A Hybrid SARIMA-ANN approach for forecasting tourist arrivals in Malaysia

Wan Nurul Ain[*1]
Seuk Yen Phoong[2]

Geliş tarihi / *Received:* 28.01.2026
Düzeltilerek geliş tarihi / *Received in revised form:* 07.02.2026
Kabul tarihi / *Accepted:* 12.06.2026
DOI: 10.17932/IAU.ABMYOD.2006.005/abmyod_v21i73001

Abstract

Accurate forecasting of tourist arrivals is essential for strategic planning and economic growth, particularly in Malaysia, where tourism is a key contributor to Gross Domestic Product. Traditional forecasting models, such as the Seasonal Autoregressive Integrated Moving Average (SARIMA), effectively capture linear and seasonal patterns but struggle with nonlinear dependencies. Conversely, Artificial Neural Network (ANN) excels at modeling nonlinear relationships but may fail to account for temporal dependencies. To address these limitations, this study proposes a hybrid SARIMA-ANN model that integrates the strengths of both models to improve forecasting accuracy. In this study, a hybrid SARIMA-ANN model is developed by first applying SARIMA to extract linear and seasonal components, followed by modeling its residuals using an ANN to capture any remaining nonlinear patterns. Empirical results demonstrate that the SARIMA-ANN model can provide a hybrid model with high accuracy due to its ability to effectively capture both linear and nonlinear patterns in time series data. SARIMA effectively captures seasonality and long-term trends, while ANN overcomes its limitations by identifying complex nonlinear relationships within the residuals. This combined model reduces forecasting errors by leveraging the strengths of both models, addressing limitations that each model individually cannot overcome. These findings highlight the effectiveness of hybrid time series modeling for forecasting tourist arrivals, suggesting its potential application in other domains

[1] Sorumlu Yazar/ Corresponding Author:Sultan Idris Education University, wnainmarzuki@gmail.com ORCID: 0009-0001-4943-0031*
[2] Sultan Idris Education University, phoong@fsmt.upsi.edu.my, ORCID: 0000-0002-9978-9771

where seasonal and nonlinear patterns exist. This study implies that it does not include external variables such as economic indicators, social media trends, or other external factors that influence tourism demand, which may limit the model's ability to capture sudden changes.

Keywords: *hybrid SARIMA-ANN, time series forecasting, tourist arrivals, hybrid model, accuracy*

Malezya'ya gelen turist sayılarını tahmin etmek için hibrit SARIMA-ANN yaklaşımı

Öz

Turist gelişlerinin doğru tahmin edilmesi, özellikle turizmin Gayri Safi Yurtiçi Hasıla'ya önemli katkı sağladığı Malezya'da stratejik planlama ve ekonomik büyüme için çok önemlidir. Mevsimsel Otoregresif Entegre Hareketli Ortalama (SARIMA) gibi geleneksel tahmin modelleri, doğrusal ve mevsimsel kalıpları etkili bir şekilde yakalar ancak doğrusal olmayan bağımlılıklarla çatışır. Buna karşılık, Yapay Sinir Ağı (YSA), doğrusal olmayan ilişkileri modellemede mükemmeldir ancak zamansal bağımlılıkları hesaba katmada başarısız olabilir. Bu sınırlamaları ele almak için, bu çalışma, tahmin doğruluğunu artırmak amacıyla her iki modelin güçlü yönlerini entegre eden hibrit bir SARIMA-YSA modeli önermektedir. Bu çalışmada, öncelikle doğrusal ve mevsimsel bileşenleri çıkarmak için SARIMA uygulanarak, ardından kalan doğrusal olmayan kalıpları yakalamak için YSA kullanılarak artıkları modellenerek hibrit bir SARIMA-YSA modeli geliştirilmiştir. Ampirik sonuçlar, SARIMA-YSA modelinin, zaman serisi verilerindeki hem doğrusal hem de doğrusal olmayan kalıpları etkili bir şekilde yakalama yeteneği sayesinde yüksek doğrulukta bir hibrit model sağlayabileceğini göstermektedir. SARIMA, mevsimselliği ve uzun vadeli eğilimleri etkili bir şekilde yakalarken, yapay sinir ağı (YSA), artıklar içindeki karmaşık doğrusal olmayan ilişkileri belirleyerek sınırlamalarının üstesinden gelir. Bu birleşik model, her iki modelin güçlü yönlerinden yararlanarak ve her bir modelin tek başına üstesinden gelemeyeceği sınırlamaları ele alarak tahmin hatalarını azaltır. Bu bulgular, turist gelişlerini tahmin etmek için hibrit zaman serisi modellemesinin etkinliğini vurgulayarak, mevsimsel ve doğrusal olmayan kalıpların bulunduğu diğer alanlarda potansiyel uygulamasını göstermektedir. Bu çalışma, ekonomik göstergeler, sosyal medya eğilimleri veya turizm talebini etkileyen diğer *dış faktörler gibi dış değişkenleri içermediğini ve bunun da modelin ani değişiklikleri yakalama yeteneğini sınırlayabileceğini ima etmektedir.*

Anahtar Kelimeler: *hibrit SARIMA-YSSA, zaman serisi tahmini, turist gelişleri, hibrit model, doğruluk*

Introduction

Forecasting of tourist arrivals is essential for effective planning and decision-making in the tourism industry (Huang and Zhang, 2024). Tourism in Malaysia plays an important role in contributing to the nation's economy. According to Tourism Malaysia (URL 1), the share of tourism income to the Gross Domestic Product (GDP) increased from 3.3% in 2000 to 7.4% in 2016. In 2017, the marketing activities from various shopping campaigns successfully boosted the tourist expenditure per capita, which expanded 3.2% with international tourist arrivals of 25.9 million and earned over RM 82.2 billion in receipts. In 2020, tourist arrivals in Malaysia decreased to 4.33 million compared to 26.1 million in 2019 due to the Covid-19 pandemic. The pandemic has put off the Visit Malaysia 2020 Campaign because of the travel restrictions worldwide.

