Time Series Models and Machine Learning for Predicting Tourism Demand in Emerging Destinations

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Abstract: - In this study, we used time series models and machine learning techniques to predict tourism demand for emerging destinations. We collected data on visitors, weather, room rates, things to do, online activities, and relationships from the beginning of 2017 to 2023. For this study, we used ARIMA, SARIMA, and LSTM models. We found that LSTM provides the most accurate predictions with the lowest mean absolute error (MAE) and root mean square error (RMSE). In situations with sudden and frequent changes, LSTM is the superior model. ARIMA is acceptable but simplistic. SARIMA took seasonal data into account but showed the highest error and failed to fit the data. The study showed that AI tools, including LSTM, can play a critical role in tourism investment, especially where conventional models have limited applications. The study recommends their use in already available tourism models.

Key-Words: - Tourism demand, Emerging destinations, Time series, Machine learning, ARIMA models, SARIMA models, LSTM networks.

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1 Introduction

Models based on time series analysis and machine learning for assessing tourism demand in emerging destinations are at the crossroads of statistical and algorithmic analysis. Accurate forecasting of tourism demand in emerging destinations is essential for strategic planning, [1], [2].

These places, which are beginning to position themselves on the radar of travelers, require intelligent approaches that allow them to optimize resources, enhance the visitor experience, and ensure sustainable development. In this context, time series models and machine learning techniques have acquired a fundamental role in predicting tourism flows, [3], [4].

Time series models, including ARIMA, analyze data over extended periods, with proven utility in tourism, as they capture data with seasonal variations and temporal trends of historical and special events, [5], [6]. However, their utility in tourism is limited, primarily when the data is nonlinear and exhibits sudden changes, a characteristic that has proven common in emerging tourist destinations.

Machine learning overcomes these challenges, and algorithms, including artificial neural networks (ANNs) and XGBoost, have proven more effective at predicting trends and time series due to their ability to reveal complex data extractions. ANNs, for example, can model nonlinear relationships between variables [7], making them ideal for capturing the changing dynamics of tourism. XGBoost, on the other hand, stands out for its accuracy and efficiency, combining multiple decision trees to improve predictions, even when sparse or noisy information is available, [8].

A recent trend has been to combine the best of both worlds through hybrid models, which integrate statistical approaches with machine learning algorithms. These models allow capturing both long-term trends and irregular or seasonal patterns, thus increasing accuracy in high-uncertainty scenarios such as those faced by emerging tourism destinations, [9], [10].

In addition, the incorporation of external data - such as tourist reviews on digital platforms, weather information or local event calendars- has further extended the predictive scope of these models. Thanks to their processing power, machine learning algorithms can integrate this type of unstructured data, offering a more complete and realistic view of the factors influencing tourism demand, [11], [12].

Thus, predicting demand in emerging destinations is no longer just a matter of looking at the past, but of building intelligent models that can learn from the present to anticipate the future with greater accuracy. Therefore, the objective of this article was to analyze and evaluate the effectiveness of time series models and machine learning techniques in predicting tourism demand in emerging destinations.

2 Materials and Methods

2.1 Models Evaluated

Time series models, including traditional methods such as ARIMA (autoregressive integrated moving average) and exponential smoothing, have been widely used in this domain, as they can effectively capture the underlying structures in historical data, [13].

SARIMA is a model that extends the capabilities of ARIMA by incorporating seasonal components, which in theory makes it ideal for cyclical phenomena such as tourism. However, in this particular case, the model failed to fit the dynamics of the data well, [14].

The last model considered was LSTM, since neural networks are particularly powerful for working with long time series and complex dynamics, which seems to have been a great advantage in the analysis of tourism demand, [15].

2.2 Data Used

This study is based on a database generated from records collected between January 2017 and December 2023. The data contains variables important for evaluating tourism in different destinations. It also provides information to understand how these variables change over time.

Some of the variables included were the number of arrivals, temperature fluctuations, accommodation rates, the number of events occurring in a month, and the search trend index (inferred from social media interest). Number of arrivals: visitors registered at migration posts.

Average temperature: taken from the weather stations of the visited sites

Lodging rate: cost of rooms in hotels and inns

Events: cultural and sports activities carried out in visited sites.

The data structure provides information on the drivers of demand in tourism, both quantitatively and qualitatively. The inclusion of climatic, economic, and digital behavior variables enhances the analysis. This allows for the training and evaluation of predictive models using a variety of methodologies. This wealth of information is particularly valuable for exploring the potential of advanced time series and machine learning tools in the framework of smart tourism and evidence-based decision making.

