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A Seasonal ARIMA (SARIMA) Model for Forecasting Domestic Passenger Traffic at Sultan Hasanuddin Airport

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Abstract

The growth of the domestic aviation industry in Indonesia has led to a significant increase in passenger numbers, particularly at major airports such as Sultan Hasanuddin Airport. Accurate forecasting of passenger traffic is essential for effective planning and resource allocation. This study aims to develop a suitable time series model to forecast the number of domestic air passengers departing from Sultan Hasanuddin Airport. Using monthly passenger data from January 2019 to April 2024 obtained from the Indonesian Badan Pusat Statistik (BPS), the Seasonal Autoregressive Integrated Moving Average (SARIMA) model was applied. The modelling process followed the Box-Jenkins methodology, involving data exploration, stationarity testing, model identification, parameter estimation, diagnostic checking, and model validation. Among several candidate models, the ARIMA $(0,1,1)(0,0,1)^{12}$ model was identified as the most appropriate, producing normally distributed, independent residuals and yielding a Mean Absolute Percentage Error (MAPE) of 4.5%. The results demonstrate that the SARIMA model provides a reliable tool for forecasting short-term domestic passenger flows at the airport.

Keywords: Time Series Forecasting; SARIMA; Domestic Air Passengers; Sultan Hasanuddin Airport; Box-Jenkins Methodology

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1. Introduction

The aviation sector in Indonesia has experienced a significant transformation following the liberalization policy introduced through the Ministry of Transportation Decree No. KM 11/2001. This policy enabled private and cooperative enterprises to enter the scheduled commercial air transport market, triggering rapid growth in airline services. With the advent of low-cost carriers (LCCs) entering the air service market, air travel has become more accessible to passengers, influencing demand (Ceddia & Bardsley, 2021).

Sultan Hasanuddin Airport, located in Makassar, South Sulawesi, serves as one of the major air traffic hubs in Eastern Indonesia. The airport plays a strategic role in connecting various regions across the archipelago, particularly for domestic flights. The continual increase in passenger volume at this airport necessitates accurate forecasting methods to support infrastructure planning, optimize service delivery, and ensure effective resource allocation.

In this context, time series forecasting becomes an essential tool for predicting future passenger flows based on historical data. Among the various forecasting techniques available, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model is one of the most widely used approaches due to its ability to capture both trend and seasonal variations within time-dependent data. The SARIMA model, an extension of the ARIMA model introduced by Box and Jenkins (1979), incorporates seasonal terms to handle repetitive cycles in the data, which is particularly suitable for monthly or quarterly datasets in transportation forecasting.

This study aims to construct a SARIMA model to forecast monthly domestic passenger departures from Sultan Hasanuddin Airport using data from January 2019 to April 2024. By identifying the best-fitting SARIMA model, this research contributes to the development of data-driven decision-making tools for airport operations and policy planning.

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2. Literature Review

2.1. Time Series

Time series data consist of a sequence of observations used to estimate deterministic components and predict future values based on historical relationships within the data (Dama & Sinoquet, 2021). The observations may be collected at various frequencies, including daily, weekly, monthly, or yearly intervals (Brockwell and Davis, 2016). A time series model for the observed process {Xt} involves specifying the joint probability distribution—often characterized by its mean and covariance structure—of the sequence of random variables {Xt}, with the observed data regarded as a realization of this stochastic process.

2.1.1. Stationarity of Time Series Data

A fundamental requirement in developing ARIMA models is that the data must be stationary, both in mean and variance. Data is considered stationary if its fluctuations revolve around a constant mean (mean stationarity) and the variance of these fluctuations remains constant over time (variance stationarity).

