Forecasting Malaysian Tourist Arrivals in Thailand from 2024 to 2027 Using the Holt-Winters Method

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Abstract

This study employs the Holt-Winters method to forecast Malaysian tourist arrivals in Thailand from 2024 to 2027. Two approaches were compared: one utilizing monthly tourist data from 2013 to 2023 and the other excluding figures from 2020 to 2022 due to the COVID-19 pandemic's impact on tourist numbers. Evaluation metrics include Mean Absolute Scaled Error (MASE) and Mean Absolute Percentage Error (MAPE). The findings reveal that the second approach, accounting for the pandemic's effects, yields superior forecasting accuracy compared to the first. By excluding these abnormal years, the forecasting model can offer more accurate estimates by reducing the impact of temporary disturbances caused by the pandemic. This strategy improves the model's capacity to forecast future tourist arrivals with increased accuracy and certainty, aiding in strategic decision-making and resource allocation within the tourism sector.

1. Introduction

Tourism plays a significant role in the economic development of nations and serves as a catalyst for growth and prosperity. As one of the most visited destinations in Southeast Asia, Thailand continues to attract a diverse array of international tourists annually, contributing substantially to its economy. Among key tourist demographics, Malaysian visitors have consistently represented a significant portion of Thailand's inbound tourism market. Tourism is a significant economic driver in Thailand, attracting millions of international tourists each year. Among these, Malaysian tourists constitute a substantial portion of the country's tourism revenue. Fig. 1 depicts the number of Malaysian tourists traveling to Thailand between the years 2013 and 2023 [1].

The tourism industry in Thailand has long been a focal point for research because of its significant economic impact and ability to attract tourists from various countries, including Malaysia. Malaysian tourists represent a substantial portion of Thailand's inbound tourism market, contributing to revenue and economic growth. However, in recent years, the tourism industry has faced unprecedented challenges, particularly the outbreak of the COVID-19 pandemic. The resultant travel restrictions and safety concerns have led to fluctuations in tourist arrivals, necessitating robust forecasting methods to accurately anticipate future trends. Forecasting tourist arrivals is crucial for stakeholders in the tourism industry, including government agencies, policymakers, and businesses, to formulate effective strategies and allocate resources efficiently.

The purpose of this study is to forecast Malaysian tourist arrivals in Thailand from 2024 to 2027 using the Holt-Winters method. With the tourism industry being a significant contributor to Thailand's economy, accurate forecasting of tourist arrivals is crucial for effective planning, resource allocation, and strategic decision-making. By employing the Holt-Winters method, which is a well-established time-series forecasting technique, this research aims to provide insights into the expected trends and patterns of Malaysian tourist arrivals in Thailand over a specified period. Accurate forecasting of Malaysian tourist arrivals is essential for various stakeholders, including government agencies, tourism businesses, and hospitality providers, as it enables them to anticipate

future demands and tailor their offerings accordingly. This study is significant in several respects. (1) Economic Planning: By forecasting Malaysian tourist arrivals, policymakers can develop informed strategies to support and promote the tourism sector, contributing to overall economic growth and development in Thailand. (2) Business Decision-Making: Tourism-related businesses, such as hotels, restaurants, and tour operators, can use the forecasted data to adjust their marketing efforts, pricing strategies, and capacity planning to meet the anticipated demand from Malaysian visitors. (3) Infrastructure Development: Anticipating future tourist arrivals enables authorities to plan and invest in infrastructure projects, such as transportation networks and accommodation facilities, to accommodate the expected influx of Malaysian tourists. (4) Risk Management: Understanding the expected trends in Malaysian tourist arrivals allows stakeholders to identify potential risks and challenges, such as seasonality fluctuations or external factors like geopolitical events, and develop mitigation strategies accordingly. Overall, this study's findings are expected to provide valuable insights into the future dynamics of Malaysian tourist arrivals in Thailand, facilitating informed decision-making and sustainable growth in the tourism industry. To achieve this objective, the Holt-Winters method, a widely used time series forecasting technique, is employed. By leveraging historical tourist arrival data and considering seasonal patterns and trends, the Holt-Winters method offers a reliable framework for predicting future tourist flows. This article presents an in-depth analysis of the forecasting process, comparing two different approaches: utilizing complete historical data from 2013 to 2023 and excluding data from 2020 to 2022 due to the disruptive impact of the COVID-19 pandemic. Evaluation metrics such as Mean Absolute Scaled Error (MASE) and Mean Absolute Percentage Error (MAPE) will be used to assess the accuracy and effectiveness of each forecasting model. Through this research, valuable insights into the anticipated trajectory of Malaysian tourist arrivals in Thailand will be provided, enabling stakeholders to make informed decisions and adapt their strategies to the evolving dynamics of the tourism industry.
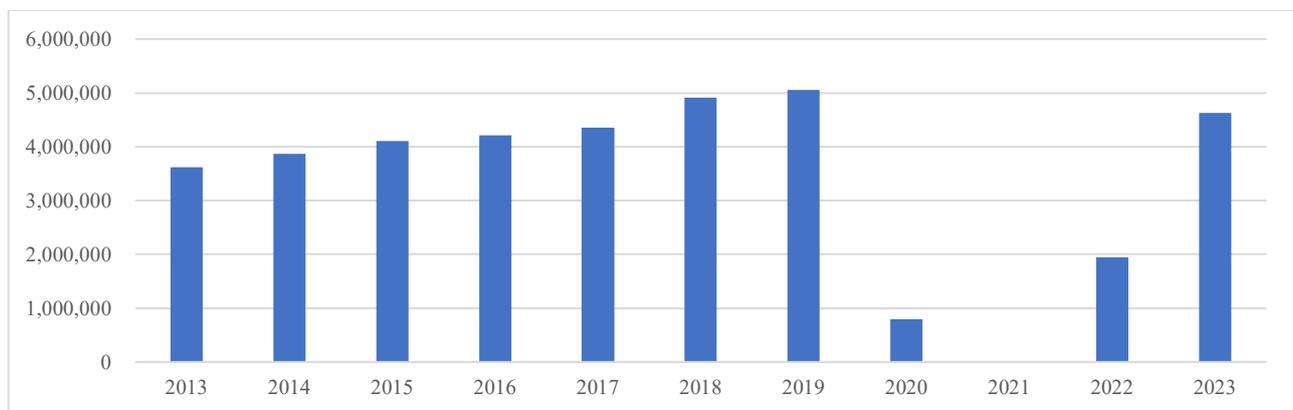

