



Research Article

A HYBRID SARIMA-BILSTM-GRADIENT BOOSTING ALGORITHM IN CRUISE DEMAND PREDICTION AND EVALUATING THE SUCCESS OF CRUISE TOURISM

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Abstract

The purpose of this paper is to use demand prediction algorithms with a strategic perspective for the management and success of cruise tourism. Tourism demand series are frequently noisy, conditionally nonstationary, and, in some situations, deterministically chaotic due to the complexity and constantly evolving nature of the tourism sector. This study presents a new methodology for cruise tourism that uses a Seasonal Autoregressive Integrated Moving Average (SARIMA), Bidirectional Long Short-Term Memory (BiLSTM), Extreme Gradient Boosting (XGBoost), Categorical Boosting (CatBoost), Adaptive Boosting (AdaBoost) and ensemble models to predict the number of cruise-type passenger ships, arriving passengers, and departing passengers. The results highlight how ensemble models can be integrated to produce more accurate and useful prediction in the ever-changing tourism sector. The prediction results can provide actionable insights for policymakers and destination managers in preparing for future growth in cruise tourism.

Keywords: Strategic Management, Cruise Tourism, Marine Business Management, Demand Prediction

Introduction

There is always something changing in life. Furthermore, not just those with great privileges and income are impacted by this rapid shift; everyone is affected. As a result, all firms must be able to predict and handle these changes in this process of rapid transformation. Currently, it is critical for firms to make accurate prediction. Because methods and techniques based on experience and past economic data are no longer sufficient for the success of businesses; accurate predictions and good determination of trends are becoming increasingly important (Szyjewski, 2020, 3476). Because the cruise sector is complex and therefore relies more on speculation than on experience, the significance of this situation is increased.

The cruise industry has been growing steadily every year since the late 1960s, except for isolated cases (such as temporary negative growth during the 1974–75 oil crisis and the closure of cruise ships during the coronavirus pandemic (COVID-19) in 2020) (CLIA, 2020; CLIA, 2024). Even during the 2008-2009 global financial crisis, cruise tourism grew, and the number of passengers on cruise lines and at cruise ports continued to increase (Pallis and Rodrigue, 2022). When all these are evaluated, it is possible to see that the importance of cruise tourism in the tourism sector will increase even more. For example, when comparing the statistics of 2022 and 2023 in Türkiye, it is seen that while the number of cruise passengers was 1,010,767 in 2022, this number reached 1,542,522 in 2023 (Ministry of Transport and Infrastructure, 2024a). Despite both years being post-pandemic, the number of cruise passengers in Türkiye increased by 52.61% in just one year.

This growth will bring with it many positive and negative situations. Especially for local destinations, cruise tourism has both positive and negative effects. On the one hand, thousands of passengers come to the destination with cruise ships and have positive effects on the economy, while on the other hand, these activities

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cause overcrowding in the destination, water and air pollution, negative interaction between local people and tourists, and pressure on the ecosystem (Hoarau-Heemstra et al., 2023). While these pose various challenges for destination management, perhaps one of the most important problems is the understanding of the difficulties of destination sustainability by local governments (Kapera, 2018).

The fragile structure of tourism is far from the idea that we should experience it and see that it will pass anyway. Various strategies need to be developed both before problems arise and when problems are encountered. For example, with the COVID-19 pandemic, various crisis management strategies and contingency plans have been created (Yeh, 2020), and various security measures have been taken against pirate threats in cruise tourism (Bowen, Fidgeon, and Page, 2013). Apart from such situations, in other words, before problems become chronic and lead to crises, tourism needs to be able to predict the future and develop strategies for what may happen. Ansoff (1980), one of the main representatives of the planning school in strategic management, explained strategy as a long-term planning process. In order to use business resources effectively and efficiently, it is important to make strategic analyses in the light of basic concepts used in strategic management, such as the field of activity of businesses, development (growth) vector, competitive advantage, and synergy, and to make decisions that will be implemented in the long term in accordance with these (Sarvan et al. 2003). At this point, cruise tourism, which is a specific area of tourism where each destination tries to gain a competitive advantage with its own unique characteristics, seems to be a sector suitable for consideration from the perspective of the planning school. To achieve this, the current situation must be examined and the future must be systematically analyzed (Moussetis, 2011). This makes it valuable to make predictions using data from the past.

Hoarau-Heemstra et al. (2023) state that cruise tourism management in a local destination consists of three basic parts. These are hospitality, service, and management. Hospitality addresses the attitudes and behaviors of local people in the destination towards tourists and the professionalization in businesses; service addresses the provision of logistics materials to cruise ships and input to the destination for local communities; and management addresses the local strategies to be used to manage cruise tourism, address its direct economic value, and determine how it can be achieved, evaluated, and measured (Hoarau-Heemstra et al., 2023). At the intersection of these three parts, prediction of cruise tourism's future becomes critical to the management of cruise tourism at destination locations. Because demand prediction will allow for appropriate planning, the taking of required safety measures against probable problems, and the provision of the greatest possible sustainable benefit.

The main objective of this paper is to evaluate cruise tourism to highlight the future direction and provide prediction methods. To this end, this paper focus on the following research questions:

- How to compare the prediction performance of SARIMA, BiLSTM, XGBoost, CatBoost, AdaBoost models in cruise tourism?
- Is the predictive performance of new ensemble models better than other methods used in cruise tourism?
- What is the importance of analyzing demand changes from a strategic management perspective?
- What are the possible effects of the increase in cruise tourism on the destination and solution suggestions for these effects?

Literature Review

According to the Cruise Lines International Association (CLIA), a cruise ship is defined as a "ship with a minimum capacity of 100 passengers, scheduled for a voyage, staying in deep waters for two days or more". Although 100 people is considered the minimum capacity, today's cruise ships have passenger capacities in the thousands.

Cruise ships are becoming more and more popular, and more people are taking part in this type of tourism every day. This circumstance can put pressure on the ability of destinations to be transported, particularly when combined with the current lodging capacity in port cities (Najafipour, Marzi, and Foroozanfar, 2014). Therefore, destination managers should handle issues such as infrastructure and superstructure for tourists coming by road, air, and sea strategically and develop plans and programs in this direction.

The number of global cruise passengers increased from 3.8 million in 1990 to 31.7 million in 2023 (Ito, Hanaoka, and Sugishita, 2023; Statista.com, 2024a). The average annual growth rate over the last 34 years has reached 6.44%, and this steady growth in the sector has led many cruise lines to quickly discover new

destinations and add new markets to their routes. Similarly, many destinations have made administrative efforts to enter these markets and routes and have tried to take part in this diversity (Brida and Zapata, 2010). While the USA ranks first in this large market with 12 million passengers, the Caribbean in particular has become the most popular and preferred cruise destination (Yan, 2019). The sector generates an annual turnover of over 25 billion dollars worldwide (Statista.com, 2024b).

Cruise tourism has emerged as a sector that has attracted the attention of researchers in recent years¹ and is growing every year. The interest of researchers in this type of tourism has led them to examine the subject from many different perspectives. Studies in the literature on cruise tourism focus on sustainability, management and organization, environmental and social impacts, cultural interaction and economic impacts (Kulkov et al., 2023). Although the discussions that emerged in public areas have highlighted the negative effects of cruise tourism on the environment, social life and destination management, scientific research has revealed that it has significant benefits and effects, especially in the management of port cities, their economy and the ecosystem of the region (Papathanassis, 2023). Previous studies also discussed the effects of cruise tourism on the behavior of tourists living in the destination and their interaction with local people, tourist satisfaction, and the social and economic life it brings to the region (Haievska, 2023).

