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Use of Change Point Analysis in Seasonal ARIMA Models for Forecasting Tourist Arrivals in Sri Lanka

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Abstract

Sri Lanka is a popular place that attracts foreign travelers, and the impact of the tourism industry has a major contribution to the Sri Lankan economy. The main objective of this study is to model the behavior and forecast tourist arrivals in Sri Lanka through a time-series approach with Change Point Analysis (CPA). Autoregressive Integrated Moving Average (ARIMA) was extended to Seasonal Autoregressive Integrated Moving Average (SARIMA) with the seasonality behavior of the tourist arrivals. The better performed models were identified using the minimum Akaike Information Criterion (AIC) while performance indicators of Mean Absolute Percentage Error (MAPE) and Normalized Root Mean Squared Error (NRMSE) were applied to evaluate the actual and fitted values. The model diagnostics were used to assess the goodness of fit of a selected model. Monthly data from January 2000 to December 2019 was used in the analysis and during this period a total of 20,217,026 tourists arrived in Sri Lanka. Moreover, there are certain decline periods of this volume mainly due to the impacts of civil war, Tsunami and many others. The findings indicate that the model ARIMA (2,1,2) $(3,1,4)_{[3]}$ captures the behavior well with a minimum MAPE of 0.1941 and NRMSE of 0.8800. Meanwhile, with the application of CPA (at most one change and pruned exact linear time), data was split into two separate windows, which are Window 1 (W1) from January 2000 to October 2011 and Window 2 (W2) from November 2011 to December 2019. In W1, the better model that was used in the prediction was ARIMA (1,1,1) $(4,1,1)_{[3]}$ with a MAPE and NRMSE of 0.1727 and 1.1190 respectively. According to the results, the better performed model (MAPE of 0.2740 and NRMSE of 0.8700) in W2, was ARIMA (0,1,1) $(3,1,3)_{[3]}$ and this model captured the behavior until April 2019. However, due to the Easter bomb attack in April, there was a sudden drop in the arrival of tourists in May and June 2019. Nevertheless, from this point onwards the predicted line captured the behavior of the actual values even though they did not coincide with each other. Again, in December 2019, the predicted and actual values were very close. Thus, this study will be a benefit for both the private and public sectors as it has a prominent impact on the economy of the country.

Key words: Tourism; Time-series; Change point analysis; Forecasting; Seasonal Autoregressive Integrated Moving Average.

1. Introduction

Tourism is a crucial scope that has a direct impact on the economy around the world. When a location becomes a major tourist destination this affects advantageously to a country. Some of them facilitate new job opportunities in different sectors like health, education, and

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agriculture, revealing the cultural and social values of the country to the world, earning profits, developing the infrastructure and many others.

According to the Sri Lanka Tourism Development Authority, modern commercial tourism was initiated in 1960 with a long history and in this period 18,969 tourists arrived in Sri Lanka. Nevertheless, the terrorist attacks from 1983 to 2009, had a negative impact on this industry for a long period. In addition, the Tsunami hazard that occurred in 2004, resulted in many deaths and property damages whereas it indicated a decline in the growth of the tourism industry. For more than 25 years, there were deprivations caused by the civil war and at the end of the war, there was a significant development in the industry of tourism in Sri Lanka. At the same time due to the Easter Sunday bomb attack in April 2019, the number of tourists who arrived in Sri Lanka decreased.

This study mainly focuses and attempts on forecasting tourist arrivals in Sri Lanka by identifying the patterns in arrivals using the time series models. Furthermore, sudden changes are identified by the change point detections.

In Sri Lanka, the planning and policy implementation activities related to tourism are implemented by the Tourism Development Authority. Therefore, this work will benefit the government as well as the private sector for their future investments and progress. Moreover, this study will support the sustainability of the tourism industry and the processes related to the conservation of resources such as wildlife, cultural heritages and other natural resources.

There are many studies conducted relevant to the prediction of tourist arrivals in many countries including Sri Lanka. However, there is no related work identified with the change point analysis (CPA) to predict the volume of tourists in Sri Lanka.

This paper is organized as follows. The subsequent section is a review of previous related works. Sections 3 and 4 consist of the methodology and data analysis respectively. Section 5 includes the discussion and section 6 consists of the conclusions of the study.

2. Literature Review

Different previous studies were conducted relevant to tourism in many countries with different techniques.

In 1984, Jozef suggested that Harrison's harmonic smoothing technique was more appropriate to predict the foreign tourists who arrived in Netherland compared to the decomposition technique and Box Jenkins generalized adaptive filtering. An exponentially weighted non-linear time series approach with a sine function in time was used by Chan (1993) to forecast the volume of tourist arrival in Singapore after de-seasonalizing data due to the seasonal behavior and model performance was evaluated from the Mean Absolute Percentage Error (MAPE). Using Seasonal Autoregressive Integrated Moving Average (SARIMA) and Multivariate Autoregressive Integrated Moving Average (MARIMA), Goh and Law (2002) forecasted the tourist demand for Hong Kong with ten arrival series and the non-stationary behavior was recognized from the Augmented Dickey-Fuller test. Lim *et al.* (2002) found that the number of tourist arrivals from Singapore to Australia followed an Autoregressive Integrated Moving Average (ARIMA) approach where arrivals to Malaysia and Hong Kong extended with the SARIMA method. Similarly, many studies applied the ARIMA and SARIMA techniques in forecasting the tourist arrivals such as Saayman and Saayman (2010); Singh (2013); Kumar and Sharma (2016); Chhorn and Chaiboonsri (2017), and many others.

Cho (2003) applied three techniques: Exponential smoothing, SARIMA and Artificial Neural Network (ANN) to identify the travel demand to Hong Kong from different countries and claimed that ANN exhibited better forecasting with minimum errors for the series with the fewer fluctuations and ARIMA approach was better for the arrival patterns with obvious patterns.

ANN and hybrid models were built as the alternatives to the ARIMA models in the study of Aslanargun *et al.* (2007) and they stated that the models with components of non-linear indicated better performance. Moreover, the studies of Law and Au (1999) and Pai *et al*. (2006) have used the data science concept in forecasting tourist arrivals.

Due to the impacts of the Civil war and political influence in Sri Lanka, there were ups and downs in the tourism industry from 2003 to 2009. After the end of the war in 2009, Sri Lanka became a significant tourist destination as per the study of Fernando *et al.* in 2017. They claimed that Sri Lanka needs to increase the accommodation and infrastructure facilities with the tourism workforce.

Arrivals from the Western European countries (UK, Germany, France, Italy and Netherland) to Sri Lanka were considered by Konarasinghe *et al.* (2016) as they were the main contributors to the market of tourism in Sri Lanka. The patterns in arrivals were detected using time series plots and Auto-Correlation Functions (ACF) with the decomposition techniques. They concluded the additive decomposition model was better and recommended the circular model to increase the accuracy in forecasting. Peiris (2016) conducted a study after identifying seasonality in the monthly data for the period from January 1995 to July 2016 with the Hegy test. In this study, the SARIMA (1,0,16) $(36,0,24)_{[12]}$ model was identified as a better performed model to forecast the arrivals of tourists in Sri Lanka. However, using the monthly time series data from June 2009 to December 2018, the study of Nyoni in 2019 identified the optimal model with the minimum MAPE of 8.6877% value in the SARIMA (0, 1, 1) $(0, 1, 1)_{[12]}$ to forecast tourist arrivals in Sri Lanka.

