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SARIMA MODELING FOR RAILWAY FREIGHT TRANSPORTATION FORECASTING ON SUMATRA

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Abstract

This study develops a time series model to forecast railway freight volume in Sumatra using monthly data from January 2013 to June 2025. A seasonal autoregressive integrated moving average (SARIMA) model with a drift component captures both trend and seasonal patterns in the data. Model selection is based on the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The results show that the SARIMA(0,1,2)(1,0,0)[12] with drift provides the best performance, yielding a log-likelihood value of 158.93 and a mean absolute percentage error (MAPE) of 0.76%. These findings indicate that the model can accurately represent freight dynamics in Sumatra and may serve as a quantitative reference for regional rail freight planning and infrastructure development.

Keywords*: Railway Freight, Forecasting, SARIMA*

1. Introduction

Rail transport is a crucial part of Indonesia's transport system, offering passenger services and facilitating freight movement. Enhancing rail transport efficiency is believed to reduce national logistics costs. Understanding the volume of freight transported by rail is essential for capacity planning, strategic infrastructure investments, and operational plans.

Sumatra is one of Indonesia's most strategic regions. According to Statistics Indonesia (BPS), the volume of freight transported by rail in Sumatra has shown a steady increase during 2013–2025. Monthly fluctuations in agricultural cycles, mining distribution patterns, and industrial demand are associated with this growth, indicating that the data contain both trend and seasonal patterns. Due to the dynamic nature of the data, a model that takes into account regular impacts and trends is needed.

A number of studies have attempted to forecast railway freight volume in Indonesia using various time series approaches. At the national level, one study found that a SARIMA$(0,1,1)(0,1,1)_{12}$ model worked well for monthly data, achieving a MAPE below 1 percent [10]. Another national study using a similar SARIMA framework reported a MAPE of 8.03 percent for twelve month ahead forecasts

[9]. Focusing on regional characteristics, a SARIMA(0,1,1)(0,2,0)$_{12}$ model was selected as the best fit for freight volume specifically on Java [14]. Expanding beyond the SARIMA framework, a simpler ARIMA(1,1,0) model was explored to forecast freight on Java, acknowledging its limitations with a notably higher MAPE of 66.6 percent [4]. Meanwhile, a Fuzzy Time Series approach using Ruey Chyn Tsaur logic achieved a MAPE of 8.05 percent for predicting freight weight on Java, showing that fuzzy methods can handle uncertainty in time series data effectively [1]. Despite these contributions, none have specifically modelled the distinct freight dynamics of Sumatra, a gap this study aims to fill.

These studies show that several time series approaches have been used to forecast railway freight volume in Indonesia. However, most of them focused on national data or Java, while research specifically modelling freight transport in Sumatra is still limited. This research gap highlights the need for localized analysis, given that freight dynamics in Sumatra may differ significantly from national patterns due to regional economic structures and logistics demands.

Building on this gap, the present study aims to develop a SARIMA model for forecasting rail freight volume in Sumatra. The methodological approach includes Box-Cox transformation, stationarity testing, model identification, parameter estimation, and residual diagnostics to ensure the accuracy of the results. This study's findings are expected to offer practical value, particularly as an additional reference for logistics policymaking in Sumatra.

2. SARIMA Modelling

This research employs a quantitative time series analysis technique to model and forecast the volume of freight transported by railway on Sumatra Island. For the period spanning January 2013 to June 2025, this research relies primarily on the monthly statistics titled "Volume of Freight Transported by Railway According to Island (Thousand Tonnes)" provided by the Badan Pusat Statistik (BPS). This study is dependable, backed by a comprehensive and robust dataset with no missing values detected.

The autoregressive integrated moving average (ARIMA) model is a widely used approach in time series analysis for modelling data based on autoregressive, differencing, and moving average components. ARIMA is generally applied when the data show non-stationary behaviour but do not contain a strong seasonal pattern. However, when recurring seasonal fluctuations are present, the ARIMA model can be extended by incorporating seasonal terms. This extended form is known as the seasonal autoregressive integrated moving average (SARIMA) model. Since the railway freight data in this study are monthly and show potential seasonal movements, SARIMA was considered more appropriate.

