Tourism Management and Technology Economy (2024) **DOI: 10.23977/tmte.2024.070301**
Clausius Scientific Press, Canada **ISSN 2616-2199 Vol. 7 Num. 3**

Predicting Tourism Demand by Combining Search Engine Data

Qingfeng Duan

School of Business, Guangxi University, Nanning, Guangxi, 530000, China

Keywords: Search engine data, Tourism demand forecast, Prediction accuracy

Abstract: This study investigates the integration of search engine data into tourism demand forecasting models, specifically focusing on Hong Kong, China. Utilizing the Seasonal Autoregressive Integrated Moving Average with Exogenous Variables (SARIMAX) model, we aimed to enhance prediction accuracy by incorporating search data related to tourist interests and activities. Our results demonstrate that the SARIMAX model, which includes exogenous search data, significantly outperforms the traditional SARIMA model in forecasting tourism demand. The study highlights the importance of using big data sources to capture real-time shifts in tourist behavior, providing valuable insights for stakeholders in the tourism industry to make informed decisions and tailor their strategies. The findings underscore the potential of combining traditional time series models with modern data analytics to achieve more precise and actionable forecasts in the dynamic field of tourism.

1. Introduction

The tourism industry plays a crucial role in the economic development of a country, contributing significantly to the GDP and creating employment opportunities. As one of the fastest-growing industries globally, tourism has become a key driver of economic growth and development in many countries. In this context, forecasting tourism demand is of utmost importance as it helps stakeholders in the industry to make informed decisions and strategize their marketing efforts. By utilizing search data, which reflects the interests and intentions of travelers, we can effectively predict future travel trends and patterns, thus enabling businesses to tailor their offerings to meet the evolving needs of consumers. In this study, we aim to explore the potential of using search data for predicting tourism demand and its implications for the tourism industry.

Seasonality is a major feature of the tourism industry. Koenig et al. (2003) conducted a comparative analysis of the seasonal pattern for different types of domestic tourism demand in the UK, discussing policy implications for tackling the seasonality problem [1]. Nadal et al. (2004) focused on the economic determinants influencing the seasonal distribution of tourist numbers, using regression analysis to examine the intra-year variation in arrivals to the Balearic Islands[2]. Bifan et al. (2015) studied the seasonal fluctuation characteristics and determinants of tourist flows in Mount Tianmu, proposing strategies to reduce seasonal risks and enhance the tourism experience. Liu et al. (2021) analyzed the spatial structure characteristics of tourism flows in China using the Baidu index and social network analysis methods. Marques et al. (2021) investigated the transformation of low-density areas into seasonal villages with a predominant tourism function, focusing on the expansion of second homes in small villages in Southern and Eastern Serbia[3]. Tang et al. (2022) conducted a study on the image of global glacier tourism destinations, analyzing destination image characteristics across seasons and regions to assist in the scientific management of core images by glacier tourism destinations. Overall, these studies provide insights into the seasonal characteristics of tourism, including factors influencing seasonal patterns, strategies to reduce seasonality risks, and the spatial and network structures of tourism flows in different regions. This paper uses the SARIMA model to identify the seasonality of tourism data.

Traveling is a complex decision. With the development of information technology, tourists often search for relevant information on the Internet before traveling and planning their routes[4]. Therefore, a lot of tourists' search information is left on the search engine. This information reflects the tourists' interests and intentions, and can well capture the tourists' attention to the tourist destination. This information can be used to help predict tourists' needs. Rich search data has become a powerful data source for predicting tourism demand[5]. The first step in obtaining search data is to determine keywords. Keywords can be divided into six categories, representing the six elements of tourism demand: food, housing, transportation, travel, shopping and entertainment. This article has identified many search keywords. However, we cannot apply all these variables to prediction because high-dimensional variables may lead to multicollinearity or overfitting problems[6]. Therefore, this paper first conducts the correlation between search keywords and tourist arrival data and then filters the search keywords based on the correlation.

