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MODELLING TOURIST ARRIVAL IN MALAYSIA USING UNIVARIATE TIME SERIES MODELS

Wan Nurshazelin Wan Shahidan[1], Nor Azriani Mohamad Nor[2]*, Nurul Ain Mohd Asri[3], Azlan Abdul Aziz[4], Siti Nor Nadrah Muhamad[5], Nur Syuhada Muhammat Pazil[6]

[1] Faculty of Computer & Mathematical Sciences, Universiti Teknologi MARA, Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia
Email: shazelin804@uitm.edu.my
[2] Faculty of Computer & Mathematical Sciences, Universiti Teknologi MARA, Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia
Email: norazriani@uitm.edu.my
[3] Faculty of Computer & Mathematical Sciences, Universiti Teknologi MARA, Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia
Email: aainasrii02@gmail.com
[4] Faculty of Computer & Mathematical Sciences, Universiti Teknologi MARA, Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia
Email: azlan172@uitm.edu.my
[5] Faculty of Computer & Mathematical Sciences, Universiti Teknologi MARA, Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia
Email: nadrahmuhamad@uitm.edu.my
[6] Faculty of Computer & Mathematical Sciences, Universiti Teknologi MARA, Melaka Branch, Jasin Campus, 77300 Merlimau, Melaka, Malaysia
Email: syuhada467@uitm.edu.my
* Corresponding Author

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Abstract:

Tourism is a crucial driver of national economies, contributing to leisure, cultural exchange, and economic growth through key sectors such as hospitality and transportation. Malaysia, a prominent tourist destination in Southeast Asia, welcomed millions of international visitors in 2019, significantly boosting its economy. However, the COVID-19 pandemic led to a sharp decline in tourist arrivals, highlighting the industry's vulnerability to global disruptions. This study models tourist arrivals in Malaysia using Univariate Time Series Models based on data from January 2012 to December 2019, obtained from the Tourism Malaysia Department. Five forecasting models—Naïve Model, Seasonal Naïve Model, Single Exponential Smoothing (SES), Holt's Linear Trend Method, and Holt-Winters' Method—were evaluated using error metrics, including Mean Absolute Scaled Error (MASE), Root Mean Square Error (RMSE), Mean Absolute Percentage Error (MAPE), and Mean Absolute Error (MAE). The results indicate that the Seasonal Naïve Model produced the lowest MAE and MAPE values, making it the most

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accurate model for forecasting tourist arrivals. These findings provide valuable insights for policymakers and tourism industry stakeholders in strategic planning and resource allocation.

Keywords:

Tourism, Univariate Time Series, Repeated Time Series-Cross Validation, Seasonal Naïve Model

Introduction

Tourism is a key driver of economic growth, employment, and foreign exchange earnings (Brida et al., 2020)), especially in countries like Malaysia, where cultural diversity, strategic geographic location, and natural attractions appeal to a global audience. Tourism significantly contributes to national GDP, fosters the development of complementary industries such as transportation and hospitality, and promotes international cultural exchange (A. Khan et al., 2020). Malaysia has long been recognized as a prominent tourist destination in Southeast Asia, with millions of international visitors recorded annually. As a culturally diverse and strategically located destination, Malaysia attracted over 26 million international tourists in 2019, making it one of the top travel destinations in the region (Malay Mail, 2019). Tourism significantly contributes to Malaysia's economic growth (Kadir et al., 2015), generating national income, employment opportunities, and foreign exchange earnings (Nair et al., 2014).. The tourism sector spans multiple industries such as hospitality, transportation, and retail, reflecting its broad economic influence.

Forecasting tourist arrivals is essential for resource planning, infrastructure development, and the optimization of promotional campaigns. Therefore, the prediction of tourist flow, especially short-term tourist flow during peak season, is crucial for tourism management departments. Time series forecasting, particularly using univariate models, is a widely adopted approach due to its simplicity and effectiveness in capturing patterns within historical data. By understanding and anticipating trends, seasonality, and irregularities in tourist flows, stakeholders can implement proactive measures to enhance the resilience and sustainability of the tourism sector.

