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Seasonal time series forecasting of Indonesian railway passengers: A comparison of Holt–Winters and SARIMA

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Abstract
Managing the number of railway passengers in Indonesia presents a significant challenge for PT Kereta Api Indonesia, particularly in relation to transport capacity planning, scheduling, and resource optimization. Forecasting therefore plays a crucial role in supporting effective decision-making. This study aimed to forecast railway passenger volumes using the Holt–Winters Triple Exponential Smoothing method and the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, and to compare their forecasting performance. This applied research utilized secondary monthly data published by Statistics Indonesia (BPS), covering the period from January 2022 to December 2024, with forecasts generated for January to June 2025. Model performance was evaluated using the Mean Absolute Percentage Error (MAPE) criterion. The results indicated that the SARIMA $(0,1,1)(0,1,0)^{12}$ model outperformed the Holt–Winters variants and other SARIMA specifications, achieving the lowest MAPE value of approximately 3%. Based on this evaluation, the SARIMA $(0,1,1)(0,1,0)^{12}$ model was identified as the most accurate model for forecasting Indonesian railway passenger volumes. The findings suggest that SARIMA-based models provide a reliable approach for supporting railway passenger demand forecasting in Indonesia.

Keywords: Forecasting, Holt–Winters, Indonesian railway, SARIMA, Time Series

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Introduction

Railways are a form of mass transportation that plays a crucial role in supporting public mobility and national economic development (Hartono et al., 2020). This is attributed to their advantages, including high passenger capacity, operational stability, and a relatively higher level of safety compared to other modes of transportation. These factors make railways one of the primary choices for the public, especially for medium to long-distance travel (Triwijaya et al., 2018).

As a public transportation service provider, PT Kereta Api Indonesia holds the responsibility of ensuring services that meet the evolving needs of society. According to (Gunawan & Cahyono, 2023), the number of railway passengers has increased at an average annual growth rate of over 10%. In the Greater Jakarta (*Jabodetabek*) area, Electric Rail Trains (KRL) have become a key solution for reducing traffic congestion. In urban areas, particularly the Greater Jakarta Metropolitan Area, Electric Rail Trains (KRL) have become the backbone of daily commuting. Statistics from KAI Commuter reveal that the number of KRL passengers grew significantly, from 239.254.813 in 2022 to 331.891.721 in 2023. This growth reflects not only the rebound of public mobility following the COVID-19 pandemic but also a renewed sense of trust in rail-based transportation services.

Forecasting is used to predict the future number of railway passengers based on historical data collected periodically. With an appropriate forecasting method, PT Kereta Api Indonesia can more effectively anticipate passenger demand and improve the efficiency of railway transportation services. This is essential for supporting travel scheduling, capacity planning, and optimal resource allocation (Midiyanti & Ramlan, 2020).