Important studies have been conducted in recent years on cruise tourism management. Many topics such as sustainability in cruise tourism (Genç, 2016; Gámez et al., 2019; Kulkov, 2023), regional management (Kulkov, 2023), consumer behavior, the role of stakeholders (Pivčević, Mandić, and Šalja, 2018), legal regulations (Hu and Li, 2022), customer relationship management (Sharples, 2019), crisis management (Li et al., 2022), resource use (Espinet-Rius et al., 2018; Ayvaz-Cavdaroglu, Gauri, and Webster, 2019; Li, Miao, and Wang, 2014), innovation and smart tourism (Di Foggia, Lazzarotti, and Pizzurno, 2012), cruise tourism in port cities (Calatayud, González, and Marquez, 2022; McCarthy, 2018) are mentioned. These studies show that there are many issues that need to be studied and focused on regarding the management of cruise tourism. These studies provide data to all destinations and stakeholders that are receiving a share from the sector. It is thought that this study, which is conducted on a subject that has not been addressed before in Türkiye, a country where cruise tourism is growing, will contribute to the developing literature and guide future studies.

In Türkiye, the increase in the number of both ships and tourists in cruise tourism will create many problems that require solutions in the coming years. These problems have been revealed in many academic studies. Dehoorne, Murat, and Petit-Charles (2009) emphasized that cruise tourism should be evaluated within the scope of mass tourism and focused on security concerns. Blas and Buzova (2015) emphasized that the 350% increase in cruise tourism in Valencia between 2004 and 2013 requires strategic management and promotion, and the resulting economic effects should be evaluated within this context. Dehoorne, Petit-Charles, and Theng (2011) showed that the development of cruise tourism in North America has strained the carrying capacity of destinations and the relationships between local people and tourists. Tommasini (2012) examined the inadequacy of infrastructure in Greenland as a major problem in the face of increasing cruise tourists and the negative social and economic impacts of this situation on the local population. The future predictions that are the subject of this study will also reveal the possible problems mentioned above. In this respect, this study will both make predictions about the future and reveal possible problems and solution suggestions. While previous studies have contributed substantially to methodological advancements in tourism demand prediction, relatively few have examined how prediction results can be operationalized within strategic management and policy-making processes in cruise tourism.

Strategic Perspective and Prediction in Cruise Tourism

Strategy is explained as actions and approaches that enable customers, employees and investors to respond positively to a business and its products in a way that provides competitive advantage in a competitive environment (Edmondson, 2018: 5). It also includes determining the strengths and weaknesses of the business (SWOT analysis) and creating appropriate moves and approaches to take advantage of the opportunities and avoid threats in the environment (Ehnert, 2009: 44). At this point, businesses that want to create and maintain a competitive advantage need a more realistic approach where they constantly evaluate their market position

¹ When the studies on cruise tourism are searched in Web of Science and Google Scholar (viewed on 11.06.2024), it is seen that the number of studies has increased since 2011. For example, in the search made with the keyword “cruise tourism”; studies conducted in the field reached double-digit figures for the first time in Web of Science in 2011 (with 26 studies). In Google Scholar, while 1710 results were reached until 2010, 14,600 results were reached after 2011.

and are alert to changes in environmental conditions, rather than taking steps by relying on luck and intuition (Okumus, Altınay, and Chathoth, 2010: 12). One way to achieve this is to use prediction tools.

Although international tourism has improved in the post-COVID-19 period, it faces significant challenges and uncertainties due to economic (increase in inflation, high interest rates, volatile oil prices and high transportation and accommodation costs due to disruptions in trade, etc.) and geopolitical obstacles (uncertainty due to Russia-Ukraine conflict, the Hamas-Israel conflict and other increasing geopolitical tensions, etc.) (WTO, 2024). One of the techniques to be used in determining the steps to be taken in situations where uncertainty is valid in strategic management is to make a prediction that answers the question "what will happen in the future" (Ülgen and Mirze, 2020: 91).

In the literature, strategic management studies on accommodation and tourism are generally influenced by the studies of mainstream strategy researchers, and therefore, studies are encountered without considering the characteristics of the tourism sector (seasonality, globalization, etc.) (Harrington et al., 2014; Okumus et al., 2017; Köseoglu et al., 2019). It was seen that topics such as the strategic impact of the changes in legislation on ports and ships on Croatian yachting (Luković and Šerić, 2009), modeling the length of stay of cruise companies in ports (Chen and Nijkamp, 2018), conducting market risk analysis of newly formed ports with fuzzy logic tools (Zhu, Wang, and Xu, 2021), planning the number and volume of land vehicles that cruise tourists will use at destination points (Jové, Petit, and Casanovas-García, 2018), the historical development of cruise tourism (Cerchiello, 2020), and the master planning of the location and shape of a port (Ward, 2019) were discussed. Maiorov and Fetisov (2018) presented a single port as a basis and tried to determine the port load by estimating the number of ships and arriving passengers for the next year. These results show that strategic management studies have been carried out in the field of cruise tourism, but they are very limited. However, the use of strategic techniques in the management of cruise tourism, which is relatively new compared to the other areas of tourism but has a rapid development curve, will enable more efficient, effective and problem-free use of tourism activities in this area. For this purpose, this study was conducted. It was aimed to provide a contribution to the field and a strategic perspective for the destinations and institutions in this sector by using the demand prediction methods.

Demand Prediction Analysis in Cruise Tourism

Since there are not many studies in the literature on demand prediction in the field of cruise tourism, it was thought that it would be more accurate to evaluate this issue primarily on the basis of general tourism. Information obtained from studies based on demand prediction in tourism can also be inspiring in terms of demand prediction in cruise tourism. Demand prediction for tourism needs to obtain a near-accurate prediction for products or services. Predictions, both short- and long-term, can be useful in ensuring that tourists have access to the facilities they need. The results of the demand prediction can be applied to pricing, workforce scheduling, supply, and marketing strategy development (Ghalekhondabi et al., 2019). Typically, countries and cities spend enormous amounts of money on preparation and planning to welcome tourists. Many businesses rely entirely or mostly on the level of demand to succeed. Since most tourism-related products are perishable, business planners can reduce decision-making risk by predicting demand for their industry (Khatibi et al., 2020). At this point, a reliable model for tourism demand prediction is essential. On the other hand, the development of a tourism demand prediction model is significantly hampered by seasonal and non-stationary features (Dong et al., 2023). The tourism market is complex and constantly evolving, and as such, tourism demand series are often noisy, conditionally nonstationary, and, in certain cases, deterministically chaotic. It is difficult to simulate these dynamic, non-stationary demand series; hence, a system that enables more precise prediction with less noise and complexity is required (Wang et al., 2018). In the literature, various methods are used to provide better prediction models in the tourism sector. There is no exact method available to be applied for tourism demand prediction, and improvements in prediction are needed. Some of the studies related to tourism demand prediction are summarized as follows.

Pavlić (2013) presented the feasibility of selecting a suitable SARIMA prediction model and its applicability as a demand prediction mechanism for the cruise tourism in Dubrovnik. In Saayman and Botha (2017), a seasonal tourist destination facing a structural break was compared between baseline seasonal Naive and SARIMA. It is determined that SARIMA models are generally the most accurate because of the seasonality of tourist arrivals. Vergori (2017) assesses how various seasonality patterns affect the ability to predict tourism demand in relation to varying tourism flow volumes. The findings showed that predictions are less accurate due to the seasonality. To prevent or lessen the negative effects of seasonality, it is crucial to comprehend how demand can change over time in order to better match supply.

Wang et al. (2018) combined a clustering technique with an artificial neural network (ANN) to create a combined tourist prediction model. The three steps of the proposed model were as follows in more detail. This method first divided the input data from the original training data series into many clusters using the k-means technique. Each cluster was then modeled by means of ANN. In second step, another ANN model was created using the nearest certain training samples. The optimal combining weights were finally found, which were used to get the final predicting value. Yao and Cao (2020) created a new model that uses a trend and a seasonal element with a multiplicative error structure. Shi (2020) focused on the use of ANN in rural tourism. First, the factors that affect the demand for inbound tourism were explained from the standpoint of that demand. To create the inbound tourist feature vector, seven factors were identified, taking into account each factor's degree of influence and quantification complexity. Finally, the model's feasibility and validity were verified using the Yangjiang tourism data set.