This study evaluates five univariate forecasting methods to determine the most accurate model for predicting monthly tourist arrivals in Malaysia. The models analyzed include Naïve, Seasonal Naïve, Single Exponential Smoothing, Holt's Linear Trend, and Holt-Winters Additive. The objectives are: (1) to evaluate and compare the performance of these models, and (2) to recommend a suitable model for forecasting tourist arrivals that supports strategic decision-making. The outcome of this study is expected to inform data-driven decision-making in tourism planning and policy formulation, particularly in light of the sector's recovery from global disruptions.

Literature Review

Tourism Industry in Malaysia Before COVID-19

The tourism industry plays a crucial role in the Malaysian economy by generating substantial income (Hanafiah et al., 2021). For instance, before the pandemic, tourist arrivals in Malaysia showed a positive trend with an increase of 499,567 from January to May 2019 compared to the same period in 2018 (Hamid et al., 2021) . A study by Yu Hao and Chun Xuan (2020) stated that a steady increase in the number of air passengers in Malaysia was recorded, rising from

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25.1 million passengers in the second quarter of 2018 to 28.2 million passengers in the fourth quarter of 2019.

Tourism Industry in Malaysia During COVID-19
In December 2019, Wuhan, a metropolis with a population of nearly 11 million, was shaken by the emergence of a new pandemic virus called the Coronavirus (COVID-19). The first four recorded cases were identified on 29 December 2019 when the initial outbreak occurred at the Huanan Seafood Wholesale Market in Wuhan. Since then, the virus has spread to countries all over the world including Malaysia (Li et al., 2020). The COVID-19 pandemic that hit Malaysia has affected many industries, including tourism. It also impacted the Visit Malaysia 2020 campaign in Malaysia (M. A. A. Khan & Hashim, 2020). To contain the spread of the epidemic, the Movement Control Order (MCO) or lockdown was implemented from 18th March 2020 to 3rd May 2020 following the order of the 8th Malaysian Prime Minister, Tan Sri Muhyiddin Yassin (Foo et al., 2021).

The implementation of MCO has affected the local tourism industry, such as in Genting Highlands. According to (Lim, 2020)Resorts World Genting has temporarily suspended all operations from 17th March 2020 until 1st April 2020, including the casino, hotel, restaurants, bars, theatres, theme parks, retail stores, and shopping centers. Furthermore, the closure of international borders in March 2020 also led to a decrease in the arrival of foreign tourists to Malaysia which has caused concern to the hospitality industry, the aviation industry, and other related industries (Yuan, 2023). In this critical and alarming situation, they have experienced a severe financial crisis due to job losses and no source of income in daily life.

According to a study by Yu Hao and Chun Xuan (2020), the number of airplane passengers significantly dropped from 19.1 million in the first quarter of 2020 to 0.8 million in the second quarter of 2020. Then, the Conditional Movement Control Order (CMCO) was enforced from 4th May 2020 to 12th May 2020 following the order from the government. During this period, tourism activities were still prohibited although a person was permitted to travel for work-related reasons during CMCO. Foo et al. (2021) said that Malaysian Airlines, Malindo Air, and Air Asia which were Malaysia's three largest airlines have implemented unpaid leave and salary reductions to all their employees ranging from 10 percent to 100 percent, depending on their position and salary range due to the lack of flights made during the pandemic Malaysian Association of Hotels (MAH) said that RM 68 million in revenue was the total loss incurred due to the cancellation of 170,085 rooms as of March 16th, according to hotel booking cancellation reports. In addition, hotel staff also experienced signs of depression due to salary reductions of 9 percent, being forced to take unpaid leave for 17 percent, and permanent layoffs for 4 percent of the workforce. In the first phase of MCO, which ran from March 18 to March 31, 2020, room revenue cost the hospitality industry RM 510 million and RM 570 million was the total losses incurred during the second phase of MCO (M. A. A. Khan & Hashim, 2020). Five hotels in Penang were also affected and had to close their operations due to the global pandemic (Abhari et al., 2022).