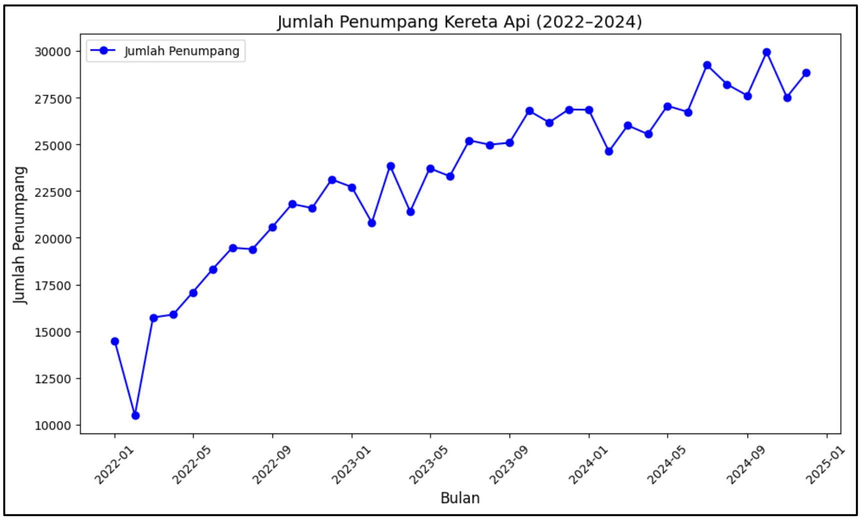

Figure 1. Plot of Indonesian Railway Passengers Data From 2022 to 2024

Figure 1 illustrates that the number of railway passengers steadily increased from January 2022 to December 2024. The graph illustrates a consistent upward trend combined with seasonal variations, such as surges during national holidays, extended vacations, and peak commuting hours. This pattern highlights that the rising demand for rail transport is influenced not only by long-term growth but also by seasonal dynamics. Such insights are valuable for shaping strategic decisions in the railway sector, particularly in areas such as travel scheduling, capacity management, and resource optimization (Midiyanti & Ramlan, 2020). Furthermore, passenger spikes during peak seasons often cause congestion at stations and inside trains, emphasizing the importance of effective capacity planning (Tripena & Amru, 2024).

As a public transportation provider, PT Kereta Api Indonesia carries the responsibility of delivering services that adapt to society's evolving needs. Recent data indicate a steady increase in passenger demand, with (Gunawan & Cahyono, 2023) reporting an average annual growth rate exceeding 10%. These figures underline the urgency for accurate forecasting to anticipate changes in demand and ensure service reliability.

Time series analysis serves as a crucial foundation for PT. Kereta Api Indonesia in decision-making processes related to travel scheduling, transport capacity planning, and resource optimization (Midiyanti & Ramlan, 2020).Passengers' surges during holiday seasons and peak hours can lead to overcrowding in stations and on trains, highlighting the need for effective capacity planning strategies (Tripena & Amru, 2024).

One forecasting method that is particularly suitable for seasonal data is the Triple Exponential Smoothing (Holt-Winters). This method incorporates three components: level, trend, and seasonality, and comes in two forms: multiplicative, which is used for increasing seasonal patterns, and additive, which is applied to constant seasonal patterns (Dewi & Listiowarni, 2020). Another method, SARIMA, is an extension of ARIMA designed to handle seasonal data through transformation and differencing processes (Prianda & Widodo, 2021). Both methods have been widely applied across various sectors, including maritime transportation, vehicle sales, and aviation. Previous studies have shown varied results. For example, (Negara, 2021) concluded that SARIMA yielded more accurate forecasts for the volume of ship passengers; similarly, (Susanti et al., 2024) found SARIMA to be the most accurate in forecasting Honda retail car sales. On the other hand, (Fahik & Jatipaningrum, 2021) determined that the multiplicative Holt-Winters method performed better for airline passengers' data, while (Tambuwun et al., 2023) stated that Holt-Winters was more suitable for seasonal domestic flight data.

Although the Triple Exponential Smoothing Holt-Winters, and SARIMA methods have been widely applied in seasonal data forecasting across various sectors, their specific application to Indonesian railway passengers' data, particularly in the Jabodetabek area, remains relatively limited. Moreover, most researchers have only examined one form of Triple Exponential Smoothing, namely Holt-Winters, either in additive or multiplicative form, and employed a single SARIMA parameter configuration without conducting broader model exploration. These limitations present an opportunity to comprehensively assess the performance of both methods on public transportation data in the post-pandemic era.

Based on the aforementioned background, this study aims to generate forecasts for the number of railway passengers using the Triple Exponential Smoothing Holt-Winters, and SARIMA methods, and to compare the forecasting performance of these methods to determine the most suitable approach for this type of seasonal transport data. Accordingly, the focus of this research is a performance comparison of the triple exponential smoothing holt-winters, and SARIMA methods in forecasting the number of railway passengers in Indonesia.

Methods

Research Type and Data Sources

This study is an applied research project aimed at providing practical solutions through forecasting the number of railway passengers in Indonesia (Aslam, 2023). The data used is secondary data obtained from an official publication by Statistics Indonesia (BPS) titled Number of Railway passengers covering the period from January 2022 to December 2024.