Inaccurate forecasting of tourist arrivals can lead to ineffective resource allocation, financial losses, and misinformed policy decisions. Traditional models often fail to capture both seasonal trends and complex nonlinear relationships, resulting in unreliable predictions that may impact strategic planning in the tourism industry (Bouhaddour et al., 2024). The tourism industry has a big impact on the economic growth in Malaysia; thus, the forecasting number of tourist arrivals is crucial since it can be used to plan and improve the tourism-related industry.

In time series forecasting, there are a few types of forecasting models, but the most commonly used are time series models and causal econometric models. Traditional statistical models, such as the Seasonal Autoregressive Integrated Moving Average (SARIMA), have been widely employed to capture linear and seasonal patterns in time series data. However, these models often struggle to account for the complex nonlinear relationships inherent in tourism data. SARIMA struggles with nonlinear patterns, which are prevalent in tourism data due to varying factors like seasonality and economic conditions (My et al., 2024). Conversely, Artificial Neural

Networks (ANNs) are adept at modeling nonlinear patterns but may not effectively handle temporal dependencies and seasonality (Hewamalage et al., 2021).

To address these limitations, recent research has explored hybrid models that integrate SARIMA and ANN approaches, aiming to leverage the strengths of both methodologies for improved forecasting accuracy. The linear models could be the chosen models if they can estimate the data generation process well, but if they fail to perform, more complex nonlinear models should be considered (Yu et al., 2017). Based on a previous study, the hybrid model of Seasonal Autoregressive Integrated Moving Average (SARIMA) and Artificial Neural Network (ANN) has been developed to build a forecasting model to predict the number of tourist arrivals through Minangkabau International Airport in the future (Yollanda and Devianto, 2020). Since the residual of the SARIMA model has not fulfilled an autocorrelation assumption, they proposed a new model of SARIMA-ANN, which has a better performance based on the smallest value of Mean Absolute Percentage Error (MAPE).

Additionally, the SARIMA-ANN hybrid model has been applied in the field of hydrology and water resources to make accurate predictions of reservoir water levels in Red Hills, Tamil Nadu, India (Azad et al., 2022). Hybrid forecasting methods were applied to predict the indices of the consumer price index (CPI) and the expected number of cancer cases in Yemen's Ibb Province (Hadwan et al., 2022). The proposed methods include three models: the ARIMA model, the backpropagation neural network (BPNN) with adaptive slope and momentum parameters, a hybridization between ARIMA and BPNN (ARIMA/BPNN), and artificial neural networks and ARIMA (ARIMA/ANN) to gain the benefits of both linear and nonlinear modeling. Both studies highlight the effectiveness of hybrid models in improving forecasting accuracy. The SARIMA- ANN model enhances hydrological predictions, while the ARIMA-BPNN hybrid is useful in economic and health-related forecasting. These findings reinforce the adaptability of the hybrid model in diverse fields requiring precise time series predictions.

By integrating SARIMA's linear modeling strengths with ANN's nonlinear learning capabilities, the hybrid model is expected to deliver more accurate and reliable forecasts. Therefore, the objective of this study is to develop a hybrid SARIMA-ANN model to describe the linear and nonlinear patterns independently. Then, it is used to forecast the tourist arrivals in Malaysia.

Materials and methods

Hybrid SARIMA-ANN model

Generally, the number of inspections contains both linear and nonlinear patterns due to the seasonality, randomness, and complexity presented in time series. Hence, it may be inadequate to apply the linear and nonlinear methods, respectively. SARIMA and ANN algorithms have the strength to model linear and nonlinear issues (Parviz, 2020). The process of the hybrid model starts with the SARIMA model is employed to extract the linear component of the time series. Then, the residuals and the lagged data are employed as input for statistical ANN techniques. Finally, predictions were made based on the chosen model. The equation can be expressed as:

$$y_t = L_t + N_t \tag{1}$$

where L_t refers to the linear pattern in SARIMA and N_t represents the nonlinear component. The residual derived from the SARIMA model can be explained as:

$$\varepsilon_t = y_t - \hat{L}_t \tag{2}$$

where $\hat{L}_t$ indicates the representative of the forecasted value of SARIMA for time t . The residual analysis is the crucial part of identifying the nonlinear pattern of data. The residual modeling can be expressed as follows:

$$\varepsilon_t = f(\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-n}) + e_t \tag{3}$$

where f is a nonlinear function that can be determined by machine learning techniques and e_t is the random error. Figure 1 shows the flowchart of the hybrid SARIMA-ANN model which was adopted from Azad et. al (2022).

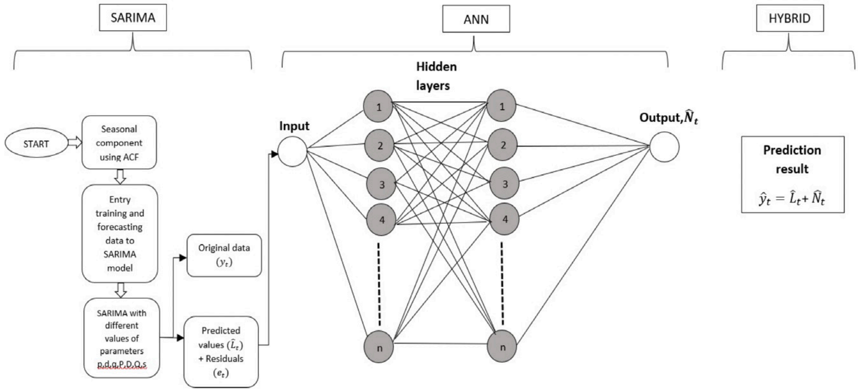

Figure 1. Flowchart of hybrid SARIMA-ANN model

The root mean square error (RMSE) and mean absolute error (MAE) are used to evaluate the performance of the hybrid SARIMA-ANN model based on the predicted and actual tourist arrivals. It can be formulated as follows:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum (\hat{y}_t - y_t)^2} \tag{4}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n} |y_t - \hat{y}_t| \tag{5}$$

where y_t denotes the value of the observation at time t, $\hat{y}_t$ refers to the fitted value for the observation at time t, and demonstrates the length of the forecast horizon. These metrics are important in assessing the effectiveness of forecasting models in many applications. The hybrid model consistently depicts lower RMSE and MAE values compared to the individual model of SARIMA or ANN. For instance, the hybrid SARIMA-ANN model outperformed traditional models in solar radiation forecasting, demonstrating superior accuracy in capturing nonlinear trends (Mukaram and Yusof, 2017).