The change point detections are vital in practical situations such as in financial analysis, climatology, and many other areas (Eckley *et al*., 2011). The At Most One Change Point (AMOC) method was repeatedly applied to detect multiple change points in climate by Wang in 2006. In addition, a study conducted by Lund *et al*. (2007) claimed the shifts in time series can be pointed out by the AMOC method.

Bakka (2018) stated that the Pruned Exact Linear Method (PELT) performed well in the univariate Gaussian series compared to the Binary segmentation method. Chapman and Killick (2020) assessed the prediction with change points in software applications using the PELT method and suggested that CPA is very useful in the cases of a large amount of data.

However, in this study, SARIMA models were built for the seasonal difference of 3, 6 and 12 separately based on combined pre and post war eras. Further, this study used the CPA to detect the important changes in arrivals. Following the CPA, separate new time series models were built for the windows with different seasonal differences. Thereafter, an attempt was made to identify the appropriate models with the lowest Akaike Information Criterion (AIC) value for each seasonal difference and recognized the better model for the prediction of tourist arrivals using the performance measures MAPE and normalized root mean squared error (NRMSE).

3. Methodology

Month wise data from January 2000 to December 2019 was obtained from the website of Sri Lanka Tourism Development Authority. Initially, the behavior of the data was recognized with the time-series plots where basic features were identified using descriptive analysis. For further analysis, time-series data was split for training and testing in a non-random manner. The stationary or the non-stationary behavior was pointed out using the ACF and PACF plots with the number of cut-off lags. Furthermore, unit root tests were applied to check the stationarity. Applied unit root tests are:

Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test

H_0: The series is stationary

H_1: The series is not stationary

Augmented Dickey-Fuller test (ADF) test and Phillips-Perron test (PP) test

H_0: The series possesses a unit root (The series is not stationary)

H_1: The series do not possess a unit root (The series is stationary)

For these three tests, if the *p*-value is less than the considered significant level, H_0 (Null hypothesis) is rejected at the significance level.

The non-stationary data was converted to stationary through the application of different transformations. Seasonality features were identified with the patterns in ACF, PACF plots and using the Webel-Ollech (WO) test. The WO is an overall seasonality test that merged results from QS-test and the Kwman-test. This test identifies the seasonality in the series by the QS-test if the *p*-value is below 0.01 and by the Kwman-test if the *p*-value is lower than 0.002.

ARIMA models are wide-ranging applications in time series analysis to realize the behavior of data and for prediction. The general form of the ARIMA model illustrates below:

$$ARIMA\ (p,\ d,\ q) \tag{1}$$

where p is the number of parameters in the autoregressive (AR) model, d is the differencing degree, q is the number of parameters in the Moving Average (MA) model. However, with the seasonality behavior, the ARIMA was extended to SARIMA. The general form of the SARIMA model is in Equation 2:

$$ARIMA\ (p,d,\ q)\ (P,D,Q)_s \tag{2}$$

where p is the number of parameters in the autoregressive (AR) model, d is the differencing degree, q is the number of parameters in the MA model, P is the number of parameters in the seasonal AR model, D is the seasonal differencing degree, Q is the number of parameters in seasonal MA model and s is the period of seasonality.

The parameters of ARIMA and SARIMA models are identified by the Auto-Correlation Function (ACF) and Partial Auto-Correlation Function (PACF). For the built SARIMA models, Akaike Information Criterion (AIC) was used to identify the better model with the minimum AIC value. Model assumptions of heteroscedasticity, autocorrelation and normality of residuals (model diagnostics) were evaluated using the tests ARCH, Ljung-Box and Jarque-Bera respectively for the selected models and they are below:

Heteroscedasticity: ARCH test

H_0: There is no heteroscedasticity in the residuals

H_1: There is heteroscedasticity in the residuals

Autocorrelation: Ljung-Box Test on Residuals

H_0: There is no autocorrelation in the residuals

H_1: There is autocorrelation in the residuals

Normality: Jarque –Bera Test

H_0: Residuals are normally distributed

H_1: Residuals are not normally distributed

The ARCH test is used to identify the behavior of the error term variance and if the residuals are homoscedastic then the p-value of the test is greater than the considered significant level. Also, in time series modeling the error terms should be free of autocorrelation and if there is no autocorrelation then the p-value is greater than the significance level for the Ljung-Box tests. Jarque-Bera test is a goodness of fit test which is used to detect the normality behavior of the residuals and in the presence of the normality for this test, the p-value is greater than the given significance level.

Then the selected model was used to predict the values in the test set (final 10% of data). The model accuracy was identified using Mean Absolute Percentage Error (MAPE) and Normalized Root Mean Squared Error (NRMSE) and calculated using Equations 3 and 4.

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|e_t|}{y_t} \times 100 \tag{3}$$

$$NRMSE = \frac{\sqrt{\sum_{t=1}^{n}\frac{(e_t)^2}{n}}}{\bar{y}} \tag{4}$$

where t is the time-period, Y_t is the actual value, $\bar{y}$ is the average of the observations and $e_t = y_t - \hat{y}_t$ is the error in the period t and n is the number of observations.

Detection of change points in modeling and prediction of time series is an important task. CPA is useful in identifying whether a change or more than one change has occurred in the data and at which time the changes have occurred. CPA is performed on a time ordered series to detect the changes that occurred (Hackl, 2013) where it identifies the multiple changes with smaller shifts. The CPA can consider both mean and variance changes and, in this study, AMOC was applied to detect the single change point (Eckley *et al.*, 2011). This method is based on the likelihood-ratio approach and the hypothesis of the change is as follows:

H_0: No change point

H_1: A singel change point

To find the test statistic from both hypothesis (null and alternative), the maximum log-likelihood is calculated and is compared it with a threshold value to accept or reject the null hypothesis. If the test statistic is greater than the considered threshold, the null hypothesis is rejected.

PELT method was used to detect multiple change points as this method is fast and accurate than the binary segmentation and other methods (Wambui *et al.*, 2015). This approach minimizes the general penalized likelihood from the Schwarz information criterion (SIC) (Yao, 1988) and points out the appropriate model. In the PELT method, the linear functions of the number of change points are the linear penalties as follows:

$$\text{pen(T)} = \beta\,|\text{T}| \tag{5}$$

where T is a set of indexes and β is a smoothing parameter that controls the goodness of fit and complexity.

The pruning rule:

If the $\left[\min V\left(T, y_{0,\ldots,t}\right) + \beta\,|T|\right] + c\left(y_{t,\ldots,s}\right) \geq \left[\min V\left(T, y_{0,\ldots,t}\right) + \beta\,|T|\right]$ then t cannot be the concluding change point before T (Truong *et al.*, 2020).

where y is a signal, t < s < T, t and s are indexes and V is a function of y and T.

In this study, both AMOC and PELT methods were employed to identify the change points considering both mean and variance change in data using the package "changepoint" in R software (Killick & Eckley (2014)). This package calculates the number of change points with their optimal positions for given penalty functions and assumed test statistics.

4. Data Analysis

This section consists of the descriptive analysis of the data and results obtained through the SARIMA and CPA approaches for each case. Case I consists of the data from January 2000 to December 2019 while case II describes the approach with the application of CPA for the data.

