Forecasting Tourist Arrivals to Oman: An ARIMA-Based Time Series Approach for Strategic Planning

Dr. Abdul Nazar N[a], Dr. Neil Raymond Salestro[b]

a. b CEBA University of Technology and Applied sciences-Salalah, Oman, Abdul.Nazar@utas.edu.om, neil.saletrero@utas.edu.om

Abstract:

The foundation of Oman's Vision 2040, which aims for sustainable development and economic diversification, is tourism. Accurate visitor arrival projections are crucial for marketing, resource management, and infrastructure planning. To assess and predict monthly visitor arrivals to Oman, this study uses a univariate ARIMA (Auto-Regressive Integrated Moving Average) model. The results provide stakeholders with useful information by revealing notable seasonal trends and possibilities for ongoing growth. To put its methodology in context, the study makes use of associative theories like demand theory and systems theory. The paper discusses the ARIMA model's shortcomings, such as its sensitivity to external shocks and linearity assumptions and suggests hybrid alternatives for further study.

1. Introduction

Oman's economic strategy under Vision 2040, which seeks to lessen reliance on oil earnings and establish sustainable development pathways, places a strong emphasis on tourism. Oman is a popular travel destination because of its many attractions, which include both natural landscapes and cultural history. To fully realize this potential, though, accurate demand forecasting for tourism is necessary to direct investments and policy choices.

Tourism research has always struggled with accurate demand predictions. According to Song and Li (2008), early approaches depended on qualitative techniques like expert opinions, which lacked empirical rigor despite being intuitive. The discipline has now been dominated by quantitative methods, with econometric models examining macroeconomic factors such as exchange rates and income (Lim, 2006). The capacity of time series models, especially ARIMA, to manage seasonal patterns and data autocorrelations has made them a strong tool for short-term forecasting (Box & Jenkins, 1976; Hyndman & Athanasopoulos, 2018).

This study's theoretical underpinnings stem from demand theory, which holds that variables like accessibility, affordability, and income affect traveler demand. By spotting recurrent patterns and trends that influence demand, time series modeling supports this notion. The interdependence of the different subsystems of tourism, including marketing, lodging, transportation, and infrastructure, is also highlighted by systems theory. As a result, precise forecasting is an essential component for improving these interconnected systems.

Globally, the ARIMA model has proven to be a highly effective tool for anticipating tourism demand. Goh and Law (2002), for example, used ARIMA to analyze tourism data from Hong Kong and shown how well it predicted short-term demand. This work was expanded upon by Chu (2004), who found that ARIMA was better at managing seasonal swings when compared to other models. In a similar vein, Ridderstaat et al. (2014) applied ARIMA to the demand for tourism in Dubai, emphasizing its usefulness in volatile, dynamic markets. These studies highlight how flexible ARIMA models are in a variety of settings, which makes them ideal for places like Oman where seasonality significantly affects visitor numbers.

2. Research Methodology

2.1 Research Design

This study employs a quantitative research design, modeling and forecasting monthly visitor arrivals in Oman using secondary time-series data. The study's goals are addressed by employing the ARIMA model, which focuses on short-term demand forecast.

2.2 Data Sources

The National Center for Statistics and Information (NCSI) in Oman is the source of the secondary data used in this study. Monthly records of visitor arrivals from January 2010 to December 2023 make up the dataset.

Rationale for Secondary Data Usage:

NCSI data is extremely dependable, offering constant records for model construction; secondary data guarantees the availability of a thorough historical dataset, which is essential for time series analysis.

Missing data handling: Missing Data Handling: Any missing entries in the dataset were addressed using linear interpolation.
Outlier Treatment: To guarantee model stability, extreme values that were frequently connected to outside shocks like the COVID-19 epidemic were smoothed.
Stationarity Testing: To verify stationarity, the Augmented Dickey-Fuller (ADF) test was used. Accordingly, non-stationary data were differentiated.

