ASM Sc. J., 20(2), 2025

https://doi.org/10.32802/asmscj.2025.1719

Tourist Arrivals in Malaysia Post-COVID-19: A Comparison Between Holt-Winters and ARIMA Model

N. Mahmud[1], N.S. Muhammat Pazil[2*] and N.A.Z. Amir Razuan[1]

[1]*Faculty of Computer and Mathematical Sciences*
Universiti Teknologi MARA (UiTM) Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia
[2]*Faculty of Computer and Mathematical Sciences*
Universiti Teknologi MARA (UiTM) Melaka Branch, Jasin Campus, 77300 Merlimau, Melaka, Malaysia

Tourism is a major contributor to Malaysia's socioeconomic growth, with visitors' investments contributing to the country's Gross Domestic Product (GDP). To capitalise on this sector, the government has announced the initiation of the Visit Malaysia 2020 campaign. However, in December 2019, the globe was threatened by the COVID-19 virus, and the first case was quickly identified in Malaysia. The number of cases grew over time, and on 11 March 2020, the World Health Organization (WHO) proclaimed the COVID-19 outbreak a pandemic. COVID-19 has caused substantial damage and severely affected the country's economy. To ensure the economy can return to normal, a systematic recovery plan must be adopted promptly. Therefore, the focus of this study is to examine the pattern of tourist arrivals before and after the COVID-19 pandemic to forecast tourist arrivals in Malaysia using the Autoregressive Integrated Moving average (ARIMA) and Holt-Winters models. The data on tourist arrivals in Malaysia from January 2018 until June 2022 were obtained from the Tourism Malaysia website. The results of this study reveal that the ARIMA model outperforms the Holt-Winters model, with the ARIMA (1,1,1) model providing the best fit for forecasting tourist arrivals in Malaysia, characterised by the lowest values of Mean Squared Error and Mean Absolute Percent Error. Future research might be conducted on alternative methods linked to the ARIMA model, such as the Fuzzy Seasonal ARIMA model (FSARIMA), or on distinct types of data series.

Keywords: tourist arrivals; tourism Malaysia; forecasting; holt-winters; ARIMA; COVID-19

I. INTRODUCTION

The tourism industry in Malaysia is the second greatest source of international exchange income, with a significant impact on the economy (Sakolnakorn, 2020). As for the term "tourism" itself, the World Tourism Organization (UNWTO) defines tourism as a social, cultural, and economic concept that involves individuals traveling to nations or locations beyond their typical surroundings for business or leisure. These individuals are known as tourists, and tourism refers to their activities, some of which include tourism expenses. Malaysia's various attractions appeal to a wide range of tourists thanks to the country's cultural richness, ancient landmarks, modern skylines, natural landscapes, and stunning beaches and islands with breathtaking views.

In December 2019, the world was threatened by the COVID-19 virus which originated in Wuhan, China. It was soon reported that the first case had been detected in Malaysia. As a result, all hopes of making Malaysian tourism the best it has ever had vanished. As time passed, the number of cases increased along with the number of lives lost. On March 11, 2020, the World Health Organization (WHO) finally declared the COVID-19 outbreak a pandemic.

Tourist arrivals in Malaysia declined in 2020 due to the country closing its borders to international tourists and restrictions on access for non-residents. This is supported by

*Corresponding author's e-mail: syuhada467@uitm.edu.my

the data from the Department of Statistics Malaysia, the COVID-19 pandemic resulted in an 83.4% decline in the number of international tourists visiting Malaysia in 2020 compared to the previous year (Ashman, 2021; Mohd Yunus *et al.*, 2025). Tourism-related industries experienced a significant decline in revenue as tourism receipts almost completely dried up (Hirschmann, 2020). In just a few months, the global tourism system has shifted from tourism to non-tourism (Păvăluc *et al.*, 2020).

