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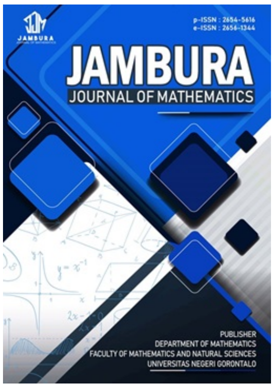

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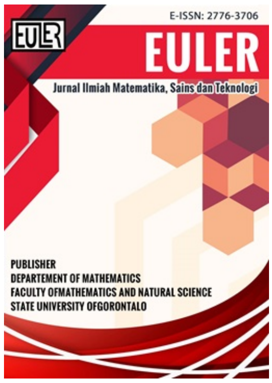

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Research Article

Evaluation of the SARIMA and Prophet Models in Forecasting Ship Passenger Numbers at Balikpapan Port

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ABSTRACT. *Balikpapan Port serves as a vital transportation hub in eastern Indonesia, particularly in supporting the development of the Nusantara Capital City (IKN). This study evaluates the performance of Seasonal Autoregressive Integrated Moving Average (SARIMA) and Prophet models in predicting short-term ship passenger volumes using monthly data from January 2006 to December 2024 obtained from the East Kalimantan Provincial Transportation Office. Our analysis identifies SARIMA (MAPE = 24%) as the more accurate model compared to Prophet (MAPE = 34%). The optimal SARIMA model was then used to generate a focused forecast for December 2025, providing targeted insights for peak-season port management. These results assist port authorities in resource allocation, infrastructure planning, and policy formulation to accommodate anticipated passenger surges during critical periods.*

1. Introduction

Indonesia, an archipelago of over 17,000 islands, relies heavily on maritime transport to ensure connectivity among its regions. Ports are essential hubs for the distribution of goods and movement of people, especially in areas difficult to reach by land or air routes [1]. Law Number 17 of 2008 regarding shipping states that a port is a designated area with specific boundaries used for vessels to dock for loading and unloading goods and passengers. It is equipped with facilities to ensure maritime safety and security. Furthermore, ports serve as transportation hubs that link various modes and regions domestically and internationally.

Balikpapan Port in East Kalimantan holds a strategic position as a key maritime gateway to the Nusantara Capital City (IKN). With the ongoing IKN development, human mobility in the region is projected to increase significantly [2]. This growth will directly affect ship passenger traffic through the port. Therefore, analyzing the dynamics of ship passengers is essential to support data-driven planning in transportation and infrastructure development.

One of the main challenges in port management in Indonesia is operational inefficiencies and infrastructure limitations, which can result in an imbalance between port capacity and service demand [3]. In the context of Balikpapan Port, structural changes due to the Nusantara Capital City's (IKN) development complicate the prediction of logistics flows and maritime transportation. The National Development Planning Agency (Bappenas) estimates that relocating the capital city will significantly increase the flow of goods and people in the surrounding region, including Balikpapan, a key transportation hub [4]. However, historical information regarding the total number of ship passengers has not been systematically analyzed to understand seasonal patterns, long-term trends, and potential spikes in demand. Therefore, a predictive approach based on accurate historical data is necessary to support managerial decision-making and infrastructure planning.

Predicting the volume of ship passengers using time series methods can be an effective solution to address this issue. Time series forecasting involves forecasting future values in a time series involves examining current structures and trends to generate reliable and informative predictions about how the series will develop. Predicting the volume of ship passengers using time series methods can be an effective solution to address this issue. Time series forecasting involves forecasting future values in a time series involves examining current structures and trends to generate reliable and informative predictions about how the series will develop over time [5].

The SARIMA model is a statistical approach utilized for investigating and predicting time series data, particularly those with seasonal patterns exhibiting both trends and seasonal variations. It builds upon the ARIMA (autoregressive integrated moving average) model by adding extra components specifically designed to address seasonality in the data [6]. On the other hand, facebook's prophet model offers great flexibility in accommodating complex trends and seasonality, and is suitable for data with outliers and missing values [7]. Using both models for forecasting is expected to yield more accurate and comprehensive predictions of passenger numbers at Balikpapan Port.

Previous studies have shown that SARIMA and prophet are effective in modelling and forecasting time series data. For instance, research conducted by Negara [8] compared the SARIMA

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model with holt winter's exponential smoothing to forecast the volume of maritime travelers at Pantai Baru Port. The findings indicated that the SARIMA model outperformed the alternative method. Furthermore, a study by Aziza et al. [9] used both the SARIMA intervention model and the prophet model to forecast passenger numbers at Soekarno-Hatta Airport, and the findings revealed that SARIMA had higher forecasting accuracy than prophet. Meanwhile, Ubaid et al. [10] conducted a comparative study of three forecasting models, SARIMA, holt-winters, and prophet, to predict container shipping demand in the Australian maritime sector along the Asia–Oceania trade route. The results displayed that the prophet model delivered the most accurate forecasts. Then, a study by Bouhaddour et al. [11] on forecasting tourist arrivals in Singapore using SARIMA and prophet models revealed that the prophet model outperformed the SARIMA model SARIMA.