Study area

The monthly number of tourist arrivals in Malaysia is taken as the study area, which was obtained from the Tourism Malaysia website (URL 1).

The dataset used in this study is from January 2000 to December 2022 and contains 270 monthly observations.

Results and discussion

Before constructing a SARIMA model, firstly, we need to evaluate the fluctuation of the data used. Figure 2 shows the time series plot of the number of tourist arrivals in Malaysia.

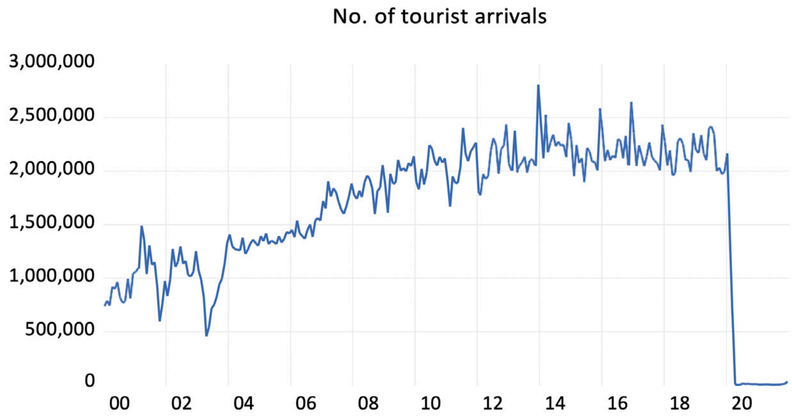

Figure 2. Time series plot of tourist arrivals in Malaysia

Based on Figure 2, the time series plot shows that the time series is an upward trend and that there is seasonality in the dataset. It also shows that the data is not stationary as its mean and variance are not constant through time. The ADF stationary test was conducted for this reason and it indicates that the dataset has a unit root which is non-stationary since the p-value is greater than

0.05. To make the data stationary, the data needs to be differencing and this process is repeated until the data is already stationary. Then, the parameters of p, q, P, and Q were identified by using ACF and PACF plots. The following figure shows the ACF and PACF plots after the first differencing.

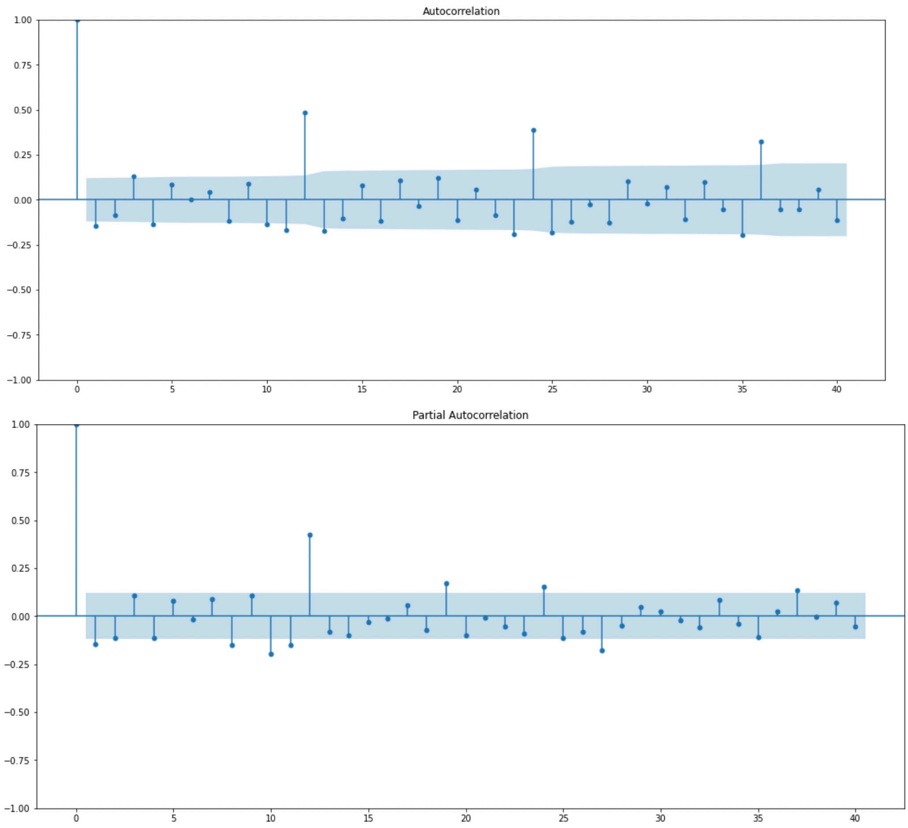

Figure 3. ACF and PACF plots after first differencing

In the earlier stage, the values for first-order non-seasonal differencing (d) and seasonal differencing (D) were determined as d = 1 and D = 0. Given that the dataset represents the monthly tourist arrivals in Malaysia, the seasonal period (S) is set to 12. To identify suitable values for p, q, P, and Q, the autocorrelation function (ACF) and partial autocorrelation function (PACF) were analyzed, as illustrated in Figure 3.