The stationarity of data can be assessed visually through time series plots and autocorrelation function (ACF) plots. A stationary time series typically exhibits an ACF plot where the autocorrelation values decline rapidly toward zero. Conversely, a non-stationary time series shows an ACF plot with autocorrelation values that decay slowly. The autocorrelation function is denoted as follows:

$$r_k = \frac{\sum_{t=1}^{n}\left(X_t - \bar{X}\right)\left(X_{t+k} - \bar{X}\right)}{\sum_{t=1}^{n}\left(X_t - \bar{X}\right)^2} \quad (1)$$

where: Xt denotes the observation at time-t; rk represents the autocorrelation at lag-k; N is the total number of observations in the time series; k is the lag being considered; t = 1,2,3,…,N

Non-stationarity in time series data can be categorized into two types: non-stationarity in the mean and non-stationarity in the variance. Time series data that are non-stationary in the mean can be made stationary through differencing of order d. In general, differencing of order d can be expressed as follows:

$$\Delta^d X_t = (1-B)^d X_t \quad (2)$$

Typically, differencing is performed up to the second order, as real-world data are usually non-stationary at only one or two levels (Cryer, 1986).

Time series data that exhibit non-stationarity in the variance can be stabilized using the Box-Cox transformation. The Box-Cox transformation produces a parameter λ, which determines the type of transformation to be applied. The values of λ along with the corresponding transformation rules are presented in Table 1 (Wei, 1990).

Table 1. Values of λ and Corresponding Transformations

λ Value	-1	-0.5	0	0.5	1
Transformation	1/Xt	$1/\sqrt{X_t}$	ln X_t	$\sqrt{X_t}$	X_t

To test whether the data are stationary, the Augmented Dickey-Fuller (ADF) test can be applied. The hypotheses for this test are: H0: The data are non-stationary; H1: The data are stationary. If the p-value is greater than the significance level α, H0 is not rejected, indicating that the data are non-stationary. Conversely, if the p-value is less than α, H0 is rejected and the data are considered stationary.

2.2. Autoregressive

The autoregressive model of order p, abbreviated as AR(p), states that the observation at time t is influenced by its own previous p observations (Makridakis et al., 1983). In other words, the value Xt depends on the values Xt−1, Xt−2, … Xt−p.

Generally, the AR(p) model is formulated as follows (Montgomery et al., 1990):

$$Xt = \mu + \phi_1 X_{t-1} + \phi_2 X_{t-2} + \ldots + \phi_1 X_{t-p} + e_t \quad (3)$$

where : *Xt* is the observation at time-t; μ is a constant term; ϕ are the autoregressive parameters; *et* is the error term at time *t*

2.3. Moving Average

The difference between the Moving Average (MA) model and the Autoregressive (AR) model lies in the independent variables used. In the AR model, the independent variables are the past values of the dependent variable itself (Xt), whereas in the MA model, the independent variables are past error terms.

The general form of a Moving Average process of order q, denoted as MA(q), is given as follows (Montgomery et al., 1990):

$$Xt = \mu - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \ldots - \theta_1 e_{t-q} + e_t \quad (4)$$

where: Xt is the observation at time t; μ is a constant term; θ1,θ2,…,θq are the MA parameters, et is the error term at time t.

2.4. ARIMA Model (p, d, q)

The Autoregressive Integrated Moving Average (ARIMA) model is a combination of an autoregressive model of order p and a moving average model of order q, applied to data that have been differenced d times to achieve stationarity.

The general form of the ARIMA(p,d,q) model is expressed as:

$$\phi_p(B)\Delta^d X_t = \mu + \theta_q(B) e_t \quad (5)$$

where: $\phi_p(B)$ is the autoregressive operator of order p; Δ^d denotes differencing of order d; X_t is the observed value at time t; μ is the constant term; $\theta_q(B)$ is the moving average operator of order q; e_t is the error term at time t.

2.5. SARIMA Model (p,d,q)(P,D,Q)^s

Incorporating seasonal components (S) into the model can reduce residuals caused by seasonal factors. The general form of the Seasonal ARIMA model, denoted as SARIMA(p,d,q)(P,D,Q)s, is as follows:

$$\phi_p(B)\Phi_{Ps}(B)\Delta^d \Delta_s^D X_t = \mu + \theta_q(B)\Theta_{Qs}(B) e_t \quad (6)$$

where: μ is the constant term; ϕ represents the parameters of the non-seasonal AR model; θ represents the parameters of the non-seasonal MA model; e_t is the error term at time t; s is the number of observations per seasonal cycle; Δ^d is the non-seasonal differencing operator of order d; $\Delta_s^D = (1 - B^s)^D$ is the seasonal differencing operator of order D; $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$ is the non-seasonal AR characteristic polynomial; $\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$ is the non-seasonal MA characteristic polynomial; $\Phi_{Ps}(B)$ is the seasonal AR characteristic polynomial; $\Theta_{Qs}(B)$ is the seasonal MA characteristic polynomial.