The SARIMA modelling process was carried out using the Box-Jenkins framework. Initially, we sought out overarching trends and potential seasonal patterns within the dataset by employing descriptive exploration and visually representing the data through graphs. The Augmented Dickey-Fuller (ADF) test was employed to provide additional confirmation of stationarity. Data manipulation became essential as rejecting the null hypothesis of non-stationarity was not an option. The mean and variance of the series were stabilised through a Box-Cox transformation combined with first-order differencing. The Box-Cox transformation is defined as follows:

$$Y^{\lambda} = \begin{cases} \dfrac{Y^{\lambda} - 1}{\lambda}, & \lambda \neq 0 \\ ln(Y), & \lambda = 0 \end{cases}$$

Model identification relied on the behavior of the autocorrelation function (ACF) and partial autocorrelation function (PACF), which guided the specification of potential SARIMA models. A general SARIMA model of order (p,d,q)(P,D,Q)s can be represented as:

$$\Phi_p(B)\,\Phi_P(B^S)(1-B)^d(1-B^S)^D Y_t = \theta_q(B)\,\Theta_Q(B^S)a_t, a_t \sim N(0,\sigma^2)$$

where $\phi_p(B)$and $\theta_q(B)$ are non-seasonal autoregressive and moving average polynomials of order p and q, while $\Phi_P(B^s)$ and $\Theta_Q(B^s)$ are seasonal autoregressive and moving average polynomials of order P and Q, respectively, with the seasonal period s and a_t residual value. Candidate models were estimated using the maximum likelihood approach, and the selection of the final specification was based on the smallest Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) values.

The AIC is expressed as

$$AIC = n \ln \widehat{\sigma_e^2} + 2k$$

while the BIC is given by

$$BIC = n \ln \widehat{\sigma_e^2} + k \ln(n)$$

where $\widehat{\sigma_e^2}$ denotes maximum likelihood estimator of σ_e^2 , k represents the number of parameters in the model, and n is the total number of observations. Based on these criteria, the preferred model is the one associated with the lowest AIC or BIC value.

To validate the adequacy of the selected model, residual diagnostics were performed. The study included the Ljung-Box test to verify that there was no serial correlation, the White test to check for homoscedasticity, and a normality assessment. Mean Absolute Percentage Error (MAPE) was used to measure the accuracy of the forecast. The MAPE formula is given below :

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{y_i - \widehat{y_i}}{\widehat{y_i}}\right| \times 100\%$$

In this context, y_i represents the actual value corresponding to the predicted value, while $\widehat{y_i}$ denotes the fitting value. Several standard methods exist for categorising the significance of MAPE values:

MAPE < 10%	: Indicates highly accurate forecasts
10% ≤ MAPE < 20%	: Represents good forecasts.
20% ≤ MAPE < 50%	: Suggests reasonable forecasts.
MAPE ≥ 50%	: Implies inaccurate forecasts.

All stages of this research, including data preparation, model estimation, and diagnostic evaluations, are conducted using the statistical software environment

3. Result and Discussion

3.1 Descriptive Analysis of Railway Freight

Railway freight transportation in Sumatra showed a steady increase, indicating non-stationarity in the initial data. A Box-Cox transformation stabilized the variance, with a lambda value of 2. First-order differencing eliminated the trend and achieved stationarity. The Augmented Dickey-Fuller test validated the improvement, rejecting the null hypothesis with a test statistic of -6.68 and a p-value less than 0.01. Figure 1 illustrates the original data pattern before the differencing process.