Forecasting of Tourist Arrivals
Forecasting is a process of predicting what will happen in the future based on past and present data analysis. It plays an important role in the tourism industry, helping business managers understand future trends and patterns and ensuring the organization's long-term viability before and during the pandemic (Velu et al., 2022). Effective forecasting also aids in creating plans to

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control overcapacity during peak times and draw tourists during off-peak times. Thus, numerous studies have explored various forecasting methods to enhance the accuracy of predicting tourist arrivals. Table 1 below compares selected studies on time series methods for forecasting tourist arrivals.

Table 1: Summary of Past Forecasting Tourist Arrivals

Author(s)	Data	Method Used	Findings
Saltsidou and Drakaki (2021)	Monthly tourist arrivals to the Ionian Islands.	Seasonal Naïve, SARIMA	Seasonal Naïve achieved better accuracy (MAPE ~19%).
Zayat and Sennaroglu (2020)	Monthly tourist arrivals data to Turkey	Holt-Winters (additive and multiplicative), SARIMA	Holt-Winters (multiplicative) outperformed others.
Intarapak et al. (2022)	Thailand international tourism data arrivals.	Holt-Winters (Multiplicative)	Achieved the lowest RMSE and MAPE.
Hirzi et al. (2023)	Indonesia International tourist arrival	Random forest, Single Exponential Smoothing (SES), Double Exponential Smoothing (DES).	DES model outperformed with the lowest MAPE.

Research Methodology

This study employed a structured methodology to model and forecast tourist arrivals in Malaysia using univariate time series models. The methodology comprised four main phases: data acquisition, Exploratory Data Analysis (EDA), model implementation, and model evaluation. Figure 1 illustrates the overall methodological flow followed in this study.

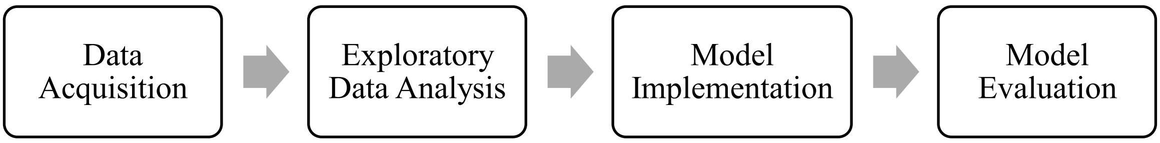

Figure 1: The Research Methodology Process Flow

Data Acquisition

The dataset includes monthly international tourist arrival figures to Malaysia from January 2012 to December 2019. This secondary data was obtained from the official Tourism Malaysia website (https://www.tourism.gov.my/). Microsoft Excel was used for data preprocessing, and RStudio (2022 version) was used for statistical modeling and visualization.

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Exploratory Data Analysis (EDA)

Under the EDA phase, a time series plot was used to visualize the presence of components such as trend, seasonality, and potential outliers in the data. Following this, time series decomposition was performed to separate the observed data into its trend, seasonal, and irregular components. This separation helps inform model selection and parameter tuning.

Model Implementation

The univariate modeling methods used in this study include: 1) Naïve Model, 2) Seasonal Naïve Model, 3) Single Exponential Smoothing Model (SES), 4) Holt's Linear Trend Method, and 5) Holt-Winters Additive Method, as described in Table 2.