Since the onset of the COVID-19 pandemic, many small businesses have been affected. They are obliged to close their company for an extended period. Since most small business owners rely solely on the money generated by their business, it severely impacted their lives. Most small companies borrow money from a bank or a government organisation to get started, and they are required to repay it monthly. However, a lockdown occurred, and they were not permitted to open for business for weeks or months, making repayment challenging. Some may argue that this is not a problem since the government has ordered banks to introduce a six-month moratorium on all bank loans. The aim is to ease the cash flow of enterprises and individuals affected by COVID-19. However, it will still have an impact on them in the long run since Bank Negara Malaysia (BNM) has entrusted banks to provide customers with information on how repayments will be treated during the six months (Annuar, 2020).

COVID-19 outbreaks affect individuals and large businesses. Some big hotels, for example, are forced to close their operations. More than 120 hotels around the country would temporarily or permanently put up their 'no vacancy' signs after being submerged in lockdowns for over a year due to the COVID-19 outbreak (Hakim, 2021).

The government's declaration of the Movement Control Order (MCO), which permitted only essential industries to open, was undoubtedly one event that directly impacted the tourism industry. As governments closed national borders and prohibited travel to limit the spread of the virus, the MCO negatively affected domestic tourism. Non-essential interstate travel, such as shopping or visiting friends and family, remained restricted, stopping domestic tourism (Hirschmann, 2020).

The government must implement a recovery plan to promote tourism and restore regular visitor arrivals. Therefore, developing a strategy and determining how to recover from the ground is crucial. Hence, this study aims to restore tourist arrivals by forecasting the number of tourist arrivals in Malaysia post-COVID-19 based on data acquired from Tourism Malaysia from January 2018 to June 2022. The trend of tourist arrivals in Malaysia was analysed to determine the effects before and after the COVID-19 outbreak. Following this, a comparison was performed between the Holt-Winters model and the Autoregressive Integrated Moving Average (ARIMA) model to determine which model would produce the most accurate forecast value of tourist arrivals in Malaysia for the forthcoming year.

A. Impact of COVID-19 on the Tourism Industry

Malaysia's economy has been severely impacted by the emergence of COVID-19, most notably in the travel and tourism industry (Arokiasamy *et al.*, 2021). The study also noted that Malaysia's inbound visits have decreased due to the COVID-19 pandemic. However, further research is needed to determine if the impact is permanent or temporary. Abbas *et al.* (2021) also mentioned that the recent COVID-19 pandemic has led to global issues, economic and healthcare difficulties, and spillover effects on international businesses, including tourism, which are vital contributors to the worldwide service economy. The tourism industry has been impacted the worst by COVID-19 and is one of the most affected businesses worldwide. Arokiasamy *et al.* (2021) reported that the Malaysian government was estimated to lose Malaysian Ringgit (RM) 3.37 billion since tour and vacation packages have been cancelled. This causes significant problems for hotels and airlines in the locality.

Moreover, Shari *et al.* (2020) claimed that COVID-19 outbreaks significantly impact the hotel industries and other related industries. This has been felt immediately due to travel restrictions, the cancellation of events, and the reluctance of individuals to travel. Meanwhile, Sharma *et al.* (2021) also reported a 22% decline in tourist members in the first quarter of 2020 compared to the same quarter 2019. The threat of a 60% to 80% decline throughout 2020 compared to 2019 highlighted the havoc that the COVID-19 pandemic for the global tourism industry.

B. Importance of Forecasting Tourism Arrivals

Forecasting is an unavoidable aspect of modern life. It involves making predictions based on a set of historical or current data, which is usually supported by trend analysis. Forecasting strategies vary depending on the source of information and the forecasting goal (Gruevski, 2021). Forecasting theory was based upon the belief that current and historical understanding may be used to create predictions. There is a widespread notion, particularly in the context of time series, that it is reliable to identify patterns in previous values and effectively apply them to forecasting future values (Petropoulos *et al.*, 2022). Forecasting has also advanced significantly over the last decade, thanks to advancements in software and technology. Forecasts can now project changes in ecosystems and landscapes in response to natural causes such as changing weather patterns or disruption events, as well as human actions, including land use change or management (Mozelewski & Scheller, 2021). Forecasting is also commonly employed in business applications. Taylor and Letham (2018) stated that forecasting is fundamental to many operations inside an organisation. For instance, organisations across all sectors must engage in goal setting and capacity planning to allocate their limited resources effectively and monitor quality compared to a standard.