This paper is structured into five comprehensive chapters, each addressing a crucial aspect of the research. Chapter 2: Literature Review. This chapter provides an in-depth review of existing literature on tourism demand forecasting. Chapter 3: Methodology. In this chapter, we outline the methodological framework used in the study. Chapter 4: Empirical Study. This chapter presents the empirical analysis conducted using monthly tourism data from January 2011 to June 2019. Chapter 5: Conclusion. The final chapter summarizes the key findings of the study, emphasizing the effectiveness of integrating search engine data into tourism demand forecasting models. We discuss the practical implications of our findings for stakeholders in the tourism industry, including policymakers, marketers, and business owners. The conclusion also addresses the limitations of the study and suggests directions for future research to further refine and expand the use of big data in tourism forecasting. By structuring the paper in this manner, we provide a clear and logical progression from the theoretical foundations and literature review through to the methodological approach, empirical analysis, and final conclusions. This comprehensive approach ensures that readers can fully understand the context, methods, and implications of our research on predicting tourism demand using search engine data.

2. Literature review

2.1. Tourism demand forecasting

Tourism demand forecasting is a crucial area of research, as accurate predictions are essential for effective tourism planning and policy-making. Various studies have explored different methods to improve the accuracy of forecasting models. Turner et al. (2001) analyzed inbound tourism to New Zealand using univariate and multivariate structural time series models, highlighting the importance of finding more accurate forecasting methods[7]. Kulendran et al. (2003) focused on international business tourism demand forecasting, emphasizing the need for comprehensive comparisons of modern forecasting methods in this context[8]. Li et al. (2006) developed time-varying parameter linear almost ideal demand system (TVP-LAIDS) models for forecasting tourism demand in Western European destinations by UK residents, demonstrating the superiority of TVP-LAIDS models over static versions[9]. Hong et al. (2011) introduced an SVR model with a chaotic genetic algorithm (CGA) for tourism demand forecasting, aiming to overcome premature local optimum in determining SVR model parameters[10]. Pai et al. (2014) developed a novel hybrid system for accurate tourism demand forecasting, highlighting the importance of accurate predictions for tourism planning and policy-making[11]. Bangwayo-Skeete et al. (2015) explored the use of Google Trends data in tourism demand forecasting, testing the forecasting performance of the indicator using Autoregressive Mixed-Data Sampling models[12]. Furthermore, Song et al. (2019) conducted a review of 211 key papers on tourism demand forecasting published between 1968 and 2018, emphasizing the ongoing evolution of forecasting methods due to the complexity of determining tourism demand[13]. Finally, Law et al. (2019) utilized a deep learning approach for forecasting monthly tourist arrival volumes, demonstrating a significant improvement in forecasting accuracy compared to other models such as support vector regression and artificial neural networks[14].

Forecasting models often used by academics are time series, econometric models, artificial intelligence methods, and hybrid methods[15, 16]. In the field of forecasting, scholars usually strive for higher prediction accuracy, but no one model can always outperform the others[17]. The tourism industry has significant seasonality due to holidays and other reasons. Regardless of the forecast model used, seasonality is a key feature to be taken into account[15]. The time series model predicts tourism demand by using the seasonality and periodicity of historical data. It is also the most widely used model in tourism forecasting research. Time series models have been a subject of interest for analysts and econometricians for several decades. Granger et al. (1976) noted that economic series often involve aggregates and measurement errors, leading to the use of mixed models in practice[18]. Harvey (1985) constructed structural time series models for annual observations, focusing on trend, cycle, and irregular components, and estimated these models using the Kalman filter with U.S. macroeconomic data[19]. Wei (2006) provided an overview of univariate and multivariate methods for time series analysis, emphasizing the importance of understanding and analyzing time-dependent data[20]. Zivot et al. (2006) and Zivot et al. (2003) extended the discussion to include vector autoregressive models for multivariate time series, highlighting their superiority in forecasting compared to univariate models[21, 22]. Fan et al. (2006) explored nonlinear time series methods, both nonparametric and parametric, to capture complex relationships in time-dependent data[23]. Chen et al. (2005) introduced a new time-series forecasting model based on the flexible neural tree (FNT), showcasing ongoing efforts to develop and improve forecasting models[24]. Overall, the literature review indicates a diverse range of approaches and methods in time series modeling, reflecting the complexity and importance of analyzing time-dependent data in various fields.

2.2. Tourism demand forecasting with search trend

The univariate time series method infers the historical tourism demand series to generate forecasts [25], but this method lacks comprehensive consideration of multiple data. Travel decisions are complex, and travelers will consider multiple factors before departure. These considerations leave their mark on search engines, so using data sources generated by search engines for forecasting has become increasingly popular [16].