Table 2: Five Univariate Time Series Model Used in Study

Univariate Time Series Model	Equation
i) Naïve Model	$\hat{y}_{t+h\mid t} = y_t$ where: y_t represents the forecast at the time t and notation $\hat{y}_{t+h\mid t}$ is the short hand for the estimate of $\hat{y}_{t+h}$ based on data $y_1, \ldots, y_t$.
ii) Seasonal Naïve Model	$y_{t+h\mid t} = y_{t+h-m(k+1)}$ where: m = the seasonal period k = the integer part of $(h-1)/m)$
iii) Single Exponential Smoothing (SES) Model	Forecast equation: $\hat{y}_{t+h\mid t} = \ell^t$ Smoothing equation: $\ell^t = \alpha y_t + (1-\alpha)\ell_{t-1}$
iv) Holt's Linear Trend Method	Forecast equation: $\hat{y}_{t+h\mid t} = \ell^t + hb_t$ Level equation: $\ell_t = \alpha y_t + (1-\alpha)(\ell_{t-1} + b_{t-1})$ Trend equation: $b_t = \beta^*(\ell_t - \ell_{t-1}) + (1-\beta^*)b_{t-1}$ where: ℓt = an estimate of the level of the series at time t bt = an estimate of the trend (slope) of the series at time t α = the smoothing parameter for the level $\beta*$= the smoothing parameter for the trend
v) Holt-Winters Additive Method	Forecast equation: $\hat{y}_{t+h\mid t} = \ell^t + hb_t + s_{t+h-m(k+1)}$ Level equation: $\ell^t = \alpha(y_t - s_{t-m}) + (1-\alpha)(\ell_{t-1} + b_{t-1})$ Trend equation:

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$b_t = \beta^*(\ell_t - \ell_{t-1}) + (1 - \beta^*)b_{t-1})$

Seasonal equation:

$$s_t = \gamma(y_t - \ell_{t-1} - b_{t-1}) + (1 - \gamma)s_{t-m}$$

where:

k = the integer of $(h-1)/m$, which ensures that the estimates of the seasonal indices used for forecasting come from the final year of the sample.

$(yt-st-m)$ = the level equation shows a weighted average between the seasonally adjusted observation

$(\ell t-1+bt-1)$ = the non-seasonal forecast for time t

Model Evaluation

Each univariate model was tested using the Repeated Time Series-Cross Validation (RTS-CV) strategy (Aziz et al., 2024), which involved splitting the data into five sets for training and testing, as presented in Table 3. The training data is used to develop a predictive model, and the testing data is used to evaluate the model's performance (Picard & Berk, 1990). To assess the performance of all models, four error measures and the percentage forecast accuracy, as summarized in Table 4, were calculated. The model that produced the smallest error and the highest percentage forecast accuracy during the testing phase was deemed the best. This evaluation process was essential in selecting the most suitable model for forecasting tourist arrivals in Malaysia.

Table 3: Training and Testing Partitioning

Set	Training (%)	Duration	Testing (%)	Duration
1	90	Jan 2012 – Feb 2019	10	Mar 2019 – Dec 2019
2	80	Jan 2012 – May 2018	20	Jun 2018 – Dec 2019
3	70	Jan 2012 – Jul 2017	30	Aug 2017 – Dec 2019
4	60	Jan 2012 – Oct 2016	40	Nov 2016 – Dec 2019
5	50	Jan 2012 – Dec 2015	50	Jan 2016 – Dec 2019

Table 4: Error Measures and Percentage Forecast Accuracy

Error measure	Equation
i) Root Mean Square Error (RMSE)	$\sqrt{\frac{\sum(e_t{}^2)}{n}}$ the formulas used to calculate the errors are: $\ell^t = y_t - \hat{y_t}$ where: y_t= the actual value in time (t) $\hat{y_t}$= the fitted value in time (t) n = sample size
ii) Mean Absolute Error (MAE)	$\sum \frac{\lvert e_t \rvert}{n}$
iii) Mean Absolute Scaled Error (MASE)	$mean(\lvert q_j \rvert)$

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where:

$$q_j = \frac{e_j}{\frac{1}{T-m}\sum_{t=m+1}^{T}|y_t - y_{t-m}|}$$

iv) Mean Absolute Percentage Error (MAPE)

$$\sum \frac{\left(\frac{e_t}{y_t}\right) * 100}{n}$$

v) Percentage Forecast Accuracy

$$\left(1 - \left(\frac{|e_t|}{y_t}\right)\right) * 100$$

Results and Discussion

The analysis began with an exploratory evaluation of monthly tourist arrival data to Malaysia, covering January 2012 to December 2019. The initial time series plot (Figure 2) revealed both upward trends and consistent seasonal patterns, illustrating the predictable fluctuations in tourist traffic over the years. An additive decomposition was performed to validate these findings further, effectively isolating the trend, seasonal, and residual components. Figure 3 shows stable, recurring seasonal peaks aligned with high-travel periods, such as public holidays and year-end vacations.