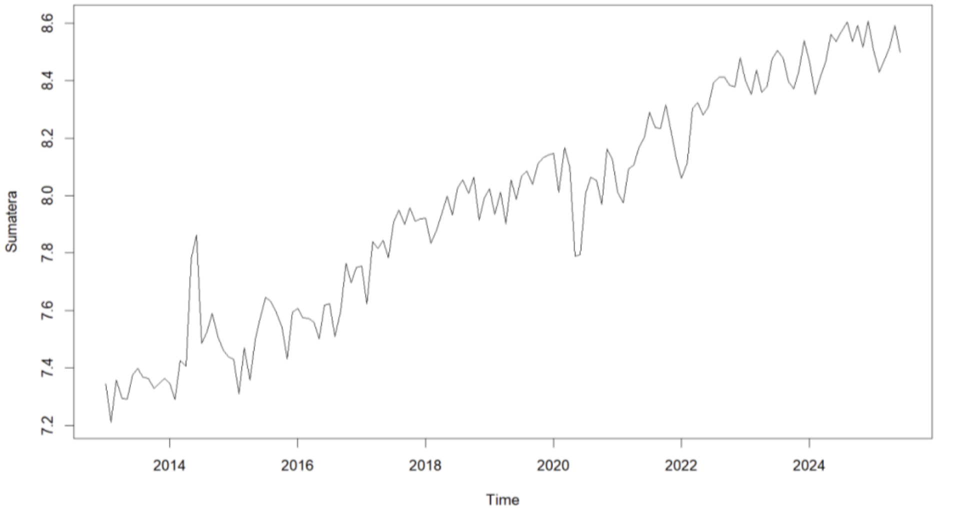

Figure. 1 Volume of Freight Transported by Rail in Sumatera

3.2 Seasonal Pattern Analysis

An important characteristic of freight transportation data is its seasonal behavior, which often reflects recurring cycles in logistics and industrial activities. In this study, a seasonal plot was employed to explore monthly variations across several years. A seasonal plot revealed consistent cyclical fluctuations, with certain months experiencing higher volumes of transported goods. This finding justifies the inclusion of seasonal parameters in the SARIMA model.

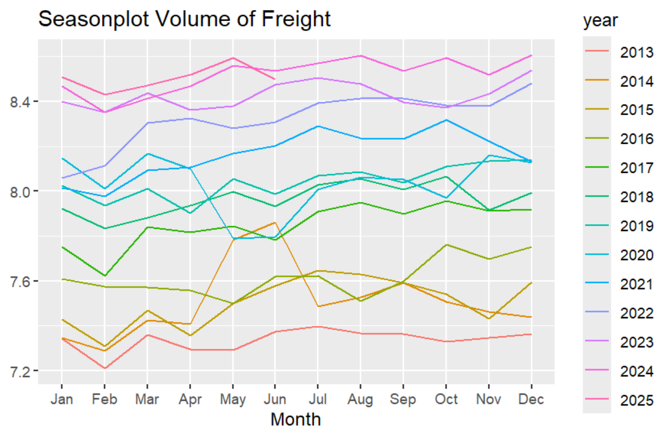

Figure. 2 Seasonplot of Volume of Freight

3.3 Model Identification and Estimation

The identification stage used the autocorrelation function (ACF) and partial autocorrelation function (PACF). After differencing, the ACF plot showed significant negative spikes at the first and second lags, while the PACF showed a slow decay pattern. These results suggested moving average terms in the model. The ACF and PACF plots can be seen in Figure 3.

