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Forecasting the number of domestic airplane passenger arrivals using the ARIMA model

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Abstract

As travel opportunities have increased, the air transport sector has expanded considerably in recent decades. Many techniques and operations management applications are utilized in the air transportation industry. These include demand forecasting, which predicts future passenger numbers and helps with planning capacity and resources. This research aims to forecast the number of domestic airplane passenger arrivals using the ARIMA model with Minitab 22 and explore the implications on the decision-making of operational management strategies in aviation industries in Indonesia. The data was collected from the Central Bureau of Statistics (Badan Pusat Statistik-BPS) database on airline domestic passenger arrivals in Indonesia. The results show that the best ARIMA model is 1,0,1. The forecasting results show the upper and lower numbers of passengers for five years. The significant increase in air passengers necessitates that airlines focus on fleet capacity, flight availability, and service quality improvements while maintaining competitive ticket prices to maintain passenger numbers. Implementing effective forecasting and dynamic pricing strategies can optimize operational efficiency and ensure sustainable growth in the aviation industry.

JEL classifications: L9, N7

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1. Introduction

The aviation industry is an important sector of the global economy, as it connects people and places around the world (Wittmer & Bieger, 2021). In Indonesia, domestic flights play a crucial role in supporting population mobility and connectivity between regions. The effectiveness of operational management in the aviation industry relies heavily on the ability of airlines and airports to correctly predict future passenger demand. This demand is measured by the number of domestic and international airplane passengers arriving at airports (Suh & Ryerson, 2019).

Forecasting the number of domestic arriving passengers is an important element of operational management for several reasons (e.g., capacity planning, inventory, workforce scheduling, strategic decision-making, and cost control) (Koksalmis, 2019). Accurate passenger forecasting is critical to ensuring smooth flight operations and providing a satisfactory experience for passengers (Ramadhani et al., 2020). With proper forecasting, airlines and airports can improve their efficiency, effectiveness, and profitability and contribute to the growth of the aviation industry as a whole (Suh & Ryerson, 2019).

In the last few decades, the air transportation industry in Indonesia has experienced significant growth. The number of passengers using domestic airline services continues to increase, giving rise to the need for better planning to manage this demand. Forecasting the number of passenger departures is very important for airlines and airport managers (Madhavan et al., 2023). Through accurate forecasting, related parties can manage flight schedules, optimize resources, and increase customer satisfaction. In addition, proper forecasting helps with long-term planning, including infrastructure development and strategic investments.

Much research has been done on the forecasting of airport passengers. For example, Tsui et al. (2014) researched Hong Kong airport passengers, Hasanah (2019) forecasted passengers at Juanda International Airport, Adeniran et al. (2018) forecasted air passenger demand in Nigeria, Anupam and Lawal (2024) researched the Norwegian aviation industry, Korkmaz and Akgüngör (2021) conducted research in Turkey, and Madhavan et al. (2023) performed short-term forecasting on the airline industry.

The autoregressive integrated moving average (ARIMA) method is a popular statistical technique used to forecast time series data (Ye et al., 2019). ARIMA can capture complex patterns in historical data and provide accurate predictions for future periods. In the current study's context, the ARIMA method was used to model and predict the number of domestic passenger departures in Indonesia. Several studies have used ARIMA models to forecast passengers, for example, in Juanda Airport (Hasanah, 2019), and to determine airport demand (Andreoni & Postorino, 2006; Ramadhani et al., 2020). Researchers have also used ARIMA to forecast airline passengers, bus passengers (Ye et al., 2019), and urban trail passenger flow (Chen, 2023). Studies have also performed forecasting at Sentani Airport (Palpialy et al., 2023), Soekarno Hatta Airport (Marnizal Putri et al., 2022), and in Central Java (Mutiara et al., 2023).