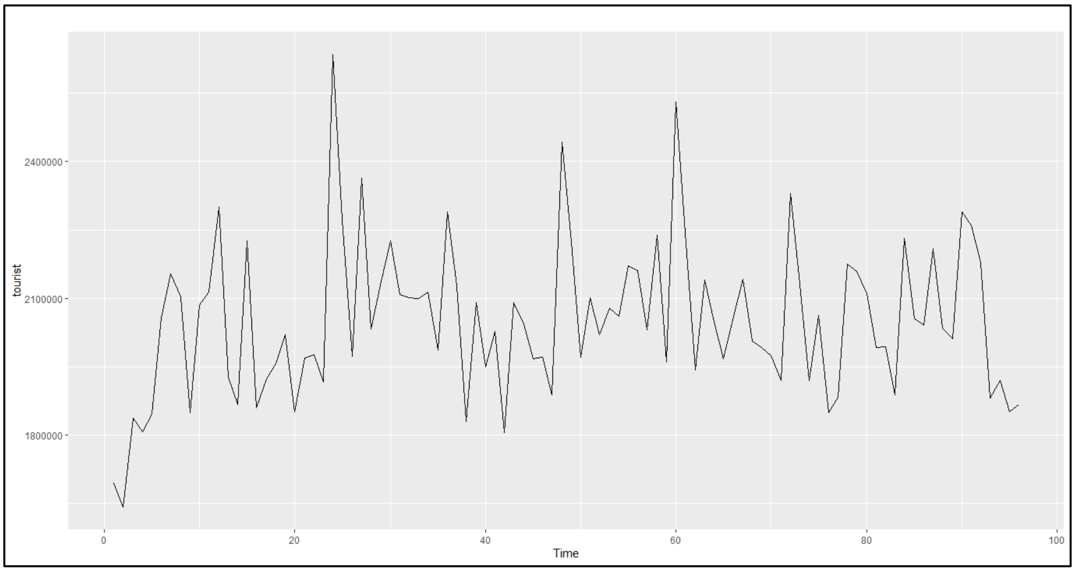

Figure 2: Original Time Series Plot

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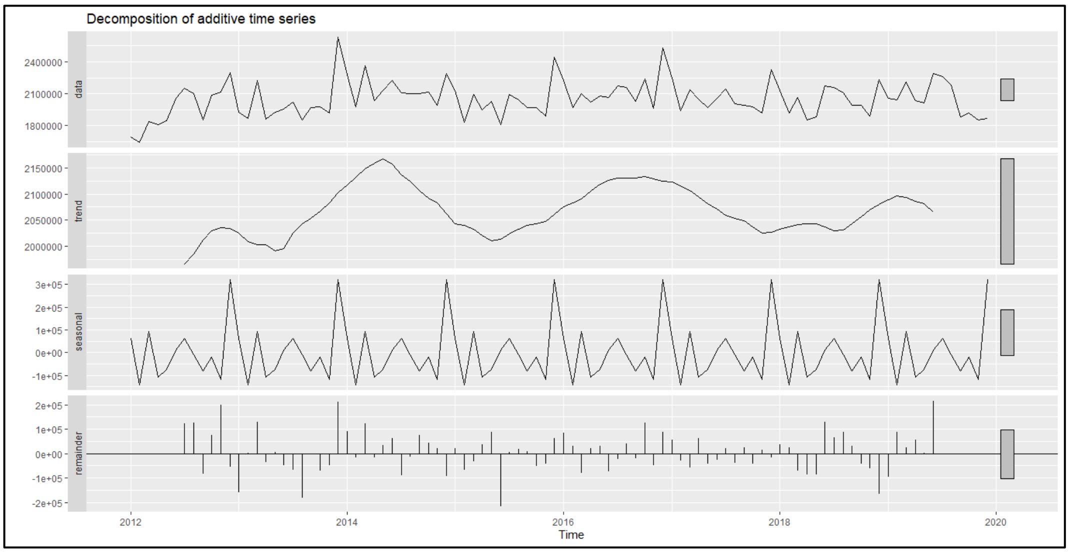