Khatibi et al. (2020) used environmental data and social media features to predict tourism demand. Because of the expensive cost of surveys and the challenges associated with reaching remote places, the proposed model was particularly intriguing for producing reliable predictions for tourist places with low availability of official visitation census data. In Bi, Li, and Fan (2021), data on tourism demand were first transformed into the type of data that deep learning needs, and after that, they were encoded into images. The obtained images' features were then extracted using the convolution and pooling layers. Long short-term memory (LSTM) networks received the extracted features as input, and actual tourism demand data used to train the whole model. Finally, the trained model predicted future demand for tourism. Zhang et al. (2021a) proposed a novel deep learning approach. The seasonal and trend decomposition using Loess was applied to overcome the overfitting problem caused on by limited data volume. Zhang et al. (2021b) implemented the noise-assisted multivariate empirical mode decomposition-based method to predict tourism demand. Hsieh (2021) used LSTM network and its variants to improve tourism demand prediction. These methods demonstrated suitability for more serious situations that may impact the travel and tourism sector. Brida et al. (2021) presented a multivariate statistical model representing the expenditure of tourists broken down by categories. The empirical findings demonstrated that the cruise tourists' place of residence and the port of arrival were the primary determinants of the average expenditure of cruise tourists.

For tourism demand prediction, Song et al. (2021) used Bayesian bootstrap aggregation that can provide a robust alternative for forecasters looking to predict tourism demand based on fluctuating historical data. Sun et al. (2022) presented a new bagging-based multivariate ensemble deep learning technique that integrates the kernel-based extreme learning machine with stacking autoencoder. Yu and Chen (2022) used stack LSTM-based autoencoders. Pretraining stage and fine-tuning network were applied in the prediction model to enhance the deep learning model's performance and produce better prediction results. To predict the demand for international tourism, Bi, Han, and Li (2022) investigated the most optimal way to choose the number of lag inputs (NLIs). The findings indicated that most machine learning models' error first rapidly declines as NLIs rise and then tends to remain steady when NLIs reach certain cutoff point. In addition, one cycle of the data should be chosen as the NLI for nonlinear and ensemble models, whereas multiple cycles can be chosen for linear models. When optimal NLIs were applied, different model categories produced considerably different prediction results. Zhang et al. (2022) expressed that even insufficient time series data, ANN models perform well. Hu, Wu, and Jiang (2023) presented a nonadditive combination method that integrates single model predictions from individual grey prediction models by applying the fuzzy integral. By capturing the spatiotemporal relationships among regional tourist flows, Yang et al. (2023) created a multivariate decomposition deep learning model to predict tourism demand. Two different international tourism instances with tourists arriving in major Southeast Asian destinations from China or Japan showed the efficacy of the method. A hybrid algorithm incorporating convolution neural network (CNN) and LSTM was proposed by Nguyen-Da et al. (2023) to precisely calculate the demand for tourism in Vietnam and some provinces.

The most recent methodological developments and research in the fields of tourism and passenger transportation demand prediction were evaluated by Ghalekhondabi et al. (2019). In addition, multiple methods that have performed better than the others are given, with the goal of demonstrating that there isn't a single method that is always better than the others. Song, Qiu, and Park (2019) also presented that there is no one method that works effectively in every circumstance due to the complexity of predicting tourism demand, and prediction methods are always evolving.

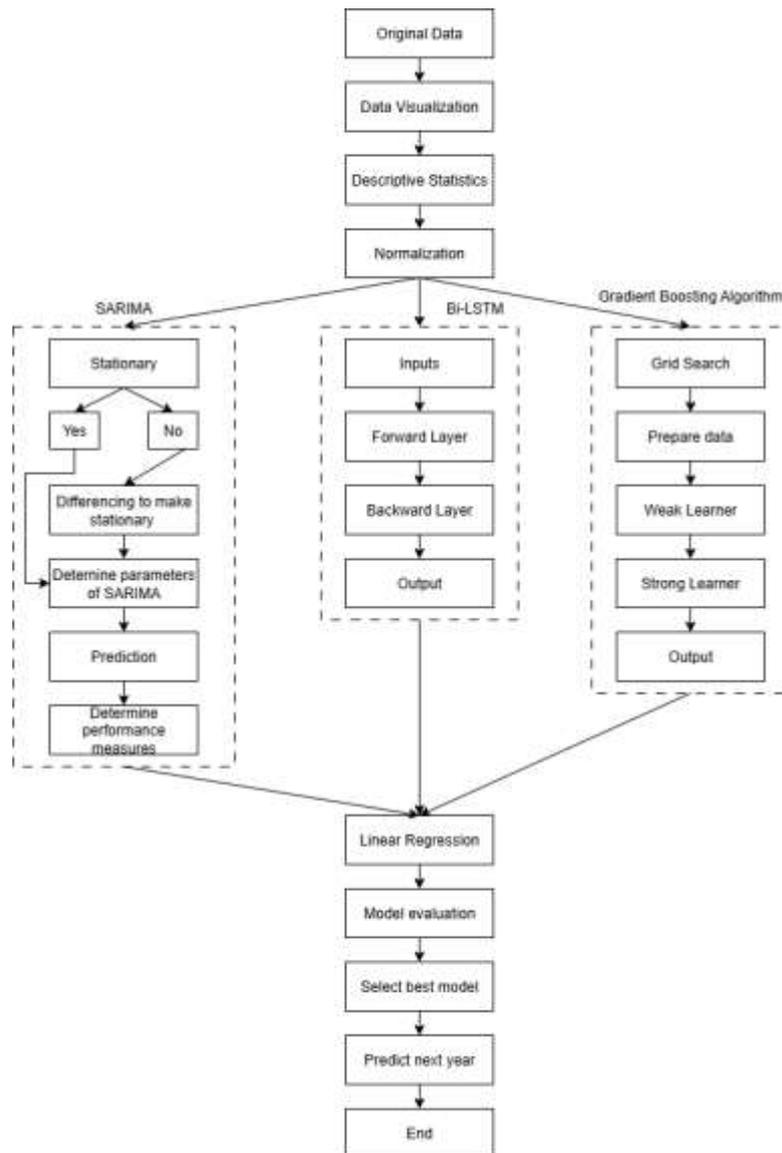
Methodology

Due to the growing number of passengers participating in cruise type of travel across worldwide, cruising has become a widespread phenomenon in recent years (Xie, Qian, and Wang, 2021). Cruises are a significant primary or additional source of tourism receipts for the places they visit. One aspect of the revenue comes from the port services provided, which are paid for by the cruise operators and often rely on the ship's tonnage and passenger number. Services and supplies including fuel, provisions, maintenance, and repairs can also contribute to the benefits to a greater or lesser degree, depending on the size and type of port. However, destinations make revenue from the on-land tourism consumption that passengers and crew members engage in, including sightseeing tours, shopping, dining, and drinking (Kester, 2003). Türkiye is located in the Mediterranean region, which has continuously risen to the second place in terms of the number of cruise passengers it hosts (Kolçak and Solmaz, 2018). Therefore, this study focus on the prediction in cruise tourism. In this study, monthly dataset between 1.01.2011 and 1.04.2025 was taken from Ministry of Transport and Infrastructure (2024b). Descriptive statistics of dataset is given in Table 1. *Since secondary data were used in this study, ethical permission is not required.*