The primary objective of this study is to develop an accurate and reliable ARIMA model for forecasting the number of airplane passengers in Indonesia using historical time series data from 1999 to 2023. A primary goal of the study is to bridge the existing research gap by exploring the integration of ARIMA-based forecasting with operational management decision-making processes. This involves examining how forecast data can be effectively utilized to inform and enhance strategic and tactical decisions in airline operations. It is hoped that the forecasting results obtained using the ARIMA method can elucidate future trends in the number of domestic passenger departures in Indonesia. With this information, airlines and airport managers can make better decisions regarding how they manage their operations and business strategies. Apart from that, the results of this research can serve as a reference for the government in formulating policies that support the development of the air transportation sector. Additionally, the study aims to analyze the practical implications of using national time series data for operational management to improve efficiency, resource allocation, and strategic planning within the aviation sector.

2. Literature review

Airlines and airports have effectively employed operations management techniques to enhance their planning and operational processes. These techniques, along with advanced operations research methods, have significantly transformed how airlines and airports function. The synergy of these methods has streamlined various aspects of operations, from daily scheduling to long-term strategic planning. Over the years, advancements in computer technology have further revolutionized these processes, enabling more complex problems to be managed while providing efficient solutions more quickly than before. This progression has been instrumental in optimizing operations within the aviation industry, leading to improved performance and customer satisfaction (Koksalmis, 2019).

The evolution of computer technology, coupled with the development of sophisticated optimization models, has allowed airlines and airports to tackle intricate challenges that were previously difficult to manage. The ability to process vast amounts of data quickly and accurately has been a game-changer. This technological advancement has facilitated the development of advanced algorithms and software that assist in solving complex problems related to scheduling, routing, and resource allocation. Consequently, the aviation industry can now implement more precise and efficient operational strategies, reducing costs and enhancing service delivery. The integration of these technologies into operations management has marked a significant leap forward in the industry’s ability to manage its operations effectively. Many techniques and operations management applications are utilized in the air transportation industry, including demand forecasting, which predicts future passenger numbers and helps with planning capacity and resources. As more travel opportunities have become available in recent decades, the air transport sector has expanded considerably. Despite this growth, the industry has faced challenges due to the pandemic, and both political and market factors are discouraging people from flying (Zachariah et al., 2023).

A time series is a sequence of data points collected at regular intervals over time (Umami et al., 2019). Time series analysis is employed to understand patterns in historical data and to predict future values based on these patterns (Colicev & Pauwels, 2022). In the context of operational management, time series analysis is often utilized to forecast demand, manage inventory, and optimize resources (Cyril et al., 2018). Time series can also be used to forecast air passenger numbers (Al-Sultan et al., 2021)

The ARIMA model is a popular method for time series forecasting (Andreoni & Postorino, 2006). This model combines three primary components: (1) the autoregressive (AR) component indicates that the current value depends on previous values; (2) the integrated (I) component involves differencing the data to make it stationary, meaning the statistical properties of the data do not change over time; and (3) the moving average (MA) component indicates that the current value depends on past errors from the model.

3. Research methods

This research uses the ARIMA method to predict domestic passenger arrivals using Minitab 22 software. The first step in this research is to import domestic passenger arrival data into Minitab, which can be used for forecasting (Iftitah & Murni, 2018; Majidnia et al., 2023; Sitohang & Karnadi, 2021). First, the data is collected from the BPS Statistics database on airline domestic passenger arrivals in Indonesia. Once the data is imported, the next step is to visualize the data using time series plots to identify patterns, trends, and possible seasonality. Then, a stationarity test is carried out using the augmented Dickey-Fuller (ADF) test and Box-Cox plot to determine whether the data is stationary or requires differencing. Based on the results of the stationarity test, the next step is to identify the ARIMA model parameters (p, d, q) by analyzing the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots. Once the parameters are identified, Minitab estimates the ARIMA model parameters that best fit the data. Forecasting with the best ARIMA model is a prominent feature in Minitab 22, which is designed to streamline the process of identifying and implementing the most suitable ARIMA model for time series data. This menu allows users to automatically search through a range of ARIMA models, evaluating their fit based on criteria such as the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Minitab 22 simplifies the complex task of model selection by presenting the best-fitting model, which can then be used to generate reliable and accurate forecasts. Model validation is carried out by checking residual diagnostics to ensure that the residuals do not show significant autocorrelation and that the model has effectively captured patterns in the data. Finally, the validated ARIMA model is used to forecast future domestic passenger arrivals.