Tourism demand forecasting has seen advancements in recent years with the integration of search trend data. Some studies have verified that search engine data can enhance the performance of tourism demand forecasting [26]. Chu (2011) utilized a piecewise linear method to model and forecast the demand for tourism in Macau, China [27], while Yang et al. (2015) used web search query volume to predict visitor numbers for a popular tourist destination in China[28]. Li et al. (2017) proposed a framework for creating a composite search index to predict tourist volumes in

Beijing[29], and Lv et al. (2018) introduced the Stacked Autoencoder with Echo-state Regression approach for tourism demand forecasting using search query data[30]. Volchek et al. (2019) focused on improving the accuracy of tourism demand forecasting at the micro level by comparing various forecasting models for visits to London museums[31]. Bokelmann et al. (2019) highlighted the value of Google Trends data for short-term tourism demand forecasting[32], while Li et al. (2020) demonstrated the benefits of using multisource big data for forecasting tourist arrivals in China[33]. Adil et al. (2021) introduced an Attention-Based STL-BiLSTM Network for forecasting tourist arrival, emphasizing the importance of accurate demand forecasting for economic sustainability [34]. Furthermore, Xie et al. (2021) optimized the hyper-parameters of the LSSVR model with GSA to forecast Chinese cruise tourism demand effectively [35]. Colladon et al. (2019) utilized social network and semantic analysis to analyze online travel forums and forecast tourism demand, presenting a new methodology for analyzing tourism-related big data[36]. These studies collectively showcase the growing interest and success in utilizing search trend data for tourism demand forecasting.

3. Methodology

The seasonal time series model not only considers the general trend and random fluctuation of data but also brings the seasonal period into the model components. The ARIMA model is a very famous representative of this kind of model, which combines the characteristics of the ARIMA model and captures the seasonal structure in the data through the built-in seasonal difference and seasonal autoregressive moving average term. SARIMA is a sophisticated approach that combines autoregressive, moving average, and differencing components to capture complex patterns and dynamics in time series data. One of the key features of the SARIMA model is its ability to handle both non-stationary and seasonal characteristics inherent in many real-world time series datasets. By incorporating seasonal terms, such as seasonal autoregressive and seasonal moving average components, SARIMA can effectively model and forecast data with recurring patterns over fixed time intervals. Moreover, SARIMA allows for the integration of differencing operations to achieve stationarity, making it suitable for a wide range of time series data that exhibit trends or other non-stationary behavior. The flexibility of SARIMA in accommodating various seasonal patterns and trends makes it a versatile and powerful tool for time series analysis and forecasting tasks. By understanding the inner workings and parameters of the SARIMA model, researchers and practitioners can leverage its capabilities to gain valuable insights, make informed decisions, and produce accurate forecasts in diverse fields such as economics, finance, healthcare, and meteorology. The comprehensive nature of SARIMA empowers analysts to explore and model complex temporal relationships, leading to improved forecasting accuracy and enhanced understanding of underlying data dynamics.

Despite its strengths, SARIMA does have certain limitations, particularly when dealing with a small number of variables. In scenarios where the relationships among variables are more intricate and additional exogenous factors need to be considered, the traditional SARIMA framework may encounter challenges in capturing the full complexity of the underlying data patterns. In addressing these limitations, the SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors) model emerges as a robust extension of SARIMA. SARIMAX introduces the concept of exogenous variables, also known as exogenous regressors, which can be leveraged to enrich the modeling process by incorporating external information that may influence the time series being analyzed. The SARIMAX model accommodates the inclusion of exogenous variables alongside the existing autoregressive, differencing, moving average, and seasonal components, thereby enhancing its ability to capture additional explanatory factors that contribute to the observed time series behavior. This expanded capability is especially valuable in applications where the influence of external factors, such as economic indicators, policy changes, or environmental variables, can significantly impact the time series dynamics. By integrating exogenous variables into the modeling framework, SARIMAX provides a more comprehensive and flexible approach to time series analysis and forecasting, allowing practitioners to account for a broader range of influences and capture more nuanced relationships within the data. Thus, SARIMAX represents a powerful advancement over SARIMA, particularly in settings where the inclusion of relevant external factors is essential for achieving more accurate and insightful modeling results.

4. Empirical study

The focus of this empirical study is to use the monthly data from January 2011 to June 2019 to analyze the tourism trends in Hong Kong, China. It is worth noting that the novel coronavirus (COVID-19) epidemic broke out at the end of 2019. The strict risk management measures subsequently implemented led to a major and sudden change in the data model, making the period after 2019 unsuitable for inclusion in the study.