Although SARIMA and Prophet have shown reliable performance in various transportation forecasting contexts, including air travel and maritime trade, there is still a lack of research that directly compares these models in the context of regional port passenger forecasting. This gap is especially relevant for Indonesian ports, such as Balikpapan Port, which will play a critical role in supporting the new capital city (IKN). The Prophet model is particularly promising due to its ability to incorporate seasonalities, holidays, and trend changes with minimal parameter tuning. Yet, its application in port passenger forecasting, especially in the Indonesian context, has not been thoroughly investigated. This study aims to evaluate the forecasting accuracy of SARIMA and Prophet models for predicting ship passenger volumes at Balikpapan Port. By identifying the most suitable model for this specific context, the research contributes to evidence-based strategies for regional logistics and transportation planning, particularly in anticipation of the operational needs of IKN.

2. Methods

2.1. Data

The data includes of the value of ship passengers as month at Balikpapan Port, East Kalimantan. This data was collected by bps.go.id from January 2006 to December 2024 and classified by month, as depicted in Table 1.

Table 1. Number of ship passengers at Balikpapan Port

No.	Year	Month	Totally
1	2006	January	19838
2	2006	Febuary	15415
3	2006	March	16200
⋮	⋮	⋮	⋮
226	2024	October	24914
227	2024	November	25174
228	2024	Desember	21276

Source: [12]

2.2. Stage of Analysis

To obtain an accurate forecasting model, it is essential to compare multiple models [13]. Therefore, this study employs the SARIMA and Prophet methods for comparison. These methods are selected because the passenger volume data at the Port of Balikpapan exhibits a clear seasonal pattern. The research methodology applied is illustrated in Figure 1.

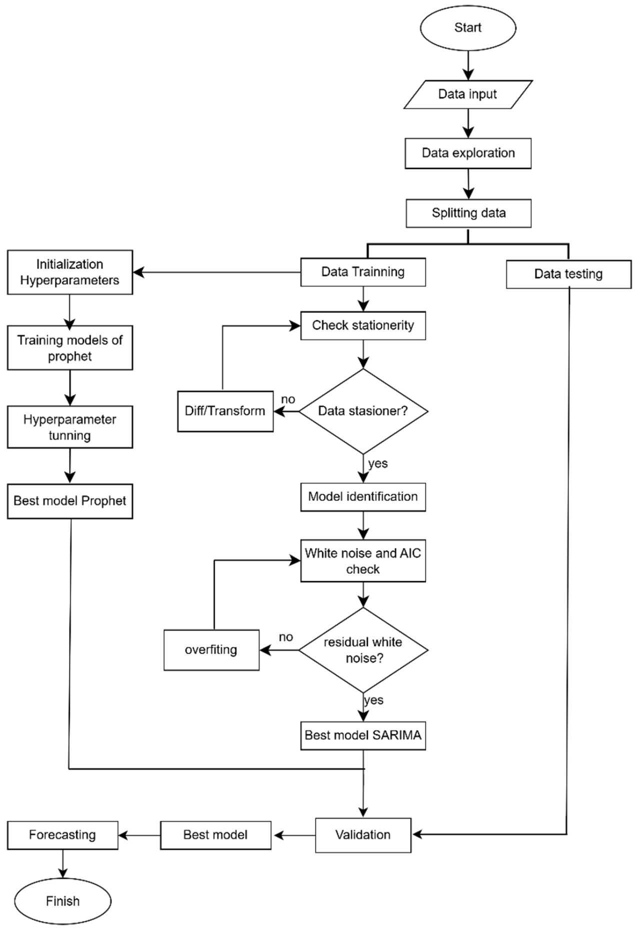


Figure 1. Stage of Analysis

1. Time series plots were used for data exploration to examine the underlying characteristics and patterns in the data.
2. The dataset was split into two subsets: a set for training the model and a set for evaluating its performance.
3. SARIMA model analysis stages
   (a) The analysis of the SARIMA model involves the following steps:
      i. ACF and PACF plots to evaluate autocorrelation patterns.
      ii. Augmented Dickey-Fuller (ADF) test to assess stationarity in the mean.
      iii. Box-Cox transformation to examine variance stationarity. A lambda $\lambda = 1$ Indicates that the data is variance stationary.
      iv. If the data is non-stationary, differencing is applied to the mean and/or variance until the data becomes stationary.
   (b) Once stationarity is reached, the SARIMA model is identified by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots.
      i. Initial inspection focuses on identifying autoregressive (AR) and moving average (MA) components based on ACF and PACF behavior.

ii. However, due to the presence of seasonal patterns in the data, the model is extended to a Seasonal ARIMA (SARIMA) framework, which incorporates both non-seasonal (AR, MA) and seasonal components to better capture the characteristics of the time series.