2.6. Box-Jenkins Method

The most commonly used method for constructing ARIMA models is the Box-Jenkins methodology (Makridakis et al., 1983), which consists of the following steps:

2.6.1. Model Identification

The model identification process begins with ensuring that the time series data is stationary. Once stationarity is achieved, a preliminary model can be proposed by examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots.

The order of the AR process can be determined by identifying the number of initial PACF coefficients that are significantly different from zero. Conversely, the order of the MA process is determined by the number of initial ACF coefficients that are significantly different from zero (Bowerman & O’Connell, 1987).

2.6.2. Parameter Estimation

The number of parameters to be estimated depends on the number of coefficients in the preliminary model. A parameter is considered significant if the absolute value of its corresponding *t*-statistic exceeds the critical *t*-value at the significance level of α/2, with degrees of freedom equal to the sample size minus the number of estimated parameters (Bowerman & O’Connell, 1987).

2.6.3. Model Diagnostics

The Portmanteau test or Box-Pierce Q-statistic is used to assess the adequacy of the model by testing whether a group of residual autocorrelations significantly differ from zero. The Q-statistic follows a chi-square distribution χ2 with degrees of freedom equal to k−n, where k is the maximum lag considered and n is the total number of estimated parameters in both AR and MA terms, including seasonal components.

The model is deemed inadequate if the Q-statistic exceeds the critical value of the chi-square distribution or if the *p*-value is less than the significance level α\alphaα. The formula for the Box-Pierce Q-statistic (Montgomery et al., 1990) is:

$$Q = (N-d)\sum_{k=1}^{K} r_k^{\ 2} \tag{7}$$

where: r_k^2 squared autocorrelation at lag k; N = number of observations in the original data; d = order of differencing; K = maximum lag.

3. Research Method

The data utilized in this study consist of monthly observations on the number of departing domestic airline passengers from Sultan Hasanuddin International Airport, as recorded by Statistics Indonesia (BPS), covering the period from January 2019 to April 2024 (a total of 64 months).

For the purpose of analysis, the data were divided into two segments: The first 52 months (January 2019 to April 2023) were used as the training set, the remaining 12 months (May 2023 to April 2024) were used as the testing set.

The analysis followed the standard steps of the Box-Jenkins approach, with the following procedures:

a. Data exploration to identify trends, seasonality, and potential anomalies in the time series.

b. Tentative model identification, based on autocorrelation and partial autocorrelation patterns.

c. Parameter estimation and model diagnostic checking to assess the adequacy and significance of each model.

d. Overfitting, by comparing more complex models to evaluate whether additional parameters enhance or hinder performance.

e. Model selection and forecasting, using the best-fitted model to generate forecasts for the test period.

All computations and modelling processes were performed using Minitab software, version 15.1.

4. Results and Discussion

4.1. Data Exploration

The time series plot indicates an upward trend in the monthly number of passengers, while the autocorrelation function (ACF) shows a slow decline (Appendix 1). This suggests that the time series is non-stationary in mean. After applying first-order differencing, the series becomes stationary in both mean and variance, as shown in Figure 1.

