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Forecasting Post-War Tourist Arrivals to Sri Lanka Using Dynamic Transfer Function Modeling Method

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ABSTRACT

Tourism plays a big role in terms of economics in the development of a country. The arrivals were less during the war period in Sri Lanka due to the uncertainty of security. Forecasting tourist arrivals is essential for planning, policy making and budgeting purposes. The objective of the study is to fit a model to predict tourist arrivals by using dynamic transfer function (DTF) modeling method. The monthly tourist arrivals from June 2009 to June 2016 are extracted from the annual reports of Sri Lanka tourism development authority for this study. Prior to model fittings, the following techniques were carried out: Augmented Dickey- Fuller test, Kruskal- Wallis test, difference method, auto-correlation function and partial auto-correlation function. For model fitting, dynamic transfer function model for univariate time series process was employed. Anderson-Darling test, Lagrange's Multiplier test and White's General test were applied for the residuals analysis. To evaluate the performance of the model on the basis of the fit of the forecasting, mean absolute percentage error (MAPE) was taken into account. It is stated that, over 7.3 million tourists had visited the island during the study period. Further it is noted that, every year there is a positive growth rate. It reveals that, there is dramatic increase in total tourist arrivals after the war. Soon after the war in Sri Lanka, a rapid increase in growth rate in the year 2010 is also observed. According to the MAPE value, it is concluded that, the fitted DTF model explains over 90% accuracy in terms of forecasting tourist arrivals. Based on the ex-post forecast, it is expected that nearly 1.105 million tourists will come to Sri Lanka in the last six months in 2016. It is approximately 14% increase in the arrivals over the last six months in the year 2015.

KEYWORDS: *Dynamic transfer function, forecasting, tourist arrivals.*

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1. INTRODUCTION

Tourism, as an industry, contributes to the national economy of a country in a large scale. Now it is one of the largest and fastest growing economic sectors in the world. The case studies (Balaguer & Cantavella, 2002; Durbarry, 2004) discovered the impact of tourism on economic growth in Spanish and Mauritius respectively. An empirical study (King & Gamage, 1994) addressed the impact of tourism on economic growth in Sri Lanka. There is a significant causal relationship from tourism receipts to the gross domestic product (GDP) of Sri Lanka (Wickramasinghe & Ihalanayake, 2006). There were several set-backs in the tourism development process in Sri Lanka such as global economic crisis in 2009, Tsunami in 2004 and the internal conflict from the year 1983 to the year 2009. During the conflict period, mainly due to the uncertainty of security, tourists did not come to Sri Lanka. Nevertheless, the conflict is over by now.

The records in Sri Lanka tourism development authority (SLTDA) show that, the tourist arrivals are dramatically increasing after the internal conflict. As per the statistical annual report 2015 of SLTDA, due to the rise of the arrivals to Sri Lanka, tourism was able to upgrade its rank to the third level as the largest source of foreign exchange earner of the national economy in 2015. Those that ranked above tourism were Foreign Remittances and Textiles & Garments industries. The portion of contribution of tourism to total foreign exchange earnings in 2015 amounted to 12.4%. It reveals that contribution of tourism to the GDP is significantly high.

Tourism basically contains two types as domestic and international. This study is mainly focused only on the international tourist arrivals to Sri Lanka. Prediction of tourist arrivals is essential for planning, policy making and budgeting purposes. Thus, the objective of the study is to fit a model to predict international tourist arrivals by using dynamic transfer function (DTF) modelling method.

2. BACKGROUND

The general theme of the studies (Bermudez *et al*., 2007; Witt *et al*., 1992; Lim & McAleer, 2001; Akuno *et al*., 2015) says that forecasting accuracy is high in exponential smoothing modelling and this approach obtains a level of accuracy comparable to those of other more sophisticated models. However, the empirical studies (Cho, 2001; Chu, 1998; Loganathan & Yahaya, 2010; Chang *et al*., 2011; Dimitrios *et al*., 2012; Saayman *et al*., 2010; Prasert *et al*., 2008) show that autoregressive integrated moving average (ARIMA) modelling is overall the most accurate method for forecasting international tourist arrivals. Nevertheless, the state space model outperforms alternative approaches for short-term forecasting and also produces sensible long-term forecasts (Athanasopoulos & Hyndman, 2006). On the other hand, the neural network modelling method performs the best in these studies (Law, 2000; Burger *et al*., 2001; Cho, 2003). Therefore, it is not that easy to assign a modelling method to a specific region or a country to forecast tourism demand. Hence, all possible modelling methods have to be employed and based on the accuracy of the forecast, best method can be recommended.