Fig. 1 *Number of Malaysian tourists traveling to Thailand between the years 2013 and 2023* [1]

2. Literature Review

This study incorporates a literature review focusing on: Tourism industry in Thailand, Malaysian tourist behavior, Holt-Winters Method, Mean Absolute Scaled Error (MASE), Mean Absolute Percentage Error (MAPE) and Related Research.

2.1 Tourism Industry in Thailand

The tourism industry in Thailand has long been the cornerstone of the country's economy, playing a vital role in driving economic growth, employment, and development. With its stunning natural landscapes, rich cultural heritage, vibrant cities, and renowned hospitality, Thailand has consistently attracted millions of tourists worldwide each year. Thailand's tourism industry began to flourish in the latter half of the 20th century, with the government actively promoting the country as a premier travel destination. Over the decades, Thailand has become synonymous with tropical beaches, ancient temples, bustling markets, and exotic cuisine, attracting a diverse range of tourists, from budget backpackers to luxury travelers.

Importance to the Economy: The tourism sector is one of the main pillars of Thailand's economy, contributing significantly to GDP, employment, and foreign exchange earnings. Here are some key aspects highlighting the importance of tourism to the Thai economy:

- Economic Contribution: Tourism generates substantial revenue for Thailand, accounting for a significant portion of the country's GDP. Revenue from tourism-related activities, including accommodation, dining, transportation, and entertainment, contributes directly to economic growth and development.

- Employment Opportunities: The tourism industry is a major source of employment in Thailand, providing jobs for millions of people across various sectors, including hospitality, transportation, retail, and tour operations. The industry's labor-intensive nature creates opportunities for both skilled and unskilled workers, supporting livelihoods and income generation.
- Foreign Exchange Earnings: Tourism generates foreign exchange earnings through spending by international tourists on goods and services in Thailand. These earnings help strengthen the country's balance of payments, support currency stability, and finance imports, investments, and external debt obligations.
- Regional Development: Tourism has played a crucial role in the development of rural and remote areas in Thailand, as tourist attractions are often located outside major urban centers. Infrastructure development, such as roads, airports, and accommodations, in these regions has spurred economic growth, reduced regional disparities, and improved living standards for local communities.
- Cultural Preservation: Tourism promotes cultural exchange and preservation by showcasing Thailand's rich cultural heritage, traditions, and customs to visitors from around the world. Cultural tourism initiatives, including heritage conservation projects, traditional performances, and cultural festivals, help safeguard Thailand's cultural identity and heritage sites.

In summary, the tourism industry in Thailand is not only a key driver of economic growth but also plays a vital role in employment generation, foreign exchange earnings, regional development, and cultural preservation. Given its significant contribution to the economy, the sustainability and growth of the tourism sector remain a priority for Thailand's government and stakeholders.

2.2 Malaysian Tourist Behaviour

Research on Malaysian tourist arrivals in Thailand often focuses on understanding their travel behavior, preferences, motivations, and expenditure patterns. Studies have explored various factors influencing Malaysian tourists' decision-making processes, including socio-demographic characteristics, travel motivations, destination attributes, and marketing strategies. Kuncharin and Mohamed explored the motivations, behaviors, and ethnocentrism of Malaysian cross-border shoppers in Hat Yai, Thailand [2]. Their findings highlighted food and beverages, clothing, and grocery products as the top three consumption items. Factor analysis revealed that the key reasons for choosing Hat Yai as a shopping destination included product variety, proximity, and favorable exchange rates. Spears *et al.* investigated the motivations and travel behaviors of Malaysian tourists in Southeast Asia, focusing on Singapore and Bangkok [3]. They discovered that Malaysian tourists, predominantly young, educated adult females, showed a strong interest in tourism and often traveled solo or with family. Their travel decisions were multifaceted, driven by various factors, and expressed a high likelihood of revisiting Bangkok and recommending it to others. Wahlam *et al.* examined the tourism patterns of Muslim Malaysian visitors to Hat Yai District, Songkhla Province [4].