The dataset is divided into a training set covering the period from January 2011 to December 2018 and a forecasting set spanning from January 2019 to June 2019. This segmentation allows for model training on historical data and subsequent testing and validation on the specified forecasting period, providing insights into the model's predictive performance. For the data analysis, the R statistical software is employed due to its robust capabilities for time series analysis and modeling. The chosen analytical model for this study is the SARIMA (Seasonal Autoregressive Integrated Moving Average) model, known for its effectiveness in capturing seasonality, trends, and other temporal patterns present in time series data. By leveraging SARIMA, the study aims to uncover and forecast tourism trends in Hong Kong, China, taking into account the intricacies of the seasonal and historical data patterns up to the specified endpoint in June 2019. The prediction results are shown in Table 1 below.

Incorporating search data into tourism demand forecasting is crucial for enhancing predictive accuracy and understanding the underlying factors influencing tourist behavior. Search data, which encompasses variables such as Hong Kong, China snacks, Mong Kok shopping guide, specialties, shopping guide, subway, subway fares, Octopus, Causeway Bay, Times Square, Disneyland guide, Free travel guide, one-day tour guide, weather forecast, hotel recommendations, accommodation, Four Seasons, what to buy, food, food guide, food introduction, shopping list, shopping guide, women's street, shopping map, shopping guide, shopping guide, map, subway map, map full HD version, subway map, travel map, Airport, subway operating hours, airport duty-free shop, Airport Express, travel guide, independent travel guide, travel guide, weather, one-day tour, tourist attractions, tourist attractions introduction, Mong Kok, Ocean Park, Avenue of Stars, Victoria Harbor, attractions, Madame Tussauds, Ocean Park guide, Ocean Park tickets, Disneyland, Disney, Ocean Park ticket prices, Disney ticket prices, Disney guide, hotels, Peninsula Hotel, hotel reservations, hotel reservation network, hotel group buying, restaurants, dollar to RMB exchange rate, Luohu Port, duty-free shops, shopping malls, self-guided tour guide, self-service Travel, hotel map, Museum of History, guide, travel. Those can provide valuable insights into consumer interest, preferences, and intent, serving as leading indicators for future tourism trends.

It is essential to carefully select and filter these search data variables before integrating them into the forecasting model to ensure that only the most relevant and influential factors are considered. By conducting a thorough screening process, we aim to identify variables that exhibit a strong correlation with tourist arrivals data (TA), indicating their potential significance in shaping tourism demand dynamics. Our variable selection method involves assessing the correlation coefficients between the search data variables and tourist arrivals data to determine the degree of association between them. Variables demonstrating a strong correlation are deemed as pertinent predictors of tourism demand and are thus selected for inclusion in the forecasting model, while less correlated variables are excluded to streamline the model's focus on the most impactful factors. Taking the correlation coefficient of 0.75 as the threshold, we screened out six search keywords, namely, specialties, MTR, Octopus, Airport Express, attractions, and Museum of History in Hong Kong, China.

Furthermore, in addition to the SARIMA model, we also leverage the SARIMAX (Seasonal Autoregressive Integrated Moving Average with Exogenous Regressors) model as the second forecasting model in our analysis. SARIMAX expands upon the traditional SARIMA framework by incorporating exogenous variables, such as the selected search data variables, to enrich the modeling process. By integrating these additional factors into the model, SARIMAX enables us to capture the influence of external factors on tourism demand and enhance forecasting accuracy by considering a broader range of predictors. See Table 1 for the forecast results.

In order to verify whether adding search data can improve the prediction effect, we compare the two models in Table 2, and we can see that the prediction effect of the SARIMAX model is better.

Table 1: Comparison of prediction results.

True value	SARIMA	SARIMAX	Prediction error percentage - SARIMA	Prediction error percentage - SARIMAX
178803.1	166591.9	165899.8	0.068	0.072
162891.1	167669.7	164543.9	-0.029	-0.010
144464.2	143349.6	143104.8	0.007	0.009
142425.2	158476	144300.2	-0.113	-0.013
152178.1	149613.3	136959.4	0.017	0.100
133366	932003.1	128869.1	-0.097	0.034

Among them, the True value represents the true value of tourist arrival data from January to June 2019, and the numerical value represents the average amount of monthly arrival data to one day. The second column represents the prediction result of the SARIMA model, the third column represents the prediction result of the SARIMAX model. The fourth column represents the percentage difference between the actual value and the SARIMA model's predicted result, while the fifth column represents the percentage difference between the actual value and the SARIMAX model's predicted result.

Table 2: Model comparison.

