

Model	*p-value*
ARIMA (1,0,0)	0.9093
ARIMA (0,0,1)	0.8694

Based on Table 6, it can be seen that the residuals of the two models have met the white noise assumption. This can be seen from the p-value > $\alpha = 0.05$.

5. Normally Distribution Residual Test

Normal distribution test on residuals using the Kolmogorov Smirnov test. The results of the normal distribution test on the residuals of the ARIMA (1,0,0) and ARIMA (0,0,1) models are shown in Table 7 below.

Table 7 Normally Distribution Residual Test

Model	*p-value*
ARIMA (1,0,0)	0.3243
ARIMA (0,0,1)	0.4172

Based on Table 7, it can be seen that the residuals of the two models fulfill the normal distribution assumption. This can be seen from the p-value > $\alpha = 0.05$.

6. Determine the Best ARIMA Model

After the parameter significance test, white noise test, and normal distribution test are carried out, it can be seen that the ARIMA (1,0,0) and ARIMA (0,0,1) models can be used. To determine the best ARIMA model, the RMSE value of the two models is calculated. A comparison of RMSE values is shown in Table 8 below.

Table 8 RMSE value in the ARIMA model

Model	RMSE
ARIMA (1,0,0)	10282685
ARIMA (0,0,1)	10252339

Based on Table 4.8, it can be seen that the ARIMA model (0,0,1) is the best because it has a smaller RMSE value than the ARIMA model (1,0,0). The following is the mathematical equation of the ARIMA model (0,0,1):

$$Z_t = a_t + 0.304975a_{t-1}$$

The results of random component forecasting using the ARIMA model (0,0,1) are shown in Table 9 below.

Table 9 RMSE value in the ARIMA model

Month-Year	Random Forecasting
January 2024	-916,176.073
February 2024	9,782.491
March 2024	9,782.491
April 2024	9,782.491
May 2024	9,782.491
June 2024	9,782.491
July 2024	9,782.491
August 2024	9,782.491
September 2024	9,782.491
October 2024	9,782,491
November 2024	9,782.491
December 2024	9,782.491

D. Combining Forecasting Results

After obtaining forecasts for each component, the results of the forecasts are then combined. The combination of forecasting results for trend, seasonal, and random components is shown in Table 10 below.

Table 10. Combining Forecasting Results

Month-Year	Trend Forecasting	Seasonal Forecasting	Random Forecasting	Forecasting
January 2024	99,962,872.00	-8,289,892.30	-916,176.07	90,756,803.63
February 2024	99,899,278.00	-5,821,082.20	9,782.49	94,087,978.29
March 2024	99,835,683.00	324,376.90	9,782.49	100,169,842.39
April 2024	99,808,223.00	-9,124,475.80	9,782.49	90,693,529.69
May 2024	99,793,278.00	-5,993,938.40	9,782.49	93,809,122.09
June 2024	99,775,185.00	816,843.20	9,782.49	100,601,810.69
July 2024	99,757,092.00	-106,354.90	9,782.49	99,660,519.59
August 2024	99,772,253.00	5,848,927.40	9,782.49	105,630,962.89
September 2024	99,787,415.00	6,489,168.00	9,782.49	106,286,365.49
October 2024	99,821,532.00	4,012,500.40	9,782.49	103,843,814.89
November 2024	99,861,687.00	11,194,914.60	9,782.49	111,066,384.09
December 2024	99,951,780.00	649,014.90	9,782.49	100,610,577.39

The plot of the results of forecasting cocoa export values using the hybrid ARIMA-decomposition method is shown in Figure 4.

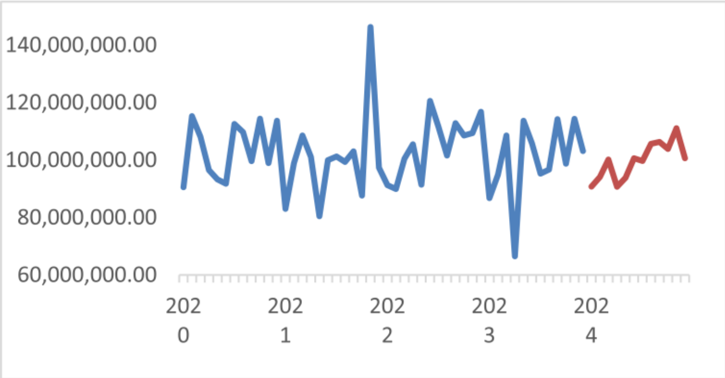

Figure 4 Plot of Forecasting Results

V.CONCLUSIONS AND SUGGESTION

The research results show that there are two models obtained, namely the ARIMA (1,0,0) and ARIMA (0,0,1) models. The ARIMA model (0,0,1) is the best ARIMA model, because it has a smaller RMSE value than the ARIMA model (1,0,0). With results of forecasting cocoa export values using the hybrid ARIMA-decomposition method, namely January 2024 is 90,756,803.63, February 2024 is 94,087,978.29, March 2024 is 100,169,842.39, April 2024 is 90,693,529.69, May 2024 is 93,809,122.09, June 2024 is 100,601,810.69, July 2024 is 99,660,519.59, August 2024 is 105,630,962.89, September 2024 is 106,286,365.49, October 2024 is 103,843,814.89, November 2024 is 111,066,384.00, and December 2024 is 100,610,577.39. The suggestion from this research is to use other methods in the time series to forecast cocoa exports and the ARIMA-decomposition method to forecast other case studies.

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