Furthermore, a comprehensive review of published studies on tourism demand modelling and forecasting since 2000 was carried out (Song & Li, 2008). One of the key findings of this review is that the methods used in analysing and forecasting the demand for tourism had been more varied. As far as the forecasting accuracy is concerned, this review shows that, there is no single model that consistently outperforms other models in all situations. Therefore, it is better to consider several approaches, to tourism demand in Sri Lanka, to identify the best model based on the forecasting accuracy.

According to the literature, empirical studies of time series behaviour of the post war international tourist arrivals to Sri Lanka had been carried out using different modelling approaches.

They are as follows: the classical time series decomposition approach (Kurukulasooriya & Lelwala, 2014) with 96% forecasting accuracy, Box-Jenkin's modelling and Holt - Winter's Exponential Smoothing approaches (Gnanapragasam & Cooray, 2016(a) & 2016(b)) with nearly 95% and 88% forecasting accuracy respectively and State Space modelling approach (Gnanapragasam *et al*., 2016) with 94% forecasting accuracy. However, dynamic transfer function (DTF) model was not tried so far for the purpose of predicting international tourist arrivals to Sri Lanka. Therefore, this study attempts to fit tourist arrivals to Sri Lanka using DTF modelling approach.

3. MATERIALS & METHODS

The monthly international tourist arrivals, from June 2009 to June 2016, recorded in the annual statistical reports of Sri Lanka tourism development authority are extracted for this study.

3.1. Preliminary Analysis

At the preliminary stage prior to fit the dynamic transfer function model (DTF) model, the following techniques were carried out to get an idea about the data and its behaviour.

3.1.1. Plot of Time Series

It is to inspect for extreme observations, missing data, or elements of non-stationary such as trend or seasonality or cyclic pattern or irregular variations.

3.1.2. Augmented Dickey- Fuller test

Augmented Dickey- Fuller (ADF) test is used to test whether the series has a unit root. It is to confirm, statistically, that the stationary of series in terms of trend availability.

The test statistic for the model $Y_t = \rho Y_{t-1} + u_t$ with $-1 < \rho < 1$, is $DF = \dfrac{\hat{\rho}}{SE(\hat{\rho})} \sim t_{n-1}$

where Y_t is the response variable at time t, u_t is the white noise and n is the number of observations. The hypothesis to be tested in this test is H_0: series is non-stationary $\left(|\rho| = 1\right)$ versus H_1: series is stationary $\left(|\rho| < 1\right)$.

3.1.3. Kruskal- Wallis test

Kruskal- Wallis test is used to confirm the seasonality in the series. The hypothesis to be tested in this test is, H_0: series has no seasonality versus H_1: series has seasonality. The test statistic of ruskal- Wallis test is defined as:

$$H = \frac{12}{N(N+1)} \sum_{i=1}^{n_i} \frac{R_i^2}{n_i} - 3(N+1) \sim \chi^2_{L-1}$$

where N is the total number of rankings, R_i is the sum of the rankings in a specific season, n_i is the number of the rankings in a specific season and L is the length of the season.

3.1.4. Differencing method

If the series has an element such as trend or seasonality, then by taking the regular or seasonal differences those elements can be eliminated from the series and it is defined as $W_t = Y_t - Y_{t-L}$, where Y_t is the response variable at time t and L is the length of the season.

Autocorrelation function and partial auto correlation function

In time series analysis, a process of examining the autocorrelation function (ACF) and partial autocorrelation function (PACF) is to determine the nature of the process under consideration.

3.1.5. Autocorrelation function

Autocorrelation function (ACF) at lag k is defined by

$$\rho_k = \frac{\operatorname{cov}\left[\left(Y_t - \hat{Y}_t\right)\left(Y_{t+k} - \hat{Y}_{t+k}\right)\right]}{\sqrt{\operatorname{var}\left(Y_t - \hat{Y}_t\right)\operatorname{var}\left(Y_{t+k} - \hat{Y}_{t+k}\right)}}$$

The first several autocorrelations are persistently large in the graph of ACF and trailed off to zero rather slowly, it can be assumed that a trend exists and the time series is non-stationary. If the series is stationary, then ACF graph must decay exponentially.