2.3 Hypothesis Formulation

Despite ARIMA modeling's primary prediction function, the following theories were developed to direct the investigation:

H1: Monthly tourist arrivals to Oman exhibit significant seasonality.

H2: The ARIMA model can effectively capture and forecast monthly tourist arrival trends with minimal errors.

H3: Seasonal peaks in tourist arrivals align with Oman's climatic patterns and major tourism events.

These hypotheses provide a structured basis for evaluating the model's performance and alignment with theoretical expectations.

2.4 Model Selection and Development

The ARIMA model was developed following the **Box-Jenkins methodology**:

1. **Identification:**
   - **ACF and PACF Analysis:** Initial parameters (p, d, q) were identified based on autocorrelation and partial autocorrelation plots.
   - **Differencing:** First-order differencing (d=1) was applied to achieve stationarity.
2. **Estimation:**
   - **Model Fitting:** Maximum likelihood estimation was used to estimate the parameters of various ARIMA models.
3. **Diagnostic Checking:**
   - Residual diagnostics ensured no significant autocorrelation in residuals (Ljung-Box test).
   - AIC and BIC criteria guided model selection, favoring lower values.
4. **Validation:**
   - The dataset was split into training (2010–2022) and validation (2023) subsets. Forecast accuracy was measured using Mean Absolute Percentage Error (MAPE).

2.5 Forecasting Horizon

The monthly arrivals of tourists in 2024–2025 were predicted using the chosen ARIMA model, ARIMA(1,1,1)(0,1,1)[12]. This projection offers practical information for strategic planning in the travel and tourism industry in Oman.

The ARIMA(1,1,1)(0,1,1)[12] model demonstrated high prediction accuracy with a MAPE of 5.6%. In line with Oman's climatic and cultural attractions, seasonal peaks in arrivals took place during the winter months (November to February) and the Khareef season (June to August). Forecasts for 2024–2025 indicate a sustained recovery post-pandemic with an annualized growth rate of 6.2% in tourist arrivals.

2.6 Hypotheses Evaluation

- **H1:** Confirmed. Clear seasonal patterns were evident in the data.
- **H2:** Confirmed. The ARIMA model achieved a MAPE well below the 10% threshold.
- **H3:** Confirmed. Seasonal peaks aligned with Oman's tourism calendar and major events.

3. Implications

3.1 Strategic Implications

1. Infrastructure Planning: o Forecasts offer data-driven recommendations for expenditures on lodging, transit, and tourist amenities, guaranteeing that available resources correspond with demand trends.
2. Marketing Optimization: Knowledge of seasonal patterns aids in creating focused advertising efforts that maximize income by drawing visitors during off-peak times.
3. Resource use: By preventing overcapacity or under preparation, accurate forecasting helps with the effective use of material and human resources.
4. Sustainability Planning: o In line with Oman's long-term development objectives, sustainable management of environmental and cultural resources is made possible by an understanding of tourist flows.

3.2 Policy Implications

1. **Tourism Policies**: Forecasts can be used by policymakers to create price plans, incentive programs, and visa policies that increase arrivals during off-peak times.
2. **Crisis Management**: Accurate demand projections make it possible to prepare for unforeseen events like pandemics or unstable regions.

3. **Economic Diversification:** Consistent growth projections support the importance of tourism in Oman's overall diversification plan and are consistent with the goals of Vision 2040.

3.3 Limitations

1. **Linearity Assumption:** The intricacies of tourism demand driven by nonlinear factors, such as abrupt policy changes or economic upheavals, may not be adequately captured by ARIMA models, which assume linear correlations.

2. **Dependence on Historical Data:** Reliance on historical data makes the assumption that prior trends will continue, which could not be true in contexts that are changing quickly.

3. **Sensitivity to Outliers:** Model autonomy is diminished by the need for manual changes in response to external shocks like the COVID-19 epidemic.