Data Analysis Technique

The steps for the Triple Exponential Smoothing Holt-Winters data analysis technique are as follows:

1. Input the dataset.

2. Initialize parameter values using RStudio programming.
3. Calculate the initial level component by averaging the first 12 data points.
4. Compute the initial trend component from the average seasonal differences.
5. Estimate the initial seasonal component based on multiplicative and additive models.
6. Performs smoothing calculations for level, trend, and seasonal components using parameters α, β, and γ.
7. Forecast future values based on the smoothing results and the Triple Exponential Smoothing Holt-Winters model.
8. Determine the forecasted number of railway passengers in Indonesia.
9. Select the best model based on the Mean Absolute Percentage Error (MAPE).

Steps for the SARIMA data analysis technique are as follows:

1. Input the dataset.
2. Identify the stationarity of the data.
   a. If the data is not stationary in terms of variance, apply a Box-Cox transformation to stabilize it.
   b. If the data is not stationary in terms of mean, apply differencing.
   c. Test stationarity using unit root tests, such as the *Augmented Dickey-Fuller* (ADF).
3. Visualize the transformed and differenced time series data through plots.
4. Determine candidate SARIMA models.
5. Estimate the model parameters.
6. Specify the SARIMA model in the form of (p, d, q) and $(P, D, Q)^s$.
7. Conduct parameter significance tests.
8. Perform a white *noise* (residual) test.
9. Conduct the Kolmogorov-Smirnov test to assess the normality of residuals.
10. Select the best model based on the MAPE value.
11. Forecast the number of railway passengers.

Triple Exponential Smoothing Holt-Winters Method

The Triple Exponential Smoothing Holt-Winters method is an advanced smoothing technique used to forecast time series data exhibiting both trend and seasonal patterns. This method consists of two forms: the multiplicative model, which is suitable for seasonal patterns that vary with the level of the data, and the additive model, which is suited for constant seasonal patterns (Harahap & Darnius, 2022; Romaita et al., 2019). The initial stage begins with the initialization of level, trend, and seasonal components using the following Formula (1) (Yuliana et al., 2022).

1. *Smoothing* level (L_s)

$$L_s = \frac{1}{s}(Y_1 + Y_2 + \cdots + Y_s) \quad (1)$$

2. *Smoothing* trend (b_s)

$$b_s = \frac{1}{s}\left(\frac{Y_{s+1}-Y_1}{s} + \frac{Y_{s+2}-Y_2}{s} + \cdots + \frac{Y_{s+s}-Y_s}{s}\right) \quad (2)$$

3. Seasonal *smoothing* for the multiplicative model (S_k) and additive model (S_k), the

formulas are as follows:

a. Multiplicative

$$S_n = \frac{y_n}{L_s} \quad (3)$$

b. Additive

$$S_n = y_n - L_s \quad (4)$$

After initialization, data smoothing is performed using the parameters α, β and γ to obtain the forecasting results as outlined in the following formulas (2) (Khoiri, 2023):

1. *Triple Exponential Smoothing* Holt-Winter Multiplicative
   a. Calculation of the smoothing equation for the level (L_t)

   $$L_t = \alpha\left(\frac{y_t}{S_{t-s}}\right) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (5)$$

   b. Calculation of the smoothing equation for trend (b_t)

   $$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (6)$$

   c. Calculation of the smoothing equation for seasonal (S_t)

   $$S_t = \gamma\left(\frac{y_t}{L_t}\right) + (1-\gamma)S_{t-s} \quad (7)$$

   d. Forecast (F_{t+m})

   $$F_{t+m} = (L_t + b_t m)S_{t-s+m} \quad (8)$$

2. *Triple Exponential Smoothing Holt Winters* Additive
   a. Calculation of the smoothing equation for the *level* (L_t)

   $$L_t = \alpha(y_t - S_{t-s}) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (9)$$

   b. Calculation of the smoothing equation for the trend (b_t)

   $$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (10)$$

   c. Calculation of the smoothing equation for (S_t)

   $$S_t = \gamma(y_t - L_t) + (1-\gamma)S_{t-s} \quad (11)$$

   d. Forecast (F_{t+m})

