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MODELING AND FORECASTING THE TOTAL VOLUME OF GOODS TRANSPORTED BY RAIL IN INDONESIA USING SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (SARIMA)

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ABSTRACT

Transportation has an important role in supporting the mobility of people in Indonesia. Trains are included in the most widely used transportation category because they are effective and efficient, not only transporting passengers, trains also have a role in the distribution of goods. This study aims to model and forecast total volume of goods transported through rail transportation in Indonesia using the Seasonal Autoregressive Integrated Moving Average (SARIMA) Method because the data has seasonal trend. The data used comes from the Central Statistics Agency (BPS) from January 2013 to April 2024. The results were obtained that the SARIMA $(0,1,1)(0,1,1)^{12}$ model is the best model with a MAPE value of 0.96% which is included in the category of accurate model. In addition to being an additional insight, this research can also be a reference in the management of railway transportation considering the number of uses both passengers, the distribution of goods that continue to increase, and can be recommendation for other research that same topic with it.

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1. INTRODUCTION

Transportation is an important aspect for humans in carrying out daily activities both in the distribution of goods, services, and manpower. Rail transportation has become one of the mobility support tools that are in demand in Indonesia since the introduction of the first railway line in 1864. Kereta Api Indonesia (Persero) is a transportation service company that manages railway services that are considered to be able to avoid people from congestion [1]. As one of the efficient modes of transportation as explained earlier, trains could transport large quantities of goods at relatively low costs and high time efficiency. This makes railways play an important role in supporting the country's economic growth. In recent decades, the volume of goods transported by rail has shown a significant upward trend in line with the increase in economic activity and trade between regions.

According to data from the Central Statistics Agency (BPS), total volume of goods transported by train also increased by 7.87 percent to 5.7 million tons [2]. This increase reflects the vital role of rail transportation in supporting people's mobility and the distribution of goods across the country. To optimize logistics operations, accurate modelling and forecasting of goods transported by rail is crucial for better decision-making in scheduling, fleet management, and infrastructure development [3]. SARIMA is effective for such forecasting as it captures seasonal patterns and trends, which is important given the seasonal variations in transport volume, such as increases during harvest seasons or holidays.

Some studies that have been conducted have used a lot of the number of passengers with various kinds of the best models and various MAE values but only a few uses total volume of goods. The research that has been conducted previously is a study entitled "Forecasting the Number of Goods Through Rail Transportation in Indonesia Using SARIMA”. This study produced a more accurate model compared to the SARIMA model in previous studies, with a lower Mean Absolute Percentage Error (MAPE) value [4].

By using the SARIMA method, it is hoped more accurate and reliable, so that it can support the improvement of operational efficiency and the development strategy of railway transportation in Indonesia. This study aims to model and forecast the total volume of goods transported through rail transportation in Indonesia using the SARIMA method. The study is based on historical data on the volume of goods transported by rail, and uses the SARIMA method to identify patterns, trends, and seasonal components in the data. The results of this study aim to benefit rail transportation management and policymakers in planning better logistics infrastructure. Accurate forecasting supports operational aspects like schedule planning and resource allocation, and aids in developing future-ready infrastructure. Optimizing train operations enhances efficiency and contributes to economic sustainability by reducing logistics costs and carbon emissions.

2. RESEARCH METHODS

2.1 Data Sources and Research Variables

The method used in this study is quantitative. The method emphasizes the study of specific samples, quantitative or statistical data analysis, and testing of predetermined hypotheses [5]. The data used in this study is secondary data in the form of historical data sourced from the Central Statistics Agency (BPS) with Range data in January 2013 – April 2024. The research variable used in the study is total volume of goods through rail transportation in Indonesia taken monthly from the period of January 2013 – April 2023, there are 124 observations for training data and May 2023 – April 2024 is used for testing data.

2.2 Time Series Analysis

Time series analysis is a statistical method based on a time order, research data used based on time measures such as daily, weekly, monthly to yearly. Forecasting based on time series is forecasting that is carried out quantitatively based on relevant data in a certain period of time [6]. Time series analysis use data from observations of various of the time strands used, such as in hours, per day, per month, quarterly, quarterly, per year or more. Time series analysis is used in fields like weather forecasting, health science, business economics, and agriculture [7]. It involves observing data points in sequence at constant time intervals.

2.3 Box-Cox Transformation

Transformation Box-Cox is carried out when data is not stationary in variance [8]. Stationary data is rechecked in variance by looking at the transformation graph Box-Cox. Data that is stationary in variance has a lower bound and an upper bound that passes the number 1 or has a value of $\lambda = 1$

$$T(Z_t) = \frac{Z_t^{\lambda}-1}{\lambda} \tag{1}$$

Where:

λ : Parameter control from the transformation
Z_t : Original data
$T(Z_t)$: Transformed original data.