   The study revealed their significant preference for local attractions, particularly cultural sites, followed by moderate interest in natural and special-interest destinations. Variations in preferences among Muslim Malaysian tourists, based on demographics such as age, education, income, and occupation, emphasized the diverse nature of their travel preferences within the Hat Yai District. Thongneaukang investigated the factors influencing the decisions of Malaysian tourists visiting Songkhla Province [5]. Their findings revealed the following: (1) A rising trend was observed in the number of tourists visiting Songkhla Province, with Malaysia being the leading country of origin. (2) The per capita income of Malaysian tourists exhibits a similar pattern to the number of foreign tourists traveling to Songkhla Province. (3) An inverse relationship exists between Malaysian tourists' average tourist expenditure in Songkhla Province and the number of foreign tourists visiting the province. (4) The exchange rate of Malaysian currency correlates closely with the number of foreign tourists traveling to Songkhla Province. Furthermore, Bunnoon *et al.* conducted a study on the behaviors and satisfaction of Malaysian tourists towards cultural tourism in Songkhla Province [6]. The findings revealed that the majority of Malaysian tourists primarily visited Songkhla Province for leisure purposes, followed by business or conference purposes. Most had visited the province 7-8 times and utilized tour companies for transportation, with a preference for traveling on weekends. Generally, Malaysian tourists stayed in Songkhla Province for two nights, spending between 2,000-3,000 Ringgit per trip. Additionally, they expressed a desire for more information on the dates and times of local events and festivals. Overall, Malaysian tourists showed a high level of satisfaction with cultural tourism in Songkhla Province. When examining satisfaction levels based on different behaviors, there were variations in terms of average expenditure per trip and intention to revisit. Furthermore, satisfaction levels varied among Malaysian tourists based on personal factors such as age, occupation, and hometown, with no significant differences observed in their satisfaction with cultural tourism in Songkhla Province.

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2.3 Holt-Winter Method

The Holt-Winters method, also known as triple exponential smoothing, is a powerful and widely used technique in time series forecasting. Introduced by Holt in 1957 and further extended by Winters in 1960, this method is particularly effective in capturing and forecasting data with both trends and seasonality. Holt-Winters method utilizes three smoothing equations to update the level, trend, and seasonal components of a time series. These equations allow the model to adapt to changes in data over time, making it suitable for forecasting in dynamic environments. One of the key strengths of the Holt-Winters method is its ability to handle data with different seasonal patterns, including additive and multiplicative seasonality. By incorporating seasonal adjustments, the model can provide more accurate and reliable forecasts for various types of time-series data. Numerous studies have demonstrated the effectiveness of the Holt-Winters method in various forecasting applications. For example, Makridakis *et al.* highlighted the superior performance of exponential smoothing methods, including Holt-Winters, compared to other forecasting techniques [7]. Similarly, Hyndman and Athanasopoulos provided comprehensive coverage of the Holt-Winters method in their book "Forecasting: Principles and Practice," emphasizing its practical relevance and versatility [8]. In addition to its forecasting capabilities, the Holt-Winters method has been widely adopted in different fields, including finance, economics, and supply chain management. Its simplicity, computational efficiency, and ability to handle complex time-series data make it a valuable tool for decision-making and strategic planning in various domains. Overall, the Holt-Winters method continues to be a prominent choice for time series forecasting due to its robustness, flexibility, and empirical success in capturing and predicting underlying patterns in data.

Winter's method is suitable for time series $\{Y_t\}$ that exhibit linear trends, have seasonal components, and experience non-constant seasonal changes or fluctuations. The variability tended to increase as the level of the time series increased. In such cases, the Multiplicative Winter's method, which accounts for both seasonality and changes in variability over time or as a function of the level of the time series, is appropriate. This method has a time series model as follows:

$$Y_t = (\mu + \beta_t)S_t + a_t, t = 1, 2, \dots, n \tag{1}$$

Where, μ represents a parameter denoting the level or the average value of the time series, β represents a parameter denoting the slope or the trend of the time series, S_t represents a parameter denoting the seasonal component of the time series, a_t represents a random error or an abnormal component, with the initial assumption that it has an average value of zero, constant variance, no correlation, and follows a normal distribution. The forecasting model for the true value Y_{t+1} at time $t + l$ from the current time (t), where: t = 1, 2,..., l) is as follows:

$$\hat{Y}_t(l) = (\hat{\mu}_t + l\hat{\beta}_t)\hat{S}_{t+1-m}, \tag{2}$$

Where, l=1,2,...,m

$$\hat{Y}_t(l) = (\hat{\mu}_t + l\hat{\beta}_t)\hat{S}_{t+1-km}, \tag{3}$$

Where, $l=(k-1)_{m+1},(k-1)_{m+2},\dots,(k-1)_{m+k}$, k=2,3,... by adjusting the estimated values of various parameter components as follows:

$$\hat{\mu}_t = \alpha\left(\frac{Y_t}{\hat{S}_{t-m}}\right) + (1 - \alpha)(\hat{\mu}_{t-1} + \hat{\beta}_{t-1}) \tag{4}$$