   $$F_{t+m} = L_t + b_t m + S_{t-s+m} \quad (12)$$

SARIMA Method

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model is employed to analyze time series data with seasonal patterns (Malki et al., 2022). It incorporates seven key parameters (p, d, q) for the non-seasonal components and $(P, D, Q)^s$ where s represents the length of the seasonal period. SARIMA operates by combining non-seasonal and seasonal differencing processes to render the data stationary before estimating the AR and MA parameters. SARIMA is particularly useful when a time series exhibits regular seasonal fluctuations and long-term trends. The modelling process involves transforming the data to achieve stationarity, both in terms of variance and mean, before identifying and estimating appropriate AR and MA parameters for both non-seasonal and seasonal components. Once a stationary series is achieved, the model parameters are estimated, and diagnostic checks are conducted to ensure adequacy of the model.

The steps for implementing the SARIMA method are as follows:

a. Stationarity is a fundamental requirement in SARIMA modelling. A dataset is considered stationary when its mean and variance remain constant over time (Makridakis et al., 1991). To achieve this, two main steps are performed:
   1. Variance stationarity (Box-Cox transformation) applied to stabilize the variance. The transformation is structured as follows (3) (Wei, 2006):
   $$Z_t{}^{\lambda} = \frac{Z_t{}^{(\lambda)}-1}{\lambda} \tag{13}$$
   2. Mean stationarity (differencing) was performed to eliminate trends and seasonal patterns in the data (Makridakis et al., 1991). This process is divided into two types
      a) Non-seasonal differencing, applied to remove long-term trends, the formula (4) is:
      $$\Delta Z_t = Z_t - Z_{t-1} \tag{14}$$
      b) Seasonal differencing is used to eliminate periodic seasonal effects. The formula (5) is:
      $$\Delta Z_t = Z_t - Z_{t-s} \tag{15}$$
      where $s = 12$, indicating the difference between the current value and the corresponding value from the previous seasonal period to remove annual seasonality..

   The Augmented Dickey-Fuller (ADF) test is used to determine whether a time series is stationary. If the *p-value* < ($\alpha = 0{,}05$), the data is considered stationary (Enders, 2014).

b. Model identification is performed using ACF and PACF plots to determine the values of p, q, P, Q. The general formula for the SARIMA model is written as follows (5):
   $$\emptyset_p(B)\Phi_P(B^s)(1-B)^d(1-B^s)^D Z_t = \theta_q(B)\Theta_Q(B^s)\varepsilon_t \tag{16}$$
   where B is the backshift operator, and ε_t represents white noise error (Suhartono, 2008). Once the model is specified and parameters estimated, significance testing is conducted. A parameter is considered significant if the *p-value* < ($\alpha = 0{,}05$) or $t_{hitung} > t_{tabel}$ (Aswi & Sukarna, 2006). The t-test is calculated using the formula (6):
   $$t_{test} = \frac{coefficient}{SE(coefficient)} \tag{17}$$

c. The white noise test is intended to ensure that the residuals of the model do not exhibit autocorrelation. The white noise test is conducted to verify that the residuals of the selected model do not exhibit autocorrelation. This assessment is performed using the Ljung–Box test, and the corresponding statistical results, including the Q-statistic and p-values at selected lags.
   This test is conducted using the *Ljung-Box* test (7):
   $$Q = n(n+2)\sum_{K=1}^{i} \frac{\hat{\rho}_k^2}{n-K} \tag{18}$$
   If the *p-value* > ($\alpha = 0{,}05$), the residuals are assumed to satisfy the white noise condition.

d. The Kolmogorov-Smirnov test is performed to examine whether the residuals follow a normal distribution. The test statistic is calculated using the corresponding formula (8):
   $$D = \sup_{x} |F_n(x) - F(x)| \tag{19}$$
   If the *p-value* > ($\alpha = 0{,}05$), the residuals are considered to meet the normality assumption.

