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Air Passenger Demand Forcasting in Tourism Destination: A Comparative Analysis of Econometric and Time Series Models

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Keywords

Air passenger demand; forecasting; econometric model; SARIMA; tourism destination; transportation planning.

Abstract

Accurate air passenger demand forecasting is essential for airport capacity planning and tourism transport policy, especially in destinations with strong seasonal travel patterns. This study compares econometric and time series models for forecasting passenger demand at I Gusti Ngurah Rai International Airport, Bali. Monthly secondary data were used to represent passenger volume, tourist arrivals, hotel occupancy rate, gross regional domestic product, and a ticket-fare proxy. Multiple linear regression was applied for the econometric approach, while Seasonal Autoregressive Integrated Moving Average (SARIMA) was used for the time series approach. Candidate models were evaluated using statistical feasibility tests, residual diagnostics, Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The best econometric model included tourist arrivals, hotel occupancy rate, and GRDP, with Adjusted R-squared of 0.929 and statistically significant variables. The selected time series model was SARIMA(0,1,1)(0,1,1)12. Out-of-sample validation using 2025 monthly data shows that SARIMA produced lower forecasting errors, with MAE of 55,332, RMSE of 63,049, and MAPE of 5.8204%, compared with the econometric model MAPE of 12.7812%. The findings indicate that SARIMA is more suitable for operational forecasting, while econometric modeling remains valuable for explaining tourism and economic demand drivers.

INTRODUCTION

Air transportation plays a strategic role in Indonesia because the country consists of many islands and tourism activities are distributed across different regions. For tourism destinations, air services are not only a means of interregional mobility but also an important gateway that connects tourist markets with local economic activities. Bali is one of Indonesia's main tourism destinations and is served by I Gusti Ngurah Rai International Airport, which accommodates domestic and international passenger movements.

The growth and fluctuation of tourism demand create important challenges for airport operators and transport planners. When passenger demand is underestimated, capacity shortages may occur in terminal facilities, airside operations, staffing, and service provision. When demand is overestimated, infrastructure and operational resources may be used inefficiently. Therefore, passenger demand forecasting is a crucial input for airport planning and policy formulation (Horonjeff 2010; Al-Sultan et al. 2021).

Forecasting air passenger traffic is complex because demand is affected by historical travel behavior, economic conditions, tourism activity, and external shocks. Previous studies have used time series, econometric, machine learning, and hybrid approaches for aviation demand forecasting (Chen and Wu 2022; Hopfe et al. 2024; Lundaeva et al. 2024). Time series models are useful because they capture trend and seasonal patterns in historical passenger data, while econometric models explain the relationship between demand and external factors such as economic activity and tourism indicators (Fildes et al. 2011; Suryan 2017).

In tourism destinations, the comparison between these two approaches is particularly relevant. Passenger movements are strongly associated with holiday periods, high-season tourism, hotel activity, and regional economic performance. A time series model may provide high forecasting accuracy when seasonal patterns are dominant, while an econometric model can provide interpretation of the tourism and economic variables that influence passenger demand.

This study aims to develop and compare econometric and time series models for forecasting air passenger demand at a tourism destination airport. Specifically, the study identifies the best econometric specification, determines the best SARIMA model, and compares both approaches using out-of-sample forecasting errors. The results are expected to support transportation planning, airport capacity management, and tourism-related policy decisions in Bali.

METHOD

Study Area and Data

The study focuses on I Gusti Ngurah Rai International Airport in Bali, Indonesia. Bali was selected based on the National Tourism Development Index (Indeks Pembangunan Kepariwisataan Nasional/IPKN) issued by the Ministry of Tourism and Creative Economy in 2024. According to the IPKN, Bali Province ranked first nationally with an index score of 5.39%, confirming its relevance as the case study location. I Gusti Ngurah Rai International Airport serves as Bali's main international airport and tourism gateway.