The ACF plot in Figure 3 exhibits a notable spike at lag 1, indicating a relationship between the current value and the previous error term, suggesting a non-seasonal MA(1) effect. Additionally, significant spikes appear at lag 12 and repeat at multiples of 12, such as 24 and 36, highlighting the presence of seasonality, which aligns with a seasonal MA(1) component.

Meanwhile, the PACF plot in Figure 3 shows a significant spike at lag 1, followed by a gradual decline, suggesting an AR(1) process. The occurrence of additional spikes at seasonal lags, particularly at lag 12, implies the presence of a seasonal AR component. The identified models would then be implemented using Python, evaluated for accuracy, and refined based on diagnostic checks and performance metrics.

The Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are commonly used for model selection, each offering distinct benefits and limitations. AIC balances model fit with complexity, aiming to minimize information loss, whereas BIC applies a stricter penalty for model complexity, making it a more conservative selection criterion. AIC is particularly beneficial when working with smaller sample sizes, as it helps identify a model that effectively explains the data while avoiding overfitting (Kuiper, 2021).

The model selection process involves evaluating different parameter combinations, comparing their AIC values, and selecting the model with the lowest AIC as the most suitable for forecasting. Numerous studies have utilized AIC and BIC to determine the optimal SARIMA model (Farsi et al., 2021).

Table 1. SARIMA model comparison

Model	AIC	BIC
SARIMA(1,1,0)(1,0,1)$_{12}$	5733.464	5746.946
SARIMA(1,1,1)(0,0,1)$_{12}$	5748.707	5762.190
SARIMA(0,1,1)(1,0,1)$_{12}$	**5727.858**	**5741.341**
SARIMA(0,1,0)(1,0,0)$_{12}$	5736.789	5743.530
SARIMA(0,1,1)(0,0,1)$_{12}$	5747.259	5757.371

The SARIMA(0,1,1)(1,0,1)$_{12}$ model was identified as the most suitable, having the lowest AIC (5727.858) and BIC (5741.341) values. The estimated model parameters were $p = 0$, $d = 1$, $q = 1$, $P = 1$, $D = 0$, and $Q = 1$. The absence of a non-seasonal AR term suggests that the model primarily relies on seasonal components and differencing for predictions. The dataset was divided into training and testing sets to evaluate the model's performance, following the commonly used 80:20 ratio, where 80% of the data was allocated for training and 20% for testing (Joseph, 2022). Figure 4 illustrates the selected SARIMA model parameters, processed using Python.

```
                                      SARIMAX Results
==========================================================================================
Dep. Variable:                          Tourists   No. Observations:                  216
Model:             ARIMA(0, 1, 1)x(1, 0, 1, 12)   Log Likelihood               -2859.929
Date:                          Tue, 27 Aug 2024   AIC                           5727.858
Time:                                  11:54:58   BIC                           5741.341
Sample:                              01-01-2000   HQIC                          5733.306
                                   - 12-01-2017
Covariance Type:                            opg
==============================================================================
                 coef    std err          z      P>|z|      [0.025      0.975]
------------------------------------------------------------------------------
ma.L1         -0.3073      0.079     -3.901      0.000      -0.462      -0.153
ar.S.L12       0.8066      0.118      6.845      0.000       0.576       1.038
ma.S.L12      -0.4487      0.190     -2.364      0.018      -0.821      -0.077
sigma2      2.857e+10   8.99e-13   3.18e+22      0.000    2.86e+10    2.86e+10
===================================================================================
Ljung-Box (L1) (Q):                   0.13   Jarque-Bera (JB):                70.23
Prob(Q):                              0.72   Prob(JB):                         0.00
Heteroskedasticity (H):               0.88   Skew:                             0.12
Prob(H) (two-sided):                  0.58   Kurtosis:                         5.79
===================================================================================

Warnings:
[1] Covariance matrix calculated using the outer product of gradients (complex-step).
[2] Covariance matrix is singular or near-singular, with condition number 3.21e+38. Standard errors may be unstable.
```

Figure 4. Model parameters

Based on Figure 5, ma.L1 represents the non-seasonal moving average (MA) term, where $q = 1$ and the estimated coefficient of -0.30703 is statistically significant, as indicated by a p-value less than 0.05. This suggests that the immediate past residual has a notable impact on the current value. The negative coefficient implies that an increase in the previous residual leads to a decrease in the current predicted value (Box et al., 2008).

The seasonal autoregressive (AR) term, $P = 1$ denoted as ar.S.L12 in Figure 4, has a coefficient of 0.8066, which is also highly significant with a p-value less than 0.05. This indicates a strong seasonal autoregressive effect, where the value from 12 periods ago—corresponding to the same month in the previous year—positively influences the current value. Similarly, ma.S.L12, representing the seasonal moving average (MA) term with $Q = 1$ is statistically significant, with a coefficient of -0.4487 and a p-value less than 0.05. This finding suggests that the error from 12 months prior has an impact on the current value, with the negative coefficient indicating that a positive residual from the same period in the previous year reduces the current forecast (Hyndman and Athanasopoulos, 2018).

The estimated residual variance, represented by sigma² in Figure 4, appears to be a large value. However, this is expected in models dealing with large-scale data, such as the number of tourist arrivals, as it reflects the magnitude of the dataset being analyzed (Chikobvu and Makoni, 2019). The SARIMA model comprised a non-seasonal MA(1), one seasonal AR(1) and one seasonal MA(1) polynomials. These polynomials are presented as:

$$(1 - \Phi_1 B^{12})(1 - B)X_t = (1 - \theta_1 B)(1 - \Theta_1 B^{12})\, Z_t \tag{6}$$

The parameters from the output given as $\Phi_1 = 0.8066$, $\theta_1 = -0.3073$ while $\Theta_1 = -0.4487$. By substituting the value of the parameters into equation (1), the SARIMA model equation can be as:

$$(1 - 0.8066B^{12})(1 - B)\, X_t = (1 + 0.3073B)(1 + 0.4487B^{12})\, Z_t \tag{7}$$

The next step is performing diagnostic checks for SARIMA models which is crucial to verify the model's adequacy and reliability in accurately capturing the underlying patterns within the data.