(c) The initial parameter estimation for the SARIMA model is grounded in insights gained from the ACF and PACF plots, which assist in selecting suitable values for the model's autoregressive, moving average, and seasonal components.

(d) White noise diagnostics on model residuals are then performed by evaluating:
  i. Residual variance homogeneity
  ii. Residual independence
  iii. Residual normality

(e) The resulting models are compared using the akaike information criterion (AIC) to identify the optimal model. The AIC is calculated using the following formula:

$$\text{AIC} = -2\ln(L) + 2k, \tag{1}$$

where L is the likelihood of the model, and k is the number of estimated parameters.

(f) The SARIMA model is also tested for potential overfitting to ensure that it performs well on the training data and generalizes effectively to the testing data.

4. Prophet model analysis stages
  (a) Construct the prophet model using the training dataset.
  (b) Defining National Holidays National holidays were manually added to the model, which includes major public holidays such as Eid al-Fitr and Christmas.
  (c) Determine the best prophet model based on performance on the testing dataset.
  (d) Grid Search for Parameter Tuning To determine the optimal parameters, a grid search was conducted on three key hyperparameters:
    i. Changepoint prior scale: controls the model's flexibility in detecting trend changes.
    ii. Seasonality prior scale: regulates the strength of the seasonal component.
    iii. Seasonality mode: specifies whether the seasonal effect is additive or multiplicative.

Table 2. Combination hyperparameter Prophet

Hyperparameter	Value
Changepoint prior scale	0.001
Seasonality prior scale	1
Seasonality mode	multiplicative

The evaluation was carried out using Prophet's cross validation and performance_metrics functions.

  (e) Perform a prediction using the selected Prophet model.
  (f) Conduct evaluation and model selection based on predictive accuracy.

5. Forecasting and Model Evaluation
  (a) Perform forecasting on the testing data using the optimal SARIMA and Prophet models.
  (b) Compute mean absolute percentage error (MAPE) and root mean square error (RMSE) for each model. The formulas are as follows:

$$\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \tag{2}$$

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{3}$$

where A_t represents the actual value at time t, F_t is the forecasted value at time t, and n denotes the number of observations.

6. Selection of the Best Forecasting Model
The forecasting model with the lowest RMSE and MAPE values is chosen as the best, demonstrating the least level of prediction error.

2.3. SARIMA (Seasonal Autoregressive Integrated Moving Average)

The seasonal autoregressive integrated moving average (SARIMA) model builds upon the ARIMA model by including seasonal patterns present in time series data. Initially introduced by Box and Jenkins in 1994, the ARIMA model is expressed as ARIMA($p,\ d,\ q$), where p indicates the order of the autoregressive (AR) component, d signifies the degree of differencing needed to achieve stationarity, and q denotes the order of the moving average (MA) component. When time series data display seasonality, the model is expanded to SARIMA$(p,\ d,\ q)(P, D, Q)^s$, where P, D, and Q correspond to the seasonal AR, differencing, and MA components, respectively, while s denotes the duration of the seasonal pattern. This formulation allows SARIMA to capture both non-seasonal and seasonal structures within the data effectively [14]:

$$\phi_p(B)\,\Phi_P(B^s)\,(1-B)^d(1-B^s)^D X_t = \theta_q(B)\,\theta_Q(B)^s e_t, \tag{4}$$

where X_t is the time series component at time t, $\phi_p(B)$ represents the non-seasonal AR component of order p, $\Phi_P(B^s)$ is the seasonal AR component of order P, $(1-B)^d$ is the differencing operator of order d, and $(1-B^s)^D$ represents the seasonal differencing operator of order D. The MA component is denoted by $\theta_q(B)$, and the seasonal MA component is $\theta_Q(B)^s$, while e_t represents the residual at time t. In process, SARIMA model operates under the assumption that the data are stationary, that is, the values vary around a constant mean and maintain a consistent variance over time [15].

2.4. Prophet

The Prophet model is an additive model-based algorithm designed for time series forecasting. In this model, non-linear trends are fitted to the data on yearly, weekly, and daily scales, including holiday effects. Prophet performs well when the time series exhibits strong seasonal patterns and the dataset is large [7]. The basic form of the Prophet model is expressed as:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon(t), \tag{5}$$

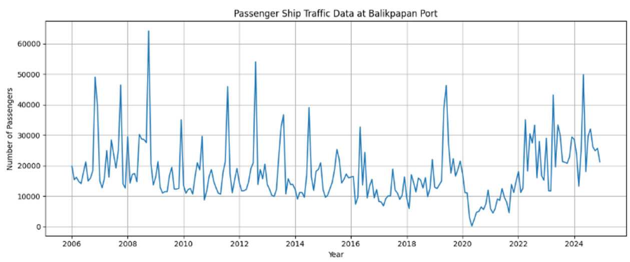
where $y(t)$ is the predicted value. The term $g(t)$ epresents the growth or long-term trend component, $s(t)$ captures recurring seasonal effects (e.g., weekly or yearly patterns), $h(t)$ models the influence of holidays or specific events, and, $\varepsilon(t)$ the error term. This additive decomposition allows the individual components of the time series to be modeled and interpreted independently, enabling clearer insights into how trends, seasonality, and external factors influence the forecast. These components will be analyzed in the Results and Discussion section to evaluate their contribution to model performance.