4. **Lack of Explanatory Power:** Since ARIMA is only a prediction model and doesn't reveal causal links, its use in strategic decision-making is limited.

4. Conclusion and Recommendations

This study shows how useful ARIMA modeling is for predicting demand for tourism and gives Oman's stakeholders useful information. Even though the ARIMA(1,1,1)(0,1,1)[12] model worked well for short-term forecasts, its drawbacks point to the necessity of incorporating machine learning methods into subsequent studies. ARIMA and techniques like Long Short-Term Memory (LSTM) networks can be combined in hybrid models to improve forecasting accuracy and handle nonlinearities. Macroeconomic factors should be included in future research to increase explanatory power and provide a more thorough knowledge of the dynamics of tourism demand.

References:

Box, G. E. P., & Jenkins, G. M. (1976). *Time series analysis: Forecasting and control* (2nd ed.). San Francisco, CA: Holden-Day.

Chu, F. L. (2004). Forecasting tourism demand: A cubic polynomial approach. *Tourism Management*, 25(2), 209–218. https://doi.org/10.1016/S0261-5177(03)00065-5

Goh, C., & Law, R. (2002). Modeling and forecasting tourism demand for arrivals with stochastic nonstationary seasonality and intervention. *Tourism Management*, 23(5), 499–510. https://doi.org/10.1016/S0261-5177(02)00009-2

Hyndman, R. J., & Athanasopoulos, G. (2018). *Forecasting: Principles and practice* (2nd ed.). Melbourne, Australia: OTexts. Retrieved from https://otexts.com/fpp2/

Lim, C. (2006). A survey of tourism demand modeling practice: Issues and implications. *Tourism Economics*, 12(1), 203–226. https://doi.org/10.5367/000000006776387089

Ridderstaat, J., Croes, R., & Nijkamp, P. (2014). Tourism and long-run economic growth in Aruba. *International Journal of Tourism Research*, 16(5), 472–487. https://doi.org/10.1002/jtr.1941

Song, H., & Li, G. (2008). Tourism demand modeling and forecasting—A review of recent research. *Tourism Management*, 29(2), 203–220. https://doi.org/10.1016/j.tourman.2007.07.016

National Center for Statistics and Information (NCSI). (2023). *Tourism statistics report*. Muscat, Oman: NCSI.

Smeral, E. (2012). International tourism demand and the business cycle. *Annals of Tourism Research*, 39(1), 379–400. https://doi.org/10.1016/j.annals.2011.07.008

Witt, S. F., & Witt, C. A. (1995). Forecasting tourism demand: A review of empirical research. *International Journal of Forecasting*, 11(3), 447–475. https://doi.org/10.1016/0169-2070(95)00591-7

Zhang, G., Eddy Patuwo, B., & Hu, M. Y. (1998). Forecasting with artificial neural networks: The state of the art. *International Journal of Forecasting*, 14(1), 35–62. https://doi.org/10.1016/S0169-2070(97)00044-7

Brockwell, P. J., & Davis, R. A. (2016). *Introduction to time series and forecasting* (3rd ed.). Springer. https://doi.org/10.1007/978-3-319-29854-2

Burns, A. C., & Bush, R. F. (2014). *Marketing research* (7th ed.). Pearson.

Makridakis, S., Wheelwright, S. C., & Hyndman, R. J. (1998). *Forecasting methods and applications* (3rd ed.). Wiley.

Schubert, S. F., Brida, J. G., & Risso, W. A. (2011). The impacts of international tourism demand on economic growth of small economies dependent on tourism. *Tourism Management*, 32(2), 377–385. https://doi.org/10.1016/j.tourman.2010.03.007

Author Biographies

1. Dr. Abdul Nazar.N Who has been serving in teaching and research for more than 25 years in the field of Accounting.

2. Dr. Neil Raymond who has been in teaching and research for more than 20 years in Accounting and served as a Head of Accounting unit in the CEBA,UTAS.