4. Results and discussion

4.1. Data visualization

The dataset utilized for this analysis was sourced from Central Bureau of Statistics (*Badan Pusat Statistik*-BPS) Indonesia and subsequently processed using Minitab 22. This comprehensive dataset spans the period from 1999 to 2022 and encompasses the number of domestic passenger arrivals in Indonesia. Through meticulous data collection and analysis, the trend over these 24 years has been effectively illustrated, providing valuable insights into the fluctuations and growth patterns in domestic passenger traffic within the country.

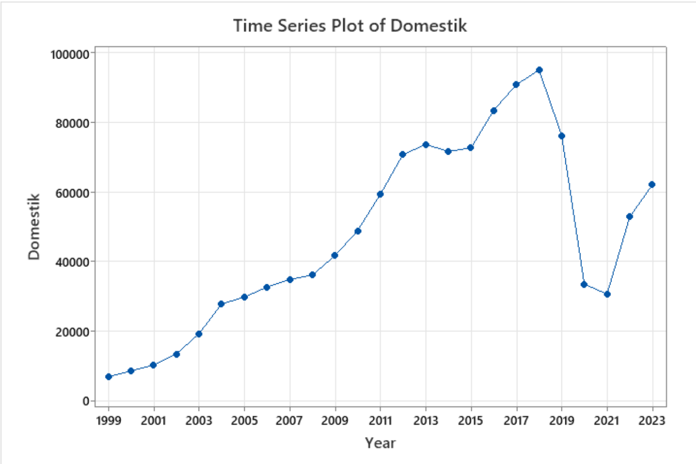

Figure 1. Time series plot of domestic passenger arrivals

The data in Figure 1 shows the fluctuation in the number of passengers each year from 1999 to 2023, including a sharp decrease from 2019 until 2021. Since 2022, passengers have started increasing; if no special events occur, the number of passengers is expected to continue to increase.

The time series plot illustrates certain variables' trends from 1999 to 2023. It shows a steady increase from 1999 to 2007, starting at a relatively low value and rising consistently, indicating positive growth. This growth rate accelerated from 2007 to 2011, reflecting a period of rapid expansion with notable annual increases. From 2011 to 2015, the upward trend continued, though the growth pace slowed slightly, and there was some fluctuation. Between 2015 and 2018, there was significant growth, which reached its peak at nearly 100,000 passengers around 2018, indicating a very prosperous period.

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However, from 2018 to 2020, there was a sharp decline, with values dropping significantly, suggesting a downturn or possible economic challenges. This decline continued through 2021, reaching the lowest point since the early growth periods, indicating a period of crisis or major disruption. From 2021 to 2023, recovery occurred, though the recovery is not yet complete, as the values have not returned to the peak levels seen in 2018. Overall, the time series plot shows a cycle of growth, a peak, a sharp decline, and gradual recovery over the 24-year period.

Historical data shows a significant increase in the number of domestic passenger arrivals over time. At the start of the period, there was a steady increase. However, the data also shows sharp fluctuations towards the end of the observed period. The peak number of arrivals occurred around the 20th period; this was followed by a significant decline until the 24th period before a slight increase again in the 25th period. In the 20th period, the COVID-19 pandemic began, and restrictions on human movement impacted the aviation industry. The decrease continued until 2021, the trend returned to normal in 2022, and an increase started in 2023. The data show the impact of COVID-19 on airline passengers. Other studies have shown the same impact of COVID-19 on airline passengers (Li et al., 2023; Zhang et al., 2021).