The LSTM mentions the use of information criteria like the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC). These criteria play a critical role in statistical modeling since they aid in assessing various models by balancing fit quality and complexity. In terms of avoiding overfitting in a dataset, both AIC and BIC are effective, as they both introduce penalties for model complexity, incentivizing a researcher to opt for a simpler and practically effective model.

Considering these criteria is important while creating statistical models. Not applying AIC or BIC assessments can help identify inappropriate models and, ultimately, compromise the validity of the results. Using these information criteria allows modelers to refine their choices and ensure that the model maintains a good statistical fit. However, at the same time, it balances a good statistical fit with simplicity. This, in turn, fosters a better understanding of the phenomenon being modeled.

2.3 Evaluation of the Models

In the context of this study, the use of metrics such as RMSE (Root Mean Squared Error) and MAE (Mean Absolute Error) has been fundamental to objectively evaluate the performance of the applied prediction models. These methods show how far the model estimates are from the true values of tourism demand. The MAE provides an idea of the average error, regardless of its size, while the RMSE is used to identify models that generally produce large and more serious errors. This is especially relevant when working with data that may experience extreme irregularities.

The structure of the data allows for a comprehensive perspective of the factors that influence tourism demand, both from a quantitative and a contextual dimension. The incorporation of climatic, economic, and digital behavioral variables adds depth to the analysis, facilitating the training and evaluation of predictive models with different methodological approaches. This wealth of information is particularly valuable for exploring the potential of advanced time series and machine learning tools in the framework of smart tourism and evidence-based decision making.

Using both metrics together allows for a more balanced and realistic assessment. In studies such as this one, where anticipating demand can impact strategic decisions - such as resource management, tourism promotion, or infrastructure planning - having clear indicators on the accuracy of each model is crucial. Beyond the numbers, these metrics help us to understand how reliable the tools we are using are and to make informed decisions about which of them is best suited to the complexity of the tourism phenomenon in emerging destinations.

3 Results

Table 1 compares the performance of the models using the RMSE and MAE parameters; it is observed that the LSTM and ARIMA models performed adequately, and the SARIMA model performed poorly

Table 1. Results of the models used

Model	RMSE ↓	MAE ↓	Relative accuracy
LSTM	**7,643.35**	**5,875.26**	⭑ Better overall performance
ARIMA	8,719.30	6,882.95	□ Adequate
SARIMA	12,605.19	10,073.87	Poor performance

Source: created by the authors.

3.1 Arima

The ARIMA model is adequately forecasting tourist flow (Figure 1) with an average monthly average (MAE) of approximately 6,883 tourists per month. On average, its predictions are not far from reality. Therefore, this is a model that can reasonably be used to provide estimates requiring a more immediate response, with a higher degree of reliability and ease of implementation, without significant resource demands.

Although it is a simpler model, the RMSE (8,719.30) suggests that its average predictions are not guaranteed to be accurate. Predicting fluctuating tourism demand is what the ARIMA model does best; predicting its dramatic changes is not within its capabilities. However, it offers an improvement over SARIMA.

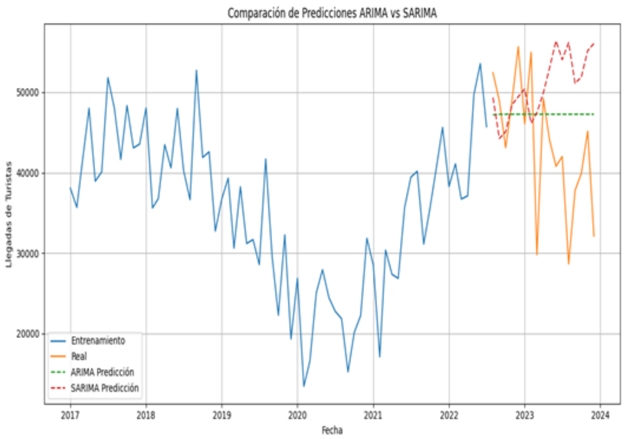

Fig. 1: Evolution of tourist arrivals at the destination evaluated
Source: created by the authors

3.2 Sarima

In this scenario, the model was unable to accurately reflect the data dynamics, resulting in an estimated maximum occupancy (MAE) of approximately 10,074 tourists. This figure represents an inaccuracy of the model in short-term predictions, which may limit operational planning.