Figure 3: Decomposition of Additive Time Series

Table 5 summarizes the error measures and forecast accuracy percentages for each univariate model tested. The Naïve model in set 1 (90:10) produced the smallest error measures: RMSE (162542.7), MAE (145345), and MAPE (7.06), resulting in the highest forecast accuracy percentage of 92.94%. The result indicates it is the best model among those evaluated. Similarly, the Seasonal Naïve model in set 5 (60:40), SES in set 5 (50:50), Holt's Linear Trend method in set 3 (70:30), and Holt-Winters' Additive model in set 2 (80:20) were also identified as the best models. All the selected models noted in Table 5 are summarized and compared in Table 6 to determine the best model for forecasting tourist arrivals data.

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Table 5: Error Measures and Percentage Forecast Accuracy for Each Model

Model	Set	Training : Testing	RMSE (Testing)	MAE (Testing)	MASE (Testing)	MAPE (Testing)	Percentage Forecast Accuracy
Naïve Model	1	90:10	162542.7	145345.0	0.89	7.06	92.94
	2	80:20	224640.8	182943.7	1.09	8.50	91.50
	3	70:30	170818.2	148069.3	0.86	7.49	92.51
	4	60:40	234958.4	204063.5	1.25	10.28	89.72
	5	50:50	399959.3	377880.5	2.19	18.76	81.24
Seasonal Naïve Model	1	90:10	158962.1	133065.5	1.02	6.60	93.40
	2	80:20	156147.3	119608.2	0.86	5.83	94.17
	3	70:30	192687.5	140187.9	0.98	6.96	93.04
	4	60:40	154613.4	107555.1	0.67	5.33	94.67
	5	50:50	161972.3	113110.1	0.65	5.43	94.57
Single Exponential Smoothing (SES)	1	90:10	162264.5	147294.4	0.90	7.19	92.81
	2	80:20	146521.3	121705.3	0.73	5.80	94.20
	3	70:30	149975.9	131951.4	0.77	6.59	93.41
	4	60:40	162918.2	137828.0	0.84	6.80	93.20
	5	50:50	141333.5	114705.1	0.66	5.53	94.47
Holt's Linear Trend Method	1	90:10	162780.4	147028.6	0.90	7.17	92.83
	2	80:20	245951.6	209360.1	1.25	9.83	90.17
	3	70:30	141906.1	123652.3	0.72	6.10	93.90
	4	60:40	162918.2	137828.0	0.84	6.80	93.20
	5	50:50	196214.3	155775.1	0.90	7.79	92.21
Holt-Winters' (Additive)	1	90:10	220070.2	155440.9	1.20	7.87	92.13
	2	80:20	187999.4	147031.2	1.06	7.04	92.96
	3	70:30	141211.7	118183.9	0.83	5.79	92.10
	4	60:40	282876.1	258717.4	1.61	12.79	83.19
	5	50:50	147577.0	118841.4	0.68	5.74	88.27

The smallest error measure for each model.

Table 6: Model Comparison for each model

Model	Best Set (Train: Test)	RMSE	MAE	MASE	MAPE	Percentage Forecast Accuracy
Naïve Model	Set 1 (90:10)	162,542.70	145,345.70	0.891	7.06	92.94
Seasonal Naïve Model	Set 4 (60:40)	154,613.40	107,555.10	0.668	5.330	94.67
Single Exponential Smoothing (SES)	Set 5 (50:50)	141,333.50	114,705.10	0.664	5.527	94.47
Holt's Linear Trend Method	Set 3 (70:30)	141,906.10	123,652.30	0.721	6.102	93.90
Holt-Winters Additive	Set 3 (70:30)	141,211.70	118,183.90	0.830	5.789	92.10

The smallest error measure for each model.