Introduced by Box and Cox in 1964, the Box-Cox table below shows some of the values with some type of lambda.

Table 1. The Value of Lambda and Its Types of Transformations

Value of λ	Types of Transformations
-1	$\frac{1}{Z_t}$
-0.5	$\frac{1}{\sqrt{Z_t}}$
0	$\ln Z_t$
0.5	$\sqrt{Z_t}$
1	Z_t
2	Z_t^2

2.4 Autocorrelation Function (ACF) and Partial Correlation Function (PACF)

Autocorrelation Function is a function that shows the magnitude of the correlation or linear relationship between observations at the present time *t* and observations at previous times [9]. In time series analysis, the ACF concept is very important for detecting the beginning of a model and data stationary. If the ACF plot tends to fall slowly or down linearly, then it can be concluded that the data is not yet stationary in the mean [10]. The autocorrelation value of the lag *k* is formulated as:

$$r_k = corr(Z_t, Z_{t-k}) = \hat{\rho}_k = \frac{\sum_{t=1}^{n-k}(Z_t-\bar{Z})(Z_{t+1}-\bar{Z})}{\sum_{t=1}^{n}(Z_t-\bar{Z})^2}. \tag{2}$$

This concept is used to measure the closeness between and if the effect of the time lag *t* = 1, 2, 3, ..., $k-1$ is considered separate. $Z_t Z_{t-k}$ *Partial Autocorrelation Function* is a function that shows the magnitude of the partial correlation (linear relationship separately) between observations at the present time *t* and observations at previous times. The partial autocorrelation value of the lag sample is formulated mathematically in the form of Durbin's formulation as follows [9].

$$\phi_{kk} = \frac{\rho_k - \sum_{j=1}^{k=1}\phi_{k-1},j\rho_{k-j}}{1-\sum_{j=1}^{k=1}\phi_{k-1},j\rho_j}. \tag{3}$$

2.5 Seasonal Autoregressive Integrated Moving Average (SARIMA)

In general, the seasonal time series analysis model is described as a model that has the following general forms: $(p,d,q)(P,D,Q)^s$ [11].

$$\Phi_p(B)\emptyset_P(B^S)(1-B)^d(1-B^S)^D Z_t = \theta_q(B)\Theta_Q(B^S)a_t,\ a_t \sim N(0,\sigma^2) \tag{4}$$

Where

p, d, q: order AR, differencing, MA non seasonal (NS)

P, D, Q: order AR,differencing, MA seasonal $(S) \longrightarrow 3, 4, 6, 12$
$\emptyset_P(B) = \left(1 - \emptyset_1 B - \emptyset_2 B^2 - \cdots - \emptyset_p B^p\right)$: Non-seasonal polynomials $AR(p)$
$\theta_q(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q\right)$: Non-seasonal polynomials $MA(q)$
$\Phi_p(B^S) = (1 - \Phi_1 B^S - \cdots - \Phi_P B^{PS})$: Seasonal Polynomial $AR(P)$
$\Theta_Q(B^S) = \left(1 - \Theta_1 B^S - \cdots - \Theta_Q B^{QS}\right)$: Seasonal Polynomial $MA(Q)$
a_t: Residual value at t time

2.6 Residual White Noise Assumption Test

The residual white noise assumption test of the SARIMA model is a basic assumption test that there is no correlation between residuals with a mean equal to zero, and constant variance [12]. The residual white noise independence test can be carried out using Ljung-Box test statistics with the following test hypotheses.

H_0: No correlation between error at time t and at time $\boldsymbol{t + k}$
H_1: There is a residual correlation between lags (there is at least one $r_k \neq 0$, where $k = 1,2,3, \ldots$).

Critical area: rejected H_0 if p-value $> \alpha$ (5%). The following are the results of the residual white noise assumption test with the Ljung-Box Test.

2.7 Forecasting

Forecasting is a calculation technique that uses data from previous times to estimate the likelihood that will occur in the future [13]. Forecasting is related to efforts to predict what will happen in the future, based on scientific methods (science and technology) and carried out mathematically. Forecasting is essential for planning budgets, sales, production, inventory, labor needs, and raw material requirements.