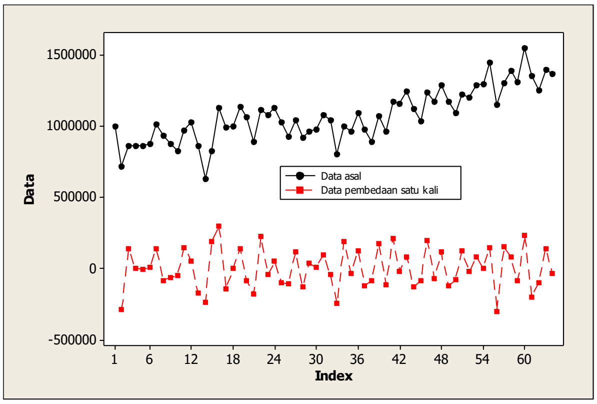

Figure 1. Monthly Number of Air Passengers Departing from Sultan Hasanuddin Airport

4.2. Stationarity Test

The test results indicate that the mean of the differenced data is not significantly different from zero (Figure 2). Therefore, the ARIMA model will be constructed without including a constant term.

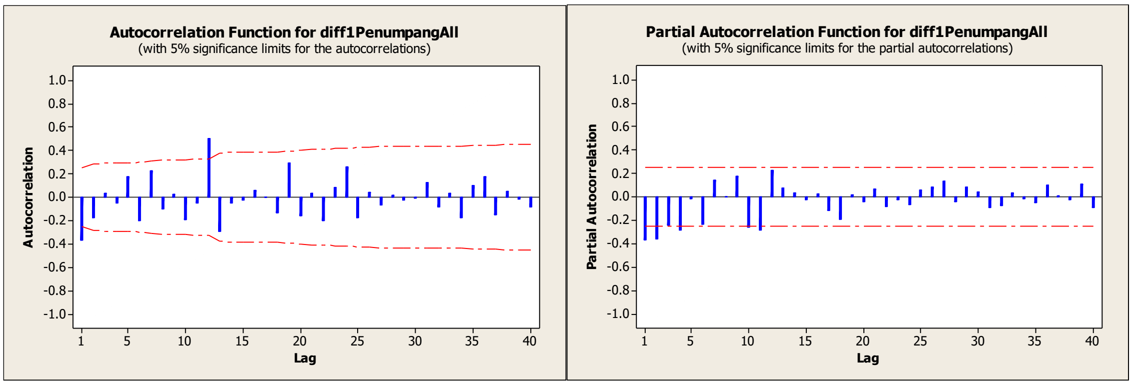

Figure 2. Plots of (a) the Autocorrelation Function (ACF) and (b) the Partial Autocorrelation Function (PACF) of the Monthly Number of Air Passengers Departing from Sultan Hasanuddin Airport

For brevity, the term "data" hereafter refers to the differenced series.

4.3. Identification of the Seasonal ARIMA (SARIMA) Model

Based on the autocorrelation function (ACF) and partial autocorrelation function (PACF) plots of the differenced data, the following patterns are observed: The ACF is significant at lag 1, not significant at lags 2 through 11, and becomes significant again at lag 12, and then the PACF shows significant values up to lag 2.

These patterns indicate the presence of a seasonal component with a period of s = 12, suggesting that a SARIMA model is appropriate for the data. Based on these observations, several tentative SARIMA models were constructed, as summarized in the Table 2.

Table 2. Several Tentative Models

Tentative Models	Regular Component			Seasonal Component (S=12)		
	AR(p)	I(d)	MA(q)	AR(p)	I(d)	MA(q)
1	0	1	1	0	0	1
2	0	1	1	1	0	1
3	0	1	1	1	0	2
4	1	1	0	0	0	1
5	2	1	0	0	0	1

4.3.1. Parameter Estimation and Residual Diagnostics of Tentative Models

Next, a significance test of the model parameters was conducted using the *t-test* at a significance level of $\alpha = 0.05$. A model parameter is considered statistically significant if the p-value is less than α. The following table presents the results of the t-tests for several tentative models, indicating which parameters were found to be significant.