3.1.6. Partial autocorrelation function

Partial autocorrelation function (PACF) between Y_t and Y_{t+k} is the conditional correlation between Y_t and Y_{t+k} and defined as follows: $\phi_{kk} = corr\left(Y_t,\ Y_{t+k} \mid Y_{t+1},\ Y_{t+2}, \ldots, Y_{t+k-1}\right)$

In other words, the PACF between Y_t and Y_{t+k} is the autocorrelation between Y_t and Y_{t+k} after adjusting for $Y_{t-1}, Y_{t-2}, \ldots, Y_{t-k+1}$.

3.2. Dynamic Transfer Function modelling method

Dynamic transfer function (DTF) model is a statistical model describing the relationship between an output variable Y_t and one or more input variables X_t 's. It has many applications especially in forecasting turning points.

3.2.1. Dynamic Transfer Function – Noise model

In practice, the output Y_t is not a deterministic function of X_t. It is often disturbed by some noise or has its own dynamic structure. The noise component N_t may be serially correlated, and it is assumed that N_t follows an ARMA(p, q) model as $\phi(B)N_t = \theta(B)e_t$, where $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - \ldots - \phi_p B^p$ and $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - \ldots - \theta_q B^q$ are polynomials in B of degree p and q respectively, and $\{e_t\}$ is a sequence of independent and identically distributed random variables with mean zero and variance σ_e^2.

It is noted that in the above ARMA model, $E\left(N_t\right) = 0$ and the usual conditions of stationarity and invertibility apply. Putting together, a simple DTF model can be obtained as

$$Y_t = c + v(B)X_t + N_t = c + \frac{\omega(B)B^b}{\delta(B)}X_t + \frac{\theta(B)}{\phi(B)}e_t$$

where c is a constant, $\theta(B)$, $\phi(B)$, $\omega(B)$ and $\delta(B)$ are defined similarly as before with degree q, p, s, and r respectively, and $\{e_t\}$ are white noise series. The parameter b is called the decay rate of the system. The noise component N_t should be independent of X_t; otherwise, the model is not identifiable.

Further it is noted that when $b > 0$ the DTF model is useful in predicting the turning points of Y_t given those of X_t.

3.2.2 Dynamic Transfer Function model for Univariate Time Series Process

A general form of a DTF model can be expressed as

$$Y_t = c + \sum_{i=1}^{m} \frac{\omega_i(B)B^{bi}}{\delta_i(B)}X_{it} + \frac{\theta(B)}{\phi(B)}e_t$$

where $\omega_i(B) = \omega_0 + \omega_1 B + \omega_2 B^2 + ... + \omega_i B^i$, $\delta_i(B) = \delta_0 + \delta_1 B + \delta_2 B^2 + ... + \delta_i B^i$, $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 - ... - \phi_p B^p$ and $\theta(B) = 1 - \theta_1 B - \theta_2 B^2 - ... - \theta_q B^q$ are polynomials in B of degree q, p, s, and r respectively , and $\{e_t\}$ are white noise series. The parameter bi is called the decay rate with the i^th variable. The order of the DTF is said to be (r, s, b) and the added noise model is of order (p, q).

Since the DTF model is a straight forward extension of the ARMA model, for $\omega_i(B) = 0$, the model is equivalent to univariate time series process (Dominique *et al*., 2002). Thus the DTF for univariate time series can be simply written as $Y_t = \dfrac{\theta(B)}{\phi(B)} e_t$.

3.3. Residual Analysis

Before using the model for forecasting, it must be checked for adequacy. Diagnostic checks are performed to determine the adequacy of the model. Accordingly, the residuals should be random and normally distributed with constant variance. The following tests are carried out for the residual analysis:

3.3.1. Anderson- Darling

The Anderson- Darling (AD) test is used to test if a sample of data comes from a population with a specific distribution. It is a modification of Kolmogorov- Smirnov (K-S) test and gives more weight to the tails than does the K-S test. Here the hypotheses are H_0: The data follow normal distribution versus H_1: The data do not follow normal distribution.

The test statistic of AD test is:

$$A^2 = -N - \sum_{i=1}^{N} \frac{(2i-1)}{N} \left[\ln F(Y_i) + \ln(1 - F(Y_{N+1-i})) \right]$$

where F is the cumulative distribution function of the specified distribution, Y_i are the ordered data and N is the total number of observations.