2.8 Mean Absolute Percentage Error (MAPE)

Mean Absolute Percentage Error (MAPE) is calculated using the absolute error in each period divided by the actual observed value for that period [14]. This approach is useful when the size or measure of a predictive variable is important in evaluating the accuracy of the prediction. MAPE shows how many errors in forecasting are compared to the actual value in the series. MAPE can also be used to compare the accuracy of the same or different methods in two different series and measure the accuracy of the model's estimated values expressed in absolute form of the mean percentage of error [9].

$$MAPE = \frac{\sum_{t=1}^{n} \left| \frac{Z_t - F_t}{Z_t} \right| \times 100\%}{n}, \tag{5}$$

Where:
Z_t: Actual data value, F_t: Forecast result value, n: Sample Size

Table 2. MAPE Value Category

Range of MAPE	Interpretation
$< 10\%$	The ability of forecasting models is excellent
$10\% - 20\%$	Good forecasting model capabilities
$20\% - 50\%$	Decent forecasting model capabilities
$> 50\%$	Poor forecasting model capabilities

2.9 Steps of Data Analysis

The method used in this data analysis is the Box-Jenkins time series analysis (SARIMA) method. The SARIMA model is used to predict future value based on past values [15]. The following are the steps to analyze data:

1. Computing statistic descriptive from the data which mean, standard deviation, minimum, maximum, Q1, median, and Q3.
2. Plotting the data of the volume of goods rail transported in Indonesia.

3. Dividing the data becomes two parts, training data from total volume of goods in January 2013 – April 2023 and testing data from total volume of goods in May 2023 – April 2024.
4. Identify the stationary of the data based on ACF plots, PACF plots, and Augmented Dickey-Fuller test. If the data is not yet stationary in variance, then the data must be transformed using the Box-Cox transform. If the data from the Box-Cox transformation is not stationary in the mean, then proceed with differencing.
5. Plotting ACF and PACF of the differenced and transformed data. SARIMA model can be used when indicate seasonal trend.
6. Determining some candidates of SARIMA model from the results of the ACF and PACF plots.
7. Estimating some candidates of SARIMA model of the order obtained.
8. Choosing the best model based on the parsimony concept.
9. Conducting the white noise test using Ljung-box method and residual normality test using the Kolmogorov-Smirnov method.
10. Create model equations and forecast for short-term.
11. Computing the MAPE based on the training data and based on the testing data,
12. If each the MAPE values is less than 10%, repeat Step 4 until step 9 to determine the next 12 months forecast.

3. RESULTS AND DISCUSSION

3.1 Data Descriptions

Based on monthly data on the number of goods loaded through rail transportation by island taken from the Central Statistics Agency (BPS) for the period January 2013 – April 2024. Descriptive statistics are obtained as follows:

Table 3. Descriptive Statistics on the Number of Goods Through Rail Transportation in Indonesia in 2013-2023

Variable	N	Mean	SE Mean	Standard Deviation	Minimum	Q1	Median	Q3	Maximum
Value	124	3683.3	88.8	989.3	1904.0	2806.5	3817.5	4398.8	5840.0

Based on the Table 3, it shows that the number of observations used in this study is 124 observations with an average of 3683.3 thousand tons with a standard deviation of 989.3. The largest total volume of goods distributed was 5840 thousand tons in December 2022 and the least was 1904 thousand tons in February 2013.

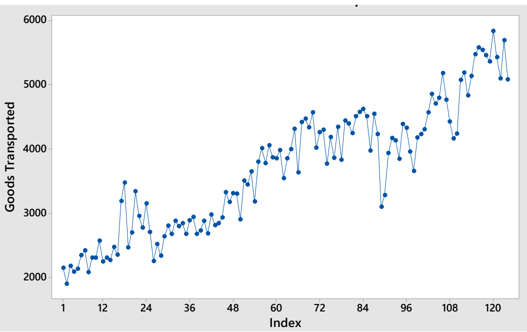


Figure 1. Plot Time Series Number of Goods Through Rail Transportation in 2013-2023

The number of goods distributed through rail transportation fluctuates up and down every month and tends to form an upward trend.

3.2 Data Stationary Identification

In SARIMA modeling, the first step is to identify the data is stationary in both mean and variance. This can be done using trend analysis graphs, ACF and PACF plots, and the Augmented Dickey-Fuller test (ADF). If the data is not stationary, apply a Box-Cox transformation followed by differencing to achieve stationarity in the mean and variance.

1. Data Stationary Identification

The first step is to examine the trend, ACF, and PACF plots of the time series data on goods transported by rail in Indonesia.