4.1. Case I

Figure 1 illustrates the number of tourists who arrived from January 2000 to December 2019. There was a significant decline in the period from the year 2000 to mid of 2011. This huge decline may be due to the destructive terrorism phenomenon which was experienced in Sri Lanka. However, there is a gradual increase from the end of the year 2011 to the end of the year 2019.

According to Figure 2, there are two outliers in the boxplot as December 2018 and February 2019. However, to implement the continuity of time series data points outliers are not removed. The right-skewed data imply that most numbers of tourist arrivals are relatively small, and only a few are long. There were no missing values in the dataset.

The minimum value of the tourist arrival was 11,758 in September 2001 while the maximum amount was 253,169 in the month of December 2018. On average 84,238 tourists arrived in Sri Lanka. From the year 2000 to 2019 total of 20,217,026 tourists arrived and the Standard deviation value was 61132.3. This means that 68% of the total tourist arrivals are between 23,106 and 145,370.

Data was split with an initial 90% for the training set from January 2000 to December 2017 and the remaining 10% for the testing set from January 2018 to December 2019 for testing. There is a clear upward trend in the training data. Therefore, the series was not stationary, and it was identified through the unit root tests. PP test indicated that the series was stationary where the ADF test and KPSS tests suggested it was not stationary at a 5% level of significance. Therefore, the log transformation was applied to the original data to make the data smoother (stabilize the variance). Then, differencing was applied to stabilize the mean of a time series by removing changes in the level of a time series (to reduce the trend). The trend was eliminated after this transformation. Through the unit root tests, the differenced log transformed training set was stationary at a 5% level of significance.

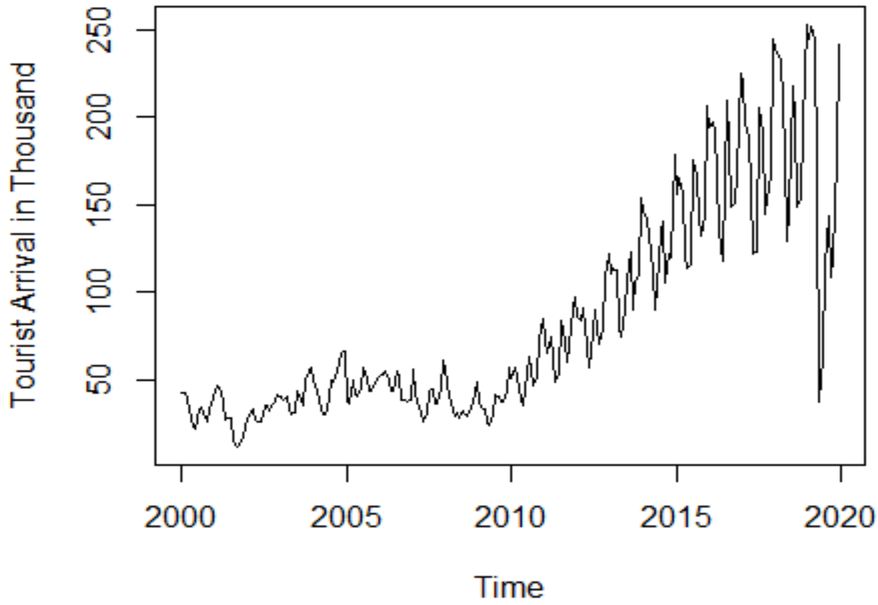


Figure 1: Time-series plot of tourist arrivals in thousand from 2000 to 2019

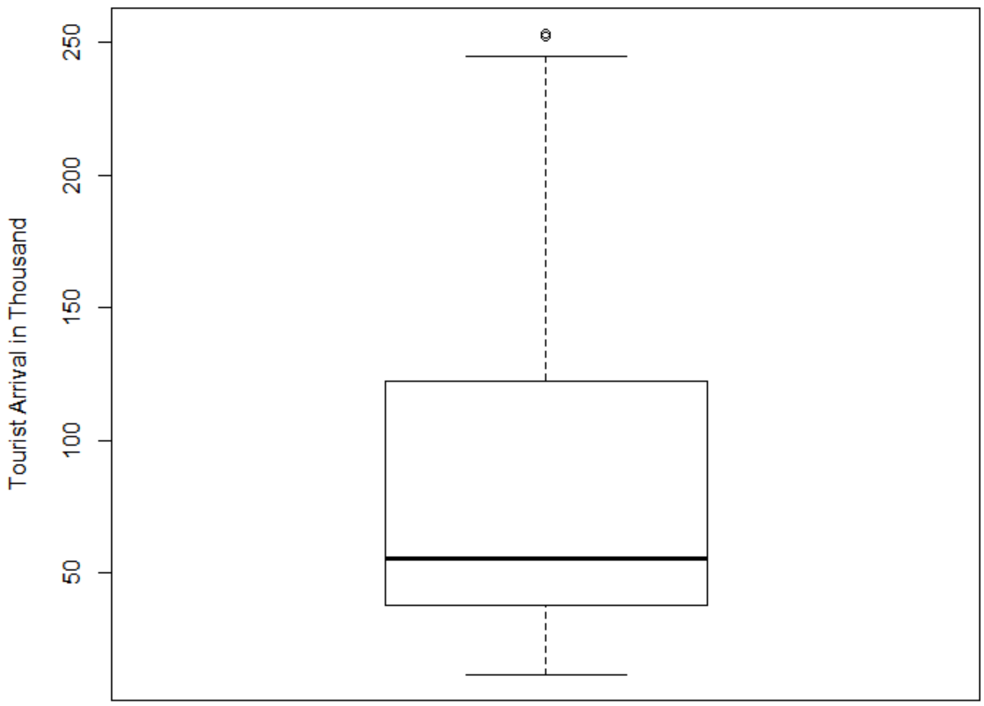
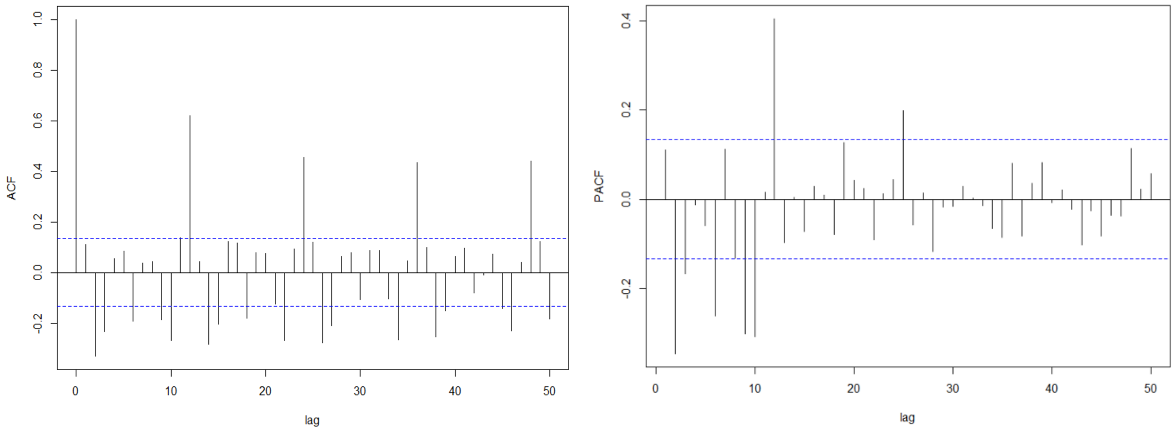


Figure 2: Boxplot of tourist arrivals

The ACF and PACF plots were used to identify the seasonal and non-seasonal lags as in Figures 3 (a) and 3 (b) respectively.