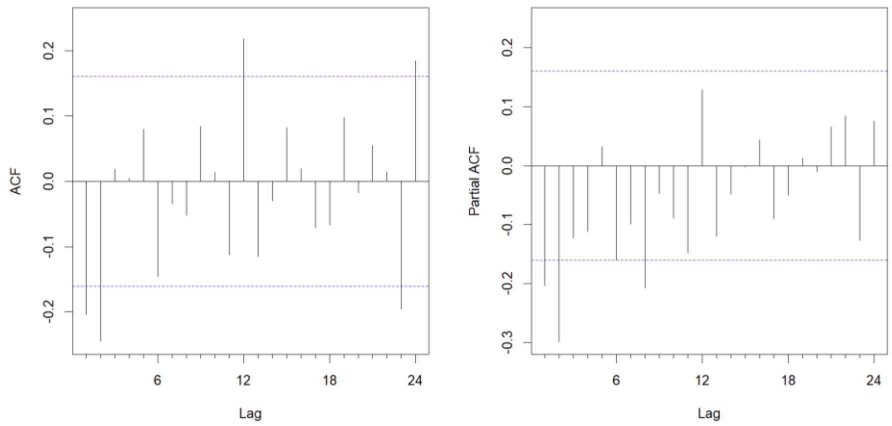

Figure. 3 ACF and PACF Plot

Four candidate models were estimated: first SARIMA(0,1,2)(1,0,0)[12] with drift, second ARIMA(0,1,2), third SARIMA(0,1,2)(2,0,0)[12] with drift, and fourth SARIMA(0,1,2)(1,0,0)[12]. The estimated parameters, along with evaluation criteria such as AIC and BIC, are presented in Table 1. The SARIMA(0,1,2)(1,0,0)[12] with drift model was identified as the best performing model, producing the lowest AIC (-307.9), lowest BIC (-292.8).

Table 1. AIC and BIC of Selected SARIMA Models

Value	Model 1	Model 2	Model 3	Model 4
AIC	-307.9	-295.7	-307.9	-302.7
BIC	-292.8	-286.7	-289.9	-290.7

The SARIMA(0,1,2)(1,0,0)[12] model with drift is expressed as

$$y_t = 0.008 + y_{t-1} + 0.201y_{t-12} - 0.201y_{t-13} + \varepsilon_t - 0.359\varepsilon_{t-1} - 0.410\varepsilon_{t-2},$$

where y_t represents freight at time t and ε_t denotes the error term.

3.4 Residual Diagnostics

Residuals from the SARIMA(0,1,2)(1,0,0)[12] with drift model passed all diagnostic tests. The results confirmed that the assumptions of normality, independence, and homoscedasticity were satisfied. Normality, independence, and homoscedasticity were confirmed, validating the model's reliability.

Table 2. Residual Diagnostics

No	Purpose	p-value	Decision (α = 0.05)	Conclusion
1	Normality	0.1111	accepted	Residuals are normally distributed
2	Independence (No autocorrelation)	0.7902	accepted	No autocorrelation detected
3	Homoscedasticity	0.3444	accepted	No heteroskedasticity detected

3.5 Model Performance

The effectiveness of the selected model is reflected in the comparison between actual and fitted values. As illustrated in Figure 4 the fitted series closely follows the observed data, capturing both the upward trend and seasonal variations. The Mean Absolute Percentage Error (MAPE) was 0.76%, demonstrating the SARIMA(0,1,2)(1,0,0)[12] with drift model provides highly accurate forecasts for railway freight transportation in Sumatra.