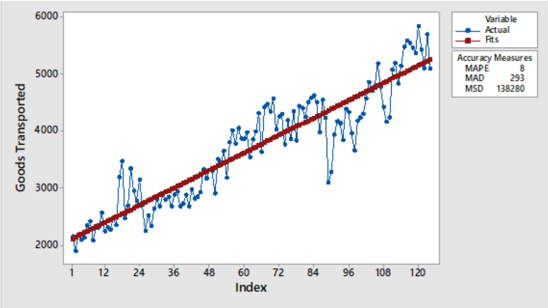
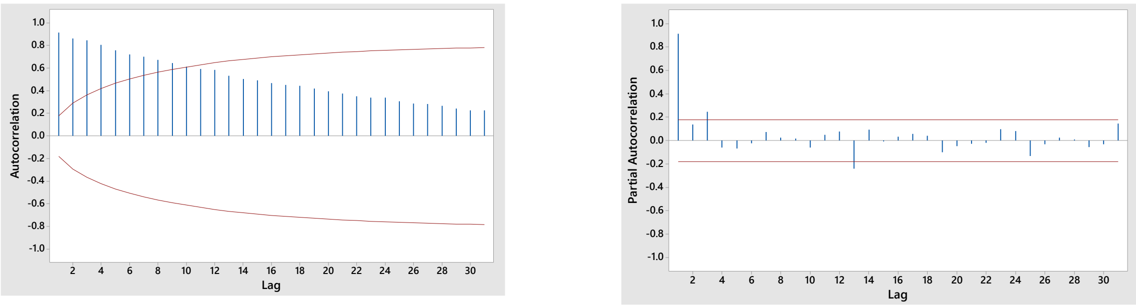


Figure 2. Trend Analysis Graph of the Number of Goods Through Rail Transportation in Indonesia in 2013-2023

Based on **Figure 2**, the number of goods distributed through rail transportation in Indonesia shows a upward trend in January 2013 – April 2023.



(a) (b)

Figure 3. Original Data Plot of the Number of Goods Through Rail Transportation in Indonesia in 2013-2023 (a)Autocorrelation Function, (b)Partial Autocorrelation Function

Figure 3 shows a slowly declining linear ACF, indicating the data is not stationary in the mean. The PACF plot shows significant lags at 1 and 12, suggesting the data is seasonal.

Table 4. Augmented Dickey-Fuller Test

Dickey-Fuller	*p*-value
-3.1976	0.09156

Based on **Table 4**, the results of the Augmented Dickey-Fuller (ADF) test obtained a p−value of 0.09156 which exceeded the alpha significance level (5%). Therefore, it can be concluded that the data is not stationary in the mean.

2. Box-Cox Transformation

Box-Cox transformation is performed to make the data stationary in variance.

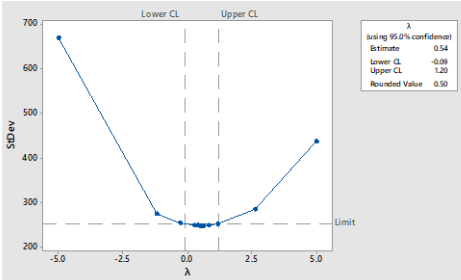
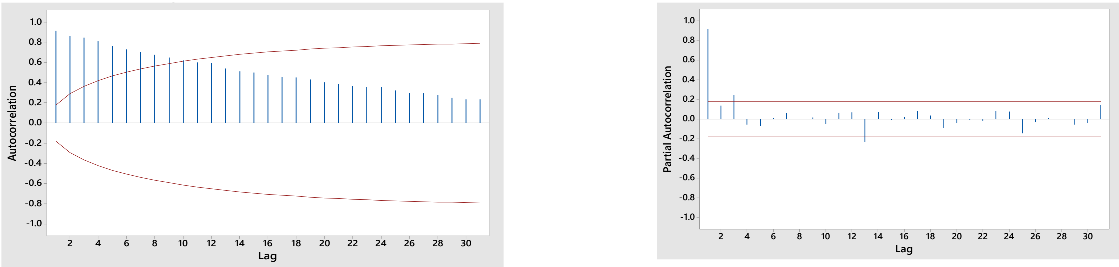


Figure 4. Box-Cox Transformation of Volume of Goods

Figure 4 indicates a rounded Box-Cox transformation parameter (lambda) of 0.50. This implies the transformation used is $\sqrt{Z_t}$. To verify if the transformed data is stationary in the mean, we check if the average value remains stable over time, with no evident upward or downward trend. Stationarity can also be assessed by examining the ACF and PACF plots of the transformed data.

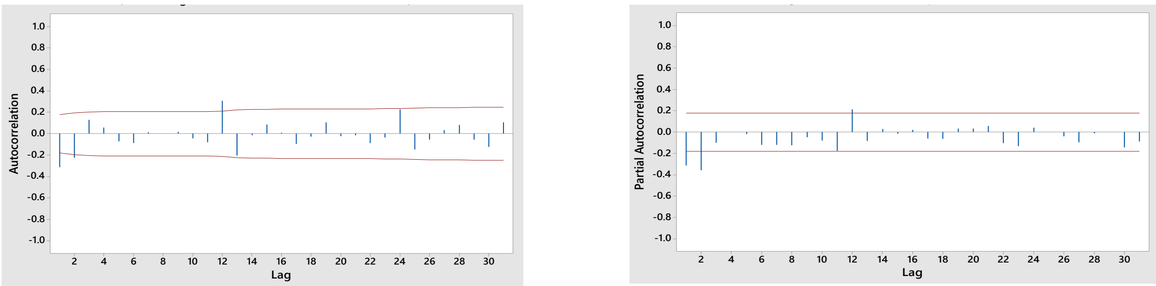


(a) **(b)**

Figure 5. Plot of The Transformed Data (a) ACF (b) PACF

Figure 5 shows a slowly declining linear ACF, indicating the data is not yet stationary in the mean. The PACF plot shows significant lags at 1 and 12, suggesting seasonality. Thus, the transformed data is not stationary in the mean, necessitating a differencing process.

