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# Passenger's Forecasting at Tanjung Api-Api Port Using The Eksponential Smoothing

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## ABSTRACT

Tanjung Api-Api Port connects South Sumatra Province and Bangka Belitung Islands Province. A total of 15 ships divided into seven trips per day cross the Bangka Strait. Sea transportation is more popular among passengers because it is cheaper than air transportation. Forecasting passenger growth is necessary as a basis for improving passenger services. The forecasting method used is the Exponential Smoothing method, as passenger data over the past five years at Tanjung Api-Api Port shows a seasonal trend. The historical data used is passenger departure and arrival data. The results of the analysis show that departure passenger data is modelled using the Simple Seasonal model, while arrival passenger data is modelled using the Winter Additive model. The departure passenger data forecast shows a stable and consistent trend without any major spikes as in the previous period. Meanwhile, the arrival passenger data forecast shows a gradual and upward trend. The accuracy of the model obtained for forecasting departure passenger data was 76.5%, and the accuracy of the model for forecasting arrival passenger data was 81.86%. With the accuracy of the model obtained, passenger growth forecasts can be used as a reference for policies in managing facilities at Tanjung Api-Api Port.

**Keywords**: Forecasting, Passengers, Simple Seasonal Model, Tanjung Api-Api Port, Winter Additive Model

## INTRODUCTION

South Sumatera Province geographically borders the Bangka Belitung Islands Province to the east, separated by the Bangka Strait. Therefore, transportation access connecting Sounth Sumatera and Bangka Belitung Provinces can be traversed by air and sea transportation. Sea Transportation access is through ports as a connection, One of the ports connecting South Sumatra Province and the Bangka Belitung Islands Province is Tanjung Api-Api Port. Tanjung Api-Api Port was inaugurated for operations starting on December 11, 2013.

Tanjung Api-Api Port is located in Banyuasin Regency, South Sumatra Province, connected to Tanjung Kalian Port in West Bangka Regency, Bangka Belitung Islands Province. The two ports are 30 nautical miles apart, with a sailing time of approximately 3 hours (Susanto et al, 2021). The route of Tanjung Api-Api Port – Tanjung Kalian Port is a route that has a very important role in connecting all economic activities between the Province of South Sumatera and Bangka Belitung Province.

There are fifteen ships operating on the route from Tanjung Api-Api Port to Tanjung Kalian Port. The regular daily schedule consists of seven trips, with details as follows: Trip I (first) at 8:00 a.m., Trip II (second) at 10:00 a.m., Trip III (third) at 12:00 p.m., Trip IV (fourth) at 2:00 p.m., Trip V (fifth) at 4:00 p.m., Trip VI (sixth) at 6:00 p.m., and Trip VII (seventh) at 9:00 p.m.(Susanto et al., 2021). The fifteen operating ships each have their own maximum passenger capacity.

Passenger services at Tanjung Api-Api Port are still largely inadequate or not fully optimal, with a compliance percentage of 23.67% and non-compliance rate of 25.65%, out of the 49.32% maximum percentage set for passenger service standards at the Port. However, as sea transportation is a mode of transportation categorised as cheaper compared to air transportation, the number of passengers is expected to increase annually, it is necessary to forecast of passenger numbers for the coming years. The forecast results can be used as a basis for developing a policy-related plan at the Port (Febriansyah et al., 2023).

As the main port serving as the gateway to the Bangka Belitung Islands, Tanjung Api-Api Port must, of course, continue to improve its services to passengers. Passenger volume forecasting is carried out to identify patterns in passenger numbers. Furthermore, passenger volume forecasting plays a crucial role in decision-making for the future, for example regarding the provision of additional facilities and infrastructure during passenger surges, staff scheduling, and other business matters.

Forecasting is the process of estimating future requirements, which encompass needs in terms of quantity, quality, timing and location, in order to meet the demand for goods and services (Lusiana & Popy, 2020). By knowing the projected passenger numbers for the coming years, the service provider, in this case the Tanjung Api-Api Port Authority can draw up plans to ensure that facilities are prepared to cope with future fluctuations in passenger numbers.

Time series data consist of four components: trend, cyclical, erratic (random) and seasonal (Theodore et al., 2002). One method that can be used to forecast the number of passengers based on historical data is the Exponential Smoothing Method. In forecasting, the aim is to obtain predictions that minimise the error rate, as measured by the forecast accuracy (Khoiriyah et al, 2023).