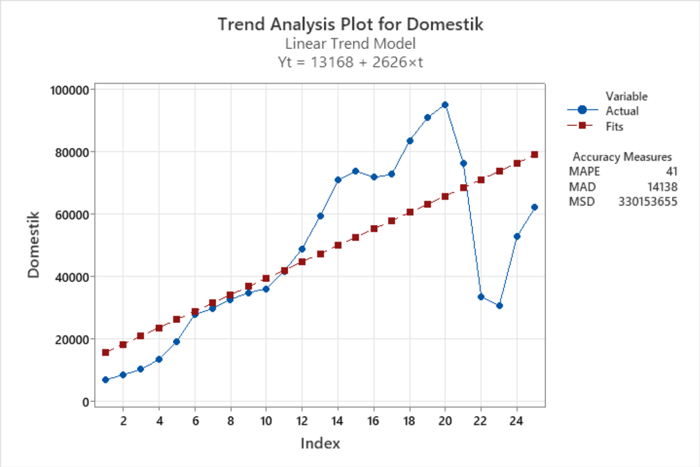

Figure 2. Trend analysis plot for domestic passenger arrivals

Based on the data above (Figure 2), the linear trend model should be Yt = 13168 + 2626 x t. In 2020 below the fits model, and until 2023 because of the pandemic, the trend was not back to normal with the trend model.

4.2. Stationarity test

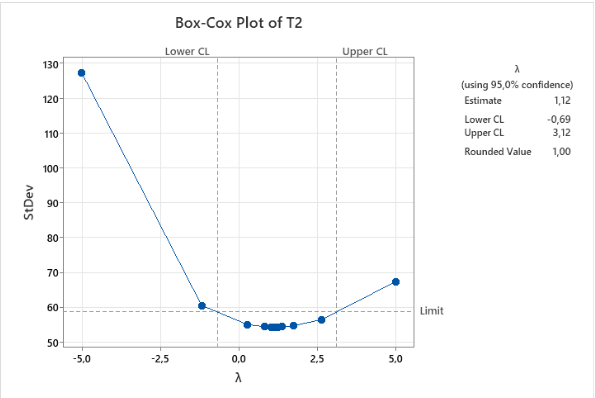

Figure 3. Box-Cox plot

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Box-Cox transformation is an important tool in ARIMA modeling to achieve data stationarity, especially in variance. The ideal "rounded value" is 1, which indicates that data has been stabilized and the ARIMA model can be built accurately and reliably. The Box-Cox number can be normal if the rounded value is 1.00. The data needed to be transformed twice to get the rounded value of 1.00.

The augmented Dickey-Fuller (ADF) test is a statistical method commonly used to test the stationarity of time series data. Stationarity is an important property in time series data, as the mean and variance of the data do not change over time.

Table 1. Augmented Dickey-Fuller test

Null hypothesis:			Data are non-stationary
Alternative hypothesis:			Data are stationary
	Test statistic	P-value	Recommendation
	-5.42569	0.000	Test statistic <= critical value of -3.03123 Significance level = 0.05 Reject null hypothesis Data appears to be stationary, not supporting differencing.

Based on the results of the augmented Dickey-Fuller (ADF) test (Table 1), it can be concluded that the data is stationary. The test statistical value (-5.42569) is smaller than the critical value (-3.03123) at the 0.05 significance level. The p-value (0.000) is smaller than the significance level of 0.05. Since the data is stationary, the mean and variance of the data tend to be constant over time.

4.3. Forecast with the best ARIMA model

Forecast with Best ARIMA Model in Minitab 22 simplifies the process of identifying the optimal ARIMA model for forecasting time series data. The software evaluates multiple ARIMA models with different combinations of p and q values (shown in the table). For each model, the LogLikelihood, AICc, AIC, and BIC values are calculated. The model with the lowest AICc value is typically selected as the best model (Table 2).