3. Differencing Non-Seasonal

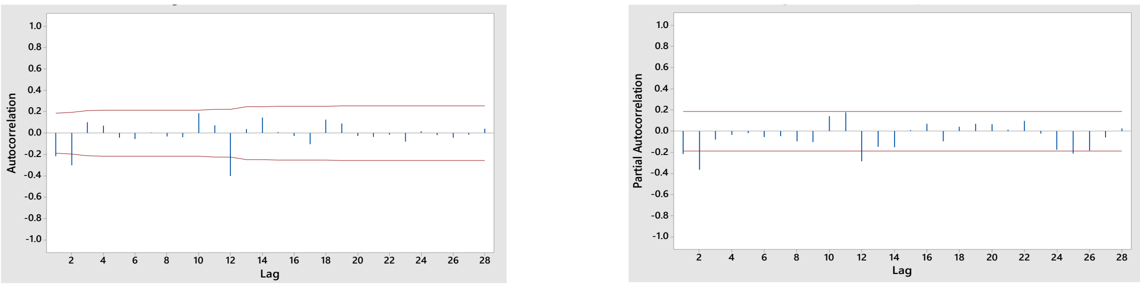


(a) (b)

Figure 6. Plot of the ACF and PACF of Differencing Lag-1 Results

In **Figure 6**, it can be seen in the ACF plot that the data of the differencing results in the 1st lag comes out of the 1st, 8th, and 12th lags. Meanwhile, on the PACF plot, the results of differencing the data at lag 1 appear on the 1st, 2nd, and 12th lags. This can be seen as an indication that the number of goods data forms a seasonal pattern in the 12th period, so it is necessary to do the differencing process in the 12th lag.

4. Differencing Seasonal



(a) (b)

Figure 7. Plot of the ACF and PACF of Differencing Lag-12 Results

Figure 7 shows that in the ACF plot, the differenced data is significant at the 1st, 2nd, and 12th lags. Similarly, in the PACF plot, the 1st, 2nd, and 12th lags are significant. This indicates the data is seasonal with a 12-period cycle.

3.3 Identification of the SARIMA Model

From the results of the previous ACF and PACF plots on **Figure 7**, it can be assumed that the model from the data is the SARIMA model with a period of 12. Identification of the conjecture SARIMA model is one of the stages to find the order $(p,d,q)(P,D,Q)^{12}$, namely with the non-seasonal order p for autoregressive (AR), d is differencing, and q is the order of moving average (MA). Then, for the seasonal order P for autoregressive (AR), D is the differencing, and Q is the moving average (MA) order. The results of the data stationarity test in the previous stage showed that the data needed to be differencing non-seasonal and seasonal each once to be stationary, this shows that the d and D orders each have a value of 1. The identification of the AR (p) and MA (q) orders is by observing the ACF and PACF patterns. The ACF plot is used to observe the MA model while the PACF is to observe the AR model. Thus, there are 15 SARIMA model candidates that should be estimated in **Table 5**.

Table 5. Seasonal Time Series Analysis Model Identification Result

Type	Name
$(1,1,1)(1,1,1)^{12}$	ARIMASARIMA
$(1,1,1)(0,1,1)^{12}$	ARIMASIMA
$(1,1,1)(1,1,0)^{12}$	ARIMASARI
$(0,1,1)(1,1,1)^{12}$	IMASARIMA
$(0,1,1)(0,1,1)^{12}$	IMASIMA
$(0,1,1)(1,1,0)^{12}$	IMASARI
$(1,1,0)(1,1,1)^{12}$	ARISARIMA
$(1,1,0)(0,1,1)^{12}$	ARISIMA
$(1,1,0)(1,1,0)^{12}$	ARISARI
$(1,0,1)(1,1,1)^{12}$	ARMASARIMA
$(1,0,1)(1,1,0)^{12}$	ARMASARI
$(1,0,1)(0,1,1)^{12}$	ARMASIMA
$(2,1,1)(1,1,1)^{12}$	ARIMASARIMA
$(2,1,1)(0,1,1)^{12}$	ARIMASIMA
$(2,1,1)(1,1,0)^{12}$	ARIMASARI

3.4 Parameter Significance Test

Following the identification of a suitable multiplexed SARIMA model based on ACF and PACF plots, parameter significance testing is essential to ensure the model's appropriateness for predictive purposes. This process involves the following hypothesis testing procedure.