$\hat{\mu}_t$ represents the estimated level value, α (0< α <1) represents the smoothing constant used for adjusting the level (or average) of the time series,

$$\hat{\beta}_t = \gamma(\hat{\mu}_t - \hat{\mu}_{t-1}) + (1 - \gamma)\hat{\beta}_{t-1} \tag{5}$$

$\hat{\beta}_t$ represents the estimated trend value, γ(0<γ<1) represents the smoothing constant used for adjusting the trend or slope of the time series,

$$\hat{S}_t = \delta\left(\frac{Y_t}{\hat{\mu}_t}\right) + (1 - \delta)\hat{S}_{t-m} \tag{6}$$

$\hat{S}_t$ represents the estimated seasonal value, δ (0< δ <1) represents the smoothing constant used for adjusting the seasonality of the time series.

2.4 Mean Absolute Scaled Error (MASE)

The MASE is a metric used to evaluate the accuracy of a forecasting model relative to that of a naive or benchmark model. It is particularly useful when comparing the performance of forecasting models across different time-series datasets or when dealing with intermittent or sporadic demand patterns. The formula for MASE [9] is as follows:

$$\text{MASE} = \frac{\text{MAE}}{\frac{1}{n-1}\sum_{i=2}^{n}|Y_i - Y_{i-1}|} \tag{7}$$

Where, MAE is the Mean Absolute Error of the forecasting model,

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|Y_i - \widehat{Y}_i| \tag{8}$$

Y_i represents the actual value at time i, $\widehat{Y}_i$ represents the predicted value at time I, n is the total number of observations in the time series.

MASE compares the Mean Absolute Error (MAE) of the forecasting model to the Mean Absolute Error of a naive or benchmark model, which forecasts each future value as the most recent observed value (i.e., a random walk model). By scaling the MAE of the forecasting model relative to the MAE of the benchmark model, MASE provides a measure of forecast accuracy that is independent of the scale of the data and can be interpreted as the relative improvement or degradation of the forecasting model compared to the benchmark. A MASE value less than 1 indicates that the forecasting model outperforms the benchmark model, while a value greater than 1 suggests that the forecasting model performs worse than the benchmark.

2.5 Mean Absolute Percentage Error (MAPE)

MAPE is a measure of the accuracy of a forecasting model, commonly used to evaluate the performance of a forecasting method by comparing its predictions to the actual values. The formula for MAPE [9] is as follows:

$$\text{MAPE} = \frac{100}{n}\sum_{t=1}^{n}|\frac{Y_t - \widehat{Y}_t}{Y_t}| \tag{8}$$

Where, Y_t represents the actual value, $\widehat{Y}_t$ represents the forecast value from the model, and n is the total number of data points.

The MAPE is expressed as a percentage to indicate the average deviation of the forecasts from the actual values. A lower MAPE indicates a higher level of forecast accuracy. However, MAPE has limitations, particularly when dealing with small or zero actual values, which can lead to division by zero or large percentage errors. Therefore, in such cases, alternative methods may be used to address the shortcomings of MAPE.

2.6 Related Research

There is a diverse range of research related to forecasting Malaysian tourist arrivals in Thailand using the Holt-Winters method, as evidenced by the following examples: Zhang *et al*. focused on forecasting tourism recovery amidst the COVID-19 pandemic [10]. Owing to the significant impact of the pandemic on global tourism activity, previous forecasts of tourism demand have become outdated. Therefore, scholars are now exploring effective methods to predict tourism recovery from the devastating effects of the pandemic. In this study, a combination of econometric and judgmental methods is utilized to forecast potential paths to tourism recovery in Hong Kong. The autoregressive distributed lag-error correction model is employed to generate baseline forecasts, supplemented by Delphi adjustments reflecting different levels of severity in the pandemic influence. These forecasts also serve to assess the economic implications of COVID-19 on Hong Kong's tourism industry. Jere *et al*. conducted a study on forecasting annual international tourist arrivals in Zambia using Holt-Winters exponential smoothing (HWES) [11]. The research focused on the significance of tourism in Zambia's economy and evaluated the model performance of HWES against Auto-Regressive Integrated Moving Average (ARIMA). The study analyzed tourist arrivals data from 1995 to 2014 and assessed various error indicators, including Mean Percentage Error (MPE), Mean Absolute Error (MAE), Mean Absolute Scaled Error (MASE), Root-mean-square Error (RMSE), and Mean Absolute Percentage Error (MAPE). The findings indicated that HWES demonstrated reasonable forecast accuracy, outperforming the ARIMA models. Specifically, the HWES model with specific parameters (α = 1, β = 0.1246865) showed the smallest error. Consequently, the study recommended the use of HWES for modeling annual international tourist arrivals in Zambia. Additionally, the forecasting results suggested a gradual increase in