The research used secondary monthly data from official sources. The dependent variable was total domestic and international air passenger volume. The econometric candidate variables were tourist arrivals, hotel occupancy rate, GRDP at constant prices for accommodation, food and beverage, and transportation-related sectors, and a ticket-fare proxy constructed from aviation fuel price, exchange rate, and transport CPI because consistent historical airfare data were limited. After data screening and pandemic-disruption treatment, 96 monthly observations were used for model estimation, while 2025 monthly passenger data were used for out-of-sample validation.

Table 1. Research variables and data sources

Variable	Role	Description	Frequency	Source
Air passengers	Dependent	Total domestic and international passengers at I Gusti Ngurah Rai International Airport	Monthly	PT Angkasa Pura I and BPS Bali
Tourist arrivals	Independent	Domestic and international tourist arrivals to Bali	Monthly	BPS and Bali Tourism Office
Hotel occupancy rate	Independent	Average occupancy rate of star and non-star hotels	Monthly	BPS and Bali Tourism Office
GRDP	Independent	GRDP at constant prices for accommodation, food and beverage, and transportation-related sectors	Monthly/interpolated	BPS Bali

Ticket-fare proxy	Independent	Composite proxy based on fuel price, exchange rate, and transport CPI	Monthly	EIA, Bank Indonesia, BPS

Econometric Modeling

Horonjeff (2010) stated that econometric methods are mathematical approaches used to analyze the relationship between dependent and independent variables, enabling air transportation activities to be measured through economic and social factors. The econometric approach used multiple linear regression estimated with Ordinary Least Squares. Because four explanatory variables were used, all possible combinations of independent variables were tested. In total, 15 econometric model combinations were evaluated. This process was conducted to ensure that the selected econometric model was not determined from a single initial specification, but through systematic model comparison. Model selection was based on several statistical and forecasting criteria, including the F-test, t-test, tolerance, variance inflation factor (VIF), Adjusted R-squared, and forecasting errors. The F-test was used to evaluate simultaneous significance, while the t-test was used to assess the partial significance of each explanatory variable. Tolerance and VIF were used to detect multicollinearity. Forecasting error indicators were used to evaluate model accuracy.

The general econometric model is expressed in Eq. (1), where Y_{est} is air passenger demand, X represents the independent variables, and a values are estimated coefficients.

$$Y_{est} = a_0 + a_1X_1 + a_2X_2 + a_3X_3 + \ldots + a_nX_n \quad (1)$$

Time Series Modeling

Time series is a quantitative approach used to analyze data based on historical observations. This method aims to identify patterns such as trends, seasonality, cyclical movements, and random fluctuations, which can subsequently be used to forecast future values (Hyndman, 2018). The time series approach used SARIMA because the passenger data are monthly and show seasonal patterns. The seasonal period was set to 12 months. The modeling process consisted of plotting the data, examining the Autocorrelation Function and Partial Autocorrelation Function, estimating candidate SARIMA models, and evaluating the residuals using the Ljung-Box test. A model was considered feasible when the residuals did not contain significant autocorrelation.

According to Box & Jenskin (2016), the general SARIMA model is expressed in Eq. (2), where p is the autoregressive (AR) order, d is the differencing degree (to eliminate trends), q is the Moving Average (MA) order, P is the AR seasonal order, D is the seasonal differencing degree, Q is the MA seasonal order, and s is the seasonal period (e.g. s = 12 for monthly data).

$$SARIMA\ (p,d,q)(P,D,Q)_s \quad (2)$$

The candidate SARIMA models included SARIMA $(1,1,0)(1,1,0)_{12}$, SARIMA$(1,1,0)(1,1,1)_{12}$, SARIMA$(1,1,1)(1,1,0)_{12}$, SARIMA$(0,1,1)(0,1,1)_{12}$, and SARIMA$(1,1,1)(1,1,1)_{12}$. The best model was selected using RMSE, MAE, MAPE, Normalized BIC, and the Ljung-Box diagnostic.