The Prophet model was chosen due to its ability to automatically capture trend and seasonal patterns, making it suitable for time series data with strong seasonal effects and nonlinear components. Additionally, Prophet is designed to be robust to outliers and missing data, which are common in real-world datasets such as commodity prices. Although Prophet is a statistical model, we compare it alongside ARIMA and SARIMA, as these three represent classical time series approaches that are widely used in practice.

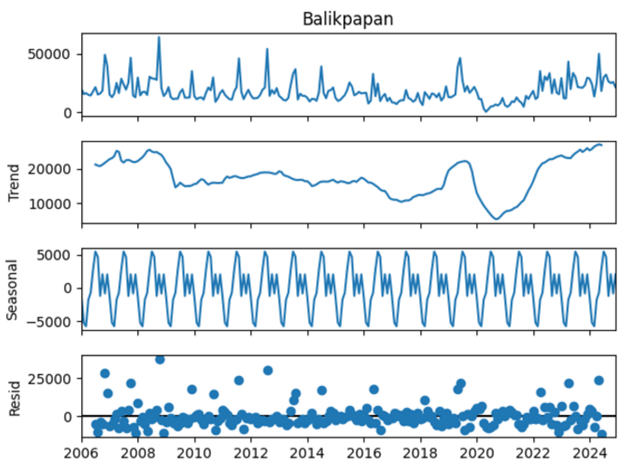
3. Results and Discussion

3.1. Data Exploration

Exploratory data analysis to identify the characteristics of passenger volume at Balikpapan Port can be conducted through visualizations, as illustrated in Figure 2.



(a) Data Plot



(b) Decomposition Plot

Figure 2. (a) Data Plot and (b) Decomposition Plot

Figure 2 illustrates the exploratory analysis of the number of ship passengers at Balikpapan Port from 2006 to 2024. Figure 2a presents the time series plot, which reveals an upward trend alongside consistent seasonal patterns, with noticeable spikes during specific periods. Figure 2b shows the breakdown of the data into trend, seasonal, and residual elements. The trend illustrates long-term movements, the seasonal component reflects repeating yearly cycles, and the residual captures random fluctuations. This decomposition is crucial for thoroughly xunderstanding the data's behavior prior to conducting forecasting.

3.2. Splitting Data

The data in this study is divided into two segments: the training data, which is used to build the model, and the testing data, which is used to evaluate the model's accuracy. The training data spans from January 1, 2006, to December 31, 2023, covering 216 months. The testing data, on the other hand, encompasses the period from January 1, 2024, to December 31, 2024, consisting of 12 monthly observations. This division ensures that the model is trained on long-term data that captures recurring seasonal patterns and trends, while the testing data provides recent information to assess the model's predictive performance.

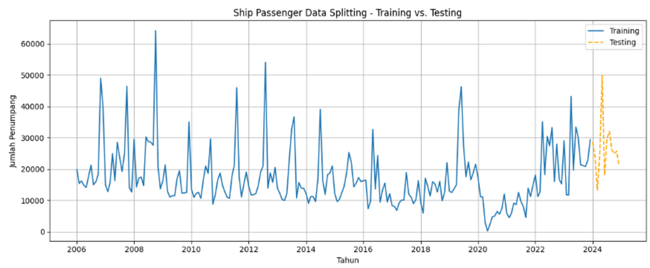


Figure 3. Plot of training and testing data split

3.3. SARIMA Model

The SARIMA model requires the data to be stationary in terms of both mean and variance. Stationarity is examined using ACF (autocorrelation function) and PACF (partial autocorrelation function) plots to observe lag patterns and the ADF (augmented dickey fuller) test to ensure that the data does not contain unwanted trends or patterns. The lambda value obtained from the Box-Cox test is also used to evaluate and determine the need for data transformation, which can help achieve stationarity.