Mean Absolute Percentage Error (MAPE)

MAPE is used to measure the level of prediction error. A lower MAPE value indicates better model accuracy. The formula for MAPE is as follows (9):

$$MAPE = \frac{1}{n}\left(\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\%\right) \tag{20}$$

Results

The optimal smoothing parameters for the Holt–Winters model were estimated using RStudio through an automated optimization procedure. For the multiplicative Holt–Winters specification, the estimated parameter values were α = 0.6837 for the level component, β = 0.1755 for the trend component, and γ = 0.5868 for the seasonal component. Meanwhile, the additive Holt–Winters model produced smoothing parameters of α = 0.7456, β = 0.1058, and γ = 1. These parameter values indicate that both model specifications assign relatively high weights to recent observations, particularly in the level and seasonal components. The explicit reporting of these optimized parameters ensures the reproducibility of the forecasting process and provides transparency regarding the sensitivity of the Holt–Winters model to data initialization, especially in the context of post-pandemic passenger recovery.

This study evaluates four forecasting models applied to Indonesia's railway passenger data from January 2022 to December 2024, including the multiplicative and additive forms of the Triple Exponential Smoothing Holt-Winters, as well as two SARIMA models $(0,1,1)(0,1,0)^{12}$ and $(1,1,0)0(0,1,0)^{12}$. The forecasting evaluation also included statistical adequacy assessments, such as parameter significance testing, residual white noise analysis, and residual normality checks, as well as the Kolmogorov-Smirnov test.

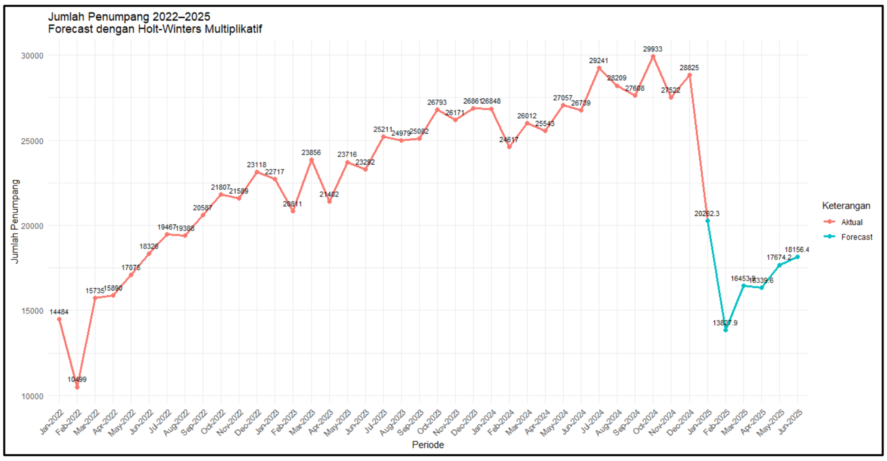

Figure 2. Forecast Plot Using the Triple Exponential Smoothing Holt-Winters Multiplicative Model

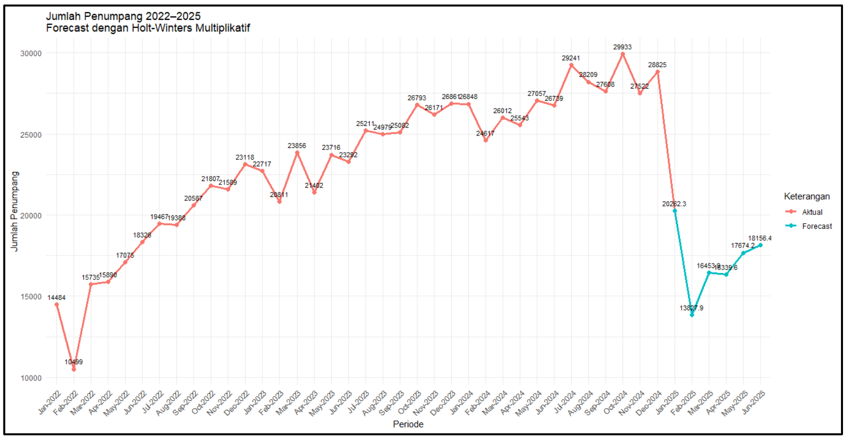

Figure 3. Forecast Plot Using the Triple Exponential Smoothing Holt-Winters Additive Model

Figures 2 and 3 present the forecasted number of railway passengers in Indonesia from January to June 2025, using the Triple Exponential Smoothing Holt-Winters method, which includes both multiplicative and additive models. Both forecasts exhibit a noticeable decline at the beginning of the forecast period, suggesting that these models have limitations in accurately capturing the upward trend in passenger volume observed in 2025. This pattern highlights that Triple Exponential Smoothing Holt-Winters models are less responsive to upward trends in non-stationary data, particularly in recovering post-pandemic transport demand. The multiplicative model produces estimates ranging from 13828 to 20262 thousand passengers, while the additive model yields projections between 18147 and 24062 thousand passengers. The patterns suggest that the models may not effectively capture the seasonal dynamics, particularly the upward trend in the number of railway passengers during 2025.