H_0 : The model parameters are not significant enough in the model.
H_1 : The parameters of the model are quite significant in the form of the model.

Critical area: rejected H_0 if the p-value $< \alpha$ (5%). Calculation results are presented in the following table form.

Table 6. Results of Model Parameter Significance Test

Type	D/P	Parameter	Significance	Decision
$(1,1,1)(0,1,1)^{12}$	Probabilistic	AR 1	0.096	Model parameters are not significant in the model
		MA 1	0.000	
		SMA 12	0.000	
$(0,1,1)(1,1,1)^{12}$	Probabilistic	SAR 12	0.95	Model parameters are not significant in the model
		MA 1	0.000	
		SMA 12	0.000	
$(0,1,1)(0,1,1)^{12}$	Probabilistic	MA 1	0.000	The parameters of the model are quite significant in the model
		SMA 12	0.000	
$(0,1,1)(1,1,0)^{12}$	Probabilistic	SAR 12	0.000	The parameters of the model are quite significant in the model
		MA 1	0.000	
$(1,1,0)(1,1,1)^{12}$	Probabilistic	AR 1	0.008	Model parameters are not significant in the model
		SAR 12	0.461	
		SMA 12	0.000	
$(1,1,0)(0,1,1)^{12}$	Probabilistic	AR 1	0.006	The parameters of the model are quite significant in the model
		SMA 12	0.000	
$(1,1,0)(1,1,0)^{12}$	Probabilistic	AR 1	0.003	The parameters of the model are quite significant in the model
		SAR 12	0.000	
$(1,0,1)(1,1,1)^{12}$	Probabilistic	AR 1	0.000	Model parameters are not significant in the model
		SAR 12	0.681	
		MA 1	0.000	
		SMA 12	0.000	
$(1,0,1)(1,1,0)^{12}$	Probabilistic	AR 1	0.000	The parameters of the model are quite significant in the model
		SAR 12	0.000	
		MA 1	0.000	
$(1,0,1)(0,1,1)^{12}$	Probabilistic	AR 1	0.000	The parameters of the model are quite significant in the model
		MA 1	0.000	
		SMA 12	0.000	
$(2,1,1)(1,1,1)^{12}$	Probabilistic	AR 1	0.4625	Model parameters are not significant in the model
		AR 2	0.005	
		SAR 12	0.635	
		MA 1	0.077	
		SMA 12	0.000	
$(2,1,1)(0,1,1)^{12}$	Probabilistic	AR 1	0.390	Model parameters are not significant in the model
		AR 2	0.003	
		MA 1	0.074	
		SMA 12	0.000	
$(2,1,1)(0,1,1)^{12}$	Probabilistic	AR 1	0.296	Model parameters are not significant in the model
		AR 2	0.027	
		SAR 12	0.000	
		MA 1	0.396	

Based on Table 6, significant models are obtained are the probabilistic models of SARIMA $(1,0,1)(1,1,0)^{12}$, SARIMA $(1,0,1)(0,1,1)^{12}$ probabilistic models of SARIMA $(0,1,1)(0,1,1)^{12}$, SARIMA $(0,1,1)(1,1,0)^{12}$, SARIMA $(1,1,0)(0,1,1)^{12}$ and SARIMA $(1,1,0)(1,1,0)^{12}$

3.5 Residual Assumption Test

In this stage, the residues generated from the significant model must meet the white noise criteria and be normally distributed. The following are the results of the significant residual assumption test of the model.

1. Residual White Noise Assumption Test

From the following model assumption in Section 2.6, residual white noise assumption for the model result we got in Table 7 bellow.

Table 7. Results of White Noise Test using Ljung-Box Test

Type	D/P	Residual				Information
		12	24	36	48	
$(1,0,1)(1,1,0)^{12}$	Probabilistic	0.456	0.016	0.041	0.087	There is a significant correlation between residual at time t and at time $t+k$ in the level of 5%
$(1,0,1)(0,1,1)^{12}$	Probabilistic	0.192	0.108	0.072	0.074	There was no residual correlation between lags at a significance level of 5%
$(0,1,1)(0,1,1)^{12}$	Probabilistic	0.267	0.145	0.095	0.093	There was no residual correlation between lags at a significance level of 5%
$(0,1,1)(1,1,0)^{12}$	Probabilistic	0.516	0.015	0.035	0.057	There is a significant correlation between residual at time t and at time $t+k$ in the level of 5%
$(1,1,0)(0,1,1)^{12}$	Probabilistic	0.003	0.003	0.000	0.001	There is a significant correlation between residual at time t and at time $t+k$ in the level of 5%
$(1,1,0)(1,1,0)^{12}$	Probabilistic	0.138	0.004	0.010	0.029	There is a significant correlation between residual at time t and at time $t+k$ in the level of 5%

Based on Table 7, the models that meet the residual white noise assumption test with Ljung-box test are the probabilistic model of SARIMA $(0,1,1)(0,1,1)^{12}$ and the probabilistic model of SARIMA $(1,0,1)(0,1,1)^{12}$.