Table 1. Descriptive Statistics of Dataset

| | Cruise type passenger ship | Arriving passengers | Departing passengers |
|---------------------------|-----------------------------------|----------------------------|-----------------------------|
| Mean | 73.45 | 9634.97 | 10300.20 |
| Standard error | 6.18 | 962.60 | 1013.88 |
| Median | 33 | 2837 | 3644 |
| Standard Deviation | 81.01 | 12624.43 | 13296.98 |
| Kurtosis | -0.53 | 0.62 | 0.51 |
| Skewness | 0.92 | 1.33 | 1.30 |
| Range | 274 | 45117 | 47218 |

Figure 1. Proposed Ensemble Model for Cruise Tourism



To analyze monthly dataset related to cruise tourism, run chart and seasonal trend decomposition using SigmaXL are used. The results showed that dataset include clustering, trends, and seasonality. Preprocessing data is crucial when working with time series data. Standardization and normalization are widely used methods that are not exclusive to time series. This preprocessing step is crucial, particularly when working with algorithms that are sensitive to the range of input values (Kern et al., 2020). The one of the most frequently used techniques in preprocessing step are min-max normalization. In min-max normalization (Equation 1), a normalized data sample x' could be obtained from the original data sample x . The majority of an attribute's dependencies are on instances of that attribute with its maximum and minimum values. The original data sample component values will be converted to the [0,1] range in this normalization technique (Ali, 2022).

$$x' = \left[\left(\frac{x - oldMin}{oldMax - oldMin} \right) * (newMax - newMin) \right] + newMin \quad (1)$$

where *oldMin* is the minimum value across all attributes in the original dataset, x is the original data sample, and x' is the normalized data sample. The original dataset's maximum data for any attribute is known as *oldMax*, the normalized dataset's minimum is known as *newMin*, and its maximum is known as *newMax* (Ali, 2022). After preprocessing step, SARIMA, BiLSTM, XGBoost, CatBoost, AdaBoost models and ensemble models are used to predict the number of cruise-type passenger ships, arriving passengers, and departing passengers, respectively. Note that XGBoost, AdaBoost, and CatBoost are machine learning methods based on the Gradient Boosting Algorithm. The proposed model is presented in Figure 1. The selection of hybrid and ensemble models in this study is motivated by the need to capture both linear seasonal

patterns and nonlinear dynamics inherent in cruise tourism demand, thereby enhancing the robustness of strategic prediction.

SARIMA

The ARIMA models have the advantage of having a parsimonious parameterization given the assumptions of linearity and stationarity. In other words, they let a large range of potentially helpful predictor functions be represented in models with relatively few of parameters (Newbold, 1983).

If seasonal patterns are needed in the time series, the model is converted into a model (SARIMA) by adding a seasonal term with ARIMA. The following steps were taken into consideration in SARIMA. The first step is to check whether the series is stationary. In the second step, if the time series is non-stationary, apply differencing to make it stationary. The first difference should be taken and the stationarity checked until it becomes stationary. Seasonal differencing should also be checked. Then, autocorrelation (AC) and moving average (MA) terms should be included. In the final step, the model should be validated by comparing the predicted values (Dubey et al., 2021). In this paper, the different SARIMA (p,d,q)×(P,D,Q)_s models are proposed according to the Akaike information criterion with a small sample size correction that is the default selection in SigmaXL. Seasonal frequency is determined as 12. Model is determined for cruise type passenger ships as ARIMA (1,1,1)(0,1,0). Model is determined for arriving passengers as ARIMA (0,1,2)(1,1,1). For departing passengers, ARIMA (0,1,2)(0,1,1) is determined.

BiLSTM

LSTM is an efficient algorithm for building a sequential time series model. A LSTM unit generally consists of a memory cell, a forget gate, an input gate, and an output gate (Luo et al., 2021). BiLSTM is generally utilized in time series analysis because it has the ability to expand according to the time series (Lu et al., 2021).

In deep learning architectures, BiLSTM demonstrates improved data representation capabilities compared to traditional LSTM (Fan et al., 2024). In the proposed BiLSTM model, activation function is sigmoid and optimizer is Adam. The BiLSTM is given in Equations (2), (3), and (4). Here, σ denotes the activation function, H_t represents the hidden layer input, and the output is produced by updating the forward structure \vec{h} and the backward structure \overleftarrow{h} (Yang and Wang, 2022). W represent the weight and b represent the bias.

$$\vec{h}_t = \sigma(W_{x\vec{h}}x_t + W_{\vec{h}\vec{h}}\vec{h}_{t-1} + b_{\vec{h}}) \tag{2}$$

$$\overleftarrow{h}_t = \sigma(W_{x\overleftarrow{h}}x_t + W_{\overleftarrow{h}\overleftarrow{h}}\overleftarrow{h}_{t-1} + b_{\overleftarrow{h}}) \tag{3}$$

$$H_t = W_{x\vec{h}}\vec{h} + W_{\overleftarrow{h}y} + b_y \tag{4}$$

XGBoost

XGBoost can construct a strong classifier from a set of weak classifier. It can effectively handle missing values and prevent overfitting. In addition, it can reduce the running time using parallel and distributed computation (Luo et al., 2021). Grid Search is a widely used technique to systematically explore the hyperparameter space to determine the optimal parameter value for a given model. In this paper, number of estimator (100, 500, 1000), learning rate (0.01, 0.05, 0.1), and maximum depth (3, 5, 7) are determined by Grid Search for Gradient Boosting algorithms including XGBoost, AdaBoost, and CatBoost. For XGBoost, number of estimator, learning rate, and maximum depth are determined as 1000, 0.01, and 3, respectively in cruise-type passenger ships and arriving passengers. In departing passengers, number of estimator, learning rate, and maximum depth are determined as 500, 0.05, and 3, respectively to propose the XGBoost model.

CatBoost

CatBoost as a base learner is a gradient boosting algorithm based on symmetric decision trees. It makes the model more versatile by reducing model overfitting and makes the model highly scalable by supporting custom loss functions (Zeng et al., 2023). Its ability makes it a preferable model for both classification and regression problems (Banyong et al., 2025). CatBoost is advantageous for small datasets as it provides fast model fitting and prediction times compared to other machine learning techniques (Maulani et al., 2025). For CatBoost, number of estimator and maximum depth are determined as 1000 and 3, respectively in cruise-type passenger ships, arriving passengers, and departing passengers. The learning rate is determined as 0.1, 0.01, and 0.05 for cruise-type passenger ships, arriving passengers, and departing passengers, respectively.

AdaBoost

The goal of boosting is to combine multiple weak classifiers to create a strong classifier. In AdaBoost process, each weak learner is trained to generate a hypothesis based on input feature. The power of AdaBoost lies in its ability to adaptively adjust the weights assigned to the training samples at each iteration (Gupta, Prakash, and Ghani, 2025). For AdaBoost, number of estimator, learning rate, and maximum depth are determined as 1000, 0.1, and 3, respectively in cruise-type passenger ships and departing passengers. In arriving passengers, number of estimator, learning rate, and maximum depth are determined as 100, 0.01, and 5, respectively to propose the AdaBoost model.

Ensemble models

Ensemble models can reduce the uncertainty related to prediction results. The aim of ensemble models is to average individual real numbers obtained from different models to reduce the risk of overfitting while providing effective predictive performance (Ahn, Kim, and Kim, 2023). In literature, various hybrid methods are proposed using SARIMA, BiLSTM, XGBoost, CatBoost, AdaBoost models (e.g. Cortez et al, 2023; Liang and Zhao, 2024; Huang et al., 2025; Sujaudeen et al., 2025; Zebari et al., 2025) while this study provide new methodology using SARIMA, BiLSTM, XGBoost, CatBoost, AdaBoost models with Linear Regression Stacking in cruise tourism. Predictions from SARIMA, BiLSTM, and gradient boosting methods are integrated using a linear regression model. This approach offers a more efficient and accurate method of prediction compared to simpler models.