Forecasting Accuracy

Forecasting model performance was evaluated by calculating forecast errors between the actual values and predicted values, following Hyndman and Athanasopoulos (2018). In this study, the performance of both models was evaluated using MAE, RMSE, and MAPE. Lower values indicate better forecasting accuracy. The equations are presented in Eqs. (3)-(5), where Y_t is the actual value, $\hat{Y}_t$ is the forecast value, and n is the number of observations.

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|Y_t - \hat{Y}_t\right| \tag{3}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2} \tag{4}$$

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \tag{5}$$

RESULTS AND DISCUSSION

Descriptive Characteristics of Passenger Demand

The study used 10 years of monthly data from 2015 to 2024, resulting in a total of 120 observations. However, the data for the COVID-19 pandemic period (2020–2021) were excluded during the data cleaning process due to the presence of outliers and extreme fluctuations caused by mobility restrictions. As a result, the final dataset used in this study consisted of 96 observations. The descriptive statistics show that air passenger demand in Bali had a wide variation during the observation period. Passenger volume ranged from 195,494 to 1,147,351 passengers per month, with an average of 838,586.98 passengers and a standard deviation of 186,546.12. Tourist arrivals also fluctuated substantially, with values ranging from 391,000 to 1,837,393 visitors per month.

The monthly passenger series indicates strong seasonal movement. Passenger volume generally increased during school holidays, mid-year travel seasons, and year-end holiday periods. This pattern supports the use of SARIMA, because seasonal behavior is a central characteristic of passenger demand at a tourism destination airport.

Econometric Model Development

Because four explanatory variables were used, all possible combinations of independent variables were tested. In total, 15 econometric model combinations were evaluated. The purpose of this process was to ensure that the selected econometric model was not determined from a single initial specification, but through systematic model comparison. The econometric model selection was based on several statistical and forecasting criteria, including the F-test, t-test, tolerance, variance inflation factor (VIF), Adjusted R-squared, and forecasting errors. The F-test was used to evaluate simultaneous significance, while the t-test was used to assess the partial significance of each explanatory variable. Tolerance and VIF were used to detect multicollinearity, and forecasting error indicators were used to evaluate model accuracy.

Based on the ranking of these criteria, the first-ranked and selected econometric specification consisted of tourist arrivals, hotel occupancy rate, and GRDP. This model was selected because all independent variables were statistically significant, the simultaneous F-test was significant, multicollinearity indicators were acceptable, and the model produced the smallest MAPE among the eligible econometric candidates.

The final econometric model is shown in Eq. (6). The coefficients indicate positive relationships between air passenger demand and the three explanatory variables. This means that increases in tourist arrivals, hotel occupancy rate, and regional economic activity tend to be followed by increases in passenger demand.

$$Y = -291{,}458.802 + 0.339\,X1 + 5{,}907.125\,X2 + 0.039\,X3 \quad (6)$$

In Eq. (6), Y represents air passenger demand, X1 represents tourist arrivals, X2 represents hotel occupancy rate, and X3 represents GRDP for accommodation, food and beverage, and transportation-related sectors. The model produced R-squared of 0.932 and Adjusted R-squared of 0.929, indicating that approximately 92.9% of the variation in passenger demand could be explained by the selected variables. The F-test significance was 0.000, while all partial t-test significance values were also below 0.05.

Table 2. Selected econometric model comparison

Rank	Independent variables	Adjusted R-squared	Sig. F	MAPE (%)	Max VIF	Result
1	Tourists + occupancy rate + GRDP	0.929	0.000	4.850	3.197	Selected
2	Tourists + occupancy rate + GRDP + ticket proxy	0.929	0.000	4.864	3.574	Not selected
3	Tourists + occupancy rate + ticket proxy	0.914	0.000	5.065	1.994	Not selected
4	Tourists + occupancy rate	0.914	0.000	5.100	1.700	Not selected
5	Occupancy rate + GRDP + ticket proxy	0.853	0.000	7.302	2.220	Not selected

SARIMA Model Development

The ACF and PACF analysis indicated significant autocorrelation at early lags and seasonal behavior around lag 12. Therefore, the SARIMA models used first-order non-seasonal differencing and seasonal differencing with a 12-month period. All candidate SARIMA models passed the residual white-noise diagnostic based on the Ljung-Box test.