Several studies on forecasting passenger numbers in the maritime transportation sector, including research conducted by Murdani & Yonlib (2021), used the ARIMA method to forecast the number of ship passengers at Ambon Port. Their analysis showed a decline in the forecasted number of passengers for the next 12 periods. Furthermore, Putri & Sofro (2022) forecast the number of domestic passenger departures at Tanjung Perak Port using both ARIMA and SARIMA methods. The results showed that SARIMA method was more effective in forecasting the number of passenger departures.

## MATERIAL AND METHOD

The data used in this study is secondary data sourced from the South Sumatra Class II Land Transport Management Agency Center (BPTD Kelas II Sumatera Selatan). The data used for forecasting consists of monthly passenger number at Tanjung Api-Api Port from 2021 to 2023. In addition, annual data on passenger numbers at Tanjung Api-Api Port from 2019 to 2023 were also used as exploratory data on passenger numbers at Tanjung Api-Api Port. The data used in this study were processed using SPSS 21 Software and R software.

Forecasting is a planning tool designed to help management address future uncertainty based on historical data and trend analysis (Subagyo, 2013). It is considered essential and provides the fundamental information required for business planning, which forms the backbone of effective industrial operations (Utami et al., 2024). In the service sector, forecasting can be used as a tool for policy-making and for estimating sales or the usage of a product, ensuring that the product is manufactured to the appropriate quality (Wardah & Iskandar, 2017).

The Exponential Smoothing method is a forecasting method. The Exponential Smoothing method assigns an exponential weight to all historical data with the aim of estimating the current level (Cryer & Chan, 2008) and using this to forecast values for several periods ahead (Nawawi et al., 2021). The Exponential Smoothing method weights past data exponentially so that the most recent data has a greater weight in the moving average (Aryati et al, 2020). The Exponential Smoothing method has been widely used in research involving data with seasonal patterns.

In the Exponential Smoothing method, there are two models: the Simple Seasonal Model and the Winter Additive Seasonal Model. The Simple Seasonal Model considers the existence of seasonal patterns (seasonality) that occur repeatedly every certain time period. For example, the number of passengers and vehicle numbers may increase at weekends or during the holiday season. The Simple Seasonal Model is an exponential smoothing model similar to the ARIMA method with zero autoregressive orders, one differencing order, one seasonal differencing order, and moving average orders of 1, p, and p + 1, where p is the number of periods in the seasonal interval (Suryani & Can, 2018). For example, the number of passengers and vehicles may increase at weekends or during the holiday season. By identifying these seasonal patterns, the Simple Seasonal model helps to anticipate fluctuations in the number of passengers and vehicle numbers, thereby enabling better planning of transport capacity.

The Winters Additive seasonal model, which uses the seasonal addition method, is suitable for forecasting time series where the amplitude (or height) of the seasonal pattern is independent of the mean level or the size of the data set and is therefore constant. The three equations used in the Winters Additive model are:

$$S_t = \alpha(X_t - I_{t-1}) + (1-\alpha)(S_{t-1} + b_{t-1})$$
$$b_t = \beta(S_t - S_{t-1}) + (1-\beta)\, b_{t-1}$$
$$I_t = \gamma(X_t - S_t) + (1-\gamma)\, I_{t-1}$$
$$Y_{t+m} = S_t + m b_t + I_{t-L+m}$$

where :

$S_t$ = the forecast smoothing value for t period
$X_t$ = Actual value at t period
$b_t$ = Trend smoothing value
$I_t$ = The seasonal component in t period
$Y_{t+m}$ = Forecast for $m$ in the next period from $t$
$m$ = The number of periods to be forecast in the future
$\alpha$ = Smoothing parameters for the trend ($0 < \alpha < 1$)
$\gamma$ = Smoothing parameters for the trend ($0 < \gamma < 1$)
$\beta$ = Smoothing parameters for the trend ($0 < \beta < 1$)
$L$ = Seasonal length

Model diagnostics were performed to assess the suitability of the identified model. The model diagnostics were based on residual analysis, which checks the independent of residuals and residual normality. The model assessment process, known as the White Noise Test, utilised the Ljung-Box test. The Ljung-Box test was used to check the independent of residuals.