Results and Discussion

In order to compare the proposed methods, three performance measures are used: mean squared error (MSE), root mean squared error (RMSE) and mean absolute error (MAE). The MSE reflects both the bias and variance of the estimator (Schluchter, 2005). RMSE represents the square root of the mean of the square of all of the error. RMSE is widely used and regarded as a superior general-purpose error metric for numerical projections (Christie, and Neill, 2021). Similar to RMSE, MAE is one of the widely used performance measures. The changes in MAE are intuitive because they are linear, in contrast to RMSE. The average of the absolute error values is used to calculate the MAE score (Schneider and Xhafa, 2022). A lower MAE and RMSE denote a more accurate prediction (Table 2-4). Although all proposed methods give satisfactory results, the prediction results showed that Stacking ensemble model_2 is the best model according the value of the MAE, MSE, and RMSE in Table 2-4 for arriving passengers and departing passengers while Stacking ensemble model_3 is the best model for cruise type passenger ships.

The comparison of actual and prediction results for test dataset is also given for cruise-type passenger ships, arriving passengers, and departing passengers, respectively in Figure 2-4. The results demonstrated that accurate prediction results can be taken from proposed models.

Table 2. The Performance Measures Prediction Result of Cruise Type Passenger Ship

| Model No | Models | MAE | MSE | RMSE |
|----------|---------------------------|-------|-------|-------|
| 1 | SARIMA | 0.122 | 0.024 | 0.155 |
| | BiLSTM | 0.102 | 0.024 | 0.153 |
| | XGBoost | 0.079 | 0.013 | 0.113 |
| | Stacking ensemble model_1 | 0.075 | 0.010 | 0.100 |
| 2 | SARIMA | 0.122 | 0.024 | 0.155 |
| | BiLSTM | 0.076 | 0.011 | 0.106 |
| | CatBoost | 0.066 | 0.009 | 0.094 |
| | Stacking ensemble model_2 | 0.061 | 0.006 | 0.079 |
| 3 | SARIMA | 0.122 | 0.024 | 0.155 |
| | BiLSTM | 0.081 | 0.013 | 0.112 |
| | AdaBoost | 0.080 | 0.013 | 0.112 |
| | Stacking ensemble model_3 | 0.059 | 0.005 | 0.072 |

Table 3. The Performance Measures Prediction Result of Arriving Passengers

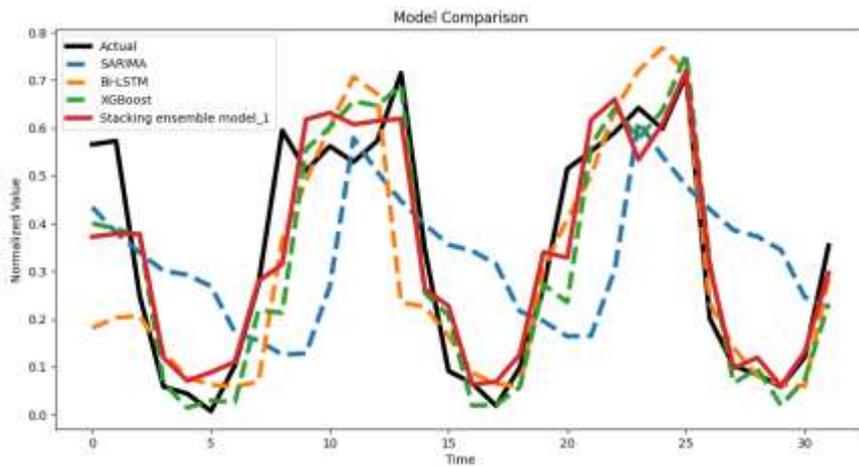
| Model No | Models | MAE | MSE | RMSE |
|----------|---------------------------|-------|-------|-------|
| 1 | SARIMA | 0.130 | 0.026 | 0.160 |
| | BiLSTM | 0.171 | 0.052 | 0.228 |
| | XGBoost | 0.091 | 0.017 | 0.130 |
| | Stacking ensemble model_1 | 0.081 | 0.011 | 0.107 |

| | | | | |
|---|---------------------------|-------|-------|-------|
| 2 | SARIMA | 0.130 | 0.026 | 0.160 |
| | BiLSTM | 0.084 | 0.016 | 0.127 |
| | CatBoost | 0.070 | 0.010 | 0.101 |
| | Stacking ensemble model_2 | 0.070 | 0.008 | 0.089 |
| 3 | SARIMA | 0.130 | 0.026 | 0.160 |
| | BiLSTM | 0.086 | 0.016 | 0.126 |
| | AdaBoost | 0.104 | 0.021 | 0.145 |
| | Stacking ensemble model_3 | 0.081 | 0.010 | 0.100 |

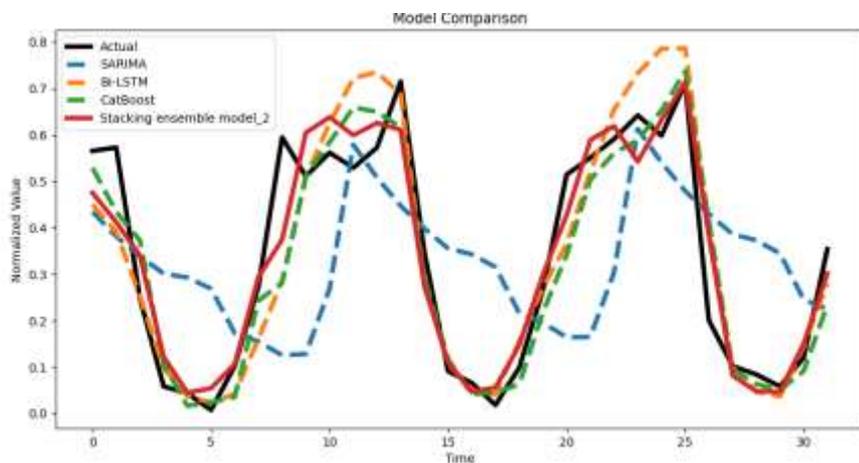
Table 4. The Performance Measures Prediction Result of Departing Passengers

| Model No | Models | MAE | MSE | RMSE |
|----------|---------------------------|-------|-------|-------|
| 1 | SARIMA | 0.170 | 0.044 | 0.211 |
| | BiLSTM | 0.080 | 0.015 | 0.124 |
| | XGBoost | 0.080 | 0.014 | 0.119 |
| | Stacking ensemble model_1 | 0.064 | 0.007 | 0.086 |
| 2 | SARIMA | 0.170 | 0.044 | 0.211 |
| | BiLSTM | 0.099 | 0.020 | 0.142 |
| | CatBoost | 0.058 | 0.008 | 0.089 |
| | Stacking ensemble model_2 | 0.057 | 0.007 | 0.082 |
| 3 | SARIMA | 0.170 | 0.044 | 0.211 |
| | BiLSTM | 0.142 | 0.036 | 0.189 |
| | AdaBoost | 0.089 | 0.017 | 0.130 |
| | Stacking ensemble model_3 | 0.075 | 0.010 | 0.101 |