3.3.2. Lagrange's Multiplier test

Lagrange's Multiplier (LM) test is used to test the independency of residuals. It is an alternative test of Durbin Watson test for auto correlation among residuals. The null hypothesis to be tested is that, H_0: there is no serial correlation of any order. The individual residual autocorrelations should be small. Significant residual autocorrelations at low lags or seasonal lags suggest that the model is inadequate. The test statistic of LM test is:

$W = nR^2 \sim \chi^2_{df}$ where, df is the number of regressors in the auxiliary regression (only linear terms of the dependent variable are in the auxiliary regression), R^2 is the determination of coefficients and n is the number of observations.

3.3.3. White's General test

White's general test is used in order to check constant variance of residuals. Accordingly the null hypothesis is H_0: Homoscedasticity against the alternative hypothesis H_1: Heteroscedasticity. Test statistic of White's General test is:

$W = nR^2 \sim \chi^2_{df}$ where, df is the number of regressors in the auxiliary regression (squared terms of the dependent variable are also included in addition to terms in the LM test in auxiliary regression), R^2 is the determination of coefficients and n is the number of observations.

Model Validation

It is important to evaluate performance of fitted model on the basis of the fit of the forecasting.

Measure of forecast accuracy should always be evaluated as part of a model validation effort.

3. 4. Mean absolute percentage error

Mean absolute percentage error (MAPE) is the average of the sum of the absolute values of the percentage errors. It is generally used for evaluation of the forecast against the validation sample. To compare the average forecast accuracy of different models, MAPE statistics is used. It is defined as, $\text{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{Y_t - \hat{Y}_t}{Y_t}\right| \times 100$, where Y_t is the response variable at time t and n is the number of observations. Practically if MAPE is less than 10% then the fitted model is highly recommended for forecasting.

4. RESULTS & DISCUSSIONS

In this section, the discussions are based on the results obtained from the results software *MINITAB* and *SAS*.

4.1. Preliminary Analysis

The Figure 1 shows the yearly international tourist arrivals from the year 1967 to 2015 to Sri Lanka.

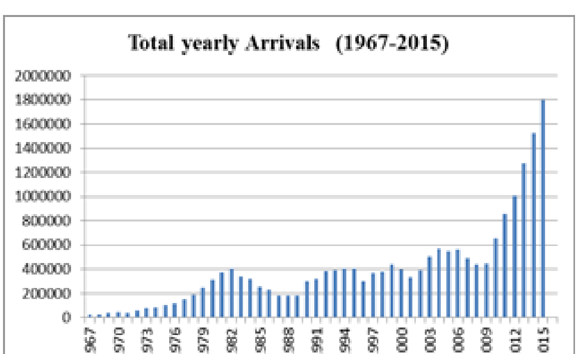

Figure 1. Plot of yearly tourist arrivals

In Figure 1, it is clearly observed that, from the years 1967 to 1982 there is an upward trend in arrivals. This is the beginning of the internal conflict in Sri Lanka. There after ups and downs in total arrivals can be seen from the years 1983 to 2009. This is the period where the internal conflict took place in Sri Lanka. Nevertheless, from the years 2009 to 2015, after the internal conflict, there is a remarkable upward trend in the total number of international tourist yearly arrivals to the island. This is the reason for this study is to mainly focus on the international tourist arrivals, only after the conflict, to Sri Lanka.

To study the behaviour of the arrivals, after the internal conflict, data from June 2009 to December 2015 are considered whereas only for growth rate calculation the data from January 2008 are taken. The relevant results are summarized in Table 1. It is noted that, the original data is named as Y in the analysis part to handle this in *SAS* and *MINITAB* software conveniently.

Table 1. Annual tourist arrivals and its growth rate

Year	Arrivals	Growth Rate	Year	Arrivals	Growth Rate
2009	260161	2.15%	**2013**	1274593	26.75%
2010	654476	46.12%	**2014**	1527153	19.81%
2011	855975	30.79%	**2015**	1798380	17.76%
2012	1005605	17.48%	**Total arrivals**		**7,376,343**

From the statistics appeared in Table 1, it can be stated that, over 7.3 million tourists had visited the island during the study period. Also only in the year 2015 nearly 1.8 million tourists had visited the island and which is the biggest hit in tourism history of Sri Lanka.

Further it is noted that, every year there is a positive growth rate. It reveals that, there is dramatic increase in total tourist arrivals after the conflict. A rapid increase in growth rate in the year 2010, soon after the internal conflict in Sri Lanka, is also noted here.

The monthly average arrivals after the conflict are also taken into account to see the pattern of the arrivals to Sri Lanka.