Figure 5 presents four plots. The top-left plot displays the residuals over time, showing no seasonal component, as it was removed during data preprocessing. In the top-right plot, the orange KDE line closely follows a normal (Gaussian) distribution, characterized by a mean (μ) and standard deviation (σ), which is desirable for model validation.

The bottom-left plot indicates that all blue dots align closely with the red reference line, suggesting that the residuals follow a normal distribution. Meanwhile, the bottom-right plot, a correlogram, demonstrates that the residuals exhibit low correlation with their lagged values, as most lags fall within the confidence intervals, confirming that the residuals are uncorrelated with the time series.

Overall, the SARIMA(0,1,1)(1,0,1)12 model effectively captures both non-seasonal and seasonal components. The Ljung-Box test in Figure 4 yielded a *p*-value of 0.13, indicating no statistically significant autocorrelation in the residuals.

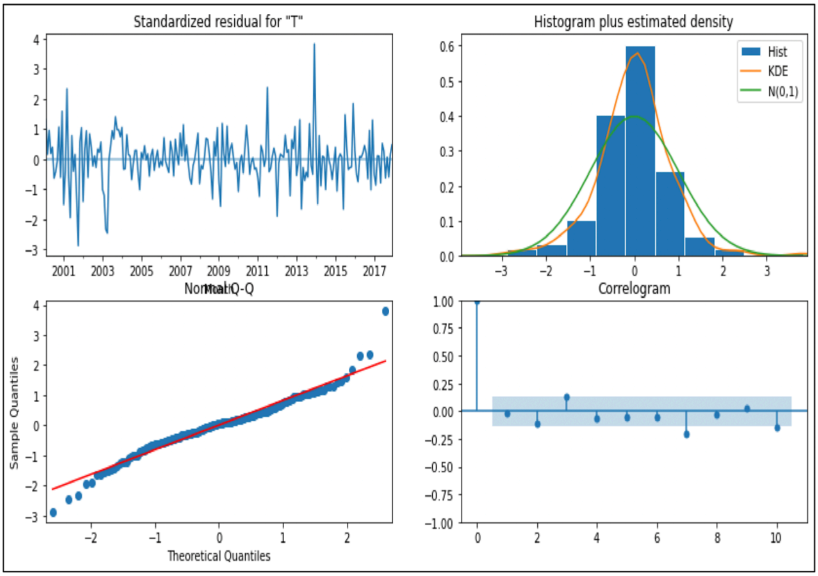

Figure 5. Residual diagnostic, histogram plus estimated density, normal Q-Q and correlogram

Figure 6 presents the actual and predicted values for the testing data. Initially, the model performs well, with the predicted values (orange line) closely aligning with the actual values (blue line) at the beginning of the series. However, at a certain point, the actual values experienced a sharp decline in March 2020, while the predicted values remained relatively stable. This noticeable discrepancy suggests that the model failed to account for a crucial structural change in the data.

The significant deviations between actual and predicted values in time series analysis often indicate that the model has not effectively captured an underlying anomaly or shift in the data (Darban et al., 2022). In this case, the decline corresponds to the COVID-19 outbreak and the subsequent implementation of the Movement Control Order (MCO) by the government in March 2020. This plot highlights that while the model performs adequately during stable periods, it struggles with sudden changes, emphasizing the need for greater model flexibility or the incorporation of a more adaptive forecasting approach.

Figure 6. Actual and predicted plot for testing data using SARIMA

Time series data is commonly forecasted using linear models; however, the residuals from these models often exhibit nonlinear patterns (Rajalakshmi and Vaidyanathan, 2022). When the residuals of a SARIMA model contain both a signal and white noise, an ANN model can be employed to capture and extract the underlying signal. This forms the foundation of the hybrid SARIMA-ANN approach, which aims to enhance forecast accuracy by leveraging both linear and nonlinear modeling techniques. In this process, the residuals from the SARIMA model are further modeled using an ANN to refine the predictions.

The neural network architecture consists of four layers: an input layer with 12 features and 12 neurons, two hidden layers containing 50 and 25 neurons, respectively, and an output layer with a single neuron. Table 2 presents the parameters utilized in constructing the hybrid SARIMA-ANN model. The model employs a window size of 12 inputs, with the number of epochs set to 500 and a batch size of 32.

Table 2. Parameters for SARIMA-ANN model building

Parameters	Values
Window size	12
Epochs	500
Batch size	32

Figure 7 provides an overview of the hybrid SARIMA-ANN model. The input layer consists of 12 features derived from SARIMA residuals, with 12 neurons utilizing the ReLU activation function. ReLU is widely used in classification tasks as it effectively eliminates negative values (Justin et al., 2024).

The first hidden layer receives 12 neurons as input from the previous layer and consists of 50 neurons. Similarly, the second hidden layer processes the output from the first hidden layer (50 neurons) and contains 25 neurons. Lastly, the output layer takes input from the second hidden layer (25 neurons) and consists of a single neuron. The number of neurons in the hidden layers was determined through an iterative trial-and-error process, considering practical guidelines for optimal performance (Pushpa et al., 2022). A common recommendation suggests that the number of hidden neurons should not exceed two-thirds of the input neurons (Mapuwei et al., 2020). Additionally, the model comprises a total of 2,107 trainable parameters, meaning all weights and biases are adjusted during the training process.