Table 2. Model selection

Model (d = 0)	LogLikelihood	AICc	AIC	BIC
p = 1; q = 1*	-262.679	535.357	533.357	538.233
p = 2; q = 1	-263.518	537.036	535.036	539.911
p = 1; q = 2	-263.549	537.098	535.098	539.973
p = 3; q = 1	-263.583	540.324	537.166	543.261
p = 2; q = 0	-269.031	545.205	544.062	547.719
p = 3; q = 3	-264.832	550.252	543.664	552.196
p = 2; q = 2	-268.589	550.335	547.177	553.271
p = 2; q = 3	-270.644	557.955	553.288	560.601
p = 0; q = 3	-276.635	563.271	561.271	566.146
p = 0; q = 2	-280.924	568.991	567.849	571.505
p = 1; q = 3	-284.182	581.521	578.363	584.458
p = 0; q = 1	-293.060	590.665	590.120	592.558

* Best model (that with the lowest AICc). Output for the best model follows.

In this case, the model with p=1 and q=1 has the lowest AICc value (-262.679). The table provides a systematic approach to comparing different ARIMA models and selecting that which best fits the data based on the specified criteria. The selected model (p=1, q=1) can then be used to forecast future values of the time series.

Table 3. Final estimates of parameters

Type	Coef	SE coef	T-value	P-value
AR 1	0.805	0.110	7.32	0.000
MA 1	-1.16710	0.00268	-436.20	0.000
Constant	7615.22	0.00	1,598,878.34	0.000
Mean	39,019.0	0.0		

The autoregressive coefficient at lag 1 (AR 1) is 0.805 (Table 3). This suggests that the current value of the series is influenced by 80.5% of the previous value. The moving average coefficient at lag 1 (MA 1) is -1.16710. This indicates that the current error term is influenced by the previous error term. The constant term in the model is 7615.22. This is the expected value of the series when all other factors are zero. The overall mean of the series is 39,019.0. All parameters have very low p-values (0.000), indicating that they are statistically significant at a conventional significance level (e.g., 0.05). This suggests that all parameters contribute meaningfully to the model.

Table 4. Model summary

DF	SS	MS	MSD	AICc	AIC	BIC
22	1,166,125,704	53,005,714	46,645,028	535.357	533.357	538.233

MS = variance of the white noise series

The mean squared error (MS) is 53,005,714 (Table 4). This represents the average squared difference between the predicted values and the actual values. A lower MS indicates a better fit. However, without a benchmark or comparison to other models, it is difficult to assess the absolute goodness of fit. The AICc, AIC, and BIC values are provided for model selection. Lower values of these criteria generally indicate a better model. However, the specific values without comparison to other models provide little information about the model's relative performance.

Table 5. Modified Box-Pierce (Ljung-Box) chi-square statistic

Lag	12	24	36	48
Chi-Square	7.76	12.22	*	*
DF	9	21	*	*
P-Value	0.558	0.933	*	*

Table 5 presents the results of a Ljung-Box test, which is used to assess whether the residuals of a time series model are independently distributed (white noise). For both lag 12 and lag 24, the p-values are significantly larger than the common significance level of 0.05. Therefore, there is insufficient evidence to suggest that the residuals are not independently distributed. In other words, the residuals appear to be white noise. White noise residuals are generally desirable, as they indicate that the model has captured the underlying patterns in the data and the remaining unexplained variation is random. However, it is essential to consider other diagnostic checks and the overall performance of the model before making definitive conclusions.

The ACF graph of the residuals is used to check whether the residuals from the time series model have a serial correlation (Figure 4). This graph helps evaluate whether the model adequately captures patterns in the data. The ACF graph shows that the residuals from the domestic model do not have significant serial correlation at the lags shown. This is an indication that the model has captured the patterns in the data well and that the residuals are random and uncorrelated. The model can be considered fit or appropriate to the data because there are no remaining patterns in the residuals that need to be explained further.