Li *et al.* (2020) stated in their study that predicting tourist arrivals is essential in the development, operation, and administration of tourism destinations. In addition, Thushara *et al.* (2019) believed that to optimise profits from the tourism sector, effective political choices, infrastructure investment, and conducive business settings must be implemented; thus, to achieve that, accurate forecasting of international arrivals is essential. As a result, it can be concluded that estimating tourist arrivals in Malaysia is vital, with the hope that a recovery plan can be adopted by analysing the pattern of tourist arrivals, allowing the industry to develop its best strategy to recover from the impact of COVID-19.

C. Autoregressive Integrated Moving Average (ARIMA) Model

A seasonal ARIMA model is written as ARIMA (p, d, q) (P, D, Q) m, where m is the number of periods in each season, and the uppercase P, D, Q represent the autoregressive (AR), differencing (I), and moving average (MR) components for the seasonal element of the ARIMA model, respectively (Dimri *et al.*, 2020).

The ARIMA model was used by Choden and Unhapipat (2018) to predict international tourist visits in Bumthang, Bhutan. The study aims to forecast future tourist visits based on the data of the monthly number of international visitors in Bumthang, Bhutan, from January 2012 to December 2016. The findings reveal that the fitted seasonal ARIMA (0,0,0) $(1,1,0)_{12}$ can forecast international tourist arrivals from January to June 2017 with 91% accuracy.

ARIMA models were also used to estimate agricultural productivity. Sharma *et al.* (2021) researched sugarcane production using data from 1950 to 2011, with out-of-sample estimates made from 2012 to 2021 for comparative analysis. The ARIMA (2, 1, 1) model was the most appropriate for predicting sugarcane production.

D. Holt-Winters Model

Holt-Winters are better suited for seasonality data that can help foretell long-term forecasts. The Holt-Winters model is comprised of two key assumptions: the multiplicative effect assumption and the addictive effect assumption. If the scale of the seasonal fluctuation increases in parallel with the data series' increasing level, this is referred to as a multiplicative effect. When the absolute extent of the variation is independent of each other, this is referred to as an additive effect (Mohd Lip *et al.*, 2020). This method is theorised to be suitable for time series with a linear time trend and multiplicative seasonal variation (Mishra *et al.*, 2018).

Jere *et al.* (2019) made a comparison between Holt-Winters Exponential Smoothing (HWES) and ARIMA models to forecast annual international tourist arrivals in Zambia from 1995 to 2014. Other than that, Mohd Lip *et al.* (2020) identified the best model for predicting international tourist arrivals in Malaysia using the Box-Jenkins SARIMA and Holt-Winters model based on the value of Mean Squared

Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The study relied on secondary data from the number of tourist arrivals from Singapore, Korea, and the United Kingdom (UK) between 2013 and 2017. The Holt-Winters model was the best model for forecasting tourist arrivals from the UK and Korea, while the SARIMA (1,1,1) $(1,1,1)_{12}$ model was the best model for forecasting tourist arrivals from Singapore.

II. MATERIALS AND METHODS

This study used monthly data on the number of tourist arrivals in Malaysia from January 2018 to June 2022. This secondary data consists of 56 data points obtained from the Tourism Malaysia website. The technique of data analysis began with the compilation of the data required for the study. The original pattern of the data is presented and analysed. Following this, the process of constructing the ARIMA model and building the Holt-Winters model proceeded. Both formulated models are designed to meet the research's primary aims. After completing the processes involved in both models, the model performance is reviewed. The findings of the ARIMA and Holt-Winters models are compared, and the best model, with the lowest values of error measures, is later employed in forecasting tourist arrivals in Malaysia for the upcoming months. Figure 1 below summarise the process of predicting tourist arrivals in Malaysia.