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 dense (Dense)               (None, 12)                156

 dense_1 (Dense)             (None, 50)                650

 dense_2 (Dense)             (None, 25)                1275

 dense_3 (Dense)             (None, 1)                 26

 activation (Activation)     (None, 1)                 0

=================================================================
Total params: 2,107
Trainable params: 2,107
Non-trainable params: 0
_________________________________________________________________
```

Figure 7. Summary of hybrid model

Figure 8 illustrates the structure of the ANN model, which consists of three layers. The input layer serves as the entry point for the data, with each neuron representing a specific feature from the dataset that the neural network will process.

The hidden layer is where the core computations take place. Each neuron in this layer applies a weighted transformation to the input values and processes them through an activation function before passing the result to the next layer.

]The output layer generates the final prediction or classification outcome. The number of neurons in this layer depends on the task type. For regression problems, a single neuron is typically used to produce a continuous value, while for classification tasks, multiple neurons correspond to different categories, each representing a probability for a specific class.

This diagram provides a visual representation of how data flows through the network, moving from the input layer through one or more hidden layers where transformations occur before reaching the output layer.

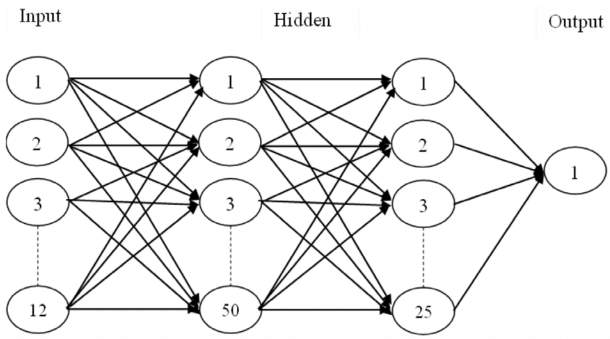

Figure 8. ANN model architecture

Figure 9 shows a comparison between the actual (blue line) and predicted (red line) values generated by the hybrid SARIMA-ANN model. The plot demonstrates that the predicted monthly tourist arrivals closely follow the pattern of the actual data, particularly in the earlier part of the series, indicating enhanced model efficiency.

The graph also highlights a sharp and sudden drop at the same point in both the actual and predicted values. This suggests that the hybrid model effectively captures this trend, outperforming individual models in adapting to abrupt changes. Following the decline, the model continues to generate stable predictions, closely tracking the overall pattern of actual tourist arrivals. While some discrepancies remain, especially toward the later part of the series, the hybrid model reduces prediction errors compared to standalone SARIMA and ANN models.

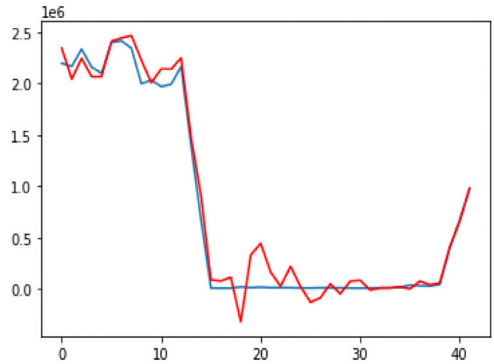

Figure 9. Actual and predicted plot using Hybrid SARIMA-ANN model

Additionally, the hybrid SARIMA-ANN model provides a more precise forecast than individual models, successfully capturing overall trends and sudden fluctuations. While some minor deviations are observed in the later data, this model significantly minimizes prediction errors, thereby enhancing its reliability as a forecasting tool. The finding of the hybrid SARIMA-ANN model in this study is consistent with previous studies, which indicate that hybrid approaches outperform individual models. For instance, Pushpa et al. (2022) demonstrated that the hybrid SARIMA-ANN model resulted in a lower Mean Absolute Percentage Error (MAPE) and high robustness in modeling the seasonal agricultural price data.

Similarly, Yollanda and Devianto (2020) reported that integrating ANN on SARIMA residuals yields significant improvements in forecasting the number of tourist arrivals at Minangkabau International Airport. Both studies reinforce the findings in current research, which reveal that while SARIMA effectively captures seasonality, it leaves behind structured residuals that are successfully modeled by ANN.

Furthermore, the hybrid model can follow the actual series during periods of drastic transition, such as the downturn during the COVID-19 pandemic, which demonstrates its ability to adapt to anomalies better than SARIMA alone. While some deviations still exist in post-pandemic observations, the hybrid approach reduces the margin of error and provides a more stable forecasting framework than the single method.

In terms of forecasting performance, the hybrid SARIMA-ANN model produced an RMSE of 136,269.69 and an MAE of 95,175.67, indicating that, on average, the predicted number of tourist arrivals deviated from the actual number by approximately 95,000 tourists. Given the scale of monthly tourist arrivals in Malaysia, which range from a few hundred to over two million visitors, this error value is relatively low. It indicates that the model is able to provide estimates that are close to real-world patterns. Meanwhile, RMSE shows larger errors more severely, further validating the robustness of the model in minimizing extreme deviations, an important feature in tourism forecasting where sudden spikes or drops, such as during the COVID-19 outbreak, can significantly affect the planning decision. Furthermore, the model can detect and adapt to the sharp drop in tourist arrivals in March 2020, which corresponds to the implementation of the Movement Control Order (MCO) and it reflects the ability to capture real anomalies in the data.

These results are consistent with those of previous studies conducted by Yollanda and Devianto (2020), who observed the improved forecast accuracy with the SARIMA-ANN model in forecasting international tourist arrivals in Indonesia. Similarly, Pushpa et al. (2022) and Azad et al. (2022) also reported reduced RMSE and MAE values when using hybrid models for agricultural and hydrological forecasts, respectively, reinforcing the strength of combining linear and nonlinear modeling techniques. In the context of Malaysian tourism, where fluctuations are influenced by factors such as seasons, festivals, and global crises, the SARIMA-ANN hybrid model has proven to be a reliable and responsive forecasting tool.