tourist arrivals by approximately 42% by 2024. The study emphasized the importance of accurate forecasts for investors and policymakers and recommended that the Zambian government utilize such forecasts to formulate policies and strategies to promote the tourism industry. The study by Lip *et al.* focused on forecasting international tourist arrivals in Malaysia using SARIMA and Holt-Winters models [12]. Tourism is a significant contributor to global economic growth, making accurate forecasting crucial for the public and private sectors. This research aimed to determine the best forecasting model for international tourist arrivals in Malaysia by comparing the Box-Jenkins SARIMA and Holt-Winters models. The evaluation was based on the Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE). Data from the Tourism Malaysia Department from 2013 to 2017 were used, focusing on tourist arrivals from Singapore, Korea, and the United Kingdom. The findings indicated that both SARIMA and Holt-Winters models were suitable for forecasting tourist arrivals. Specifically, the Holt-Winters model was found to be appropriate for forecasting arrivals from the United Kingdom and Korea, while SARIMA (1,1,1) (1,1,1)12 was deemed suitable for forecasting arrivals from Singapore.

3. Research Methodology

The research procedure for constructing a forecasting model for the number of foreign tourists involves the following steps:

3.1 Data Preprocessing

The dataset utilized for developing the forecasting model consisted of monthly records of foreign tourist arrivals to Thailand, spanning from January 2013 to December 2026, encompassing a total of 132 months. Historical data on Malaysian tourist arrivals in Thailand sourced from [1] was gathered to ensure completeness and accuracy, while also conducting checks for any missing values, outliers, or inconsistencies within the dataset and subsequently resolving them as needed.

3.2 Model Parameter Selection

In the forecasting procedure, we utilize the Holt-Winters method, a renowned technique tailored for time series data characterized by intricate, dynamic trends, such as Malaysian tourist arrivals, which often fluctuate due to seasonal variations or economic factors. This method aids in projecting forthcoming tourist figures by integrating three key parameters: trends, seasonality, and smoothing. To optimize forecasting accuracy, we embark on determining the most suitable values for these parameters, denoted as α for trend and β and γ for seasonality, through meticulous parameter selection or optimization strategies. This iterative process entails evaluating various parameter combinations to identify those that yield the most precise forecasting outcomes. The procedure encompasses several stages: First, computing the moving average involves calculating the mean of the time series data across predefined intervals to discern the underlying trend. Determining the seasonal average requires establishing the mean of the data over seasonal periods to unveil recurring patterns. Subsequently, seasonalizing values involve adjusting the data to accommodate seasonal fluctuations by normalizing it with the seasonal average. Following this, computing coefficients involves deriving coefficients for the time-series data, encompassing those for the moving average, seasonal average, and seasonalized values. Finally, the forecasting phase involves leveraging the computed coefficients to predict the future values of the time-series data. This method stands out for its adaptability and efficacy in long-term forecasting, underscoring the significance of past data and seasonal tendencies in refining the precision of future projections.

3.3 Model Validation

To validate the forecasting models, we employ rigorous data analysis techniques, focusing on comparing the Mean Absolute Scaled Error (MASE) and the Mean Absolute Percentage Error (MAPE). These metrics, calculated as $e_t = Y_t - \hat{Y}_t$, allow for a comprehensive assessment of two distinct forecasting methodologies: (1) utilizing monthly tourist data spanning from 2013 to 2023, and (2) employing the same dataset range but excluding figures from 2020 to 2022 due to the disruptive impact of the COVID-19 pandemic.

4. Research Result

4.1 Utilizing Monthly Tourist Data from 2013 to 2023

Fig. 2 illustrates that utilizing monthly tourist data from 2013 to 2023 enables a thorough examination of long-term trends in Malaysian tourist arrivals. However, this extended timeframe covers the duration of the COVID-19 pandemic, which severely disrupts global travel patterns. Consequently, incorporating data from these years may introduce disturbances or irregularities into the forecasting model, potentially resulting in less precise predictions.
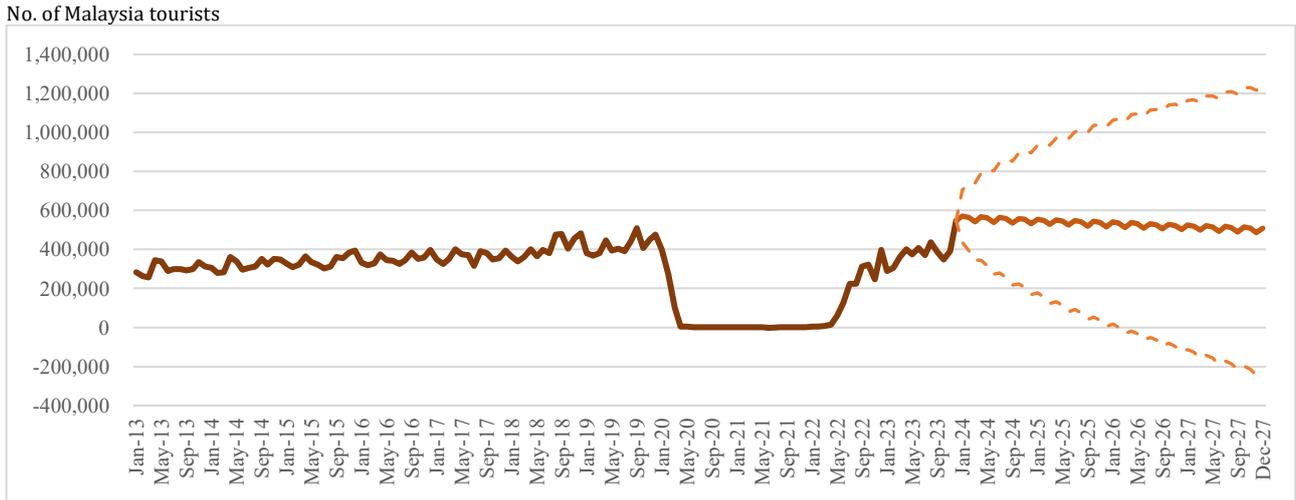
No. of Malaysia tourists