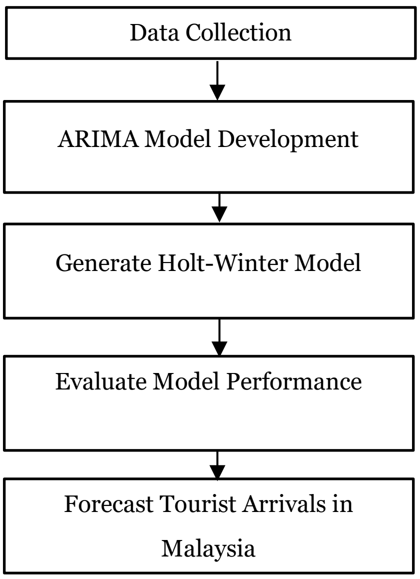

Figure 1. Process of Predicting Tourist Arrival in Malaysia

A. *Stages in The ARIMA Model Development*

Three significant steps must be completed first: model identification in stage one, model estimation and validation in stage two, and model application in stage three. The diagrammatic depiction of these steps is displayed in Figure 2 below.

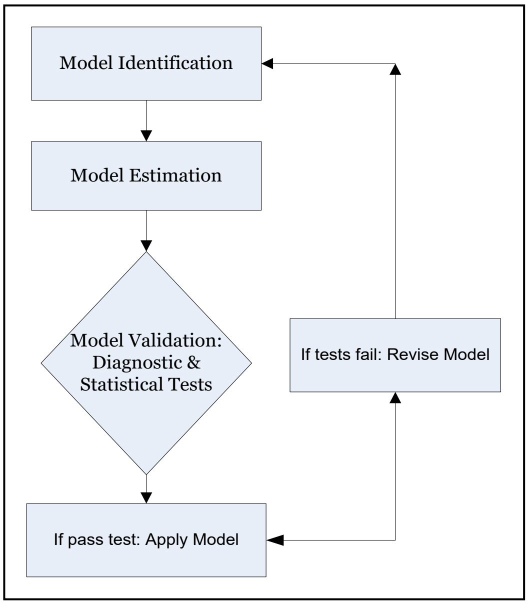

Figure 2. ARIMA Model Development

The ARIMA model is categorised into three terms: *p*, *d*, and *q*. Accordingly, *p* is the order of the autoregressive (AR) term, *q* is the order of the moving average (MA) term, and *d* is the number of differencing used to obtain stationary time series data. These are mathematical formulas for each term:

Autoregressive (AR), p term,

$$y_t = c + \phi_1 y_{t-1} + \phi_1 y_{t-2} ..... + \phi_p y_{t-p} + \varepsilon_t \quad (1)$$

Moving Average (MA), q term,

$$y_t = c + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} ..... + \theta_q \varepsilon_{t-q} \quad (2)$$

where ε_t represents white noise.

Number of differencing, d term,

$$\nabla^k y_t = (1-B)^k y^t \quad (3)$$

where B is the lag operator.

Therefore, the general formula for the ARIMA model is as follows:

$$y'_t = c + \phi_1 y'_{t-1} + ... + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} ..... + \theta_q \varepsilon_{t-q} + \varepsilon_t \quad (4)$$

where, y'_t is a differenced series.

In this study, ARIMA (1,1,1) was computed for the ARIMA model from the result generated using R-studio software. The general equation can be expressed using equation 4.

B. Multiplicative Holt-Winters

The Holt-Winters method is a well-known time series forecasting process that comprises both trend and seasonality factors. This method consists of three main equations describing the level component, the trend component, and the seasonality component. Assuming that the relationship between these components is multiplicative, the equations are expressed as follows:

Level Component:

$$L_t = \alpha\left(\frac{Y_t}{S_{t-s}}\right) + (1-\alpha)(L_{t-1} + b_{t-1}) \quad (5)$$

Trend Component:

$$b_t = \beta(L_t - L_{t-1}) + (1-\beta)b_{t-1} \quad (6)$$

Seasonal Component

$$S_t = \gamma\left(\frac{Y_t}{L_t}\right) + (1-\gamma)S_{t-s} \quad (7)$$

The m-step-ahead forecast

$$F_{t+m} = (L_t + b_t m)S_{t-s+m} \quad (8)$$

where L_t denotes an estimate of the level of the series at time, t, b_t denotes an estimate of the trend of the series at time, t, S_t is an estimate of the seasonality at time t, F_{t+m} is the seasonality length , is the forecast for m time ahead, and F_{t+1} is the forecast within the data set.