(a) ACF **(b) PACF**

Figure 3: ACF and PACF plots of the transformed series of tourist arrivals

From the ACF plot, it is visible that the significant lags are 2, 3, 6, 9, 10, 12, 14, 15 and 18 and from the PACF plot, lags 1, 2, 6, 9, 10 and 12 are significant (Figure 3). The seasonality of the transformed data was identified using the WO test. Through the ACF and PACF plots, different seasonal lags were recognized as 3, 6 and 12. Subsequently, candidate models for each case of seasonal differences were identified.

Initially, the transformed data was seasonally differed by 3, 6 and 12 separately. By considering the results of unit root tests, all the series were stationary at a 5% level of significance. From the ACF and PACF plots of the seasonality differed series, significant non-seasonal lags and seasonal lags were obtained as in Table 1.

Table 1: Seasonal lags and non-seasonal lags from ACF plots and PACF plots for Case I

	ACF		PACF	
Seasonal difference	Seasonal lags	Non-seasonal lags	Seasonal lags	Non-seasonal lags
3	3,9,12	1.2	3,6,9	1,2
6	6,12,18	1,2,3	6,18	1,2,3
12	12, 24	-	12,24,36	-

The models (relevant to seasonal difference by 3) were built from identified lags as in Table 1 in Annexure. In the table, the minimum AIC was –229.76 in the model ARIMA (2,1,2)(3,1,4)$_{[3]}$. For this model, the Jarque-Bera test violated the normality assumption and satisfied the assumptions of homoscedasticity and the absence of autocorrelation in residuals through the ARCH and Ljung-Box tests respectively. Aryani *et al.* (2018) stated that even the residual normality assumption of the ARIMA model is violated (it reflected the data with high volatility), the model can be used in forecasting. Hence, the model was used to forecast as all the other candidate models violated the assumption of normality in residuals.

Using the seasonal lags and non-seasonal lags, appropriate models were recognized similar to the procedure in Table 1 in Annexure for the seasonal difference of 6 and 12. The minimum AIC was –236.53 in the model ARIMA (1,1,1) $(3,1,2)_{[6]}$ and through the model diagnostic tests, it only violated the normality assumption. Therefore, the aforementioned model was used in prediction among the models with the seasonal difference of 6.

The minimum AIC was –240.44 in the model ARIMA (0,1,0) $(2,1,1)_{[12]}$ (relevant to seasonal difference by 12) and in here, all the models violated the assumption of normality. Therefore, this model was used in forecasting tourist arrivals among all the models with the seasonal difference of 12.

4.2. Case II

In Case II, the CPA (both AMOC and PELT methods) were employed to identify the change points. There are many penalty functions that can be applied in the CPA which are AIC, Bayesian information criterion (BIC), SIC and Hannan-Quinn. In addition, the assumed test statistic can take Normal, Gamma, Exponential and Poisson distributions (Killick and Eckley (2014)). This study used AIC, BIC and SIC methods for the penalty functions in CPA (Wambui *et al.*, 2015). The test of fit for the probability distribution of Gamma was identified using the test of variance ratio for Gamma distributions (see Villasenor and Gonzalez-Estrada, 2015; Gonzalez-Estrada, 2020). For the test of fit, the test statistic value was 2.0834 and the *p*-value was 0.1407. They indicated that the null hypothesis of data follow a Gamma distribution was not rejected at a 5% level of significance. As data follow a Gamma distribution, the assumed test statistic was considered with the Gamma distribution in this study.

Multiple change points were not identified from the PELT method. From both AMOC and PELT methods only one change point was identified for all the information criteria. It is the 142^{nd} observation as in Figure 4 and the change point was detected in the month of October 2011. From 2000 to mid of 2011, there was a decline period in tourist arrivals and that might be due to the impact of civil war. However, from the end of 2011, there is an increase in tourist arrivals. Therefore, theoretically and practically, it can be concluded that a better change point was identified from the AMOC and PELT methods.

Therefore, Window 1 (W1) was built based on the data from January 2000 to October 2011 and Window 2 (W2) was based on the time period from November 2011 to December 2019.

4.2.1. Window 1

In Window 1 (Figure 5), the minimum value of the tourist arrival was 11,758 in September 2001 while the maximum amount was 84,627 in the month of December 2010. On average 42,311 tourists had arrived in Sri Lanka from January 2000 to October 2011 which was a total of 6,008,152.

Observations from January 2000 to October 2010 were used as the training set while observations from November 2010 to October 2011 were used as the testing set.

ADF and PP tests exhibited that the training set was stationary at a 5% level of significance. However, the KPSS test indicated that the series was not stationary. The difference transformation for the log transformed variable was used to make data smooth and to remove the trend. The transformed series was stationary at a 5% level of significance.