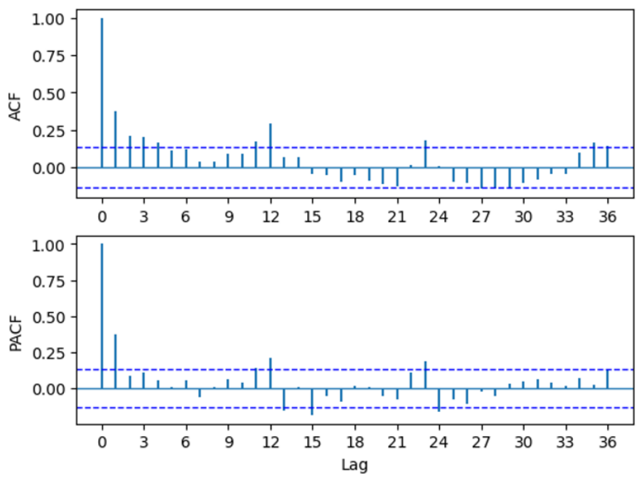


Figure 4. ACF and PACF plots of the training data

Table 3. ADF Test

ADF Test	P-*value*
0,06	0, 05

Based on the test results, the p-value is 0.06, greater than 0.05, indicating that the data is non-stationary. This suggests that the data contains trends or patterns that change over time; therefore, to attain stationarity, differencing is applied. The ACF and PACF plots following the first differencing suggest that the series has become more stable. However, there are still signs of seasonality at lag 12 (every 12 months). To address this pattern, seasonal differencing with 12 months is applied. Seasonal differencing subtracts each data point by the value from 12 periods earlier, which effectively removes the seasonal component and makes the data seasonally stationary.

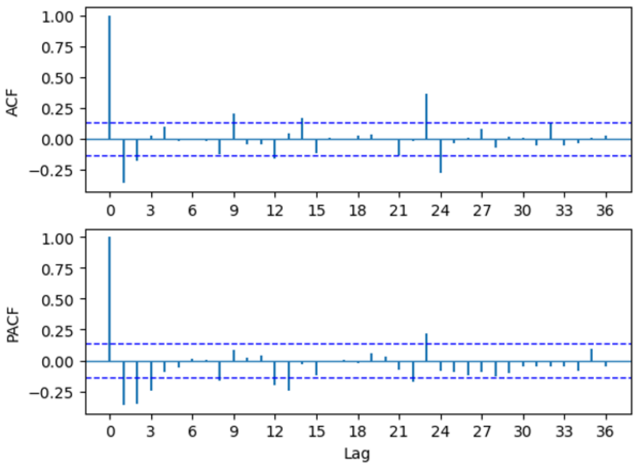


Figure 5. ACF and PACF plots after differencing

Table 4. Stationary check

Test	Value	Description
ADF	$1,920 \times 10^{-8}$	Stationary
Lambda Value	1,225	Stationary

Figure 5 shows the ACF (a) and PACF (b) plots after applying first-order and seasonal differencing with 12 months. Following the first differencing, the data exhibits a more stable pattern. The value of the ADF test (Table 3) indicate a p-value of 1.920×10^{-8}, which is less than 0.05, suggesting that the data is now stationary regarding the mean. Additionally, the Box-Cox transformation provides a lambda value of 1.225, indicating that the data is closer to a normal distribution and has achieved variance stationarity [16]. The proposed model based on Figure 5 can be seen in Table 5.

Based on Table 5, the SARIMA model (0,1,2)(0,1,2)[12] has a lower AIC value compared to model SARIMA (0,1,2)(2,1,0)[12] (3688,899), despite one non-significant parameter, which is MA(2); other components are significant. This may occur because the model tends to rely on MA(1) [17]. This model was chosen for further analysis so that diagnostic tests on the residuals could be conducted. Diagnostic testing is essential to confirm that the residuals exhibit characteristics of white noise, as indicated by the assumptions of normality and absence of autocorrelation in the distribution [9].

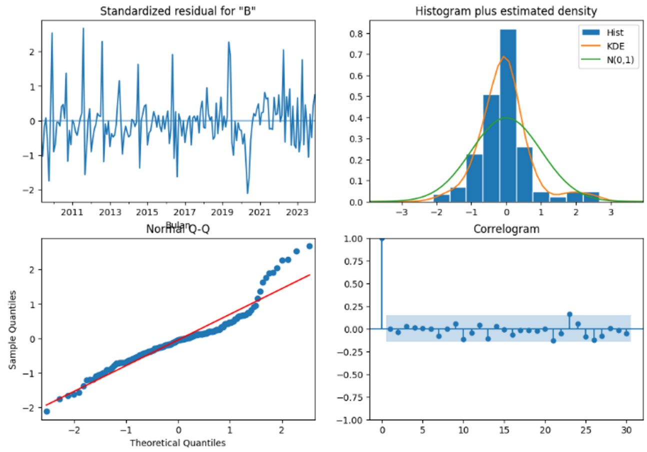


Figure 6. Diagnostic model

Table 6 presents the results of the residual assumption tests. Results from the Jarque-Bera test suggest that the residuals deviate from normal distribution. Meanwhile, the Ljung-Box test results reveal that there is no autocorrelation in the residuals, as the p-value exceeds 0.05. However, the outcome of the Jarque-Bera test can be accepted since the data used is significant. In this study, 228 data points were included, leading to the conclusion that the data follows a normal distribution [18]. Next, overfitting is performed to ensure that the model provides accurate predictions.