C. Model Validation

The final evaluation for both models (ARIMA and Holt-Winters) in this study will be based on three measurements: Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE). The best model will be selected based on the lowest MSE, RMSE, and MAPE. These error measurements were formulated as follows:

$$\text{MSE} = \frac{\sum e_t^2}{n} \quad (9)$$

$$\text{RMSE} = \sqrt{\frac{\sum e_t^2}{n}} \quad (10)$$

$$\text{MAPE} = \left(\frac{1}{n}\sum\left|\frac{e_t}{y_t}\right|\right)(100) \quad (11)$$

where the forecast error is e_t, and it is calculated by subtracting the forecast value from the series' actual value; y_t. Here, n is the number of effective observations used to match the model. The minimum values of these accuracy measures indicate the best fitting models.

III. RESULT AND DISCUSSION

Figure 3 displays the time series plot of the original data from January 2018 to June 2022. The highest number of visitors were recorder in July 2019. The pattern of oscillations remained consistent until January 2020, when the COVID-19 pandemic was reported in the country. The downturn in tourist visits has continued throughout the year, with only 5,411 tourists recorded in May 2020, as the government enforced the MCO during this period to curb the spread of the virus. However, after significant efforts to address the problem, tourism began to recover steadily again, beginning in March 2022, as the MCO was gradually loosened to allow more people to travel.

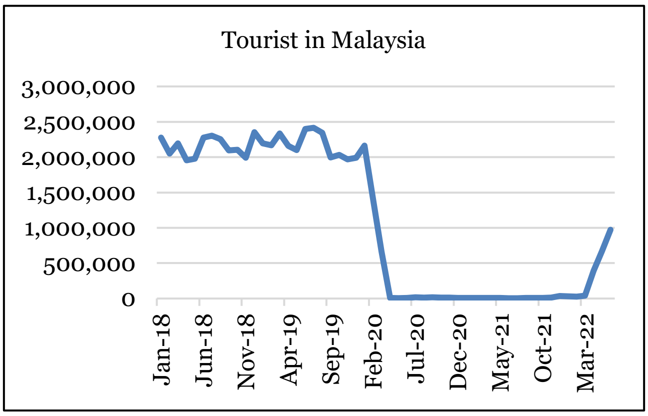

Figure 3. Time Series plot of Original Data

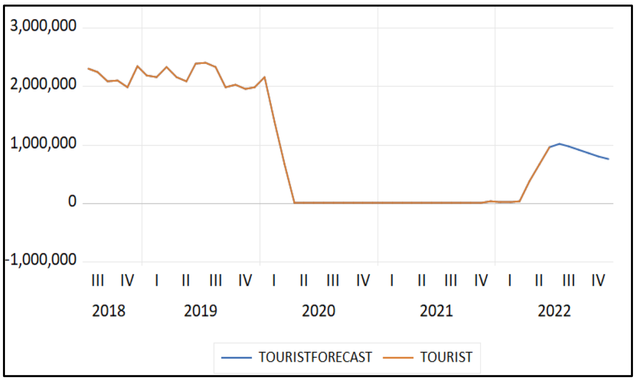

Figure 4. Forecast and actual values for 6 months ahead

A. Selection the Best Model

From the generated models, the goodness of the model is measured by the errors in the accuracy of the forecasted data compared to the actual data. The ARIMA and the Holt-Winters models were compared based on the lowest error measurements on the test part of the models. There are three measurements of error that were examined in this study, Mean Squared Error (MSE), Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE).