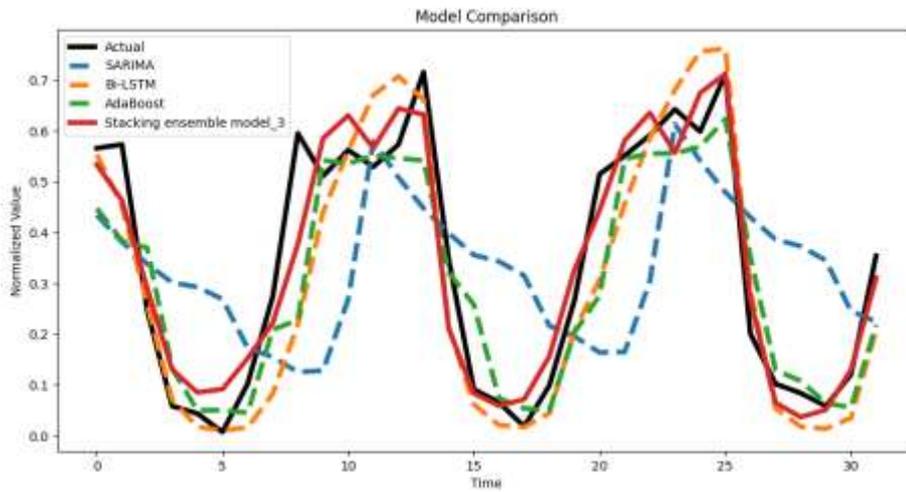
Figure 2. The Comparison of Actual and Prediction Results for Cruise-Type Passenger Ships



a

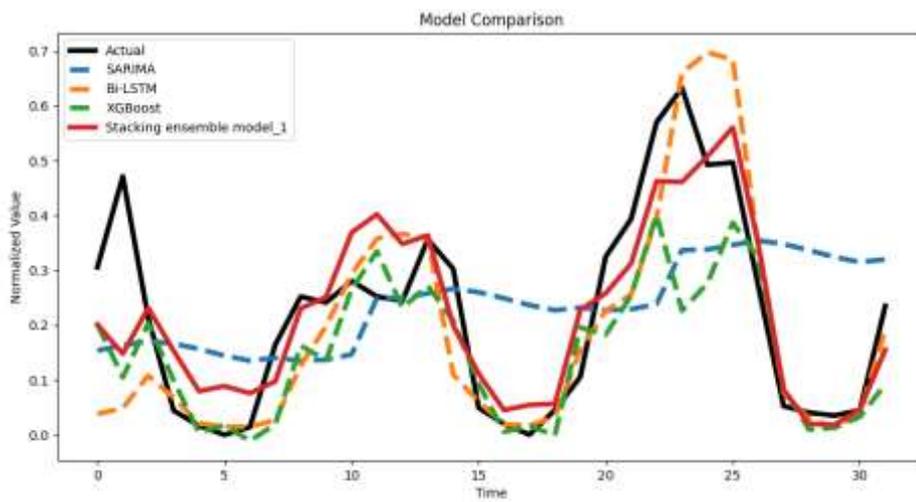


b

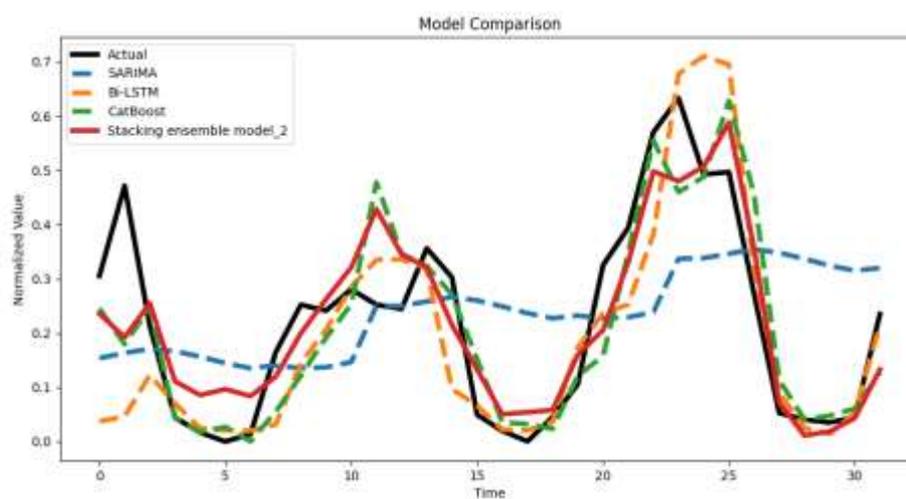


c

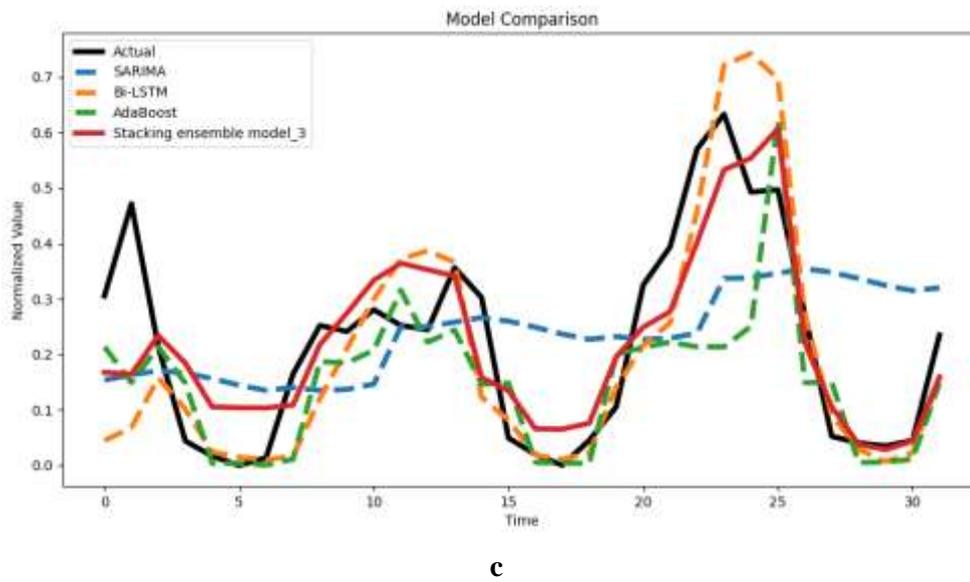
Figure 3. The Comparison of Actual and Prediction Results for Arriving Passengers