Table 3. Parameter Estimation Test

Model	Parameter	P-Value	Significance
ARIMA $(0,1,1)(0,0,1)^{12}$	MA 1	0.000	Yes
	SMA 12	0.000	Yes
ARIMA $(0,1,1)(1,0,1)^{12}$	SAR 12	0.000	Yes
	MA 1	0.000	Yes
	SMA 12	0.000	Yes
ARIMA $(0,1,1)(1,0,2)^{12}$	SAR 12	0.000	Yes
	MA 1	0.000	Yes
	SMA 12	0.000	Yes
	SMA 24	0.014	Yes

Based on Table 3, the models that meet the significance criteria are marked as “Yes” in the significance column, with a p-value $< \alpha = 0.05$, namely: ARIMA$(0,1,1)(0,0,1)^{12}$, ARIMA$(0,1,1)(1,0,1)^{12}$, and ARIMA$(0,1,1)(1,0,2)^{12}$.

4.3.2. White Noise Test

Subsequently, model selection is carried out based on the Mean Squared Error (MSE) and white noise diagnostics for the ARIMA$(0,1,1)(0,0,1)^{12}$, ARIMA$(0,1,1)(1,0,1)^{12}$, and ARIMA$(0,1,1)(1,0,2)^{12}$ models. The adequacy of the model and the randomness of the residuals are assessed using the Ljung-Box test, which also serves to evaluate the model's accuracy level. The results of this diagnostic test are presented in the Tabel 4.

Table 4. White Noise Test

Model	(k)	Df	Ljung-Box Value	P-Value	White noise
ARIMA $(0,1,1)(0,0,1)^{12}$	12	10	7.1	0.719	Yes
	24	22	24.0	0.346	Yes
	36	34	30.9	0.619	Yes
	48	46	36.3	0.848	Yes
ARIMA $(0,1,1)(1,0,1)^{12}$	12	9	11.3	0.259	Yes
	24	21	27.9	0.142	Yes
	36	33	43.2	0.109	Yes
	48	45	46.8	0.400	Yes
ARIMA $(0,1,1)(1,0,2)^{12}$	12	8	11.0	0.202	Yes
	24	20	19.6	0.480	Yes
	36	32	46.6	0.046	No
	48	44	50.2	0.241	Yes

Based on Table 4 above, it can be observed that only the ARIMA$(0,1,1)(0,0,1)^{12}$ and ARIMA$(0,1,1)(1,0,1)^{12}$ models satisfy the white noise test.

4.4. Model Evaluation

The evaluation of the ARIMA$(0,1,1)(0,0,1)_{12}$ and ARIMA$(0,1,1)(1,0,1)_{12}$ models was conducted based on the accuracy level achieved using the testing dataset. Specifically, the suitability of each model was assessed by comparing the Mean Absolute Percentage Error (MAPE) values. The model with the lowest MAPE was considered the most appropriate. The MAPE values for each model are presented as follows:

Table 5. Comparison of MAPE Values

Model	MAPE
ARIMA $(0,1,1)(0,0,1)^{12}$	0.045
ARIMA $(0,1,1)(1,0,1)^{12}$	0.059

Based on Table 5, the model with the lowest MAPE value is ARIMA$(0,1,1)(0,0,1)^{12}$, with a MAPE of only 0.045 (4.5%). According to the MAPE classification criteria, this indicates that the forecasting performance of the ARIMA$(0,1,1)(0,0,1)^{12}$ model is highly accurate, as the MAPE value is less than 10%. Therefore, the ARIMA$(0,1,1)(0,0,1)^{12}$ model is considered to be highly suitable for forecasting the monthly number of domestic air passengers departing from Sultan Hasanuddin Airport.

Diagnostic checks indicate that this model produces residuals that are random, homoscedastic, and normally distributed (see Figure 3). Therefore, the ARIMA $(0,1,1)(0,0,1)^{12}$ model is considered the best candidate for modelling the time series data at this stage.

