forecasting

Editorial

Editorial for Special Issue: "Tourism Forecasting: Time-Series Analysis of World and Regional Data"

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This Special Issue was honored with six contribution papers embracing the subject of tourism forecasting. The papers focused on forecasting tourism demand in the USA, Vienna—Austria, Vietnam, Marrakech-Safi region of Morocco, Dubai, and China.

The time series were spread from tourism interest in the USA, hotel room demand in Vienna, number of tourists in Vietnam, annual tourist arrivals to the Marrakech-Safi region of Morocco, tourist arrivals to Dubai from the UK and the daily and weekly number of passengers at urban rail transit stations in China. The used datasets, in some cases, included the COVID-19 pandemic period, which was a severe challenge for the forecasting models.

The forecasting models used embrace the following parameters: descriptive analysis techniques, seasonal naïve, Error Trend Seasonal (ETS), Seasonal Autoregressive Integrated Moving Average (SARIMA), Trigonometric Seasonality, Box–Cox Transformation, ARMA Errors, Trend and Seasonal Components (TBATS), Seasonal Neural Network Autoregression (Seasonal NNAR), Seasonal NNAR with an external regressor, Artificial Neural Network (ANN) forecasting model, ARIMA, AR, linear regression, Support Vector Regression (SVR), eXtreme Gradient Boosting (XGBoost), Long Short-Term Memory (LSTM) models, ensemble models, Box–Jenkins time series models, and the Facebook Prophet algorithm.

The authors are in consensus in terms of concluding that the developed models serve as valuable tools for policymakers and firm managers of their countries to make better investment and strategic decisions.

Godovykh et al. [1] analyzed the influence of COVID-19 on tourism interest in the USA through positive and negative sentiments toward tourism. The authors used the number of positive cases of COVID-19 and the number of daily fully vaccinated people, news sentiment, the total number of daily mentions of tourism, and the share of voice for positive and negative sentiment toward tourism in the USA until October 2021. Several data analysis techniques were used, such as descriptive analysis, visual representation of data, data decomposition into trend and cycle components, unit root tests, Granger causality test, and multiple time series regression. The analysis demonstrated that the COVID-19 statistics and media coverage significantly affected interest in tourism in general and the positive and negative sentiment toward tourism in particular.

Gunter [2] used daily data on hotel room demand in Vienna for the total of hotels as well as per hotel class. The time period analyzed was from 1 January 2010 to 31 January 2020. The study employed six different forecasting models (seasonal naïve, ETS, SARIMA, TBATS, Seasonal NNAR, and Seasonal NNAR with an external regressor) and five different forecasting combination techniques (mean forecast, median forecast, regression-based weights, Bates–Granger weights, and Bates–Granger ranks). While not all individual forecasting models achieved first ranks in terms of MAPE and other accuracy measures, all of them survived forecasting encompassing tests and were thus considered for forecasting combination. Overall, the results of this study showed the benefits of forecasting combination, particularly of Bates–Granger weights and Bates–Granger ranks, which were characterized by the smallest forecasting errors in 13 out of 28 cases.

Citation: Teixeira, J.P.; Gunter, U. Editorial for Special Issue: "Tourism Forecasting: Time-Series Analysis of World and Regional Data". *Forecasting* **2023**, *5*, 210–212. https://doi.org/10.3390/forecast5010011

Received: 26 January 2023
Accepted: 27 January 2023
Published: 2 February 2023

Nguyen et al. [3] developed a forecasting model based on an ANN to predict the tourism demand in Vietnam. The number of tourists in Vietnam had increased over the last two decades and had become a key driver of the country's development. Nevertheless, the border closed due to the COVID-19 pandemic, and the number of tourists decreased suddenly from March 2020 until the end of the analysis period (July 2021). This abrupt change in the tourism demand was a major challenge for the ANN forecasting model making predictions based on the past, and this was a new reality. The authors solved this situation using months of this new period in the training dataset. The finally selected model achieved a MAPE between 7.9% and 9.2%, considering months before and after the COVID-19 period in the test set.

Ouassou et al. [4] experimented and compared three conventional models and three Artificial intelligence (AI) models in forecasting the regional tourism demand in a Moroccan region. The number of annual tourist arrivals to the Marrakech-Safi region from 1999 to 2018 was used. ARIMA, AR, and linear regression models were used as conventional models, and the SVR, XGBoost, and LSTM models were used as AI models. Finally, the authors experimented robust forecasting using ensemble learning, which combines the output models using different methods such as bagging, boosting, adaptive boosting (AdaBoost), a mixture of experts or stacked generalization. The ensemble model that combined LSTM and AR models was consistently more accurate than the other combined techniques and the conventional models, achieving a MAPE of 6.1%.

Rashad [5] developed a model exploring the 'Destination Insights with Google', a new Google tool, to improve the forecasting of tourist arrivals to Dubai from the UK. The paper compared the forecast accuracy of the traditional model with the Google-augmented model. The traditional model relied on conventional economic variables such as the UK GDP, Real Effective Exchange Rate (REER), and a dummy variable to capture the COVID-19 period. The Google-augmented model combines the same traditional variables and the Google search variable. Data from January 2019 to April 2022 were used. The study's findings suggested that the model incorporating the Google destination insight data fits the data better and outperforms the model with the classical variables, improving the MAPE from 18% to 6%.

Finally, Chuwang et al. [6] explored time series forecasting models for predicting the daily and weekly number of passengers at urban rail transit stations in China, using 365 days of historical inbound passenger demand data. The authors used the Box–Jenkins time series models and the Facebook Prophet algorithm to analyze the characteristics of urban rail transit passenger demand and thus achieved improved computational forecasting performance accuracy. The results showed that the Facebook Prophet model performs better for daily passenger demand, while the ARMA model is best for weekly time series.

Funding: This research was funded by the Foundation for Science and Technology (FCT, Portugal) through national funds FCT/MCTES (PIDDAC) to CeDRI (UIDB/05757/2020 and UIDP/05757/2020).

Acknowledgments: The authors are grateful to the Foundation for Science and Technology (FCT, Portugal) for financial support.

Conflicts of Interest: The authors declare no conflict of interest.

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