2. Normally Distributed Residual Assumption Test

The residual white noise assumption testing led to the identification of two models: a deterministic and probabilistic SARIMA $(0,1,1)(0,1,1)^{12}$ model, and a probabilistic SARIMA $(1,0,1)(0,1,1)^{12}$ model. Therefore, the error normality assumption test is carried out by applying the Kolmogorov-Smirnov test based on residual of the model. The hypotheses of the test are.

H_0 : Error of the model is normally distributed
H_1 : Error of the model is not normally distributed

Critical area: H_0 is rejected if p-value $< \alpha$ (5%)
After carrying out the normality test for the remaining 2 models, it was found that only the model $(0,1,1)(0,1,1)^{12}$ was satisfactory met the p-value = 0.06.

3.6 Selection of the Best Model

The conditions that must be possessed by the best model are that the parameters are significant p-value $< \alpha$ (5%) characterized by having the smallest MSE (Mean Square Error) and having residual white noise. The following are the results of the parameter estimation of all possible models presented in the form of a table as follows.

Table 8. Selection of the Best Models

Type		Parameter Significance	Ljung-Box Test	Residual	MSE
SARIMA $(0,1,1)(0,1,1)^{12}$	Probabilistic	Significant	*White Noise*	Normally distributed	6.514

Based on **Table 9**, the best model obtained is the SARIMA $(0,1,1)(0,1,1)^{12}$ probabilistic model. By meeting the significance test, the residual assumption test is normally distributed has a white noise and a small MSE.

Table 9. Parameter Estimation Results

Type	Coeff.	SE Coeff.	T-value	*p*-value
MA 1	0.568	0.079	7.12	0.000
SMA 12	0.837	0.073	11.52	0.000

3.7 SARIMA Model Equations $(0,1,1)(0,1,1)^{12}$

After determining the best model, namely SARIMA $(0,1,1)(0,1,1)^{12}$ probabilistic. Furthermore, the equation of the SARIMA $(0,1,1)(0,1,1)^{12}$ probabilistic model is determined as follows. The SARIMA Model (p, d, q) (P, D, Q)^S is:

$$\phi_p(B)\Phi_p(B^s)(1-B)^d(1-B^s)^D Zt = \theta_q(B)\Theta_Q(B^s)a_t \text{ with } a_t\sim N(0,\sigma^2) \quad (6)$$

By following the equation (6), the SARIMA $(0,1,1)(0,1,1)^{12}$ model can be presented as:

$$\phi_p(\mathrm{B})\,(1-\mathrm{B})^d(1-B^s)^D Z_t = \theta_q(\mathrm{B})\,\Theta_q(\mathrm{B})^s a_t$$
$$\Phi_p(B^s)\phi_p(\mathrm{B})(1-B^s)^D(1-\mathrm{B})^d Z_t = (1-\theta_q\mathrm{B})\,(1-\Theta_q\mathrm{B}^s)a_t$$
$$\left(1-\Phi_p B^s\right)\left(1-\phi_p\mathrm{B}\right)(1-B^s)^D(1-\mathrm{B})^d Z_t = (1-\theta_q\mathrm{B})\,(1-\Theta_q\mathrm{B}^s)a_t$$
$$(1-\Phi_0 B^{12})(1-\phi_0\mathrm{B})(1-B^{12})^1(1-\mathrm{B})^1 Z_t = (1-\theta_1\mathrm{B})\,(1-\Theta_1\mathrm{B}^{12})a_t$$
$$(1-B^{12})^1(1-\mathrm{B})^1 Z_t = a_t-\theta_1 a_t\mathrm{B}-\Theta_1 a_t\mathrm{B}^{12}-\theta_1\Theta_1\mathrm{B}^{13}a_t$$
$$(1-\mathrm{B}-B^{12}-B^{13})Z_t = a_t-\theta_1 a_t\mathrm{B}-\Theta_1 a_t\mathrm{B}^{12}-\theta_1\Theta_1\mathrm{B}^{13}a_t$$
$$Z_t-Z_tB-Z_tB^{12}-Z_tB^{13} = a_t-\theta_1 a_t\mathrm{B}-\Theta_1 a_t\mathrm{B}^{12}-\theta_1\Theta_1\mathrm{B}^{13}a_t$$
$$Z_t = a_t-\theta_1 a_t\mathrm{B}+Z_tB-\Theta_1 a_t\mathrm{B}^{12}+Z_tB^{12}-\theta_1\Theta_1\mathrm{B}^{13}a_t+Z_tB^{13}$$

After get fixed presented model SARIMA $(0,1,1)(0,1,1)^{12}$, insert value of model with the rounded value is 0.50 and presented as:

$$Z_t = a_t-0.5679a_{t-1}+Z_{t-1}-0.8367a_{t-12}+Z_{t-12}+0.4751\,a_{t-13}+Z_{t-13} \quad (7)$$

3.8 Forecasting

To validate the selected SARIMA model, the model is applied to the testing data, so that given forecast value of the volume of goods transported by train for the next 12 months (May 2023 - April 2024) is displayed on **Table 10**.