1) Hyphothesis
   $H_0$: there is no residual autocorrelation;
   $H_1$: there is residual autocorrelation;
2) Test Statistics (Montgomery et al, 2008)
   $$Q = n(n+2)\sum_{k=1}^{K}\left(\frac{1}{n-k}\right) r_k^2$$
   details :
   $n$ : the volume of data;
   $k$ : lag to- $k$;

$K$ : maximum lag;
$r_k^2$ : the autocorrelation coefficient between residuals at lag-$k$;

3) Decision-making criteria
If $Q$ value < $x^2_{\alpha(K-p-q))}$ with is the order of the AR model and $q$ is the order of the MA model, or if the *p-value* is greater than α, then we do not reject $H_0$, meaning there is no autocorrelation in the residuals.

After making a forecast, the forecast accuracy can be determined by calculating the Mean Absolute Percentage Error (MAPE), which is calculated by dividing the absolute error for each period by the actual observed value for that period. The absolute percentage errors are then averaged. MAPE is a measure of error that calculates the percentage deviation between actual data and forecast data (Montgomery, 2008).

The MAPE value can be calculated using the following equation (Utami et al., 2024).

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

Where :
$X_t$ : actual data for $t$ period ;
$F_t$ : estimated value for the $t$ period ;
$n$ : data volume

MAPE is a frequently used criterion for assessing the accuracy of forecasting methods as it provides relatively accurate results. According to (Chang et al., 2007), there are four MAPE value criteria, as shown in Table 1. The lower the MAPE, the better the forecasting model's performance (Darmawan et al., 2022). According to (Chang et al., 2007), there are four MAPE criteria as shown in Table 1. The lower the MAPE, the better the forecasting model's performance (Darmawan et al., 2022).

Table 1. MAPE Value Criteria

| MAPE's Value | Forecast Ability Crtieria |
|---|---|
| <10% | Very Good |
| 10%-20% | Good |
| 20%-50% | Adequate |
| >50% | Bad |

## RESULT AND DISCUSSION

### Data Exploration

Based on the data obtained, it is evident that passenger numbers at Tanjung Api-Api Port have continued to increase year on year. Since Tanjung Api-Api Port began operations in 2013, passenger numbers have never decreased; in fact, the trend shows a fairly rapid increase. Passenger throughput at Tanjung Api-Api Port from 2019 to 2023 is shown in Figure 1. The graph showing passenger productivity growth over the past five years at Tanjung Api-Api Port is shown in Figure 1 below:

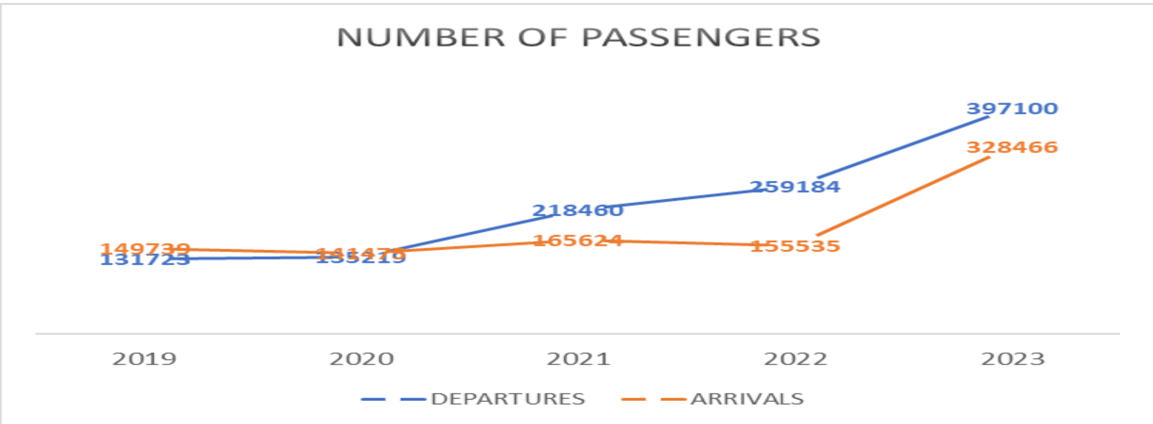


Figure 1. Passenger Productivity Graph of Tanjung Api-Api Port

Figure 1 shows that the data trend is steadily increasing. When viewed on a monthly basis, the increase in passenger numbers exhibits a seasonal pattern. It is recorded that the number of passengers rose sharply from 131.723 people in 2019 to 397.100 people in 2019, using ferry transport to travel to Bangka Island via Tanjung Api-Api Port. Similarly, the number of arriving passengers from Bangka Province has also been increasing annually. In 2019, the number of arriving passengers reached at 149.739 people, more than doubling to 328.466 people. This clearly indicates that the use of Tanjung Api-Api Port's services is on the rise and urgently requires attention in terms of service improvements.