Fig. 2 *The forecasting outcomes derived from employing monthly tourist data spanning from 2013 to 2023*

4.2 Using Monthly Tourist Data from 2013 to 2023 but Excluding Figures from 2020 to 2022

Fig. 3 depicts that excluding figures from 2020 to 2022, a period marked by travel restrictions and safety concerns, allows the model to concentrate on pre-pandemic trends and better understand the tourism demand in Thailand.
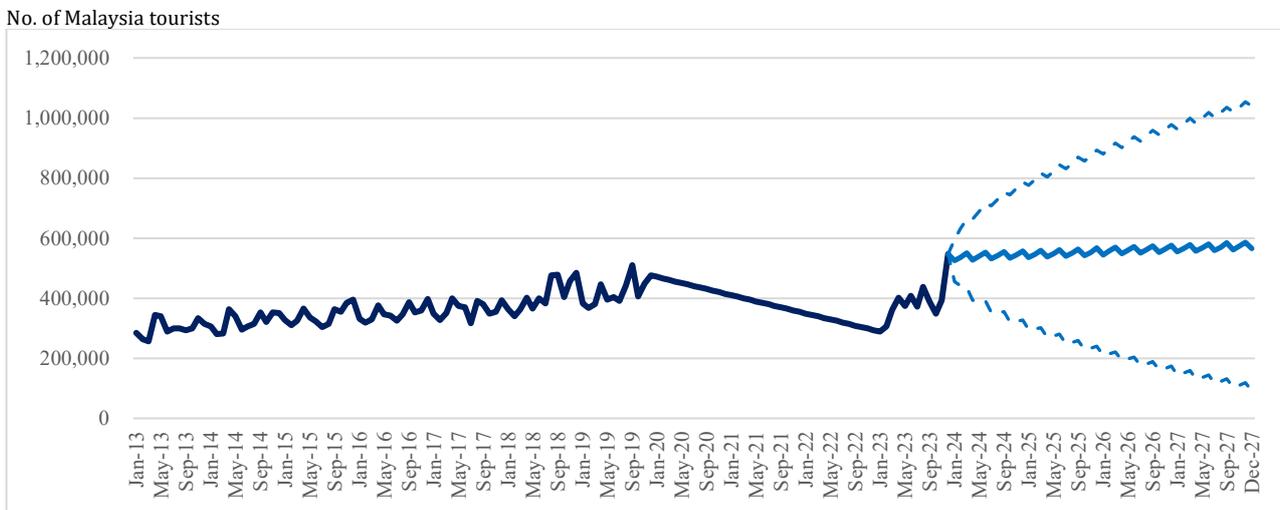
No. of Malaysia tourists

Fig. 3 *The forecast results obtained by utilizing monthly tourist data from 2013 to 2023, while excluding data from 2020 to 2022*

Table 1 highlights the comparison between statistical measurements and forecasting errors when utilizing complete datasets, including information from the COVID-19 period and excluding data from this specific timeframe. It aims to elucidate how the presence or absence of COVID-19 data affects the statistical analyses and the accuracy of predictions made using the dataset.

Table 1 *Contrasts the statistical metrics and prediction inaccuracies when employing complete datasets versus omitting data from the COVID-19 period*

Statistics	Utilizing monthly tourist data from 2013 to 2023	Excluding data from 2020 to 2022
Alpha (α)	0.751	0.900
Beta (β)	0.001	0.001
Gamma (γ)	0.001	0.099
Mean Absolute Scaled Error (MASE)	2.31	0.96

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| Mean absolute percentage error (MAPE) | 7.06% | 6.29% |

Table 2 presents a comparison of monthly tourist arrival forecasts from 2024 to 2027, highlighting the contrast between using complete datasets and excluding data from the COVID-19 period. This analysis elucidates the impact of including or excluding COVID-19 data on the precision of forecasting tourist arrivals during these years.