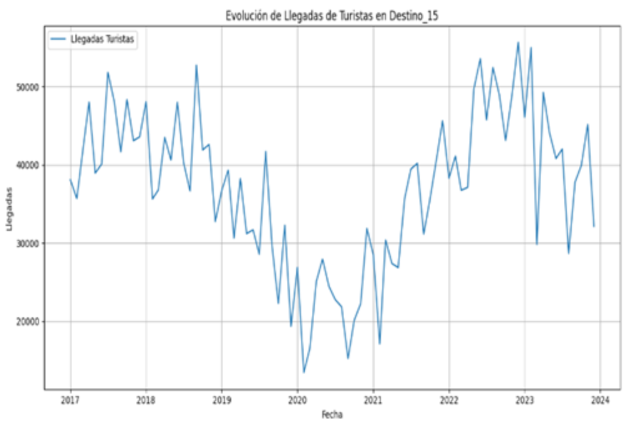

Fig. 2: Comparison of a RIMA vs SARIMA predictions
Source: created by the authors.

The even higher RMSE (12,605.19) reinforces the idea that SARIMA is not only wrong on average, but also tends to make considerable errors in some months. There are several reasons why this might occur, such as poorly defined seasonality in the analyzed destination, suboptimal model parameter settings, or simply high data variability that this type of model cannot capture. In short, although SARIMA is a great model, in this case, it did not yield the expected results compared to the ARIMA model (Figure 2).

3.3 LSTM (Neural Network)

The LSTM model was the most effective of the three analyzed, achieving an MAE of only 5.875,26 tourists and an RMSE of 7.643 (Figure 3). These metrics indicate that its predictions are closer to reality, even in the presence of fluctuations or less obvious patterns. LSTM neural networks are particularly powerful in working with long time series and complex dynamics, which seems to have been a great advantage in the analysis of tourism demand.

LSTMs can also learn nonlinear relationships and remember previous sequences. It is not necessary to establish parameters for seasonality or differentiation. These capabilities make LSTMs very useful in situations where industry demands, in this case, tourism, are influenced by many interrelated factors. Although it requires more resources and training time, its superiority in evaluation metrics justifies its use when a more refined and robust prediction is sought.

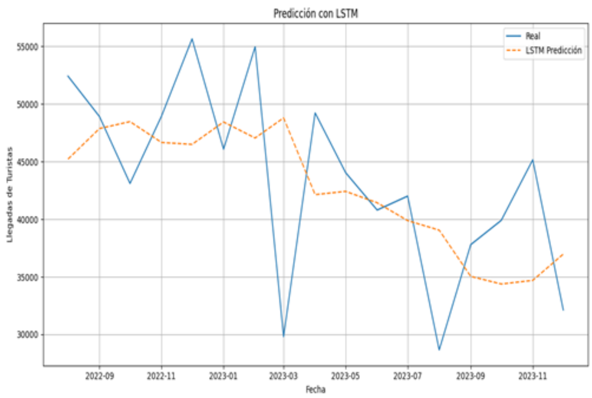

Fig. 3: Prediction with LSTM
Source: created by the authors.

4 Discussion

The ARIMA model has shown an acceptable performance in predicting tourist flow, standing out for its simplicity and ability to provide relatively reliable estimates in contexts where well-structured historical data are available. Its results, with an MAE of 6,883 tourists and an RMSE of 8,719.30, indicate a reasonably good performance that, although not the most accurate, may be adequate for short-term operational uses. As noted in the literature, [16], [17]. ARIMA models continue to be a valid tool in time series analysis when interpretability and speed of implementation are required.

However, their limitations are also clear. The fact that the RMSE is significantly larger than the MAE suggests the presence of notable errors at certain points in the series, which may compromise their usefulness in contexts where demand extremes need to be anticipated more accurately. This is in line with those who argue that ARIMA tends to underestimate non-linear or abrupt fluctuations typical of sectors such as tourism, [18], [19]. Therefore, its use may be more appropriate as a baseline or reference model, rather than as a final solution for highly complex scenarios.

In the case of the SARIMA model, which incorporates seasonal components, the results were less encouraging. Despite the fact that this type of model is usually used to capture common cyclical patterns in tourism demand, in this study, it presented an MAE of 10,073.87 and an RMSE of 12,605.19, negatively outperforming ARIMA in both indicators. This difference suggests that seasonality, at least in the destination analyzed, is not clearly defined or is highly variable. This has been pointed out by those who claim that the success of SARIMA depends largely on the stability of the temporal cycles, which can be altered by external factors or unforeseen events, [20], [21].

Furthermore, the general challenges associated with fine-tuning seasonal components can contribute to the model's lower performance. Depending on the opposition, sensitivity to data noise and the lack of rigorous calibration with SARIMA can be more problematic. Although this model is theoretically a good option for use in tourism-related contexts, it still underperformed compared to more flexible alternatives based on neural networks. Its performance in this study suggests that its application should be carefully evaluated on a case-by-case basis, especially when working with emerging destinations where visitation dynamics may not follow traditional seasonal patterns, [22], [23].