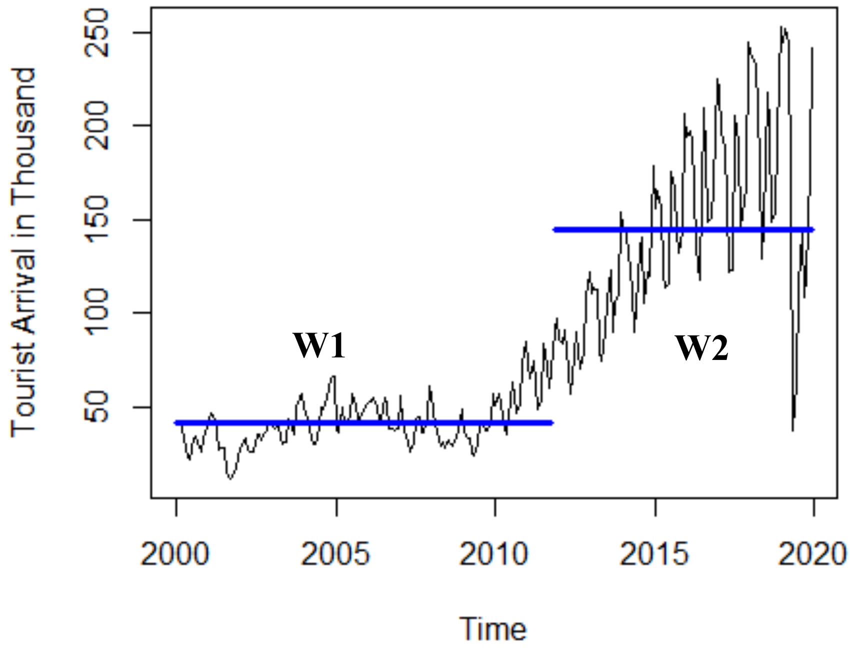


Figure 4: Detection of Change point using AMOC and PELT methods

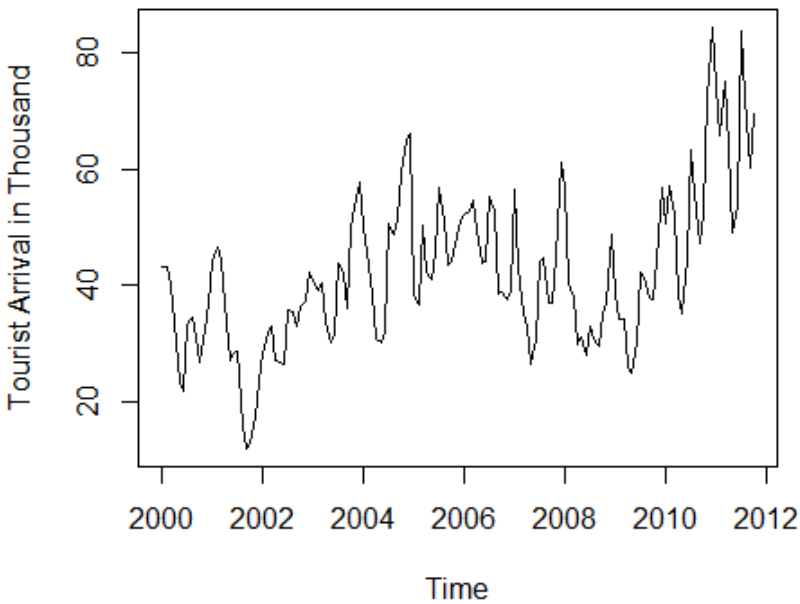
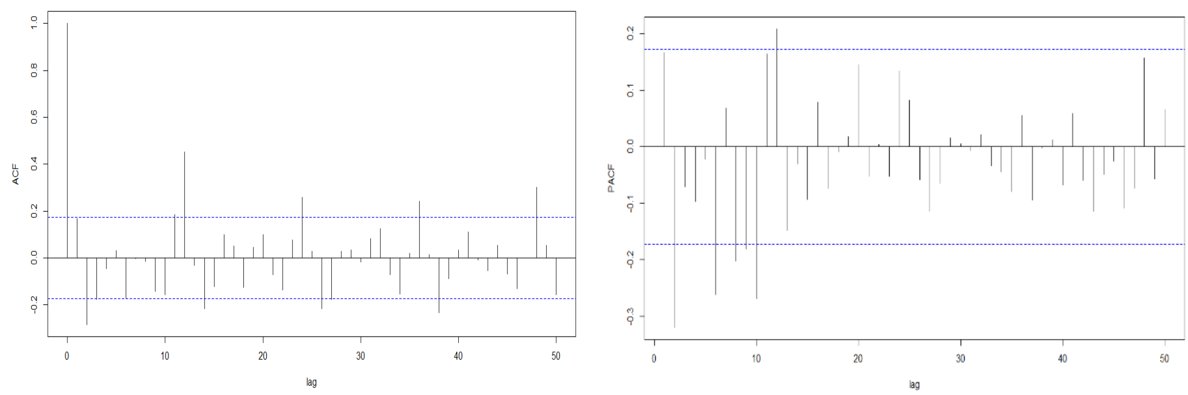


Figure 5: Time-series plot of tourist arrivals from January 2000 to October 2011

The WO test indicated the seasonality feature. Then the ACF and PACF plots were used to identify the seasonal and non-seasonal lags.

From Figure 6, the ACF plot indicates that the significant lags are 2, 3, 6, 11, 12, 24, 36 and 48 and the PACF plot indicates that the significant lags are 2, 6, 8, 9, 10 and 12. From the ACF and PACF plots, three seasonal differences were identified as 3, 6 and 12. The models were built separately for each seasonal difference of 3, 6 and 12.



(a) ACF **(b) PACF**

Figure 6: ACF and PACF plots of the transformed series of tourist arrivals

The seasonally differed series by 3, 6 and 12 were stationary at a 5% level of significance. As in Table 2, found the significant seasonal and non-seasonal lags from ACF and PACF plots to identify a better model in forecasting. Candidate models were built for each seasonal difference (same task as in Table 1 in Annexure) for Window 1.

Table 2: Seasonal lags and non-seasonal lags from ACF plots and PACF plots for W1

	ACF		PACF	
Seasonal difference	Seasonal lags	Non-seasonal lags	Seasonal lags	Non-seasonal lags
3	3,6,12,24	1,2	6,9,12	1,2
6	6,12,24,36	1,2,3	6,12	1,2
12	12,24,36,48	1,2,3	12	1,2

The minimum AIC (relevant to seasonal difference by 3) was in the ARIMA (1,1,1) $(4,1,1)_{[3]}$ which of –94.70. From the model diagnostic tests of ARCH, Ljung-Box and Jarque-Bera, this model satisfied all the assumptions in residuals.

The lowest AIC was in the model ARIMA (2,1,2) $(1,1,4)_{[6]}$ with a –103.39 value (relevant to seasonal difference by 6). However, the model violated the assumption of normality whereas all the other candidate models violated that assumption. Therefore, the aforementioned model was used to forecast the arrival of tourists among models with the seasonal difference of 6.

The seasonality differed series by 12 was stationary and the least AIC was –107.57 in the model ARIMA (2,1,2) $(1,1,4)_{[12]}$. This model violated the normality assumption. However, the model was used for forecasting as all other candidate models violated the assumption of normality in residuals.

4.2.2. Window 2

Window 2 was built based on the time period from November 2011 to December 2019. There is an upward trend in Figure 7. There is a sudden drop in May 2019 due to the Easter bombings on 28th April 2019 on Easter Sunday. In Window 2, the minimum value of the tourist arrival was 37,802 in May 2019 while the maximum amount was 253,169 in

December 2018. On average 144,989 tourists arrived in Sri Lanka from 2011 November to 2019 December while a total of 14,208,874.

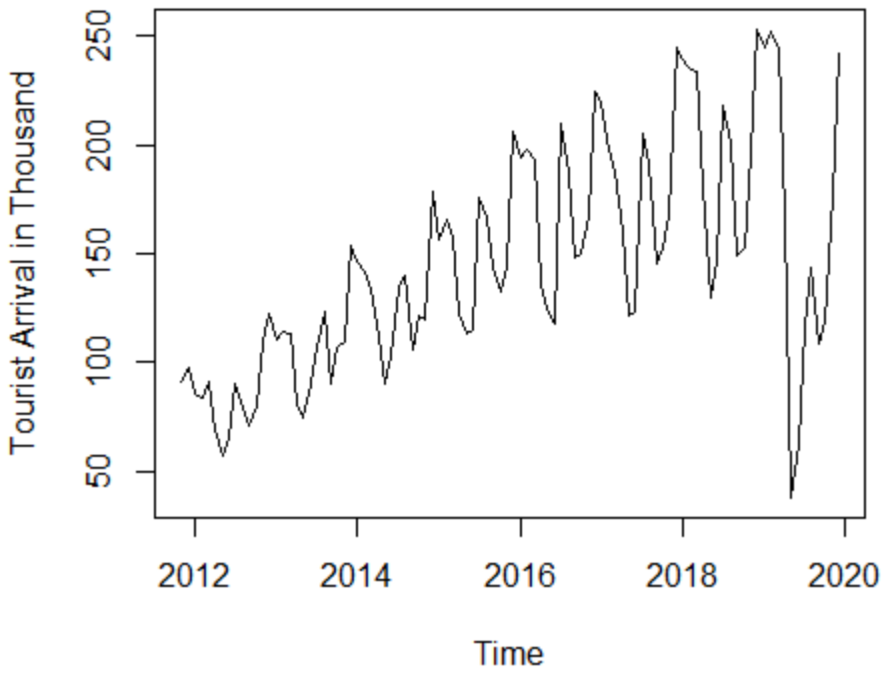
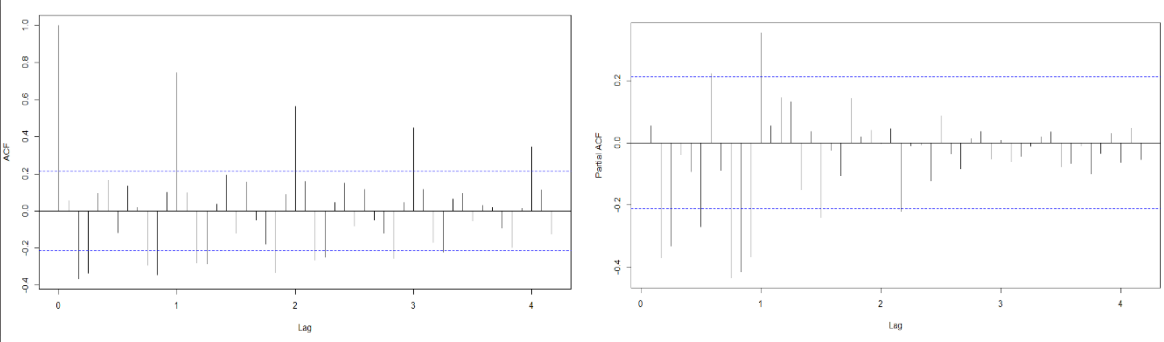