Table 2 *Comparison of monthly tourist arrival forecasts from 2024 to 2027 between using complete datasets and excluding data from the COVID-19 period*

Year	Using complete datasets	Excluding data from the COVID-19 period
Jan-2024	571,341	525,484
Feb-2024	565,121	536,569
Mar-2024	543,457	549,515
Apr-2024	567,555	527,913
May-2024	561,335	538,998
Jun-2024	539,671	551,944
Jul-2024	563,769	530,341
Aug-2024	557,549	541,427
Sep-2024	535,885	554,372
Oct-2024	559,983	532,770
Nov-2024	553,762	543,856
Dec-2024	532,099	556,801
Jan-2025	556,197	535,199
Feb-2025	549,976	546,285
Mar-2025	528,312	559,230
Apr-2025	552,410	537,628
May-2025	546,190	548,713
Jun-2025	524,526	561,659
Jul-2025	548,624	540,057
Aug-2025	542,404	551,142
Sep-2025	520,740	564,088
Oct-2025	544,838	542,486
Nov-2025	538,618	553,571
Dec-2025	516,954	566,517
Jan-2026	541,052	544,914
Feb-2026	534,832	556,000
Mar-2026	513,168	568,946
Apr-2026	537,266	547,343
May-2026	531,046	558,429
Jun-2026	509,382	571,374
Jul-2026	533,480	549,772
Aug-2026	527,260	560,858
Sep-2026	505,596	573,803
Oct-2026	529,694	552,201
Nov-2026	523,474	563,287
Dec-2026	501,810	576,232
Jan-2027	525,908	554,630
Feb-2027	519,688	565,715
Mar-2027	498,024	578,661
Apr-2027	522,122	557,059
May-2027	515,901	568,144
Jun-2027	494,238	581,090

Jul-2027	518,336	559,488
Aug-2027	512,115	570,573
Sep-2027	490,451	583,519
Oct-2027	514,549	561,916
Nov-2027	508,329	573,002
Dec-2027	486,665	585,947

From Fig. 4, the graph illustrates the comparison of tourist arrival forecasts from 2024 to 2027, contrasting between utilizing complete datasets and excluding data from the COVID-19 period. It is observed that in the first approach, where complete datasets are used, the forecasted values show a declining trend. This suggests that including COVID-19 data in the analysis may lead to lower forecasted tourist arrivals during the specified period.
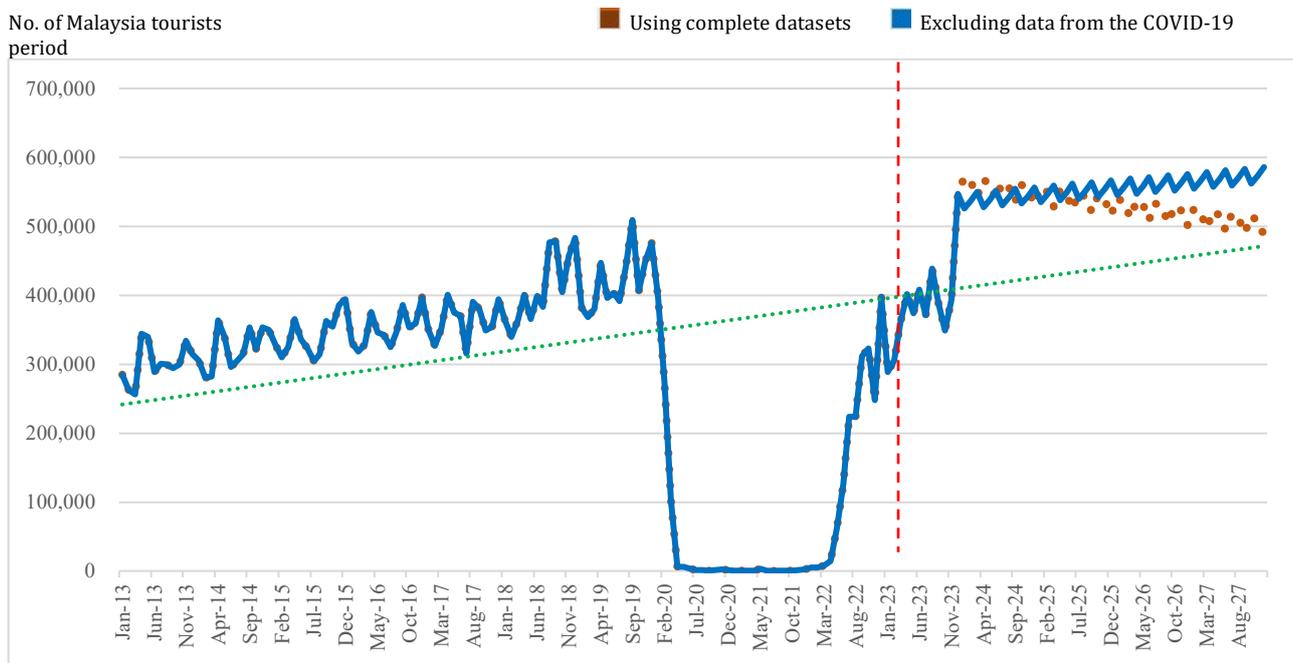

Fig. 4 *Comparison of tourist arrival forecasts from 2024 to 2027 between using complete datasets and excluding data from the COVID-19 period*