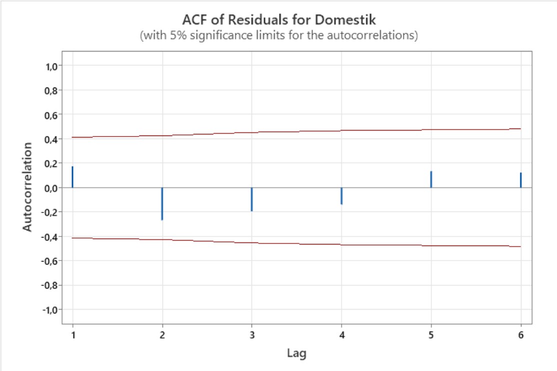

Figure 4. ACF of residuals

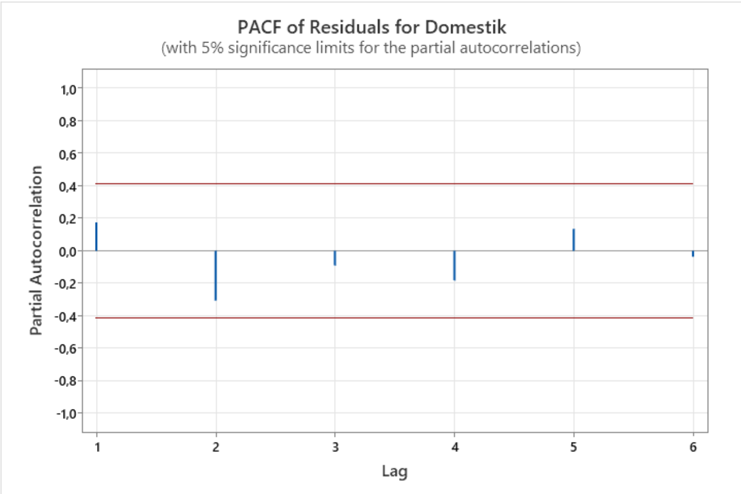

Figure 5. PACF of residuals

PACF plots for residuals help validate estimated time series models (Figure 5). Once an ARIMA model is applied to the data, the residuals from the model should not show significant autocorrelation if the model is a good fit. If the PACF plot for residuals shows that most of the partial autocorrelation values are within the significance limits, this indicates that the residuals do not have significant autocorrelation, indicating the model has captured the pattern in data well. Based on the figure above, all the partial autocorrelation values are within the significance bounds, and the residuals appear to be uncorrelated. This implies that the time series model adequately captures the underlying patterns in the data, and the residuals are behaving like white noise. If there were significant spikes outside the bounds, it would suggest that the model would need to be adjusted to account for the correlation at those lags. The PACF plot indicates that the residuals of the model do not exhibit significant autocorrelation, suggesting that the model is well-fitted to the data.

Table 6 presents the results of forecasting the number of domestic passenger arrivals for time periods 26 to 30, using the identified and validated ARIMA model. Each row in the table includes a specific time period, forecast value, standard error of forecast (SE Forecast), lower limit (Lower), and upper limit (Upper) of the 95% confidence interval, as well as actual value (Actual), if available.

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Table 6. Forecast from the time period

			95% Limits		
Time Period	Forecast	SE Forecast	Lower	Upper	Actual
26	61,922.6	7280.5	47,650.0	76,195.3	
27	57,452.6	16,097.2	25,895.7	89,009.4	
28	53,854.9	19,814.9	15,009.9	92,700.0	
29	50,959.5	21,888.7	8049.0	93,869.9	
30	48,629.1	23,133.0	3279.3	93,978.8	