According to Table 7, the overfitting model has a lower AIC value compared to the SARIMA model (0,1,2)(0,1,2)[12]; however, more coefficients are insignificant [19]. Therefore, the SARIMA model (0,1,2)(0,1,2)[12] is selected as the best model, with the following model equation:

$$\left(1-B\right)\left(1-B^{12}\right)y_t = \theta_1\left(1-B\right)\left(1-B^{12}\right)\varepsilon_t + \theta_2\left(1-B\right)\left(1-B^{12}\right)\varepsilon_t,$$

with an RMSE of 9,331.33 and a MAPE of 24.063%.

3.4. Prophet Model

The Prophet model forecasts passenger numbers by incorporating trend components, annual seasonality, and holiday effects. Its decomposition results are displayed in three key plots: long-term trends, holiday impacts, and yearly seasonal patterns, along with the overall forecast output [7]. The Prophet model's performance was evaluated using metrics such as Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). Residual analysis indicated higher errors during peak travel seasons, highlighting the model's difficulty in predicting abrupt demand surges. A key limitation is its assumption of additive seasonality, which may oversimplify complex interactions between trends and holiday effects. Furthermore, the model does not account for external factors like economic conditions or special events, potentially reducing its predictive accuracy.

To illustrate how the Prophet model separates trend, seasonality, and holiday effects, Figure 7 presents the decomposition results based on the best-performing model obtained through hyperparameter tuning.

Table 5. Estimation of the tentative SARIMA model parameters

Model	Parameters	Coefficient	P Value	Parameter Significant	AIC	White Noise
$SARIMA(0,1,2)(1,1,0)^{12}$	MA(1)	-0.653	0.000	Sig.	4038.301	Yes
	MA(2)	-0.048	0.464	No sig.		
	SAR(1)	-0.252	0.000	Sig.		
$SARIMA(0,1,2)(0,1,2)^{12}$	MA(1)	-0.620	0.000	Sig.	3687.256	Yes
	MA(2)	-0.110	0.363	No sig.		
	SMA(1)	-0.583	0.000	Sig.		
	SMA(2)	-0.292	0.007	Sig.		

*Parameters tested at a 5% significance level

Table 6. Residuals assumption test

Jarque-Bera Test	Ljung-Box Test
0,823	0, 000

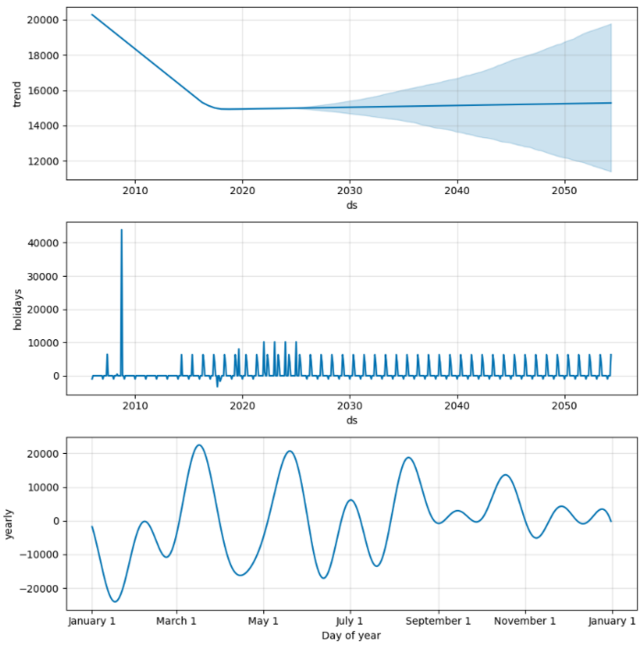


Figure 7. Decomposition of Ship Passenger Numbers in Balikpapan (2006–2024)

The decomposition plot visualizes the internal components of the Prophet model, which is expressed by the following equation:

$$y(t) = g(t) + s(t) + h(t) + \varepsilon_t,$$

where, $g(t)$ denotes the trend component, $s(t)$represents the seasonality component, $h(t)$ captures the effects of public holidays, and ε_t is the error term.

This structure corresponds with the Prophet model implementation in this study, where a grid search was conducted to determine the optimal combination of hyperparameters. The best configuration was found to be changepoint_prior_scale = 0.001 to allowing flexibility in detecting small changes in trend, seasonality_prior_scale = 1.0 to giving a balanced weight to seasonal fluctuations, and seasonality_mode = 'multiplicative', which implies that seasonal effects grow proportionally with the trend.

These tuned parameters guided the decomposition results shown in the figure. The top panel illustrates a generally increasing trend from 2006 to 2024, with a significant spike around 2008, likely caused by the global financial crisis when maritime transport became a more affordable option [20]. he middle panel shows the effect of national holidays, which were manually specified and included holidays such as Eid al-Fitr and Christmas. Finally, the bottom panel reveals a strong yearly seasonal pattern, which aligns with recurring events and climate-driven fluctuations.