In this study, the hybrid SARIMA-ANN model combines the linear SARIMA forecast with the non-linear residuals forecasted by the ANN. Thus, the general equation for the hybrid model is:

$$\hat{Y}_{hybrid}(t) = \hat{Y}_{SARIMA}(t) + \hat{E}_{ANN}(t) \tag{8}$$

where $\hat{Y}_{hybrid}(t)$ is the final hybrid forecast at time *t*, $\hat{Y}_{SARIMA}(t)$ is the SARIMA forecast at time *t* and is the residual forecasted by the ANN at time *t*.

Hybrid SARIMA$(0,1,1)(1,0,1)_{12}$ – ANN(1,2,1) model was developed to forecast the number of tourist arrivals for the following 12 months. For the SARIMA component model, the equation is as in equation (5). When expanding this equation becomes:

$$y_t - By_t - 0.8066B^{12}y_t + 0.8066B^{13}y_t = e_t + 0.3073Be_t + 0.4487B^{12}e_t 0.13789B^{13}e_t \quad (9)$$

The SARIMA forecast, $\hat{Y}_{SARIMA}(t)$ is calculated using this equation for each time step *t.* Next, for the ANN component, the residual from the SARIMA model, $E(t) = y_{actual}(t) - \hat{Y}_{SARIMA}(t)$, contains nonlinear patterns that the SARIMA model does not capture. The ANN is trained on these residuals to model nonlinear patterns and predict future residuals. For the ANN part,

$$\hat{E}_{ANN}(t) = f\left(E(t-12), E(t-11), \ldots, E(t-1)\right) \quad (10)$$

where f is the nonlinear function learned by the ANN model and $E\,(t - i)$ are the residuals from previous time steps (up to 12 months).

$$\hat{Y}_{hybrid}(t) = \hat{Y}_{SARIMA}(t) + f\left(E\,(t-12), E\,(t-11), \ldots, E\,(t-1)\right) \quad (11)$$

where $\hat{Y}_{SARIMA}(t)$ is the SARIMA forecast from SARIMA(0,1,1)(1,0,1)12 and $E\,(t - i)$ are the residuals from previous time steps (up to 12 months).

Conclusion

The hybrid SARIMA-ANN model developed for forecasting tourist arrivals in Malaysia demonstrated significant improvements in accuracy. Results show that the hybrid model for tourist arrivals in Malaysia is $\hat{Y}_{hybrid}(t) = \hat{Y}_{SARIMA}(t) + f(E(t-12), E(t-11), \ldots, E(t-1))$ where $\hat{Y}_{SARIMA}(t)$ is the SARIMA forecast from SARIMA(0,1,1)(1,0,1)12 and $E(t - 1)$are the residuals from previous time steps (up to 12 months). These findings suggest that the hybrid model successfully integrates SARIMA's ability to model seasonality with ANN's capacity to capture complex nonlinear dependencies. The improved performance indicates that the residuals from the SARIMA model contained meaningful nonlinear patterns, which the ANN effectively learned, leading to significantly lower forecast errors. The residuals, which represent the errors or discrepancies not accounted for by the SARIMA model, contain meaningful nonlinear patterns and information that can be leveraged to improve performance accuracy.

This aligns with recent studies that reveal the effectiveness of the hybrid model in addressing complex forecasting tasks. Saba et al. (2022) reported that the advantage of combining a linear model, such as SARIMA, with a nonlinear model, such as ANN, demonstrated significant improvement in forecasting tourist arrivals in New Zealand, Australia, and London. Moreover, the hybrid model SARIMA-ANN has been successfully applied to different datasets, including forecasting daily tourist arrivals to Macau, China. This study also revealed that the SARIMA component addressed linear trends and seasonal patterns, while the ANN captured complex nonlinear patterns (Wu et al., 2021).

This study also contributes to the growing body of literature that supports the use of hybrid models in real-world forecasting applications, particularly in industries where accurate predictions are crucial for resource allocation, marketing, and policy formulation. The ability of the hybrid SARIMA-ANN model to accurately forecast tourist arrivals is critical for the Malaysian tourism sector, where significant seasonal fluctuations and non-linear dependencies exist. This research highlights the importance of hybrid models in tourism demand forecasting, as they offer a more robust and flexible solution compared to traditional forecasting methods.

Furthermore, the hybrid SARIMA-ANN model can be generalized to other regions facing similar challenges in tourism forecasting. The model's regional applicability extends to other areas such as the United States and Indonesia, where the hybrid model has been used to forecast monthly tourist arrivals with high accuracy (Misengo et al., 2023). Similarly, in a study on tourism demand forecasting in the Philippines, the hybrid SVR-SARIMA model was found to be the best forecasting model, outperforming other considered models in terms of error magnitude, directionality, and trend change (Abellana et al.,2021).

In conclusion, the hybrid SARIMA-ANN model offers a powerful framework for forecasting tourist arrivals in Malaysia, yielding accurate predictions by incorporating both linear and nonlinear components. This approach provides a promising avenue for future studies and practical applications in tourism demand forecasting. Given the increasing need for precise forecasting in the tourism sector, the hybrid model can serve as an effective tool for policymakers, industry professionals, and researchers alike.

Conflict of interest statement

There is no conflict of interest between the authors.

Ethics statement

This study did not involve human participants, animal subjects, or any sensitive personal data. Therefore, approval from an ethics committee was not required. The research was conducted using publicly available secondary data on monthly tourist arrivals in Malaysia obtained from the official Tourism Malaysia website. All procedures adhered to academic integrity and ethical research standards.