Among the candidate models, SARIMA$(0,1,1)(0,1,1)_{12}$ produced the lowest RMSE, MAE, MAPE, and Normalized BIC. Although SARIMA$(1,1,1)(1,1,1)_{12}$ had the highest R-squared, the model was not selected because its error values were higher than those of SARIMA$(0,1,1)(0,1,1)_{12}$. This confirms that model selection in forecasting should prioritize error measures and residual diagnostics rather than R-squared alone.

Table 3. Comparison of candidate SARIMA models

No.	SARIMA model	R-squared	Stationary R-squared	Ljung-Box Sig.	Conclusion
1	$(1,1,0)(1,1,0)_{12}$	0.631	0.120	0.978	Feasible, not best
2	$(1,1,0)(1,1,1)_{12}$	0.713	0.316	0.991	Feasible
3	$(1,1,1)(1,1,0)_{12}$	0.632	0.121	0.972	Feasible, not best
4	$(0,1,1)(0,1,1)_{12}$	0.712	0.313	0.975	Best model
5	$(1,1,1)(1,1,1)_{12}$	0.714	0.317	0.989	Feasible, higher error

Out-of-Sample Forecasting Comparison

The econometric and SARIMA models were then tested using 2025 monthly actual data. The comparison shows that the SARIMA forecasts were closer to actual passenger volume in most months. For example, in May 2025 the actual value was 1,008,792 passengers, while the SARIMA forecast was 979,817 and the econometric forecast was 865,124. In June 2025, the actual value was 1,076,059, while SARIMA forecasted 1,040,672 and the econometric model forecasted 929,888.

The superiority of SARIMA can be explained by the strong historical and seasonal patterns in Bali passenger demand. SARIMA directly models temporal dependence and annual seasonality, while the econometric model does not explicitly include monthly or high-season dummy variables. Therefore, SARIMA is more effective for short-term operational forecasting in this case.

Table 4. Actual and forecasted passenger demand in Bali, 2025

Month	Actual	Econometric forecast	SARIMA forecast
Jan	965,710	806,364	858,178
Feb	791,140	713,954	834,977
Mar	777,189	697,570	875,394
Apr	1,036,968	866,337	941,474
May	1,008,792	865,124	979,817
Jun	1,076,059	929,888	1,040,672
Jul	1,181,942	987,248	1,144,953
Aug	1,136,393	980,082	1,107,265
Sep	1,045,797	938,974	1,064,161
Oct	1,019,675	906,556	1,048,822
Nov	874,221	818,246	948,426
Dec	1,047,886	894,326	1,114,610