The LSTM model proved to be the most efficient alternative, with an MAE of 5,875.26 and an RMSE of 7,643.35, outperforming classical models in both accuracy and adaptability. Its ability to capture nonlinear relationships and complex patterns makes it a highly valuable tool for time series prediction in tourism, as supported by recent studies, [24], [25]. These models benefit from their ability to retain long-term information and adapt to unforeseen variations, common factors in tourism demand influenced by economic, social, and climatic elements.

The specialized literature also emphasizes the potential of deep neural networks in post-pandemic tourism prediction, where traditional patterns have been modified, and conventional techniques have shown limitations, [26], [27]. Despite requiring higher computational capacity and a steeper learning curve, the LSTM model justifies its application when seeking a more robust prediction that is sensitive to changing tourism dynamics.

The accuracy of forecasting models can differ greatly based on how far into the future the predictions are made. Generally, short-term predictions show improved precision because their data points are closer to current values, making it easier for models to utilize recent trends and behaviors, [28]. Generally, the duration and length of forecast periods vary with the models, and the degree of uncertainty reflects market unpredictability, post-institution consumer volatility, and/or unforeseen externalities. Therefore, the validity of forecasts is inversely proportional to the inherent, temporary, and constructive lack of control in the underlying modeling techniques and base data.

With longer forecast periods, the unpredictability linked to predictions also increases. This trend can be explained by numerous factors, including the buildup of possible errors as time progresses and the growing intricacy of the influencing factors, [29]. Taking a long-term view, economic trends, technological disruptions, and demographic changes should likely be considered as factors to take into account. Millions of possible variables can cause fluctuations in predictive outcomes. Attempting to predict the future due to these variable potential outcomes reduces the accuracy of predictions.

To adapt to the increasing uncertainties of long-term predictions, practitioners must implement more robust modeling methodologies and techniques that reduce variability to anticipate divergences in potential outcomes. These could include the use of ensemble forecasting, which combines, or in other words, unifies several predictive models, providing a deeper understanding of possible outcomes, or the use of scenario forecasting to assemble potential futures based on conflicting beliefs. Being aware of the limitations of prediction and confronting the inherent uncertainties leads forecasters to improve their predictive processes and better prepare for future uncertainties, [30].

Finally, the optimal selection of time series models is often achieved through a grid search. This method systematically estimates a range of hyperparameters and then identifies the optimal combination for a specific dataset, [31]. This grid search allows researchers and analysts to understand different parameter combinations to ensure that the selected model accurately describes the past and generalizes to the future. Furthermore, using grid search improves the modeling process and increases the likelihood of accurate predictions. It is also important to include diagnostics to uncover potential flaws in the assumptions and to design the models appropriately to balance functional effectiveness with the adequacy of the assumptions.

In addition to grid search, diagnostics such as the augmented Dickey-Fuller test for stationarity, the Ljung-Box test for autocorrelation, and residual analysis are essential for establishing the validity of the selected model. These diagnostics work to identify potential problems such as non-stationarity and autocorrelation, which can compromise the reliability of the model's predictions, [32]. The frequent application of these diagnostics allows analysts to refine their model selection and ensure that the chosen model accurately captures the data and adheres to fundamental statistical principles. This comprehensive approach leads to the production of sound and reliable time series predictions, which are essential for informed decision-making in many fields, including, but not limited to, finance, economics, and environmental science.

5 Conclusions

The results of this study demonstrate the superior performance of the LSTM model, not only in providing the best quantitative results in terms of accuracy, but also in adapting to the turbulent and rapid changes in tourism in growing destinations. LSTM's modeling of nonlinear relationships and time lags significantly improves tourism demand forecasting and offers considerable advantages over the more conventional competing methods, ARIMA and SARIMA. The results reaffirm the need for the use of complex machine learning algorithms in tourism research.

Furthermore, given the current state of technology in tourism forecasting (TSG), it is possible to analyze the future more effectively in situations where the past is no longer a reliable predictor of the present. When the present is increasingly unpredictable due to disruptive factors such as pandemics, climate change, and evolving social patterns, and when the future of tourism flows is increasingly uncertain, the need for agile and robust models is paramount. For these reasons, this study offers a contribution beyond technological foundations and calls for the development of more creative and future-oriented tourism forecasting methods.

Based on the results, it is recommended that tourism planners in both the public and private sectors use deep learning models such as LSTM in tourism-related decision-making. These models improve the accuracy of demand forecasting and remain consistently dynamic in the face of volatile and/or disruptive situations. It is also suggested that, in addition to these estimates, predictions be supplemented with other types of data, such as online search trends, weather data, or economic data, to further enhance the analysis and management of tourism in developing tourist destinations.

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