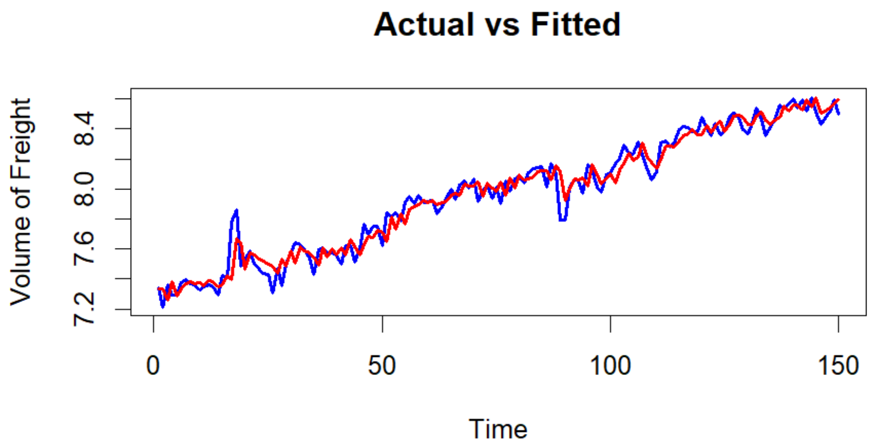

Figure. 4 Comparison Actual and Fitted Data

3.6 Model Validation and Robustness Analysis

Model validation was carried out using a 70:30 train-test split on the monthly data from 2013 to June 2025. The first 105 observations were used as training data, while the remaining 45 observations were used as testing data. The selected SARIMA model was estimated using the training data and then applied to predict the testing period. Based on this evaluation, the model produced a testing MAPE of 0.69%. This result indicates that the model still performs well when applied to data outside the estimation sample.

To strengthen the evaluation, the selected SARIMA model was compared with an ARIMA(0,1,2) model with drift. The comparison shows that the SARIMA model gives slightly better results. In the full-sample evaluation, the MAPE of SARIMA was 0.76%, while the ARIMA model produced 0.80%. A similar pattern was also found in the train-test split evaluation, where the testing MAPE of SARIMA was 0.69%, compared to 0.70% for ARIMA. In addition, the SARIMA model had a lower AIC value than the ARIMA model, indicating that the seasonal component improved model performance.

A robustness analysis was also conducted by examining the consistency of the results under different evaluation settings. The results show that the SARIMA model consistently produced slightly lower error values than the ARIMA model, both in the full-sample evaluation and in the train-test split. Although the difference is not large, the pattern remains the same. This suggests that the selected SARIMA model is relatively stable and provides consistent forecasting results.

The small MAPE values obtained in this study need to be interpreted carefully. However, the results do not directly indicate overfitting. For the selected SARIMA model, the training MAPE was 0.95%, while the testing MAPE was 0.69%. A similar pattern was also found for the ARIMA model, with a training MAPE of 0.96% and a testing MAPE of 0.70%. Since the model still performs well on the testing data, the low error values suggest that the forecasting results remain reliable.

3.7 The Implications of Railway Freight Projections for Infrastructure Planning

This study's findings highlight several implications for infrastructure planning. The inclusion of a drift term in the selected model reflects a long-term upward trend in railway freight volume, which is consistent with the rapid development of logistics and industrial sectors in Sumatra. Accurate demand forecasts are crucial for railway operators to plan capacity expansion, schedule rolling stock, and optimize maintenance strategies.

Seasonal fluctuations, influenced by agricultural harvests, industrial supply chains, and peak transportation periods, are evident in the data. Recognizing these patterns allows policymakers and practitioners to anticipate demand surges and allocate resources more effectively.

This research confirms SARIMA modeling as a reliable statistical approach for forecasting transport demand. The results provide actionable insights for supporting infrastructure development and operational efficiency in Sumatra's railway system. Future studies may consider hybrid models, such as ARIMA-LSTM, to capture nonlinear effects and enhance predictive accuracy.

4. Conclusion

Railway freight in Sumatra from January 2013 to June 2025 shows noticeable fluctuations along with a consistent upward trend. Freight activity in the region continues to grow over time, with seasonal variations remaining evident. Accurate forecasting is essential for effective planning and management of railway freight services in Sumatra.

The SARIMA(0,1,2)(1,0,0)[12] model with drift was identified as the most appropriate model for forecasting railway freight in Sumatra. The model is expressed as

$$y_t = 0.008 + y_{t-1} + 0.201y_{t-12} - 0.201y_{t-13} + \varepsilon_t - 0.359\varepsilon_{t-1} - 0.410\varepsilon_{t-2},$$

where y_t represents freight at time t and ε_t denotes the error term. The equation shows that current freight levels are influenced by the previous period, seasonal patterns from the previous year, and past error terms. The positive drift term indicates a steady increase in freight over time. Therefore, the model provides reliable forecasts and can be used as a practical reference for logistics planning and railway freight management in Sumatra.

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