Table 10. Results Forecast Value of the Volume of Goods Transported by Train for May 2023 - April 2024

Month	Forecast	95% Confidence Interval	
		Lower Limit	Upper Limit
May 2023	5350.78	4745.91	5955.64
June 2023	5378.84	4719.94	6037.75
July 2023	5670.85	4962.02	6379.69
August 2023	5716.21	4960.73	6471.69
September 2023	5728.33	4928.92	6527.73
October 2023	5828.47	4987.43	6669.51
November 2023	5730.56	4849.86	6611.27
December 2023	5792.86	4874.2	6711.53

Month	Forecast	95% Confidence Interval	
		Lower Limit	Upper Limit
January 2024	5618.95	4663.88	6574.11
February 2024	5324.90	4334.68	6315.12
March 2024	5822.91	4798.79	6847.04
April 2024	5682.61	4625.66	6739.55

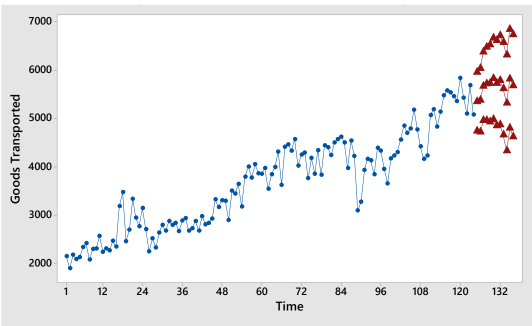


Figure 9. Time Series Plot Data Prediction Results

Figure 9 shows the time series plot of the forecast value for the next 12 months, namely from May 2023 to April 2024.

Table 11. Comparison of Forecasting Results with Original Data

Month	Forecast	Original Data
May	5350.78	5337
June	5378.84	5732
July	5670.85	5957
August	5716.21	5898
September	5728.33	5515
October	5828.47	5432
November	5730.56	5722
December	5792.86	6265
January	5618.99	5803
February	5324.90	5264
March	5822.91	5679
April	5682.61	5803

Then calculations are carried out to analyze the MAPE (Mean Absolute Percentage Error) value, which is the absolute average percentage of error. The MAPE calculation table is obtained as follows:

Table 12. MAPE Results

Original Data	Forecast	Original Data – Data Forecast (Variance)	Discrepancy/Actual Data	APE
5337	5350.78	-13.78	0.00	-0.26
5732	5378.84	353.16	0.06	6.16
5957	5670.85	286.15	0.05	4.80
5898	5716.21	181.79	0.03	3.08
5515	5728.33	-213.33	-0.04	-3.87
5432	5828.47	-396.47	-0.07	-7.30
5722	5730.56	-8.56	0.00	-0.15
6265	5792.86	472.14	0.08	7.54
5803	5618.99	184.00	0.03	3.17

Original Data	Forecast	Original Data – Data Forecast (Variance)	Discrepancy/Actual Data	APE
5264	5324.90	-60.90	-0.01	-1.16
5679	5822.91	-143.91	-0.03	-2.53
5803	5682.61	120.39	0.02	2.07
		MAPE		**0.96**

The model's accuracy with MSE in training data result is 6.514. Then model was evaluated using Mean Absolute Percentage Error (MAPE) in testing data, which resulted in 0.96%. This low MAPE value suggests high prediction accuracy. Based on this result, the model appears suitable for forecasting the number of goods distributed by rail from May 2023 to April 2024. However, to ensure a comprehensive evaluation, it is recommended to also calculate and consider the MAPE for the training data.

4. CONCLUSIONS

Based on the analysis that has been carried out, the following conclusions can be drawn.

1. Data on the number of goods through rail transportation in Indonesia from January 2013 to April 2023 fluctuated with an upward trend.
2. The appropriate and best model for data on the number of goods distributed through rail transportation for the next 12 months, namely January 2013 to April 2023. is a probabilistic SARIMA $(0,1,1)(0,1,1)^{12}$ model with the following equation.

$$Z_t = a_t - 0.5679a_{t-1} + Z_{t-1} - 0.8367a_{t-12} + Z_{t-12} + 0.4751\, a_{t-13} + Z_{t-13}$$

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