**Passengers Forecasting**

Passenger data at Tanjung Api-Api Port shows a seasonal pattern, as illustrated in the time series graph below. In Figures 2. And Figure 3. show that the passenger numbers data exhibits a recurring pattern at regular intervals, yet exhibits an upward trend over time. The passenger data is divided into data on passengers departing from Tanjung Api-Api Port and data on passengers arriving at Tanjung Api-Api Port.

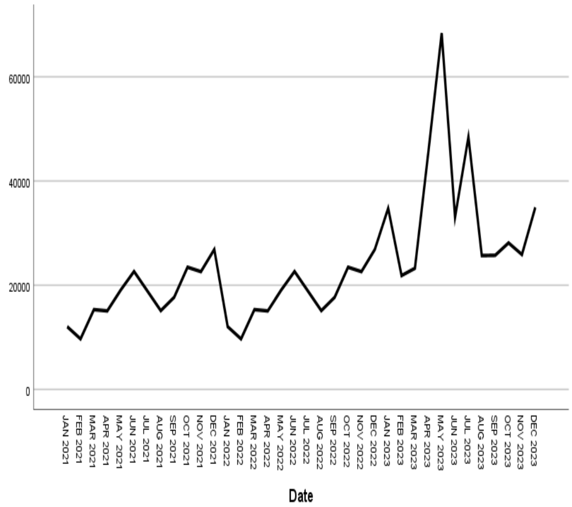


Figure 2. Time Series Chart of Departing Passenger Numbers

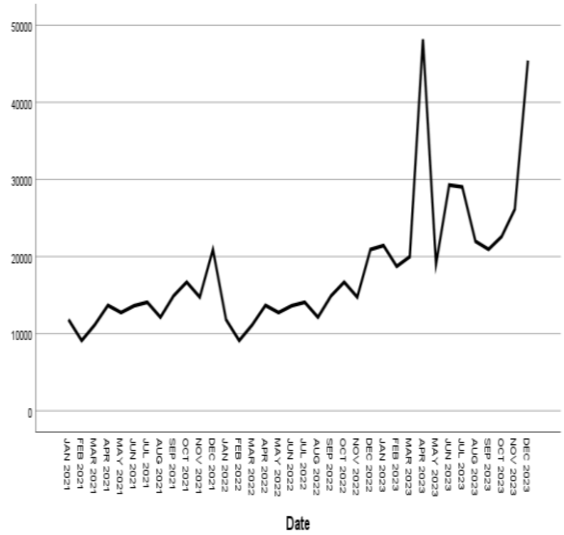


Figure 3. Time Series Chart of Arriving Passenger Numbers

Table 2. *Output of* Departing Passenger Data Model

| Model Description | | | |
|---|---|---|---|
| | | | Model Type |
| Model ID | Number of passengers | Model_1 | **Simple Seasonal** |

| Exponential Smoothing Model Parameters | | | | | | |
|---|---|---|---|---|---|---|
| Model | | | Estimate | SE | t | Sig. |
| Number of passengers-Model_1 | No Transformation | Alpha (Level) | 0.500 | 0.156 | 3.204 | 0.003 |
| | | Delta (Season) | 9.652E-06 | 0.287 | 3.362E-05 | 1.000 |

Table 3. *Output of* Arrival Passenger Data Model

| Model Description | | | |
|---|---|---|---|
| | | | Model Type |
| Model ID | Number of passengers | Model_1 | **Winters' Additive** |

| Exponential Smoothing Model Parameters | | | | | | |
|---|---|---|---|---|---|---|
| Model | | | Estimate | SE | t | Sig. |
| Number of passengers_2-Model_1 | No Transformation | Alpha (Level) | 0.301 | 0.131 | 2.291 | 0.028 |
| | | Gamma (Trend) | 5.032E-06 | 0.023 | 0.000 | 1.000 |
| | | Delta (Season) | 0.001 | 0.184 | 0.005 | 0.996 |

Based on the results in Table 2., it can be seen that a Sig. (P-value) of 0.003 indicates that this Alpha value is statistically significant at the 5% significance level (since 0.003 < 0.05). This means that the smoothing level has an effect on the model. Meanwhile, for delta (season), a Sig. (P-value) of 1.000 was obtained, indicating that there is no statistical significance for the Delta parameter. In other words, there is no strong evidence that seasonality contributes significantly to this model.