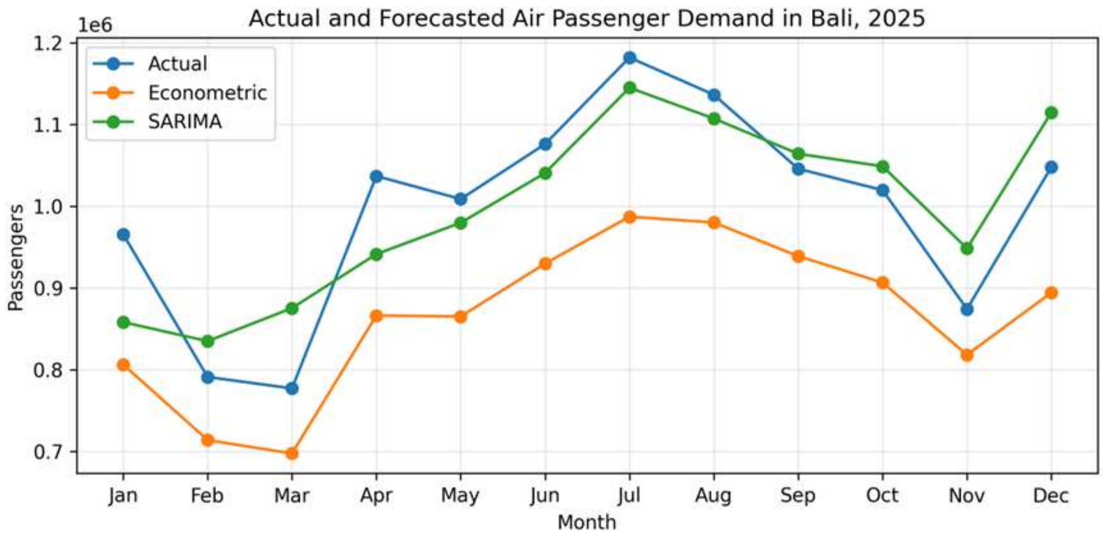

Figure 1. Actual and forecasted air passenger demand in Bali, 2025

Table 5. Forecasting accuracy comparison

Method	Best model	MAE	RMSE	MAPE
Econometric	Y = -291,458.802 + 0.339X1 + 5,907.125X2 + 0.039X3	129,758.6255	136,037	12.7812%
Time series	SARIMA(0,1,1)(0,1,1)$_{12}$	55,332.2500	63,049	5.8204%

Implications for Transportation Planning

The findings indicate that SARIMA is more appropriate when the main planning objective is operational forecasting, such as anticipating passenger peaks, adjusting terminal staffing, managing passenger processing facilities, and preparing airport services during high-season periods. A MAPE of 5.8204% shows that the model can provide relatively accurate short-term forecasts for monthly planning.

However, the econometric model remains important for strategic interpretation. It explains that passenger demand is positively associated with tourism activity, accommodation utilization, and regional economic performance. For policy and infrastructure planning, this interpretation helps stakeholders understand which external factors are related to passenger growth. Therefore, the two approaches should be viewed as complementary: SARIMA for accurate operational forecasting and econometric modeling for explaining demand drivers.

CONCLUSION

This study compared econometric and time series models for forecasting air passenger demand at I Gusti Ngurah Rai International Airport, Bali. The best econometric model used tourist arrivals, hotel occupancy rate, and GRDP as explanatory variables. The model had strong explanatory power, with Adjusted R-squared of 0.929, and all variables showed positive and significant relationships with passenger demand. The coefficient of tourist arrivals (X1) was 0.339, indicating that an increase in tourist arrivals was associated with an increase in air passenger demand, assuming other variables remained constant. The coefficient of hotel occupancy rate (X2) was 5,907.125, showing that higher hotel occupancy rates tended to increase the number of air passengers. Meanwhile, the coefficient of GRDP (X3) was 0.039, indicating a positive relationship between regional economic growth and passenger demand. All variables showed positive and statistically significant relationships with air passenger demand.

The best time series model was SARIMA(0,1,1)(0,1,1)$_{12}$. This model passed the Ljung-Box residual diagnostic and produced the lowest error among the SARIMA candidates. Based on out-of-sample validation using 2025 monthly data, SARIMA outperformed the econometric model, with MAE of 55,332.2500, RMSE of 63,049, and MAPE of 5.8204%, compared with the econometric model MAPE of 12.7812%. Therefore, SARIMA is the preferred model for short-term operational forecasting of air passenger demand in tourism destination.

For transportation planning in tourism destinations, the results suggest that seasonal time series models should be prioritized for passenger-volume forecasting, especially when demand has strong monthly and holiday patterns. Nevertheless, econometric modeling should still be used as a complementary tool to explain the influence of tourism and economic variables. Future research should consider adding seasonal dummy variables to the econometric model, testing hybrid models, using actual airfare data, and extending the analysis to other tourism destination airports.

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