Figure 7: Time-series plot of tourist arrivals from 2011 of November to 2019 of December

The train set is from November 2011 to December 2018. The test set is from January 2019 to December 2019. The train set consists of a clear upward trend. In addition, it seems to have a seasonal pattern. The series was not stationary and it was examined through the unit root tests.

The difference transformation for the log transformed variable was used to make data smooth and to remove the trend. The transformed series was stationary at a 5% level of significance. The seasonality behavior was identified using the WO test. Significant lags from ACF and PACF plots (Figures 8) were used to build the models. From ACF plot, significant lags are 2, 3, 9, 10, 12, 14, 15, 22, 24, 26, 27, 34, 36, 39 and 48 while PACF plot illustrates the significant lags as 2, 3, 6, 7, 9, 10, 11, 12 and 18. The seasonality was identified in 3, 6 and 12 seasonal differences. Therefore, applied the seasonal differences in 3, 6 and 12 separately and identified seasonal and non-seasonal lags for each case as in Table 3.



(a) ACF (b) PACF

Figure 8: ACF plot of the transformed series of tourist arrivals

Table 3: Seasonal lags and non-seasonal lags from ACF plots and PACF plots for W2

	ACF		PACF	
Seasonal difference	Seasonal lags	Non-seasonal lags	Seasonal lags	Non-seasonal lags
3	3,9,12,15	1,2	3,6,9,12,18	1,2
6	12,24,36	1,2,3	6,12,18	1,2,3
12	12,24,36,48	1,2,3	12	1,2,3

Seasonally differed series by 3 was stationary and the least AIC was –146.09 in the model ARIMA (0,1,1) $(3,1,3)_{[3]}$ and it satisfied all the model diagnostics assumptions of the model.

Seasonally differed series by 6 was stationary and the minimum AIC was –166.12 in the model ARIMA (2,1,3) $(1,1,6)_{[6]}$. Moreover, this model satisfied all the model diagnostics assumptions.

Seasonally differed series by 12 was stationary and among all the candidate models, minimum AIC was –155.55 in the ARIMA (0,1,1) $(1,1,1)_{[12]}$ model. Even the normality assumption is violated, used this model in forecasting. The next least AIC value –154.23 was in model ARIMA (1,1,2) $(1,1,1)_{[12]}$ and it satisfied all the assumptions of model diagnostics.

5. Discussion

In this section, the better performed models in forecasting tourist arrivals were identified for Case I and Case II.

5.1. Case I

Table 4 indicates the performance measures, assumption satisfaction or violation of model diagnostics with their AIC values for better performed models in each seasonal difference. ARIMA (0,1,0) $(2,1,1)_{[12]}$ has the lowest AIC value. However, among all the models in Table 4, it has the highest MAPE and NRMSE values. The MAPE value was minimum in the model ARIMA (2,1,2) $(3,1,4)_{[3]}$ (Model A). However, it violated the assumption of normality in residuals and satisfied all the assumptions of model diagnostics. Therefore, model A is the better model that can use in forecasting tourist arrivals in Case I.

Table 4: Better performed models to identify the behavior of the arrival of tourists from January 2000 to December 2019

Case I	Model	Assumptions			AIC	MAPE	NRMSE
		Heteroscedasticity	Autocorrelation	Normality			
ARIMA (2,1,2)(3,1,4)[3]	A	Absence	Absence	Absence	–229.76	0.1941	0.8800
ARIMA (1,1,1)(3,1,2)[6]	B	Absence	Absence	Absence	–236.53	0.2340	0.9740
ARIMA (0,1,0)(2,1,1)[12]	C	Absence	Absence	Absence	–240.44	0.2786	1.2630

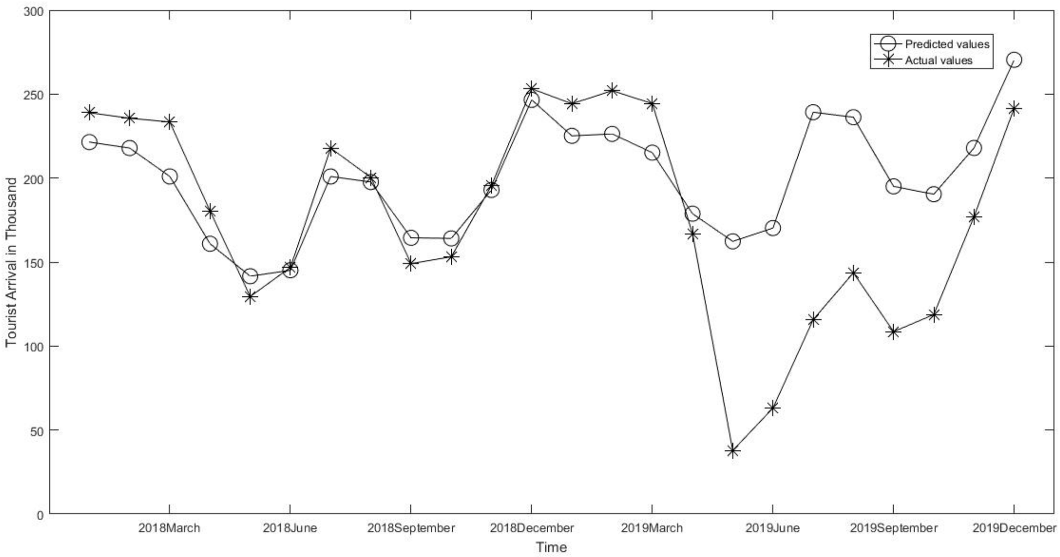


Figure 9: Actual and Predicted values of tourist arrivals from ARIMA (2,1,2) (3,1,4)[3]

Figure 9 indicates the actual and predicted values where the asterisk marks illustrate the actual values and the point marks show the predicted values for the test set from the beginning of 2018 to the end of 2019. Until April 2019, the fitted model captured the behavior of tourist arrivals in Sri Lanka and due to the Easter bomb attack in April 2019, there was a sudden drop in May 2019. However, model A identified the actual behavior till the end of 2019 even two lines do not coincide with each other.