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Table 6 summarizes each model's error metrics and forecast accuracy based on its optimal training and testing data partition. While all models generated reasonably accurate forecasts, the Seasonal Naïve Model exhibited the most consistent and effective performance in modeling seasonal behavior. It achieved the lowest MAE and MAPE, which are widely considered robust indicators of forecast reliability in real-world scenarios. Although the SES model attained the lowest MASE and the Holt-Winters model yielded the lowest RMSE, the Seasonal Naïve Model ultimately provided the highest overall forecast accuracy at 94.67%, underscoring its effectiveness in capturing cyclical tourist behavior.

The preference for the Seasonal Naïve Model aligns with prior literature emphasizing the effectiveness of simpler models in datasets exhibiting clear, repetitive patterns. Given Malaysia's consistency of tourism seasonality, the model's simplicity and high accuracy make it particularly suitable for short-term forecasting and strategic planning. Its ease of implementation is an added advantage for decision-makers in governmental and private tourism sectors who may not have access to advanced computational tools.

The analysis highlights that higher model complexity does not necessarily yield improved predictive performance. Instead, understanding the underlying structure of the data, such as stable seasonality, can often point to more practical and equally accurate solutions. The Seasonal Naïve Model is a valuable forecasting tool for guiding resource allocation, promotional timing, and infrastructure readiness in Malaysia's tourism industry.

Conclusion

This study investigated the application of univariate time series models to forecast monthly tourist arrivals in Malaysia using historical data from January 2012 to December 2019. The analysis explored five forecasting techniques: Naïve Model, Seasonal Naïve Model, Single Exponential Smoothing (SES), Holt's Linear Trend Method, and Holt-Winters Additive Method. Model performance was evaluated using four key error metrics: RMSE, MAE, MASE, and MAPE across multiple training and testing splits.

The Seasonal Naïve Model achieved the best forecasting accuracy, with the lowest MAE and MAPE values and the highest overall forecast accuracy of 94.67%. This indicates that it effectively captures recurring seasonal patterns in tourist arrivals, making it a reliable model for short-term forecasting. While more complex models like Holt-Winters and SES showed strong performance in some metrics, they did not significantly outperform the Seasonal Naïve Model regarding practical forecasting utility.

The results reinforce the value of simple, interpretable models in forecasting applications where seasonal structures are prominent and stable. These findings offer valuable insights for tourism authorities and policymakers aiming to anticipate visitor trends and make informed decisions regarding promotional efforts, infrastructure investments, and operational planning.

Overall, the objectives of this study have been fully achieved. The comparative evaluation of five univariate forecasting models successfully identified the Seasonal Naïve Model as the most effective for predicting monthly tourist arrivals in Malaysia. This outcome fulfills the study's aim of recommending a reliable, data-driven forecasting approach that can support strategic decision-making in the tourism sector.

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Recommendations

This study contributes academically by validating that simple models like the Seasonal Naïve Model can outperform complex forecasting methods in highly seasonal tourism data. For industry practitioners, the findings offer a practical forecasting solution that is easy to implement without requiring advanced computational tools. At the national level, the results support tourism agencies in making data-driven decisions to optimize resources, especially during recovery periods such as post-COVID-19.

Given the effectiveness of the Seasonal Naïve Model, tourism agencies and planners are encouraged to incorporate this model into their routine forecasting efforts, especially for short-term strategic decisions. Its ease of use and high forecast accuracy make it particularly advantageous in operational settings where timely and reliable projections are essential. However, there are limitations to consider. The dataset used in this study includes data only up to December 2019, which does not account for the disruptions brought by the COVID-19 pandemic. Therefore, the current model may not be entirely suitable for forecasting periods marked by structural breaks or unforeseen global events. For future research, it is recommended to incorporate post-pandemic data to understand changes in travel behavior and tourism dynamics.

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