Based on the results in Table 3, it can be seen that the Sig. (P-value) for alpha (Level) of 0.028 indicates that this level component (alpha) is statistically significant at the 5% significance level (since 0.028 < 0.05). This means that the smoothing level has an effect on the model. Meanwhile, for gamma (trend) and delta (season), the Sig. (P-value) is greater than 0.05. In other words, there is no strong evidence that trends and seasonal patterns contribute significantly to this model.

Based on the above, it is clear that the forecasting of departing passenger numbers is carried out using the *Simple Seasonal* Model, whilst the forecasting of arriving passenger numbers uses the *Winters Additive* Model. The forecasting involves predicting passenger numbers for the next two years based on historical data, specifically passenger numbers up to December 2025.

The graphs showing the forecast passenger numbers can be seen in Figures 4 and Figure 5 below.

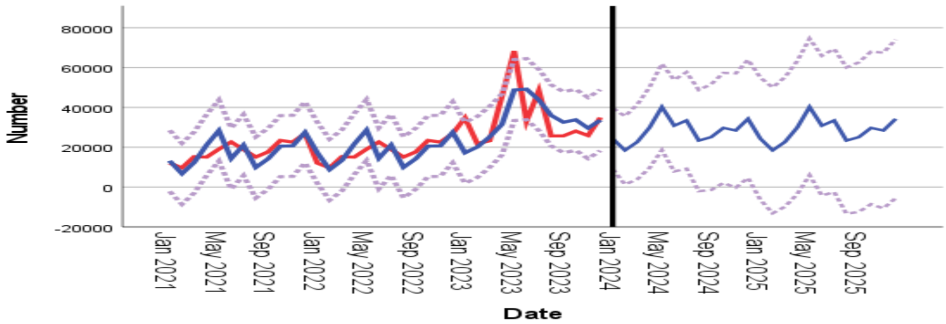


Figure 4. Graph of Forecast Departing Passenger Numbers


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Description:


UCL (Upper confident interval): Upper Bound of the Predicted Value
LCL (Lower confident interval): Lower Bound of the Predicted Value
*Forecast*: Predicted number of passengers
*Observed*: Actual Number of Passengers

The graph in Figure 4 shows that there were significant fluctuations in passenger numbers during the 2021–2023 period, with the highest peak occurring in mid-2023. However, the forecast for the subsequent period (2024–2025) indicates a more stable and consistent trend, without the major spikes seen in the previous period. Uncertainty increases for the forecast in 2025. The upper and lower control limits (UCL and LCL) show greater variation, indicating that the forecast for passenger numbers in the more distant period has the potential for significant deviation. This is normal in forecasting, as the further ahead the forecast is made, the greater the potential for deviation.

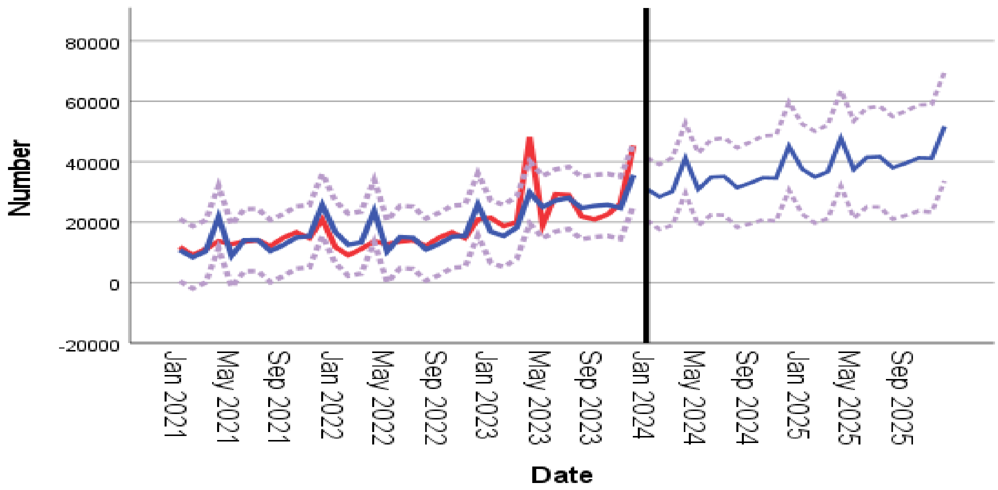


Figure 5. Graph of Forecast Arrival Passenger Numbers

Description:


UCL (Upper confident interval): Upper Limit of the Predicted Value
LCL (Lower confident interval): Lower Bound of the Predicted Value
Forecast: Predicted number of passengers
Observed: Actual Number of Passengers

The graph above shows that there were significant fluctuations in passenger numbers during the year 2021–2023 period, with the highest peak occurring in mid-2023. However, the forecast for the subsequent period (2024–2025), represented by the blue line as a projection of future passenger numbers, indicates a gradual increase in passenger numbers from January 2024 to September 2025, with passenger numbers tending to rise towards 50.000

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people. From the graph, after January 2024, the UCL and LCL ranges widen significantly, indicating higher uncertainty in future forecasts.

Following the forecasting process, the goodness-of-fit of the resulting model was then assessed. In Table 4 and 5, present the MAPE values for departure passenger data and arrival passenger data at Tanjung Api-Api Port.

Table 4. MAPE Value for Departing Passenger Numbers

| Model | Number of Predictors | Model Fit statistics: Stationary R-squared | R-squared | MAPE |
|---|---|---|---|---|
| Number of passengers-Model_simple_seasonal | 0 | .567 | .592 | 23.521 |

Based on the results of the model goodness-of-fit tests, the Simple Seasonal Model performed reasonably well, with a relatively high R-squared of 56.7% (0.567) and a Stationary R-squared of 59.2% (0.592), indicating that the model was fairly successful in capturing most of the patterns in the passenger volume data. As for forecasting accuracy, as measured by the MAPE value of 23.52%, this model provides fairly accurate predictions, indicating that the success rate in forecasting is around 76.5%.

From the results of the Ljung-Box test above, the p-value (Sig.) of 0.928 is greater than the significance level of 0.05; therefore, the decision is to accept the null hypothesis. In other words, there is no autocorrelation at any of the lags tested, and the residuals in the data do not exhibit a repeating pattern or show any correlation across time.

Table 5**.** MAPE Value for Arrival Passenger Numbers

| Model | Number of Predictors | Model Fit statistics: Stationary R-squared | R-squared | MAPE |
|---|---|---|---|---|
| Number of passengers-Model_winters additive | 0 | .620 | .682 | 18.137 |

Based on the results of the model goodness-of-fit tests, the Winters Additive Model demonstrates fairly good performance, with a relatively high R-squared of 62% (0.620) and a Stationary R-squared of 68.2% (0.682), indicating that the model is fairly successful in capturing most of the patterns in the passenger count data. In terms of forecasting accuracy, with a MAPE value of 18.14%, this model provides good (fairly accurate) predictions, indicating that the success rate in forecasting is approximately 81.86%.

From the results of the Ljung-Box test above, the p-value (Sig.) of 0.701 is greater than the significance level of 0.05; therefore, the decision is to accept the null hypothesis. In other words, there is no autocorrelation at any of the lags tested, and the residuals in the data do not exhibit a repeating pattern or show any correlation across time.

Based on the graph in Figure 1, the number of arrival and departure passengers at Tanjung Api-Api Port shows a fairly linear and consistent upward trend year on year. The data begins in 2019 with 131,723 passengers and continues to increase to 397,100 passengers in 2023. Similarly, the number of arriving passengers, which stood at 149,730 in 2019, increase to 328,466 in 2023. A trend of increasing passenger numbers is evident in Figures 2 and 3, with certain spikes during specific periods. There are several factors causing these spikes in the passenger numbers graph, such as school holidays, major events or celebrations, such as Eid al-Fitr and Christmas, or other religious events.

In the forecasting stage, a simple seasonal model was used to model passenger departure data from Tanjung Api-Api Port. Meanwhile, the model used for arrival passenger data is the Winter Additive model. Although the data does not show a strong seasonal pattern, incorporating a seasonal effect into the model yields better accuracy than when no seasonal effect is included.