In Table 1, the ARIMA (1,1,1) model yields the lowest MSE and MAPE measurement errors, achieving the highest accuracy of the assessment forecast. At the same time, the Holt-Winters model resulted in the lowest measurement error for RMSE. The lowest MSE indicates that the model's prediction is generally close to the actual values. In contrast, the lowest MAPE demonstrated that the model's prediction is relatively close to the actual values on average, suggesting better performance. Therefore, ARIMA (1, 1, 1) is selected as the best model to forecast the number of tourist arrivals in Malaysia. The monthly tourist arrivals are later predicted for the evaluation part from May 2021 to June 2022.

Table 1. Measurement errors for the model developed

Model	MSE	RMSE	MAPE
Holt-Winters	109593554675.72	**51007.89**	537.59
ARIMA (1,1,1)	**21218991422.76**	145667.40	**310.71**

B. Prediction of Tourists Arrival in Malaysia

Monthly data on tourist arrivals were further being predicted for the next six months from July 2022 to December 2022, using the best ARIMA (1,1,1) model selected earlier as outlined in Table 2.

Table 2. Predicted Number of Tourist Arrivals in Malaysia

Month	Tourist Arrivals
July 2022	1017616
August 2022	982143
September 2022	916970
October 2022	866175
November 2022	813056
December 2022	759679

Figure 4 illustrates the forecast values for the next six months of tourist arrivals in Malaysia indicates a rise for July 2022, with an estimated 1,017,616 tourists. In June 2022, it grew by 4.74% from the previous month's data of 971,574 tourists. However, the following expected numbers for August 2022 present a 3.49% drop from the predicted value for July 2022, with 982,143 tourists. This downward trend appears to continue in the next few months, as the number of tourist arrivals forecasted continues to fall as the month progresses.

However, the real data that was just made public for July, August, and September of 2022 did not reflect the same outcomes as the data began to climb each month as displayed in figure 5. For July, August, and September of 2022, the gap between actual and forecast values ranges from 5.76% to 12.27% to 35.80%. Although the difference may not be substantial huge, it seems to be the opposite direction of the actual data that increase.

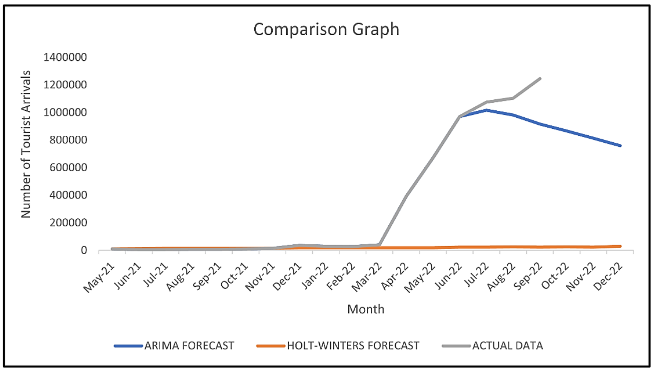

Figure 5. Comparison between forecast and actual data

These scenarios are not foreign, as depicted by Kumar *et al.* (2022). It is incorrect to claim that accurate prediction is achievable, as it depends on several aspects that are unknown variables in the community. However, the model accuracy can surely be improved with additional data. A structure and model have been developed to analyse and forecast behaviour, and the predictions will improve as more data is collected.

IV. CONCLUSION

This research first reviewed the actual data patterns of tourist arrivals in Malaysia from January 2018 to June 2022. Then, it examined the forecasting performance of two multiplicative univariate time-series models: the Holt-Winters model and the ARIMA model, to generate a more accurate forecast of tourist arrivals in Malaysia. The time series plot of monthly data on tourist arrivals in the nation demonstrates an increasing trend, followed by a sharp declined caused by the global COVID-19 pandemic. Furthermore, the comparison of MSE, RMSE, and MAPE reveals that the ARIMA (1, 1, 1) model has superior predictive performance in the case of tourist arrivals in Malaysia.