a

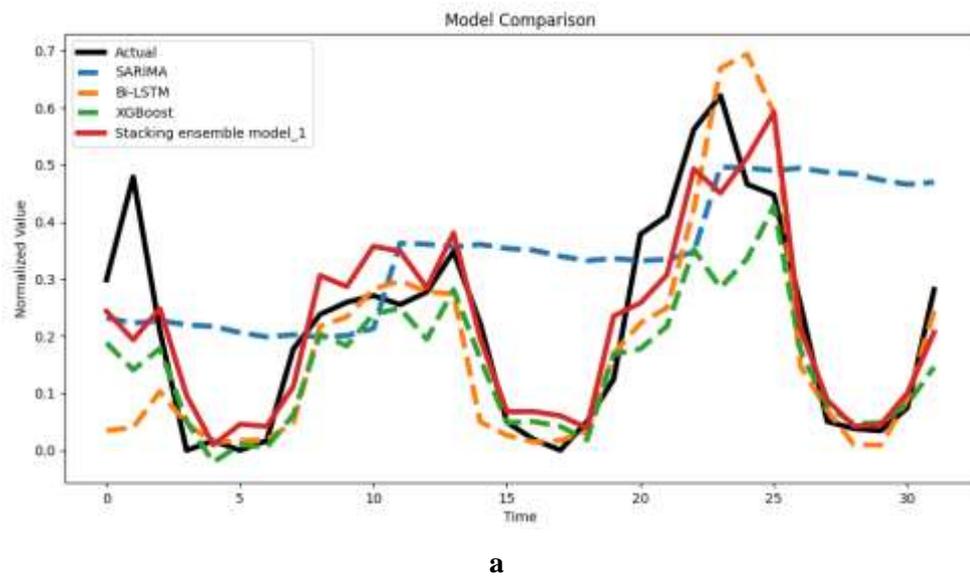


b

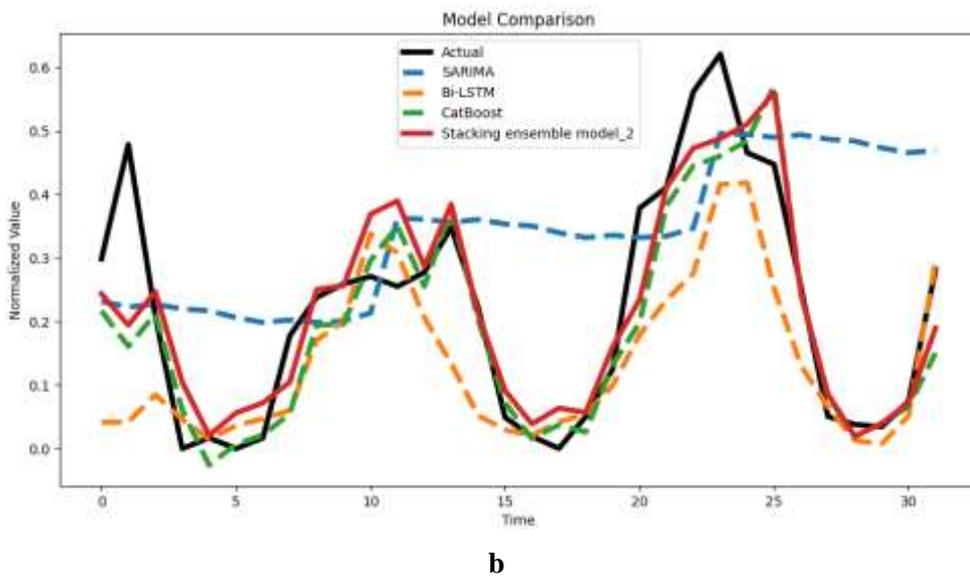


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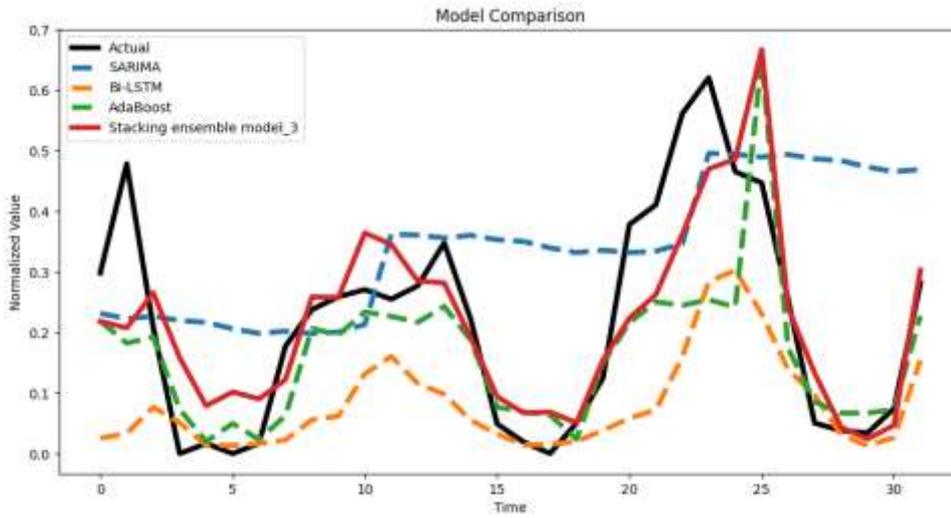
Figure 4. The Comparison of Actual and Prediction Results for Departing Passengers



a



b



c

Türkiye is a popular travel destination for both domestic and international travelers. Therefore, tourism is an important sector for the country's economy. It is essential to keep up with the expected changes and developments in Turkish Tourism Industry during the following years. Even if these predictions are helpful for preparing the future, the presence of uncertainties emphasizes how crucial it is to implement flexible management strategies and include more variables to improve predictions. Proposed methods not only enhance the management of visitor flows but also greatly contributes to the formulation of more effective educational tourist programs.

Figure 5. Next Twelve Months' Prediction for Arriving Passengers

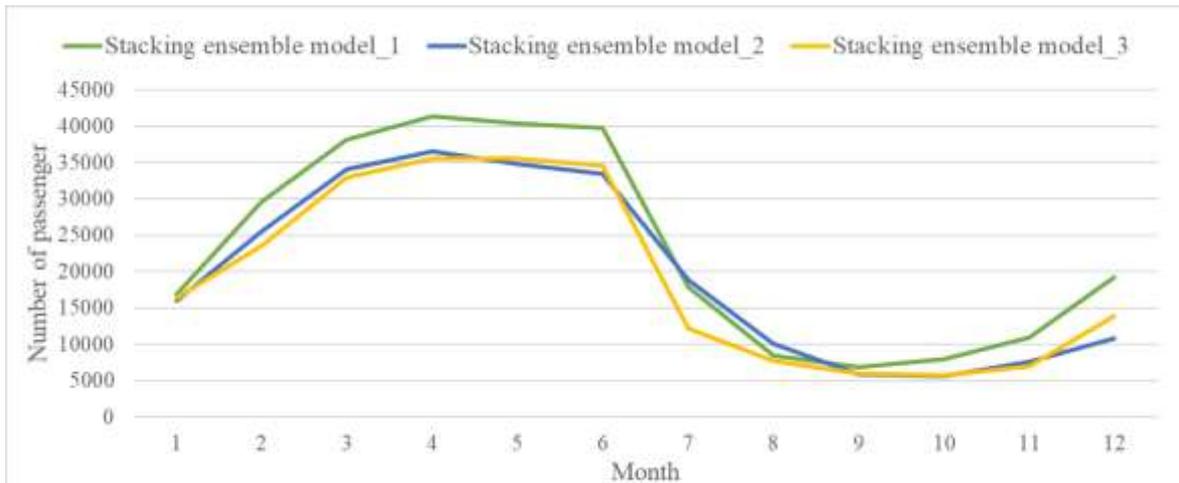


Figure 6. Next Twelve Months' Prediction for Departing Passengers

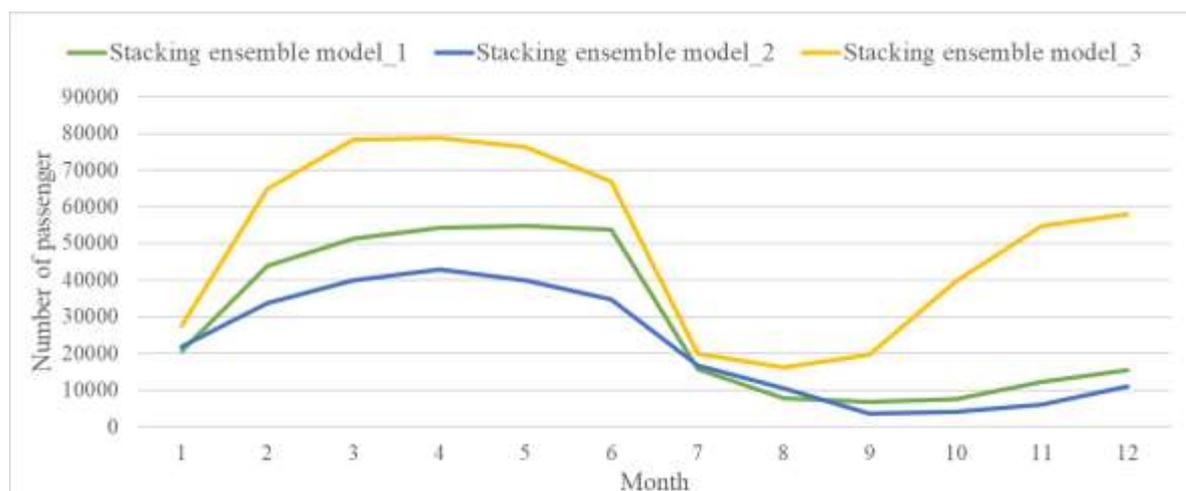
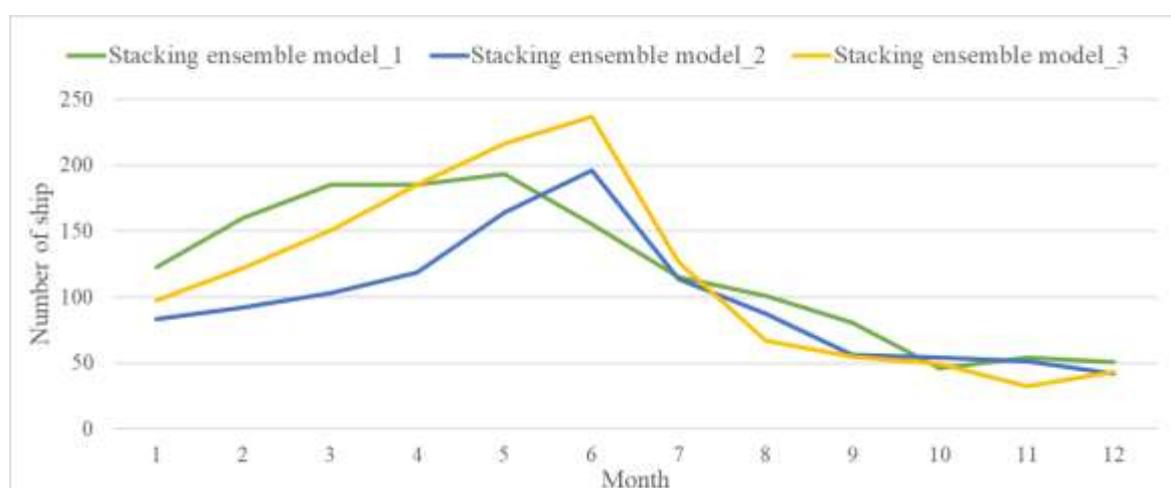