From the forecasting results on the test data, a MAPE value of 23.52% was obtained for departing passenger data and 18.14% for arriving passenger data. The forecast results in Figure 4 show that the forecast values generally follow the trend of the actual data, although there are some discrepancies, particularly in the period of May 2023. Similarly, the graph in Figure 5 shows a fairly clear discrepancy between the forecast values and the actual data in May 2023; however, the forecast and actual values for other periods exhibit a fairly similar trend. In the forecast graph, the values are slightly higher or lower than the actual data; this is because the dataset does not account for the effect of public holidays. However, based on the graph and the MAPE values obtained, it is evident that the forecasting model demonstrates a reasonably good forecasting capability.

Table 6. Forecasting the Number of Departure and Arrival Passengers In Tanjung Api-Api Port

| Month,Year | Forecasting Result (People) | |
|---|---|---|
| | Departure Passangers | Arrival Passengers |
| Jan-24 | 24350 | 31121 |
| Feb-24 | 18476 | 28403 |
| Mar-24 | 22689 | 30188 |
| Apr-24 | 29937 | 41264 |
| May-24 | 40234 | 30923 |
| Jun-24 | 30854 | 34931 |
| Jul-24 | 33477 | 35148 |
| Aug-24 | 23369 | 31502 |
| Sep-24 | 25099 | 32999 |
| Oct-24 | 29743 | 34744 |
| Nov-24 | 28430 | 34618 |
| Dec-24 | 34284 | 45164 |
| Jan-25 | 24350 | 37669 |
| Feb-25 | 18476 | 34952 |
| Mar-25 | 22689 | 36737 |
| Apr-25 | 29937 | 47813 |
| May-25 | 40234 | 37471 |
| Jun-25 | 30854 | 41479 |
| Jul-25 | 33477 | 41697 |
| Aug-25 | 23369 | 38050 |
| Sep-25 | 25099 | 39548 |
| Oct-25 | 29743 | 41293 |
| Nov-25 | 28430 | 41167 |
| Dec-25 | 34284 | 51713 |

Based on Table 6 above, the forecast for passenger numbers at Tanjung Api-Api Port shows an upward trend each month. This should be taken into account by the management at Tanjung Api-Api Port when preparing facilities and infrastructure to cope with the annual increase in passenger numbers. This will, of course, have an impact on passenger services, ensuring that passenger comfort is maintained.

In 2019, Farri and Irhamah carried out a forecast of passenger numbers for the Surabaya–Jayapura sea route using the ARIMA method, which yielded a MAPE value of 62.16, indicating that the ARIMA model was not sufficiently effective for forecasting passenger numbers at Tanjung Perak Port. Furthermore, in 2021, Adiputra et al. also conducted research on passenger forecasting, specifically forecasting the number of sea passengers using the Chen High-Order Fuzzy Time Series method; the forecasting results yielded a very low MAPE value of 0.143. The research results, using a third-order plot method, demonstrated excellent precision, and the forecast results were almost identical to the actual data.

Furthermore, forecasting of passenger numbers using the Seasonal ARIMA and Winters' Exponential Smoothing methods was previously carried out by Negara (2021), with the results showing that the Seasonal ARIMA model performed better than the Winters' Exponential Smoothing model; Furthermore, using the same methods, Multiningsih (2022), Khoiriyah et al. (2023), and Riung et al. (2024) forecast passenger numbers on ships, achieving good results in their forecasts.

Of the various studies conducted on passenger numbers at the port, methods that incorporate seasonal trends have proven to be more effective at forecasting. This is evident from the relatively low MAPE values obtained. Furthermore, the availability and adequacy of historical data are key factors in forecasting.

## CONCLUSION

The results of passenger forecasting using the Exponential Smoothing method show that forecasts for departing passengers indicate a stable and consistent trend without any major spikes, unlike in previous periods. Meanwhile, the results of forecasting arrival passenger data indicate a gradual increase and an upward trend.

The model developed for forecasting the number of departing passengers has an accuracy of 76.5%, whilst the model for forecasting the number of arriving passengers has an accuracy of 81.86%. These are good accuracy rates, meaning that, based on the forecast results, the number of passengers at Tanjung Api-Api Port is expected to continue to rise in the coming year. Consequently, the management of Tanjung Api-Api Port must prepare the necessary facilities and infrastructure to cope with the increase in passenger numbers in the coming years.

Management of Tanjung Api-Api Port can provide facilities and infrastructure for passengers, for example by increasing the number of seats in waiting areas and adding extra ferry services during certain periods, such as during holidays and public holidays.

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