In contrast to the Triple Exponential Smoothing Holt-Winters model, the SARIMA models provided more stable and consistent forecasts, reflecting their robustness in capturing both seasonal and trend components.

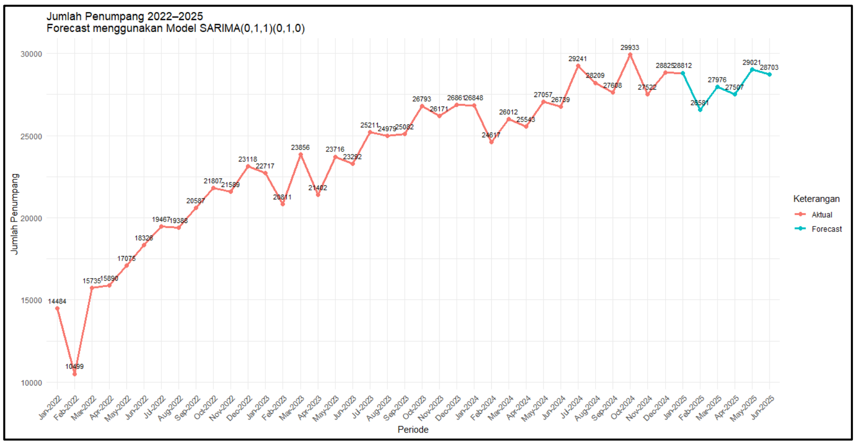

Figure 4. Forecast plot using the SARIMA model $(0,1,1)(0,1,0)^{12}$

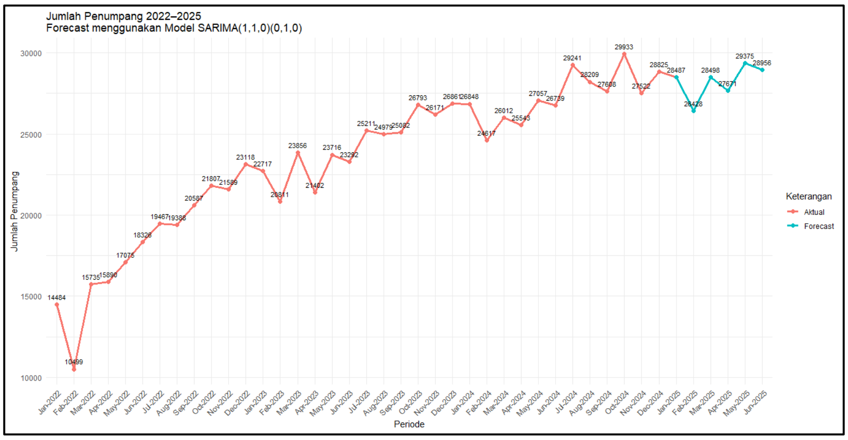

Figure 5. Forecast plot using the SARIMA model $(1,1,0)(0,1,0)^{12}$

Figures 4 and 5 present the forecasted number of railway passengers in Indonesia for the period from January to June 2025, results using the SARIMA model $(0,1,1)(0,1,0)^{12}$ and $(1,1,0)(0,1,0)^{12}$. Both models exhibit a gradual and consistent growth pattern through mid-2025. SARIMA model $(0,1,1)(0,1,0)^{12}$ produces passenger estimates ranging from 26428 to 29375 thousand passengers, while the model $(1,1,0)(0,1,0)^{12}$ generates forecasts between 26581 and 29021 thousand passengers. These outcomes indicate that SARIMA is capable of effectively representing seasonal patterns and long-term trends. Furthermore, both SARIMA models passed the parameters significance tests, white noise tests, and Kolmogorov-Smirnov normality tests, confirming their statistical adequacy.