5.2 Window 1

Window 1 was build based on the data from January 2000 to October 2011. From Table 5, the minimum AIC is in Model F while it violated the normality of assumption of residuals and has higher MAPE and NRMSE values. The better model that can used in the prediction is ARIMA (1,1,1) (4,1,1)[3] (Model D). In addition, it satisfied all the assumptions of model diagnostics while all other models dissatisfied the assumption of the normality of the error terms. Compared to all the models in Table 5, the lowest performance measures were in Model D. Hence, Model D was used to forecast tourist arrivals in Window 1.

Table 5: Better performed models to identify the behavior of the arrival of tourists from January 2000 to October 2011

Window 1	Model	Assumptions			AIC	MAPE	NRMSE
SARIMA		Heteroscedasticity	Autocorrelation	Normality			
ARIMA (1,1,1)(4,1,1)$_{[3]}$	D	Absence	Absence	Presence	–94.70	0.1727	1.1190
ARIMA (2,1,2)(1,1,4)$_{[6]}$	E	Absence	Absence	Absence	–103.39	0.2751	1.5520
ARIMA (2,1,2)(1,1,4)$_{[12]}$	F	Absence	Absence	Absence	–107.57	0.3034	1.7460

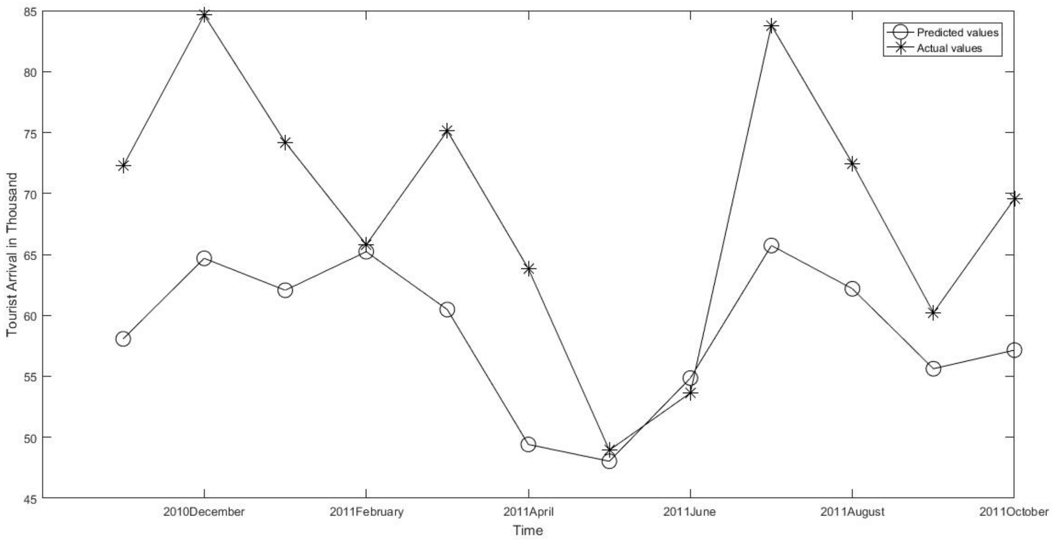


Figure 10: Actual and Predicted values of tourist arrivals from ARIMA (1,1,1) (4,1,1)$_{[3]}$

Observations from November 2010 to October 2011 were used as the testing set. Sri Lankan civil war was ended in May 2009 and as a result of that, there are fluctuations in the actual values of tourist arrivals (asterisk marks) in Figure 10. Thus, the predicted values (point marks) are not very similar to actual values.

5.3. Window 2

Window 2 was built based on the data from November 2011 to December 2019. The lowest AIC is in Model H as per Table 6 and it has higher MAPE and NRMSE values compared to model G. The better model that can be used in forecasting tourist volume is ARIMA (0,1,1) (3,1,3)$_{[3]}$ (Model G) in Window 2. Further, it consists of the lowest MAPE and NRMSE compared to all other models in Table 6 and it satisfied all the assumptions in the model diagnostics with a lower AIC value.

Table 6: Better performed models to identify the behavior of the arrival of tourists from November 2011 to the December 2019

Window 2	Model	Assumptions			AIC	MAPE	NRMSE
SARIMA		Heteroscedasticity	Autocorrelation	Normality			
ARIMA (0,1,1)(3,1,3)$_{[3]}$	G	Absence	Absence	Presence	–146.09	0.2740	0.8700
ARIMA (2,1,3)(1,1,6)$_{[6]}$	H	Absence	Absence	Presence	–166.12	0.3447	1.0520
ARIMA (0,1,1)(1,1,1)$_{[12]}$	I	Absence	Absence	Absence	–155.55	0.3473	1.1050
ARIMA (1,1,2)(1,1,1)$_{[12]}$	J	Absence	Absence	Presence	–154.23	0.3460	1.1000

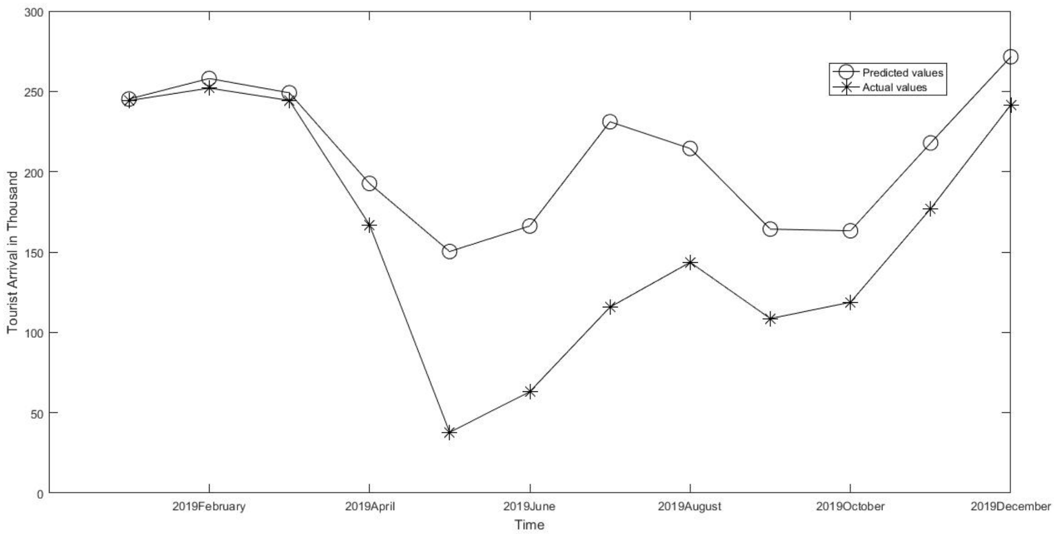


Figure 11: Actual and Predicted values of tourist arrivals from ARIMA (0,1,1) (3,1,3)$_{[3]}$

Figure 11 indicates the predicted (point marks) and actual data (asterisk marks) values in the test set from January 2019 to December 2019. The fitted model captures the behavior until April 2019. However, there was a sudden drop in the arrival of tourists in May 2019 due to the Easter bomb attack in April. Nevertheless, from this point onwards the predicted line captures the behavior of the actual values even though they do not coincide with each other. Again in December 2019, the predicted and Actual values are very close to each other.