The ARIMA (1,1,1) model was used to analyse the data in this study, as since it was regarded as the best way to determine significant tourist arrival data in Malaysia. The approach used for the research should produce prediction outcomes that correspond to the actual behaviour of the time series data. These findings are relevant for the policy community working on the country's long-term tourist growth. The discovery of a high number of tourist arrivals compared to the beginning of the year suggest that the government and private stakeholders must remain prepared to welcome an increasing number of tourists in the years to come. Stakeholders in the tourism industry and policymakers can make more informed decisions, better prepare for future uncertainties, and enhance the resilience and sustainability of the tourism sector in Malaysia.

V. FUTURE RESEARCH

This study solely employs two approaches to analyse actual visitor arrivals data in Malaysia: ARIMA and Holt-Winters According to the results of this investigation, the Holt-Winters model produced the largest measurement error values when compared to the ARIMA (1,1,1) model. This topic's analysis suggested that the study be done by applying more time series approaches to evaluate the accuracy of forecasted tourist arrivals figures. The model created is the best model for providing high accuracy in estimating expected tourist arrivals, as it has the fewest measurement errors among all approaches.

In this way, this research makes a significant contribution to the field of forecasting tourist arrivals. The selection of an effective forecasting model aids the Malaysian tourism sector in planning for the optimal utilisation of various operational resources. However, the study had certain drawbacks. Only the predicted results of two univariate tools were compared. As a result, there is potential for future investigation.

There are several approaches for comparing and determining which method is best for forecasting. The predicted value can be improved using various methods to obtain a more accurate result. In that case, time series models can be evaluated to determine whether the accuracy of the ARIMA predictions changes as more data becomes available. Future research might also be conducted on alternative methods linked to the ARIMA model, such as the Fuzzy Seasonal ARIMA model (FSARIMA), and develop robust methods for detecting and handling outlier to improve model accuracy.

VI. ACKNOWLEDGEMENT

This research was not funded by any grant. Special thanks to the reviewers for their useful suggestions.

VII. REFERENCES

Abbas, J, Mubeen, R, Iorember, PT, Raza, S & Mamirkulova, G 2021, 'Exploring the impact of COVID-19 on tourism: transformational potential and implications for a sustainable recovery of the travel and leisure industry', Current Research in Behavioral Sciences, vol. 2, p. 100033. doi: 10.1016/j.crbeha.2021.100033

Annuar, A 2020, 'Bank Negara announces automatic six-month moratorium on all bank loans — except for credit card balances', Malay Mail, pp. 23–25.

Arokiasamy, ARA, Smith, PMR & Kijbumrung, T 2021, 'Conceptualizing Post-COVID-19 Malaysia's Tourism Recovery: An Auto-Regressive Neural Network Analysis', Emerging Science Journal, vol. 5(Special issue), pp. 119–129. doi: 10.28991/esj-2021-SPER-10

Ashman, A 2021, 'Stats Dept: Covid-19 pandemic slashed Malaysia's 2020 tourist arrivals by 83.4pc, worst drop in history', MalayMail, <https://www.malaymail.com/news/malaysia/2021/09/23/stats-dept-covid-19-pandemic-slashed-malaysias-2020-tourist-arrivals-by-83/2007765>.

Choden & Unhapipat, S 2018, 'ARIMA model to forecast international tourist visit in Bumthang, Bhutan', Journal of Physics: Conference Series, vol. 1039, no. 1, p. 012023. doi: 10.1088/1742-6596/1039/1/012023

Dimri, T, Ahmad, S & Sharif, M 2020, 'Time series analysis of climate variables using seasonal ARIMA approach', Journal of Earth System Science, vol. 129, no. 1, p. 149. doi: 10.1007/s12040-020-01408-x

Gruevski, I 2021, 'Basic time series models in financial forecasting', Journal of Economics, vol. 6, no. 1, pp. 76–89. doi: 10.46763/JOE216.10076g

Hakim, A 2021, 'More than 120 hotels In Malaysia forced to close because Lockdowns', TRP.

Hirschmann, R 2020, 'Travel and tourism in Malaysia', In Statista.