In this period, the forecast value for the number of domestic passenger arrivals was 61,922.6, with a standard error of 7280.5. The 95% confidence interval indicates that the number of passenger arrivals is expected to be between 47,650.0 and 76,195.3. Actual values for this period are not available in the table. For period 27, the forecast number of passenger arrivals is 57,452.6, with a standard error of 16,097.2. The 95% confidence interval ranges between 25,895.7 and 89,009.4. No actual values are presented for this period. In period 28, the number of passenger arrivals is estimated at 53,854.9, with a standard error of 19,814.9. The 95% confidence interval is between 15,009.9 and 92,700.0. Actual values for this period are not available in the table. Forecasting for period 29 shows a value of 50,959.5, with a standard error of 21,888.7. The 95% confidence interval for this forecast is between 8,049.0 and 93,869.9. Actual values are not presented. In this period, the number of passenger arrivals is estimated at 48,629.1, with a standard error of 23,133.0. The 95% confidence interval indicates that the number of passenger arrivals is expected to be between 3,279.3 and 93,978.8. No actual values are presented for this period.

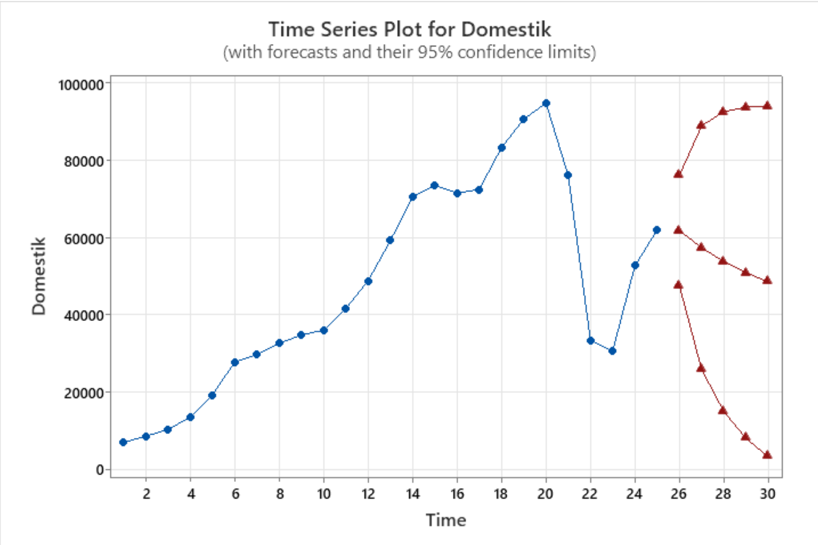

Figure 6. Time series plot forecast

The forecasted values for the subsequent time periods (26 to 30) show a diverging trend with a wide confidence interval (Figure 6). This indicates uncertainty in the future values of the arrival of domestic passengers with possible scenarios ranging from a significant increase to a further decline. The broad confidence limits suggest that while the central forecast predicts a continued increase, the actual future values could vary considerably, emphasizing the need for cautious interpretation and consideration of various potential outcomes.

Forecasts for the future period (from the 26th to the 30th period) show significant uncertainty, with wide confidence intervals. This shows that although there is an upward trend, there are various factors that can cause significant variations in the number of passenger

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arrivals. Such factors include changes in government policies, economic conditions, natural disasters, and global situations.

In facing this uncertainty, all parties need operational management strategies that are adaptive and flexible. There are some strategies related to the data—for example, ensuring that transportation infrastructure, such as airports and railways, is prepared to handle increased passenger numbers. This includes increasing capacity and routine maintenance to avoid operational disruptions, adopting the latest technology to predict passenger arrival trends more accurately, and optimizing daily operations through advanced monitoring and management systems. There are a lot of applications that can be used for forecasting in the aviation industry beyond passenger forecasting (Kolesár et al., 2015).

The forecasting results are expected to provide valuable information for operational planning and management in the domestic aviation industry (Zachariah et al., 2023). This is of particular interest to analysts and decision-makers seeking to understand and predict future trends with precision, thereby enabling data-driven strategies and optimized planning (Kolesár et al., 2015).