Model	RMSE	MAE	MAPE
SARIMA	10039.38	8275.912	5.531478
SARIMAX	8430.353	6251.028	3.97686

5. Conclusion

In this study, we have explored the effectiveness of incorporating search engine data into the forecasting models for predicting tourism demand in Hong Kong, China. By leveraging the SARIMA and SARIMAX models, we aimed to capture the intricate patterns of tourist arrivals and improve the accuracy of our predictions.

Our findings indicate that the SARIMAX model, which incorporates exogenous variables derived from search engine data, outperforms the traditional SARIMA model. The integration of search data allows the SARIMAX model to account for external factors that influence tourism demand, providing a more comprehensive understanding of tourist behavior. The empirical analysis demonstrated that search engine data, such as keywords related to Hong Kong (China)'s attractions, transportation, and accommodations, significantly enhance the forecasting accuracy. These variables serve as proxies for tourists' interests and intentions, reflecting real-time changes in demand that traditional models might overlook. By utilizing a threshold correlation coefficient to select relevant search keywords, we ensured that only the most impactful variables were included in the SARIMAX model. This method streamlined the model and focused on the key factors driving tourism demand, thus improving the predictive performance.

The study's results underscore the value of incorporating big data sources, like search engine data, into tourism demand forecasting. This approach not only enhances prediction accuracy but also provides deeper insights into the factors shaping tourist behavior. Consequently, stakeholders in the tourism industry can leverage these findings to make more informed decisions and develop strategies that align with emerging trends. In conclusion, the combination of traditional time series models with modern data sources represents a powerful tool for tourism demand forecasting. The improved performance of the SARIMAX model highlights the potential benefits of integrating search engine data, offering a promising direction for future research and practical applications in tourism management.

6. Limitation and Future Research

Despite the promising results obtained in this study, there are several limitations that should be acknowledged. One of the primary limitations is the scope of the data used. The study focused exclusively on search engine data and its correlation with tourism demand in Hong Kong, China. Another limitation is the time frame of the data. The study uses data up to June 2019, which does not account for the significant disruptions caused by the COVID-19 pandemic. Advanced machine learning techniques, such as deep learning models, could potentially offer improved predictive performance by capturing intricate patterns. Incorporating other data sources, such as social media analytics, travel blogs, and real-time data from booking platforms, could also enhance the model's accuracy and robustness.

In conclusion, while this study demonstrates the potential of using search engine data for tourism demand forecasting, addressing these limitations through the inclusion of broader data sources, advanced modeling techniques, and consideration of recent global events will be crucial for refining and enhancing the accuracy of future forecasts.

References

[1] Koenig, N. and E.E. Bischoff, Seasonality of Tourism in Wales: A Comparative Analysis. Tourism economics: the business and finance of tourism and recreation, 2003. 9(3): p. 229-254.

[2] Nadal, J.R., A.R. Font and A.S. Rosselló, The economic determinants of seasonal patterns. Annals of tourism research, 2004. 31(3): p. 697-711.

[3] Marques, R.P., et al., Transformation to Seasonal Villages: Second-Home Tourism as Initiator of Rural Diversification. 2021, Springer International Publishing AG: Switzerland. p. 125-148.

[4] Fesenmaier, D. R., et al., A framework of search engine use for travel planning. Journal of Travel Research, 2011. 50(6): p. 587-601.

[5] Yang, X., et al., Forecasting Chinese tourist volume with search engine data. TOURISM MANAGEMENT, 2015. 46: p. 386-397.

[6] Varian, H.R., Big Data: New Tricks for Econometrics. The Journal of economic perspectives, 2014. 28(2): p. 3-27.

[7] Turner, L.W. and S.F. Witt, Forecasting Tourism Using Univariate and Multivariate Structural Time Series Models. Tourism economics: the business and finance of tourism and recreation, 2001. 7(2): p. 135-147.