Jere, S, Banda, A, Kasense, B, Siluyele, I & Moyo, E 2019, 'Forecasting annual international tourist arrivals in Zambia using holt-winters exponential smoothing', Open Journal of Statistics, vol. 09, no. 02, pp. 258–267. doi: 10.4236/ojs.2019.92019

Kumar, A, Misra, SC & Chan, FTS 2022, 'Leveraging AI for advanced analytics to forecast altered tourism industry parameters: A COVID-19 motivated study', Expert Systems with Applications, vol. 210, p. 118628. doi: 10.1016/j.eswa.2022.118628

Li, H, Hu, M & Li, G 2020, 'Forecasting tourism demand with multisource big data', Annals of Tourism Research, vol. 83, p. 102912. doi: 10.1016/j.annals.2020.102912

Mishra, P, Rout, H & Pradhan, B 2018, 'Seasonality in tourism and forecasting foreign tourist arrivals in India', Iranian Journal of Management Studies, vol. 11, no. 4, pp. 629–658. doi: 10.22059/IJMS.2018.239718.672776

Mohd Lip, N, Jumery, NS, Ahmad Termizi, FA, Mulyadi, NA, Anuar, N & Ithnin, H 2020, 'Forecasting international tourist arrivals in Malaysia using SARIMA and holt-winters model', Journal of Tourism, Hospitality and Environment Management, vol. 5, no. 18, pp. 41–51. doi: 10.35631/JTHEM.518004

Mohd Yunus, AA, Ismail, S & Ibrahim, MS 2025, 'Estimating active cases of infectious disease using SEIRD model: Case of COVID-19 diseases in Malaysia', Journal of Advanced Research Design, vol. 125, no. 1, pp. 1–9. doi: 10.37934/ard.125.1.19

Mozelewski, TG & Scheller, RM 2021, 'Forecasting for intended consequences', Conservation Science and Practice, vol. 3, no. 4, pp. 1–13. doi: 10.1111/csp2.370

Păvăluc, C, BrÎnză, G, Anichiti, A & Butnaru, GI 2020, 'COVID-19 pandemic and its effects on the tourism sector', CES Working Papers, vol. 12, no. 2, pp. 111–122.

Petropoulos, F, Apiletti, D, Assimakopoulos, V, Babai, MZ, Barrow, DK, Ben Taieb, S, Bergmeir, C, Bessa, RJ, Bijak, J, Boylan, JE, Browell, J, Carnevale, C, Castle, JL, Cirillo, P, Clements, MP, Cordeiro, C, Cyrino Oliveira, FL, De Baets, S, Dokumentov, A, ... Ziel, F 2022, 'Forecasting: theory and practice', International Journal of Forecasting, vol. 38, no. 3, pp. 705–871. doi: 10.1016/j.ijforecast.2021.11.001

Sakolnakorn, TPN 2020, 'Important factors and policies that contributed to tourism in Malaysia between 1991 and 2018', International Journal of Innovation, Creativity and Change, vol. 14, no. 12, pp. 969–980.

Shari, NS, Mohammad Yazid, MF & Shamsudin, MF 2020, 'The strengthen strategies during post covid 19 after the virus crisis hit hotel industry in Malaysia', Journal of Postgraduate Current Business Research, vol. 1, no. 1, pp. 1–5.

Sharma, GD, Thomas, A & Paul, J 2021, 'Reviving tourism industry post-COVID-19: A resilience-based framework', Tourism Management Perspectives, vol. 37, p. 100786. doi: 10.1016/j.tmp.2020.100786

Sharma, HK, Kumari, K & Kar, S 2021, 'Forecasting sugarcane yield of India based on rough set combination approach', Decision Making: Applications in Management and Engineering, vol. 4, no. 2, pp. 163–177. doi: 10.31181/dmame210402163s

Taylor, SJ & Letham, B 2018, 'Forecasting at Scale', The American Statistician, vol. 72, no. 1, pp. 37–45. doi: 10.1080/00031305.2017.1380080

Thushara, SC, Su, J-J & Bandara, JS 2019, 'Forecasting international tourist arrivals in formulating tourism strategies and planning: The case of Sri Lanka', Cogent Economics & Finance, vol. 7, no. 1, p. 1699884. doi: 10.1080/23322039.2019.1699884.