The optimistic result, based on the data in Table 6 concerning the number of air passengers, indicates a significant increase from 76,195.3 to 93,978.8. This rise reflects the growing interest in and need for air transportation among the public. In the context of national operational management, this increase necessitates that airline service providers focus on fleet capacity, flight availability, and service quality improvements to maintain customer satisfaction. This involves adding more aircraft, increasing flight frequency, and enhancing airport facilities. The operational management strategy that must be considered in addressing the rising number of passengers includes operational efficiency and better scheduling. As demand increases, airlines must ensure that they have sufficient resources to accommodate passengers without compromising comfort and safety. Additionally, optimizing flight routes and managing time effectively are crucial to avoiding delays and overbooking, which can damage a company's reputation.

Moreover, ticket pricing significantly influences the number of passengers. When demand increases, airlines tend to raise ticket prices to optimize revenue. However, this must be done carefully to avoid reducing attractiveness to price-sensitive passengers. Maintaining competitive ticket prices while offering attractive deals and special discounts can help companies maintain a high number of passengers.

Decreases or stagnation in the number of passengers indicated by the data have different implications for operational management strategies. A decline in passenger numbers may indicate issues with service quality or passenger dissatisfaction. Airlines need to conduct in-depth evaluations to understand the factors causing this decline and take corrective actions such as improving customer service, refining flight schedules, or reducing ticket prices to regain passenger interest. Stagnation in passenger numbers also requires airlines to be more creative in developing marketing and promotional strategies. Diversifying services, such as offering holiday packages or additional services, can be an effective way to attract more passengers. Additionally, collaborating with travel agencies and online platforms to expand marketing reach can help overcome the challenges of stagnation and ensure sustainable growth in the aviation industry.

The sustainability strategy for the national aviation business, in relation to effective forecasting and ticket pricing, can be optimized through analytical technology and dynamic pricing management. By leveraging forecasting data about passenger demand, airlines can identify demand trends and travel patterns, which will allow them to adjust flight capacity and routes more efficiently, thus reducing operational costs. Additionally, by implementing flexible pricing strategies based on demand predictions, airlines can set lower fares during low-demand periods to attract more passengers. The combination of operational efficiency and competitive ticket pricing not only lowers ticket prices but also ensures sustainable growth and enhances the competitiveness of the national aviation industry.

5. Conclusion

Forecasts of the number of domestic passenger arrivals in Indonesia show a positive trend but a high level of uncertainty. The implementation of appropriate operational management strategies can help the transportation and tourism sectors in Indonesia prepare to face challenges and take advantage of existing opportunities to continue to increase the number of domestic passenger arrivals. Adaptive and innovative strategies will be essential to ensuring continued growth and providing the best service for passengers. This research has limitations ARIMA models rely heavily on historical data for forecasting, making them less adaptable to sudden changes or unforeseen events that could significantly impact passenger arrivals. ARIMA models primarily focus on predicting future values rather than explaining the underlying factors driving changes in passenger arrivals. This limits their ability to identify potential causes of fluctuations or guide strategic decision-making. Overall, this article demonstrates the importance of forecasting in air transport management and how the ARIMA method can be used as an effective tool for this purpose. With the right approach, it is hoped that this research can contribute to the development of the domestic aviation industry in Indonesia. Airlines must prioritize fleet capacity, flight availability, and service quality improvements, ensuring operational efficiency and effective scheduling to avoid delays and overbooking. Ticket pricing plays a crucial role, and airlines need to balance optimizing revenue with maintaining attractiveness to price-sensitive passengers through competitive pricing and special offers. By leveraging analytical technology and implementing dynamic pricing strategies, airlines can efficiently adjust capacity and routes, reduce costs, and ensure sustainable growth while enhancing competitiveness in the aviation industry.

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