Figure 7. Next Twelve Months' Prediction for Cruise Type Passenger Ships



The mean number of arriving passengers in the next twelve months is expected to be between 19272 and 23138 (Figure 5) while the mean number of departing passengers in the next twelve months is expected to be between 22094 and 50083 (Figure 6). When the arriving passengers and departing passenger's data are compared given in Table 1 with Figures 5-6, it was determined that the mean value increased significantly.

Although the mean number of cruise type passenger ships in Table 1 is 73, the mean number of cruise type passenger ships in the next twelve months is determined to be between 97 and 121. In addition, the number of cruise type passenger ships in the next twelve months could reach a maximum of 237 (Figure 7). This situation reveals the need to increase supply capacity significantly and appeal to all tourists with differentiated supply sources.

Conclusion and Implications

Recent developments in cruise tourism indicate an increasing global demand for this kind of tourism (CLIA, 2020; CLIA, 2024). It appears that the Turkish market is in a similar scenario (Ministry of Transport and Infrastructure, 2024b). Despite this, it seems that strategy development and planning through demand prediction have not yet been presented in the cruise tourism field. It is thought that this study will make a significant contribution to the strategic planning literature in cruise tourism. Although proposed models are used for cruise tourism in this study, it is valuable in that it will provide the most realistic results in all types of tourism. In this way, it can help make the right decisions in situations where making short-term plans and creating emergency action plans are vital, such as economic changes, war periods, and pandemic processes. Because even if the increase in demand for cruise tourism is evaluated as positive for tourism, questions such as whether the infrastructure of the destinations will be able to meet this increasing load, whether the tourists will be able to meet the quality standards they expect, whether the protection of the environment will be ensured, and whether the local people will be able to approach the increasing number of tourists positively should be asked as soon as possible, and, if necessary, various strategic steps should be determined. Therefore,

it is important to estimate the burden that both tourists and destinations will face in the field of cruise tourism in the future in order to protect them from problems.

Especially in Türkiye, due to the increase in the number of ships in cruise tourism, necessary arrangements should be made in maritime transportation and improvements should be made for the increased capacity. In this respect, studies that will reveal the current situation should be carried out meticulously and the increased capacity should be managed by considering the supply sources and carrying capacity with public control. Maiorov and Fetisov (2018) presented that results of the study can be used for both daily operational plans and long-term strategic plans by making a demand prediction for a single port for the next year. Although there is no direct study on demand prediction from a strategic perspective in cruise tourism in Türkiye, there are strategy reports of various public and private sector organizations. This situation is addressed in the strategic assessments and reports of various chambers, unions and public/private organizations in Türkiye regarding cruise tourism, and problems such as the ineffective use of existing ports, some ports turning into cargo ports entirely, the need to renew coastal structures legislation, etc. are mentioned (Turkish Ports 2023 Assessment, 2023; Fethiye Cruise Port Study Final Report, 2014).

New technologies should be used by the public and private sectors for the future increase in both tourist and ship numbers. Developments in this direction should be integrated for cruise tourism and managed in an integrated manner with the supply sources that will be increased. For example, it is known that 98% of new ships expected to enter service are built to have shore power connection, but as of 2023, ports with cruise berths/quays equipped with land-based power connection will constitute less than 2% of all ports in the world (TÜRKLİM- Turkey Port Sector 2023 Report Sustainable Ports, 2023). Decision-support systems should be established, especially in cities that will host cruise tourism, and technologies in this direction should be transferred to these provinces.

The increase in the number of tourists coming to cities with cruise tourism will negatively affect the sustainable tourism policies of the cities. Pollution and transportation problems are especially important problems. In this respect, sustainable environmental policies should be developed with the cooperation of the public and private sectors in the cities that will host cruise tourism and applications should be made in direct proportion to the increasing number of ships and tourists. For example, actions such as increasing charter flights to ensure easy transportation by plane for passengers boarding ships from different ports, establishing an uninterrupted transportation network between the airport and the cruise port, and improving the bed capacity of accommodation facilities if the region is insufficient should be considered (Chamber of Marine Commerce, 2023). Because in numbers exceeding the carrying and supply capacity, management weaknesses may occur and sustainable tourism policies of cities may not work properly. Blas and Buzova (2015) presented similar problems in their studies and emphasized the necessity of strategic management planning. Therefore, strategic action plans to be developed for situations exceeding the carrying and supply capacity should be implemented strictly. In addition, economic, social and psychological impact assessments should be made within these plans and should be evaluated at certain periods.

Information on sustainable tourism should be provided to businesses involved in cruise tourism, and both action plans and strategic plans to be put forward should be explained. Travel agencies, especially those that provide transportation for tourists arriving by ship, should be informed about this issue, and the damage that tourists may cause to the environment should be minimized, while conflicts that may arise with the local population should be reduced. Tourists should not be seen as merely economic income during this process, and the sustainability of the destination should be prioritized. When necessary, public institutions should impose penal sanctions on these businesses. Antonenko et al. (2022) focused on the same problems in their study and emphasized that local governments should be evaluated in this context in their arrangements between local people and service businesses due to the increasing number of tourists. Overall, this study demonstrates that proposed models can function not only as technical tools for demand prediction but also as strategic decision-support instruments for cruise tourism management. By integrating advanced prediction techniques with a strategic perspective, the study contributes to more informed destination planning and sustainable tourism governance.

Limitations and Future Research

It is necessary to interpret this study's contribution to the relevant literature while also recognizing its limitations. The study was limited to Türkiye. This study can be compared with predictions of cruise tourism demands of different countries. Future studies can integrate big data in cruise tourism to improve prediction results. In this study, short-term prediction was discussed and the next year was predicted. By utilizing

proposed models or improving existing models, researchers can conduct studies covering not only a single year but also longer periods of time to assist in medium and long-term planning. In the coming years, the effects of the increase in cruise tourism on the local people and the region should be examined by academics. The social, economic, and psychological effects of the country should be investigated within the scope of sustainable tourism. Current problems and solution suggestions should be put forward by academics depending on the number of tourists and ships that will emerge in the coming years. In particular, projects should be developed by public institutions and organizations depending on the problems that will arise and the participation of all stakeholders in these project processes should be ensured.

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