Acknowledgement

The authors would like to express their deepest appreciation to Universiti Pendidikan Sultan Idris for their support and encouragement, which made this paper complete efficiently.

References

[1] Abellana, D.P.M., Rivero, D.M.C., Aparente, M.E., & Rivero, A. (2021). Hybrid SVR-SARIMA model for tourism forecasting using PROMETHEE II as a selection methodology: a Philippine scenario. *Journal of Tourism Futures*, 7(1), 78-97.

[2] Azad, A.S., Sokkalingam, R., Daud, H., Adhikary, S. K., Khurshid, H., Mazlan, S. N. A., & Rabbani, M. B. A. (2022). Water level prediction through hybrid SARIMA and ANN models based on time series analysis: Red hills reservoir case study. *Sustainability*, 14(3), 1843.

[3] Bouhaddour, S., Sbihi, M., Guerouate, F., Saadi, C. (2024). Assessing tourism prediction models: A comparative study of SARIMA, Random Forest, and LSTM, Considering nonlinear trends and the influence of COVID-19. *International Information and Engineering Technology Association*, 29(6), 2443-2454.

[4] Box, G.E.P., Jenkins, G.M., Reinsel, G.C. (2008). *Time series analysis: Forecasting and control* (4th ed.). John Wiley and Sons, Hoboken, New Jersey.

[5] Chikobvu, D., Makoni, T. (2019). Statistical modelling of Zimbabwe's international tourist arrivals using both symmetric and asymmetric volatility models. *Journal of Economic and Financial Sciences*, 12(1), 1-10.

[6] Darban, Z.Z., Webb, G.I., Pan, S., Aggarwal, C.C., Salehi, M. (2022). Deep learning for time series anomaly detection: A survey. *ACM Computing Surveys*, 57(1), 1-42.

[7] Farsi, M., Hosahalli, D., Manjunatha, B.R., Gad, I., Atlam, E.S., Ahmed, A., Elmarhomy, G., Elmarhoumy, M., Ghoneim, O.A. (2021).

Parallel genetic algorithms for optimizing the SARIMA model for better forecasting of the NCDC weather data. *Alexandria Engineering Journal*, 60(1), 1299-1316.

[8] Hadwan, M., Al-Maqaleh, B.M., Al-Badani, F.N., Khan, R.U., Al-Hagery, M.A. (2022). A hybrid neural network and box-jenkins models for time series forecasting. *Computers, Materials and Continua*, 70(3), 4829-4845.

[9] Hewamalage, H., Bergmeir, C., Bandara, K. (2021). Recurrent neural networks for time series forecasting: Current status and future directions. *International Journal of Forecasting*, 37(1), 388- 427.

[10] Huang, J., Zhang, C. (2024). Daily tourism demand forecasting with the iTransformer Model. *Sustainability*, 16(23), 10678.

[11] Hyndman, R.J., Athanasopoulos, G. (2018). Forecasting: Principles and practice. OTexts, Melbourne, Australia.

[12] Joseph, V.R. (2022). Optimal ratio for data splitting. Statistical Analysis and Data Mining, 15(4), 531-538.

[13] Justin, S., Waoo, A., Waoo, A.A. (2024). Performance analysis of activation functions in neural networks. ShodhKosh: *Journal of Visual and Performing Arts*, 5(1), 588-598.

[14] Kuiper, R.M. (2021). AIC-type Theory-Based Model selection for structural equation models. *Structural Equation Modeling: A Multidisciplinary Journal*, 29(1), 151-158.

[15] Mapuwei, T.W., Bodhlyera, O., Mwambi, H. (2020). Univariate time series analysis of short-term forecasting horizons using artificial neural networks: The case of public ambulance emergency preparedness. *Journal of Applied Mathematics*, 2020(1), 2408698.

[16] Misengo, E.E., Prastyo, D. D., and Kuswanto, H. (2023). Modeling and Forecasting Monthly Tourist Arrivals to the United States and Indonesia Using ARIMA Hybrids of Multilayer Perceptron Models. *AIP Conference Proceedings*, 2540.

[17] Mukaram, M. Z., and Yusof, F. (2017). Solar radiation forecast using hybrid SARIMA and ANN model. *Malaysian Journal of Fundamental and Applied Sciences*, 13, 346–350.

[18] My, H., Setyowati, S.L., Notodiputro K.A., Angraini, Y., Mualifah,

L.N.A. (2024). Comparison of seasonal ARIMA and support vector machine forecasting method for international arrival in Lombok. *Jambura Journal of Mathematics*, 6(2), 212-219.

[19] Parviz, L. (2020). Comparative evaluation of hybrid sarima and machine learning techniques based on time-varying and decomposition of precipitation time series. *Journal of Agricultural Science and Technology*, 22(2), 563-578.

[20] Pushpa, P., Kumar J, Vikram, G. (2022). Hybrid Sarima-Ann model for forecasting monthly wholesale price and arrival series of tomato crop. *Biological Forum – An International Journal*, 14(4a), 591- 596.

[21] Rajalakshmi, V., Vaidyanathan, S.G. (2022). Hybrid time-series forecasting Models for traffic flow prediction. *Promet - Traffic - Traffico*, 34(4), 537-549.

[22] Saba, T., Shahzad, M. N., Iqbal, S., Rehman, A., & Abunadi, I. (2022). A New Hybrid SARFIMA-ANN Model for Tourism Forecasting. *Computers, Materials & Continua*, 71(3), 4785–4801.

[23] Wu, D. C. W., Ji, L., He, K., and Tso, K. F. G. (2021). Forecasting Tourist Daily Arrivals With A Hybrid Sarima–Lstm Approach. *Journal of Hospitality and Tourism Research*, 45(1), 52–67.

[24] Yollanda M, Devianto D. (2020). Hybrid Model of Seasonal ARIMA-ANN to forecast tourist arrivals through Minangkabau International Airport. *Proceedings of the 1st International Conference on Statistics and Analytics*, ICSA 2019, 2-3 August 2019, Bogor, Indonesia.

[25] Yu Y, Wang Y, Gao S, Tang Z. (2017). Statistical modeling and prediction for tourism economy using dendritic neural network. *Computational Intelligence and Neuroscience*, 2017(1), 7436948.

Internet references

URL 1 Tourism Malaysia. (2019). Putrajaya, Malaysia Tourism Promotion Board (MTPB); [accessed October 2020]. https://www.tourism.gov.my/activities/view/tourism-malaysia-2017-annual- report