The accuracy of each model was assessed using the Mean Absolute Percentage Error (MAPE), which measures the relative forecast error. Based on the evaluation results, SARIMA demonstrated higher accuracy compared to the Triple Exponential Smoothing Holt-Winters method. The SARIMA model $(0,1,1)(0,1,0)^{12}$ recorded the lowest MAPE value at 3.049%. Meanwhile, the multiplicative *Triple Exponential Smoothing Holt Winters* model had an MAPE of 12,9196%, the additive model achieved 8,4980% and the model $(1,1,0)(0,1,0)^{12}$ recorded an MAPE of 3,122%. The accuracy results for each model are summarized in Table 1.

Table 1. MAPE results of Triple Exponential Smoothing Holt-Winters, and SARIMA

Method	MAPE
Multiplicative Triple Exponential Smoothing Holt Winters	12,9196%
Additive Triple Exponential Smoothing Holt Winters	8,4980%
SARIMA model $(0,1,1)(0,1,0)^{12}$	3,049%
SARIMA model $(1,1,0)(0,1,0)^{12}$	3,122%

Table 1 illustrates the MAPE comparison across all models, clearly demonstrating the superior accuracy of the SARIMA model $\mathbf{(0,1,1)(0,1,0)^{12}}$. These findings suggest that SARIMA $\mathbf{(0,1,1)(0,1,0)^{12}}$ not only achieves the lowest forecast error but also maintains consistent alignment with the upward trend and seasonal variation of railway passengers' data. Therefore, this model is considered the most appropriate for short-term forecasting.

Discussion

This study aims to compare the forecasting accuracy of Indonesian railway passenger numbers using two methods: Triple Exponential Smoothing Holt-Winters, and SARIMA. In addition to the accuracy metrics, the visual patterns of the forecasts also reveal key differences between the models. The Triple Exponential Smoothing Holt-Winters models, particularly the multiplicative form, exhibit a sharp decline at the beginning of the forecast period, indicating an inability to adequately follow the increasing trend of passenger numbers. In contrast, both SARIMA models successfully capture a gradually increasing trend aligned with the observed historical patterns, demonstrating better responsiveness to seasonal and long-term fluctuations. Analysis results show that the SARIMA model $(0,1,1)(0,1,0)^{12}$ produced the lowest MAPE value at 3,049% compared to the multiplicative Triple Exponential Smoothing Holt-Winter model with 12,9196%, the additive model with 8,4980% and the SARIMA model $(1,1,0)(0,1,0)^{12}$ with 3,122%. These findings indicate that SARIMA models have higher forecasting accuracy than the Triple Exponential Smoothing Holt-Winters method. The strength of the SARIMA model lies in its ability to handle complex data patterns, such as annual seasonality and irregular trends. The stationarity process, achieved through Boc-Cox transformation and differencing, successfully addresses seasonal fluctuations and trends, allowing the model to be optimally constructed. In addition, SARIMA is supported by significance tests, the white noise test, and the Kolmogorov-Smirnov test. On the other hand, the Triple Exponential Smoothing Holt-Winters method relies on weighting the level, trend, and seasonal components to forecast. But it is less responsive to non-stationary data. This is reflected in its relatively higher MAPE values. The method is more suitable for stable and recurring seasonal and trend patterns.

The sharp decline observed in the early forecast produced by the Holt–Winters model is primarily attributable to the data initialization process rather than to model responsiveness alone. The time series used in this study begins in January 2022, which corresponds to the post-pandemic recovery phase of railway transportation in Indonesia, a period characterized by unusually low passenger volumes. As a result, the initial level and seasonal components estimated by the Holt–Winters procedure were influenced by this temporary structural condition, leading to an artificially low baseline that affected the early forecast trajectory. This sensitivity to initial values is a well-recognized characteristic of exponential smoothing models, particularly when applied to time series with abrupt level shifts or recovery phases. In contrast, the SARIMA model demonstrated greater robustness to the initial data conditions, producing more stable and consistent forecasts. This difference in model behavior further supports the selection of SARIMA as the preferred forecasting approach in this study.