6. Conclusions

The findings of the study are important to make the major decisions relevant to tourism to achieve sustainable development of the sector. Tourist arrivals in Sri Lanka indicate a seasonality pattern and a clear upward trend after 2010. According to this study, there were models built which were relevant to seasonal lags 3, 6 and 12. The outperformed model that can be used in forecasting tourist arrivals from January 2000 to December 2019 was the ARIMA (2,1,2) (3,1,4)$_{[3]}$ model which exhibits the lowest MAPE and NRMSE values with the satisfaction of all model diagnostics assumptions except the normality of the residuals. With the application of CPA, from January 2000 to October 2011 (Window 1) the better performed model was ARIMA (1,1,1) (4,1,1)$_{[3]}$. However, the model did not capture the actual behavior of tourist arrivals due to the fluctuations in values of tourist arrivals after the end of the civil war in May 2009. From November 2011 to December 2019 (Window 2), the better model that can be used in forecasting was ARIMA (0,1,1) $(3,1,3)_{[3]}$ and it satisfied all the model diagnostics assumptions. Thus, this study is a benefit for both the private and public sectors as tourist arrivals have a prominent impact on the economy of the country. Moreover, future forecasting information is vital in the decision making for industries related to tourism. For further implications, supervised machine learning algorithms can be used to build forecasting models to forecast the tourist arrivals in Sri Lanka with higher accuracy.

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ANNEXURE

Table 1: SARIMA Models with seasonal difference of 3

Model	AIC	Model	AIC
ARIMA (1,1,1)(1,1,1)$_{[3]}$	–99.66	ARIMA (0,1,1)(1,1,3)$_{[3]}$	–117.70
ARIMA (1,1,1)(1,1,3)$_{[3]}$	–122.20	ARIMA (0,1,1)(1,1,4)$_{[3]}$	–142.60
ARIMA (1,1,1)(1,1,4)$_{[3]}$	–149.80	ARIMA (0,1,1)(2,1,1)$_{[3]}$	–109.30
ARIMA (1,1,1)(2,1,1)$_{[3]}$	–115.00	ARIMA (0,1,1)(2,1,3)$_{[3]}$	–162.90
ARIMA (1,1,1)(2,1,3)$_{[3]}$	–161.40	ARIMA (0,1,1)(2,1,4)$_{[3]}$	–151.30
ARIMA (1,1,1)(2,1,4)$_{[3]}$	155.96	ARIMA (0,1,1)(3,1,1)$_{[3]}$	–180.70
ARIMA (1,1,1)(3,1,1)$_{[3]}$	–185.90	ARIMA (0,1,1)(3,1,3)$_{[3]}$	–195.70
ARIMA (1,1,1)(3,1,3)$_{[3]}$	–196.70	ARIMA (0,1,1)(3,1,4)$_{[3]}$	–223.10
ARIMA (1,1,1)(3,1,4)$_{[3]}$	–226.80	ARIMA (0,1,2)(1,1,1)$_{[3]}$	–111.30
ARIMA (1,1,2)(1,1,1)$_{[3]}$	–115.40	ARIMA (0,1,2)(1,1,3)$_{[3]}$	–135.40
ARIMA (1,1,2)(1,1,3)$_{[3]}$	–139.00	ARIMA (0,1,2)(1,1,4)$_{[3]}$	–158.30
ARIMA (1,1,2)(1,1,4)$_{[3]}$	158.51	ARIMA (0,1,2)(2,1,1)$_{[3]}$	–129.70
ARIMA (1,1,2)(2,1,1)$_{[3]}$	–131.90	ARIMA (0,1,2)(2,1,3)$_{[3]}$	–166.00
ARIMA (1,1,2)(2,1,3)$_{[3]}$	–181.20	ARIMA (0,1,2)(2,1,4)$_{[3]}$	–167.70
ARIMA (1,1,2)(2,1,4)$_{[3]}$	–168.10	ARIMA (0,1,2)(3,1,1)$_{[3]}$	–184.70
ARIMA (1,1,2)(3,1,1)$_{[3]}$	–183.80	ARIMA (0,1,2)(3,1,3)$_{[3]}$	–203.50
ARIMA (1,1,2)(3,1,3)$_{[3]}$	–203.10	ARIMA (0,1,2)(3,1,4)$_{[3]}$	–223.20
ARIMA (1,1,2)(3,1,4)$_{[3]}$	–227.80	ARIMA (1,1,0)(1,1,1)$_{[3]}$	–87.43
ARIMA (2,1,1)(1,1,1)$_{[3]}$	–113.30	ARIMA (1,1,0)(1,1,3)$_{[3]}$	–117.60
ARIMA (2,1,1)(1,1,3)$_{[3]}$	–142.00	ARIMA (1,1,0)(1,1,4)$_{[3]}$	–142.00
ARIMA (2,1,1)(1,1,4)$_{[3]}$	–160.70	ARIMA (1,1,0)(2,1,1)$_{[3]}$	–106.00
ARIMA (2,1,1)(2,1,1)$_{[3]}$	–144.50	ARIMA (1,1,0)(2,1,3)$_{[3]}$	–159.70
ARIMA (2,1,1)(2,1,3)$_{[3]}$	–190.70	ARIMA (1,1,0)(2,1,4)$_{[3]}$	–150.30
ARIMA (2,1,1)(2,1,4)$_{[3]}$	–176.00	ARIMA (1,1,0)(3,1,1)$_{[3]}$	180.67
ARIMA (2,1,1)(3,1,1)$_{[3]}$	–184.60	ARIMA (1,1,0)(3,1,3)$_{[3]}$	–195.70
ARIMA (2,1,1)(3,1,3)$_{[3]}$	–204.50	ARIMA (1,1,0)(3,1,4)$_{[3]}$	–223.10
ARIMA (2,1,1)(3,1,4)$_{[3]}$	–228.20	ARIMA (2,1,0)(1,1,1)$_{[3]}$	–109.00
ARIMA (2,1,2)(1,1,1)$_{[3]}$	–147.50	ARIMA (2,1,0)(1,1,3)$_{[3]}$	–125.00
ARIMA (2,1,2)(1,1,3)$_{[3]}$	–140.00	ARIMA (2,1,0)(1,1,4)$_{[3]}$	–156.80
ARIMA (2,1,2)(1,1,4)$_{[3]}$	–158.70	ARIMA (2,1,0)(2,1,1)$_{[3]}$	–128.40
ARIMA (2,1,2)(3,1,1)$_{[3]}$	–194.70	ARIMA (2,1,0)(2,1,3)$_{[3]}$	–171.10
ARIMA (2,1,2)(3,1,3)$_{[3]}$	–211.00	ARIMA (2,1,0)(2,1,4)$_{[3]}$	–158.80
ARIMA (2,1,2)(3,1,4)$_{[3]}$	–229.76	ARIMA (2,1,0)(3,1,1)$_{[3]}$	–183.20
ARIMA (0,1,1)(1,1,1)$_{[3]}$	–89.47	ARIMA (2,1,0)(3,1,3)$_{[3]}$	–200.60
		ARIMA (2,1,0)(3,1,4)$_{[3]}$	–222.80