[8] Kulendran, N. and S.F. Witt, Forecasting the Demand for International Business Tourism. Journal of travel

research, 2003. 41(3): p. 265-271.
[9] Li, G., H. Song and S.F. Witt, Time varying parameter and fixed parameter linear AIDS: An application to tourism demand forecasting. International journal of forecasting, 2006. 22(1): p. 57-71.
[10] Hong, W., et al., SVR with hybrid chaotic genetic algorithms for tourism demand forecasting. Applied soft computing, 2011. 11(2): p. 1881-1890.
[11] Pai, P., K. Hung and K. Lin, Tourism demand forecasting using novel hybrid system. EXPERT SYSTEMS WITH APPLICATIONS, 2014. 41(8): p. 3691-3702.
[12] Bangwayo-Skeete, P.F. and R.W. Skeete, Can Google data improve the forecasting performance of tourist arrivals? Mixed-data sampling approach. Tourism management (1982), 2015. 46: p. 454-464.
[13] Song, H., R.T.R. Qiu and J. Park, A review of research on tourism demand forecasting: Launching the Annals of Tourism Research Curated Collection on tourism demand forecasting. Annals of tourism research, 2019. 75: p. 338-362.
[14] Law, R., et al., Tourism demand forecasting: A deep learning approach. Annals of Tourism Research, 2019(75): p. 410-423.
[15] Hu, M., et al., Hierarchical pattern recognition for tourism demand forecasting. Tourism management (1982), 2021. 84: p. 104263.
[16] Li, X., et al., Forecasting tourism demand with composite search index. TOURISM MANAGEMENT, 2017. 59: p. 57-66.
[17] Song, H. and G. Li, Tourism demand modelling and forecasting - A review of Recent research. TOURISM MANAGEMENT, 2008. 29(2): p. 203-220.
[18] Granger, C.W.J. and M.J. Morris, Time Series Modelling and Interpretation. Journal of the Royal Statistical Society. Series A. General, 1976. 139(2): p. 246-257.
[19] Harvey, A.C., Trends and Cycles in Macroeconomic Time Series. Journal of business & economic statistics, 1985. 3(3): p. 216.
[20] Wei, W.W.S., Time series analysis: univariate and multivariate methods. 2006, Boston: Pearson Addison Wesley.
[21] Zivot, E. and J. Wang, Vector Autoregressive Models for Multivariate Time Series. 2003, Springer New York: New York, NY. p. 385-429.
[22] Zivot, E. and J. Wang, Modeling Financial Time Series with S-PLUS. 2006: Springer-Verlag.
[23] Fan, J. and Q. Yao, Nonlinear time series: nonparametric and parametric methods. Vol. 11. 2006, Beijing: Science press.
[24] Chen, Y., et al., Time-series forecasting using flexible neural tree model. Information sciences, 2005. 174(3): p. 219-235.
[25] Wu, D.C., H. Song and S. Shen, New developments in tourism and hotel demand modeling and forecasting. INTERNATIONAL JOURNAL OF CONTEMPORARY HOSPITALITY MANAGEMENT, 2017. 29(1): p. 507-529.
[26] Hu, M., et al., Tourism demand forecasting using tourist-generated online review data. TOURISM MANAGEMENT, 2022. 90.
[27] Chu, F., A piecewise linear approach to modeling and forecasting demand for Macau tourism. TOURISM MANAGEMENT, 2011. 32(6): p. 1414-1420.
[28] Yang, X., et al., Forecasting Chinese tourist volume with search engine data. TOURISM MANAGEMENT, 2015. 46: p. 386-397.
[29] Li, X., et al., Forecasting tourism demand with composite search index. TOURISM MANAGEMENT, 2017. 59: p. 57-66.
[30] Lv, S., L. Peng and L. Wang, Stacked autoencoder with echo-state regression for tourism demand forecasting using search query data. APPLIED SOFT COMPUTING, 2018. 73: p. 119-133.
[31] Volchek, K., et al., Forecasting tourist arrivals at attractions: Search engine empowered methodologies. TOURISM ECONOMICS, 2019. 25(3): p. 425-447.
[32] Bokelmann, B. and S. Lessmann, Spurious patterns in Google Trends data - An analysis of the effects on tourism demand forecasting in Germany. TOURISM MANAGEMENT, 2019. 75: p. 1-12.
[33] Li, H., M. Hu and G. Li, Forecasting tourism demand with multisource big data. ANNALS OF TOURISM RESEARCH, 2020. 83.
[34] Adil, M., et al., Attention-Based STL-BiLSTM Network to Forecast Tourist Arrival. PROCESSES, 2021. 9(10).
[35] Xie, G., Y. Qian and S. Wang, Forecasting Chinese cruise tourism demand with big data: An optimized machine learning approach. TOURISM MANAGEMENT, 2021. 82.
[36] Colladon, A.F., B. Guardabascio and R. Innarella, Using social network and semantic analysis to analyze online travel forums and forecast tourism demand. DECISION SUPPORT SYSTEMS, 2019. 123