Thus, the SARIMA model $(0,1,1)(0,1,0)^{12}$ is the most effective model for forecasting the number of railway passengers in Indonesia, as it accurately accommodates annual seasonality along with fluctuating trends. Therefore, the research objective has been achieved through the identification of the appropriate forecasting model. Moreover, the higher accuracy of SARIMA forecasts can serve as a practical foundation for PT Kereta Api Indonesia in designing transport capacity, scheduling operations, and planning short to medium-term strategies. This model can also support budget projections and resource allocation based on predicted passenger volumes.

These findings align with (Milenkovic et al., 2016), who showed that the SARIMA model effectively captures complex seasonal patterns in train passenger flows. (Li et al., 2021) also identify SARIMA as a robust baseline before integrating multi-source data. The strong performance of the Triple Exponential Smoothing–Holt-Winters additive model in this study, with a mean absolute percentage error of 8.5%, highlights its continued value when seasonal patterns are stable. (Chuwang & Chen, 2022) confirm that classical forecasting methods, including ARIMA, SARIMA, and Holt–Winters, remain competitive for datasets with simple seasonal fluctuations due to their practicality and interpretability.

Additionally, diagnostic results show that both SARIMA models passed the parameter significance, white noise, and Kolmogorov–Smirnov tests. This reinforces the findings of (Devianto et al., 2024; Zuo et al., 2025) which emphasize the role of the Box–Jenkins diagnostic stage in ensuring model validity before it is used for short- and medium-term forecasting. In Indonesia, this study builds on earlier evidence from (Saputro et al., 2023) applied SARIMA to train passenger data in Java and Sumatra. With a broader scope and direct comparison to TES–HW, this study adds new evidence confirming SARIMA's superiority for complex seasonal patterns. It also demonstrates the relevance of Holt–Winters for stable trends. Therefore, the results align with international findings and contribute to the local literature. Furthermore, they provide practical implications for PT Kereta Api Indonesia to support strategic planning, scheduling, resource allocation, and budget planning based on more accurate forecasts.

Conclusion

This study concludes that both the Triple Exponential Smoothing Holt-Winters, and the SARIMA models are applicable for forecasting the number of railway passengers in Indonesia, although with different characteristics and performance levels. The Triple Exponential Smoothing Holt-Winter approach relies on the decomposition of level, trend, and seasonal components, making it particularly effective for relatively stable seasonal patterns. The multiplicative model yielded forecasts ranging from 13828 to 20262 thousand passengers with a MAPE of 12,9196%, while the additive model produced passenger estimates between 18147 and 24062 thousand passengers with a MAPE of 8,4980%. In contrast, SARIMA models demonstrated superior performance in modelling complex seasonal data patterns after appropriate stationarity treatments and ACF or PACF analysis. The SARIMA model $(0,1,1)(0,1,0)^{12}$ provided estimates between 26428 and 29375 thousand passengers with an MAPE of 3,049%, while the model $(1,1,0)(0,1,0)^{12}$produced forecasts ranging from 26581 to 29021 thousand passengers and a MAPE of 3,122%. Both SARIMA models passed all diagnostic checks, including parameter significance testing, white noise examination, and Kolmogorov-Smirnov tests, indicating their statistical adequacy. Therefore, the SARIMA method is recommended for datasets with complex and evolving seasonal structures, while the Triple Exponential Smoothing Holt-Winters approach remains a practical choice for simpler, stable seasonal trends. The empirical results indicate that PT Kereta Api Indonesia could adopt the SARIMA model for short- to medium-term forecasting to support more accurate strategic planning, scheduling, resource allocation, and budgeting. This confirms that the research objective—identifying the most appropriate forecasting model for Indonesian railway passenger data—has been successfully achieved.

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Declarations

Author Contribution	:	GIC: Conceptualization, Methodology, Resources, Writing - Original Draft, Editing, and Visualization. BAN: Writing - Review & Editing, Formal Analysis. IA: Data Curation, Validation and Supervision.
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