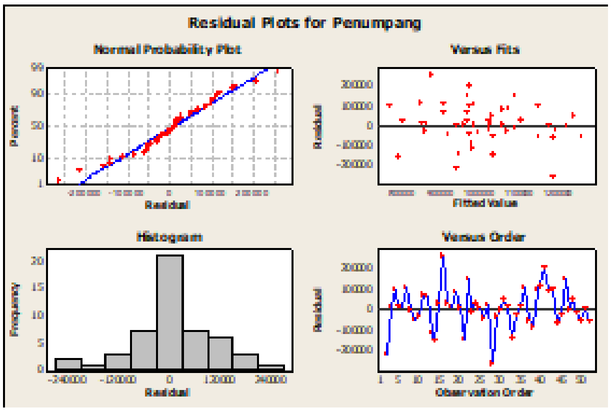

Figure 3. Diagnostic checks indicate that this model produces residuals that are random, homoscedastic, and normally distributed

4.5. Forecasting

Based on the entire series of analyses, it can be concluded that the final model for the monthly number of air passengers is ARIMA $(0,1,1)(0,0,1)^{12}$, with the estimated parameters. By transforming the model back to its original (non-differenced) form, the final model can be expressed as follows:

$$X_t - X_{t-1} = (1-\theta_1 B)(1-\Theta_{12}B^{12})e_t$$

$$X_t - X_{t-1} = (1-\theta_1 B - \Theta_{12}B^{12} + \theta_1\Theta_{12})e_t$$

$$X_t - X_{t-1} = e_t - \theta_1 e_{t-1} - \Theta_{12}e_{t-12} + \theta_1\Theta_{12}e_{t-13}$$

$$\hat{X}_t = X_{t-1} + e_t - \hat{\theta}_1 e_{t-1} - \hat{\Theta}_{12} e_{t-12} + \hat{\theta}_1 \hat{\Theta}_{12} e_{t-13}$$

$$\hat{X}_t = X_{t-1} + e_t - 0.6176e_{t-1} + 0.5949e_{t-12} - 0.3674e_{t-13}$$

The figure 4 show time series plot presents a comparison between the actual data and the forecasted values, along with the Lower Control Limit (LCL) and Upper Control Limit (UCL).

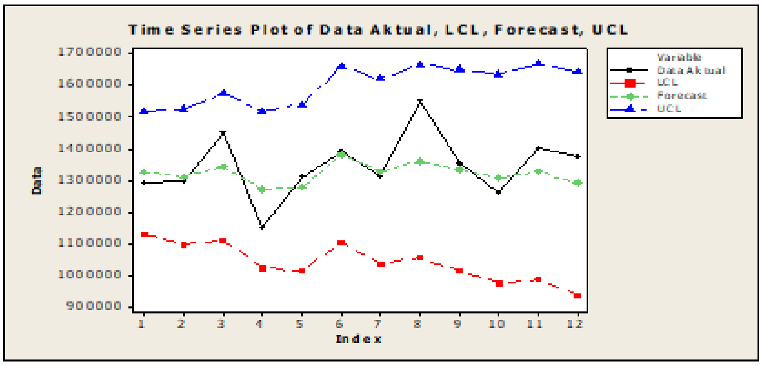

Figure 4. The comparison between actual values and forecasted results

5. Conclusion

The SARIMA (Seasonal Autoregressive Integrated Moving Average) model is one of the time series analysis methods that captures seasonal patterns in data. The modelling process involves several stages: model identification, parameter estimation, diagnostic checking, and model implementation. Based on the fulfilment of the required assumptions, the best-fitting model for the data is ARIMA $(0,1,1)(0,0,1)^{12}$. The model equation is as follows:

$$\hat{X}_t = X_{t-1} + e_t - 0.6176e_{t-1} + 0.5949e_{t-12} - 0.3674e_{t-13}$$

Based on the final selected model, the following are the forecasted values of the number of air passengers for the next 12 months:

Table 6. The forecasted values of the number of air passengers for the next 12 months

Monts	Forecasting	LCL	UCL
2024-Mei	326.090	306.784	345.396
2024-Juni	286.853	266.184	307.522
2024-Juli	273.913	251.965	295.861
2024-Agustus	368.815	345.658	391.972
2024-September	300.102	275.797	324.407
2024-Oktober	214.909	189.507	240.311
2024-November	271.931	245.478	298.384
2024-Desember	154.809	127.345	182.273
2024-Januari	254.142	225.703	282.581
2024-Februari	278.844	249.463	308.225
2024-Maret	207.111	176.816	237.406
2024-April	308.044	276.862	339.226

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