After selecting the optimal Prophet model through grid search and validating its components, a long-term forecast was generated to examine future passenger trends. The result is illustrated in Figure 8.

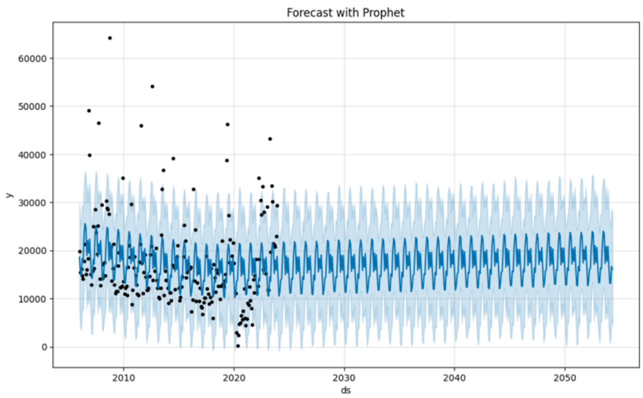


Figure 8. Forecast of Ship Passenger Numbers Using the Prophet Model (2006–2050)

This figure presents the forecast of ship passenger numbers in Balikpapan generated by the optimized Prophet model. The forecast was produced using the best hyperparameter combination determined through grid search, and national holidays were incorporated to improve the model's realism. The results demonstrate a gradually increasing trend extending to 2050, along with strong annual seasonality captured in the forecast. The model achieved a Root Mean Squared Error (RMSE) of 12,427 and Mean Absolute Percentage Error (MAPE) of 34% on the test dataset, indicating a reasonable level of predictive accuracy.

3.5. Evaluation Model

It is utilized to generate forecasts for the test dataset, which consists of 16 data points. Figure 9 presents a comparison between the cross-validated forecasts from both models and the actual test data.

The evaluation results on the test dataset (16 data points)

Table 7. Estimation of Tentative Parameters for the SARIMA Model

Model	Parameters	Coefficient	P Value	Parameter Significant	AIC
$SARIMA(1,1,2)(0,1,2)^{12}$	AR(1)	-0.4564	0,673	No sig.	3688,794
	MA(1)	-0,168	0,874	No sig.	
	MA(2)	-0,404	0,557	No sig.	
	SMA(1)	-0,583	0,000	Sig.	
	SMA(2)	-0.289	0,008	Sig.	
$SARIMA(0,1,3)(0,1,2)^{12}$	MA(1)	-0,630	0,000	Sig.	3656,250
	MA(2)	-0,138	0,296	No sig.	
	MA(3)	-0,051	0,713	No sig.	
	SMA(1)	-0,591	0,000	Sig.	
	SMA(2)	-0,299	0,002	Sig.	
$SARIMA(0,1,2)(0,1,3)^{12}$	MA(1)	-0,634	0,000	Sig.	3432.099
	MA(2)	-0,084	0,625	No sig.	
	SMA(1)	-0,547	0,000	Sig.	
	SMA(2)	-0,289	0,044	Sig.	
	SMA(3)	-0,019	0,890	No sig.	
$SARIMA(0,1,2)(1,1,2)^{12}$	MA(1)	-0,629	0,000	Sig.	3687,801
	MA(2)	-0,104	0,425	No sig.	
	SAR(1)	-0,356	0,213	No sig.	
	SMA(1)	-0,256	0,359	No sig.	
	SMA(2)	-0,561	0,011	Sig.	