5. Discussion

The findings of this study suggest that excluding data from the COVID-19 period when forecasting Malaysian tourist arrivals in Thailand using the Holt-Winters method yields more accurate results compared to utilizing data from previous years. This discussion can be contextualized by comparing it with similar research endeavors and their outcomes. Previous research on tourism forecasting has often emphasized the importance of incorporating relevant external factors, such as economic indicators, geopolitical events, and public health crises, into forecasting models. Research conducted by Zhang *et al*. has shown how external disruptions, such as disease outbreaks, influence tourist arrivals, underscoring the necessity to adapt forecasting methodologies accordingly [10]. The approach of excluding data from the COVID-19 period aligns with the recommendations of scholars such as Zhang *et al*., who argue for the recalibration of forecasting models in response to unprecedented disruptions [10]. By focusing on pre-pandemic data, the forecasting model can capture underlying trends and patterns more accurately, avoiding distortions caused by temporary shocks. Moreover, the evaluation metrics used in this study, specifically the Mean Absolute Scaled Error (MASE) and Mean Absolute Percentage Error (MAPE), provide robust measures for assessing forecasting accuracy. Similar evaluation methods were employed in studies by Thoplan, indicating their effectiveness in gauging the performance of forecasting models in the tourism context [13].

Excluding data from the COVID-19 period can be considered a form of data cleaning aimed at removing outliers. During the COVID-19 pandemic, there were significant disruptions in travel patterns and tourism activities worldwide. Consequently, the tourist arrival data for this period may deviate significantly from the usual trends observed in the dataset. By excluding these outlier data points, the analysis can focus on the underlying patterns and trends in tourist arrivals without distortion caused by the exceptional circumstances of the

pandemic. This process of data cleaning enhances the accuracy and reliability of the analysis by ensuring that the forecasting model is built on more consistent and representative data.

Overall, the findings of this study contribute to the ongoing discourse on tourism forecasting methodologies, highlighting the importance of adapting models to account for external disruptions, such as the COVID-19 pandemic. By employing a data-driven approach and rigorous evaluation metrics, researchers can enhance the accuracy and reliability of tourism forecasts, thereby assisting policymakers and industry stakeholders in making informed decisions.

6. Conclusion

A comparative analysis of forecasting methods for Malaysian tourist arrivals in Thailand presents valuable insights for tourism management and decision-making processes. The utilization of the Holt-Winters method, with adjustments for the COVID-19 pandemic, offers a robust approach to accurately anticipate tourist influx. By excluding data from the pandemic period, the forecasting model demonstrates improved accuracy, as evidenced by lower Mean Absolute Scaled Error (MASE) and Mean Absolute Percentage Error (MAPE) values. This study aligns with broader research trends, such as those highlighted by Zhang *et al.*, emphasizing the significance of adapting forecasting methodologies in response to external shocks, such as disease outbreaks [10]. Such adjustments are crucial for ensuring the reliability and effectiveness of tourism forecasts, thereby aiding stakeholders in making informed decisions and implementing appropriate strategies to manage tourism flows effectively.

7. Recommendation

Based on the findings of this study, several recommendations can be proposed: (1) Continuous Monitoring and Adaptation: Given the dynamic nature of external factors affecting tourism, such as disease outbreaks, it is recommended to continuously monitor global trends and adapt forecasting methodologies accordingly. Regular updates to the forecasting model will enhance its accuracy and reliability, ensuring that it remains effective in predicting tourist arrivals. (2) Collaboration and Data Sharing: Collaboration among stakeholders in the tourism industry, including government agencies, tourism boards, and research institutions, is essential for data sharing and knowledge exchange. By sharing data and insights, stakeholders can collectively improve forecasting models and develop more informed strategies for tourism management and promotion. (3) Scenario Planning: Given the inherent uncertainty in predicting future tourism trends, scenario planning can be valuable for decision-making. By developing multiple scenarios based on different assumptions and potential outcomes, policymakers and industry stakeholders can better prepare for various eventualities and implement flexible strategies to mitigate risks and capitalize on opportunities. (4) Investment in Tourism Infrastructure and Marketing: To attract and accommodate tourists effectively, it is essential to invest in tourism infrastructure, including transportation, accommodation, and attractions. Additionally, targeted marketing campaigns aimed at key tourist segments can help promote destinations and stimulate demand, contributing to sustainable tourism growth.

Overall, adopting a proactive and collaborative approach to tourism forecasting and management will be crucial for enhancing the resilience and competitiveness of Thailand's tourism industry in the face of evolving challenges and opportunities.

Further research could refine forecasting models by incorporating additional variables or adopting advanced analytical techniques. Additionally, ongoing monitoring of global trends and developments, particularly those impacting tourism, will be essential for continuously enhancing the accuracy and reliability of future forecasts. Overall, this study contributes to the body of knowledge on tourism forecasting and underscores the importance of dynamic and adaptive approaches in addressing the complexities of tourist arrival predictions. Moreover, future research could explore the inclusion of additional variables such as economic indicators, travel restrictions, and consumer sentiment to further enhance the predictive power of the forecasting model. Incorporating these variables can provide a more comprehensive understanding of the factors influencing tourist arrivals and improve forecasting accuracy.

Acknowledgement

Conflict of Interest

Authors declare that there is no conflict of interests regarding the publication of the paper.

Author Contribution

The author confirms sole responsibility for the following: study conception and design, data collection, analysis and interpretation of results, and manuscript preparation.

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