*Parameters tested at a 5% significance level

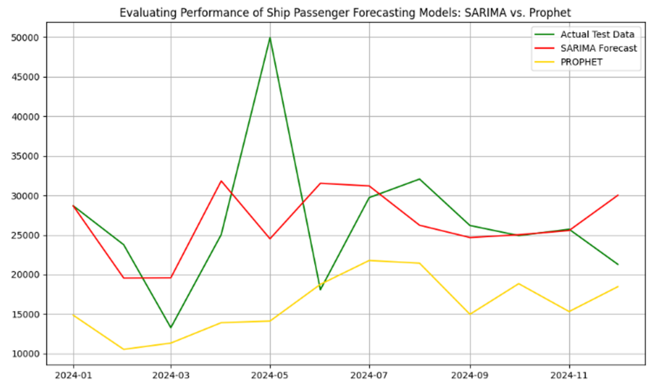


Figure 9. Plot of Test Data and Forecasts Using SARIMA and Prophet

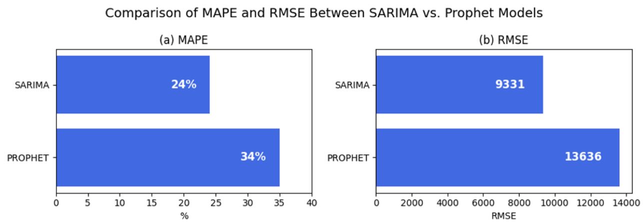


Figure 10. Comparison of MAPE and RMSE between SARIMA vs Prophet Models

reveal distinct forecasting patterns between the SARIMA and Prophet models. SARIMA demonstrated better alignment with the actual trends in the early period (January–April 2024), while Prophet consistently produced lower estimates. However, during the data peak in May 2024, SARIMA overpredicted the spike, whereas Prophet failed to capture its magnitude, resulting in a flatter forecast. Although both models broadly followed the actual trend, SARIMA achieved higher accuracy at specific points, while Prophet tended to smooth out fluctuations. This suggests that SARIMA is more responsive to short-term variations, whereas Prophet prioritizes stability but may lack sensitivity to sudden changes.

Based on Figure 10, according to the two metrics used, the SARIMA model performs better than Prophet in forecasting the number of ship passengers at Balikpapan Port. Regarding MAPE, SARIMA has a mean error of 24%, while prophet has 34%, indicating that SARIMA's predictions are more accurate. Similarly, regarding RMSE, SARIMA records a value of 9331, which is lower than Prophet's value of 13636, meaning SARIMA's predictions are closer to the actual values than prophet [21].

3.6. Forecasting Using the Best Model

The number of ship passengers at Balikpapan Port from January 2025 to December 2025 was forecast using the $SARIMA(0,1,2)(0,1,2)^{12}$ model, which was selected as the best-performing model based on the lowest AIC and adequate diagnostic checks. The results of the monthly forecasts are presented in Table 7. The forecast indicates that passenger traffic will reach its peak in May 2025 with an estimated 40,771.72 passengers, while the lowest value is expected in March 2025 at 18,257.39 passengers. Another increase is also seen in July and August, showing possible seasonal demand patterns related to holidays or weather conditions.

Based on the forecasted fluctuations in passenger numbers at Balikpapan Port throughout 2025, totalling approximately 355,458 individuals, with the highest peak in May (around 40,772 passengers) and a low period in March (approximately 18,257 passengers), Port Authorities and Shipping Companies must implement proactive strategies. This includes optimising resource

Table 8. Forecasting

Date	SARIMA Forecasting
January 2025	30,454.90
February 2025	23,499.04
March 2025	18,257.39
April 2025	34,298.76
May 2025	40,771.72
June 2025	28,487.90
July 2025	33,399.14
August 2025	34,921.91
September 2025	27,140.98
October 2025	30,182.50
November 2025	27,856.86
Desember 2025	26,185.76

allocation—such as increasing staff levels, ship availability, and facilities—prior to peak periods (particularly April–May and July–August), while utilising low periods (February–March) for infrastructure and fleet maintenance.

In addition to providing practical implications for passenger flow management, this study contributes to the literature by applying and validating the SARIMA model in the context of maritime transportation forecasting, specifically at Balikpapan Port. Although SARIMA and similar models are widely used, their application to port-specific monthly passenger traffic in Indonesia remains limited. Therefore, this research highlights the usefulness of classical time series methods in operational planning for regional port authorities and offers a baseline for further model comparisons, including hybrid or machine learning-based approaches. This contribution is expected to guide both future studies and practical implementations in similar maritime contexts.

Planning fleet capacity is crucial, especially during months with high passenger volume such as May. Marketing strategies should focus on promotions during low-demand months to stimulate interest, and on service information during busy months. Moreover, it is essential to anticipate the need for additional services and to enhance safety and security awareness during peak periods, considering that the SARIMA model highlights a recurring seasonal pattern likely to reappear annually.

4. Conclusion

Based on performance evaluation metrics, the SARIMA model outperformed the Prophet model in forecasting monthly domestic passenger departures at Balikpapan Port. SARIMA achieved a MAPE of 24% and an RMSE of 9,331, compared to Prophet's MAPE of 34% and RMSE of 13,636. These results indicate that SARIMA more effectively captured the seasonal and trend patterns present in the dataset, making it a more reliable choice for short-term maritime passenger forecasting.

Although the Prophet model did not perform as well in this study, it remains a promising tool due to its modular structure, ease of implementation, and built-in handling of holidays and missing values. Future studies could improve Prophet's performance by thoroughly tuning its parameters, incorporating external variables such as regional events, weather conditions, or economic indicators, and customizing seasonalities to match domain-specific patterns better. Prophet also holds potential as a component in hybrid models, particularly when interpretability and flexibility are key requirements. The findings of this study offer practical insights for port authorities and policymakers in anticipating passenger fluctuations and planning operational resources effectively.

For future research, it is recommended to explore hybrid forecasting models, combining classical time series models like SARIMA or Prophet with machine learning approaches such as Support Vector Regression (SVR) or Random Forest, to enhance predictive accuracy. Comparative studies across multiple ports and time horizons can also help strengthen the generalizability and strategic value of forecasting models in the maritime transport sector.

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