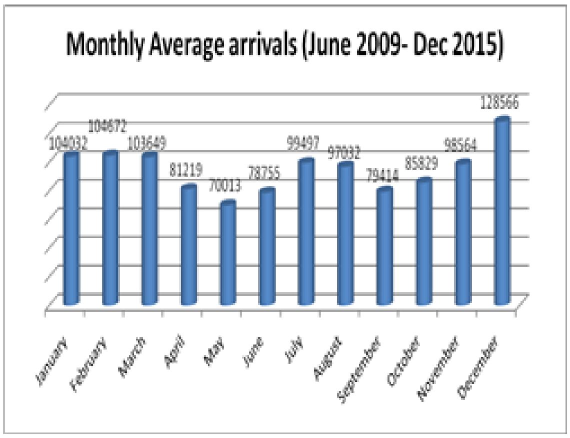

Figure 2. Plot of monthly average arrivals

It can be clearly observed a pattern of arrivals, on the average, from Figure 2 that in the months of December, January and February more tourists do come to Sri Lanka whilst the lower numbers of arrivals are recorded in the months of May and June on average in every year.

4.2. Checking stationary condition

Figure 3 provides the time series plot of the original series Y from June 2009 to December 2015.

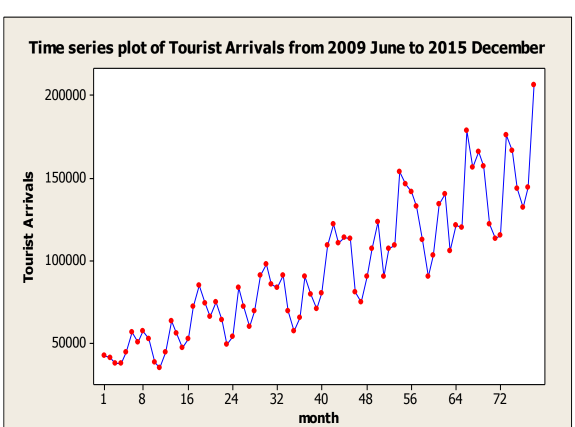

Figure 3. Plot of Time series

An upward trend with seasonal pattern can be clearly seen from the time series plot of the original series in Figure 3. Hence, it is obvious that, the original series Y is non- stationary.

Further, to check the stationary condition of the series Y, statistically, ACF graph with ADF and Kruskal- Wallis tests are employed as follows:

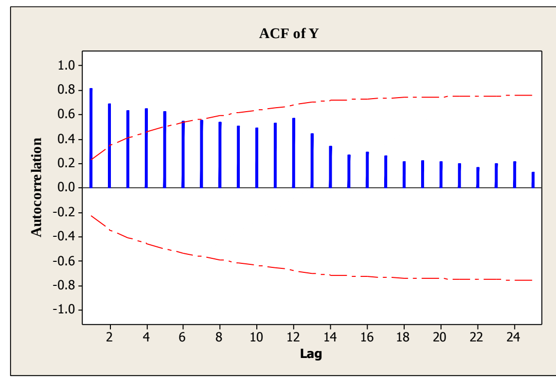

Figure 4. ACF graph of the series Y

It is very clear from the graph of ACF of Y in Figure 4 that it does not decay exponentially and thus it can be claimed that the original series Y is non- stationary.

Since the p- value (0.99) of ADF test confirms the existence of the trend in the series Y, the regular difference is taken to remove the trend and now the first differenced series is named as D1Y. Again the time series plot of the series D1Y is obtained to observe the behaviour of the regular differenced series.

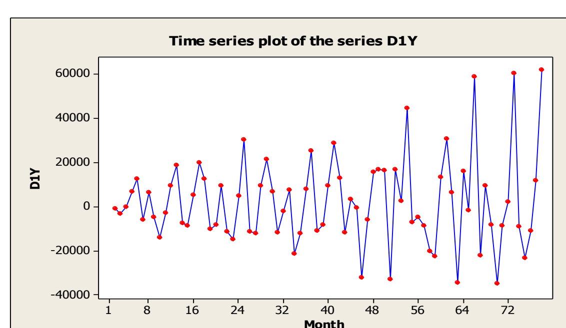

Figure 5. Time series plot of D1Y

Now it seems from the time series plot in Figure 5 that there is no trend in the series D1Y. Again ADF test for the series D1Y is also applied and hence it concludes that the series D1Y has no trend as the p-value of ADF test for D1Y is 0.00. However, the p- value (0.00) of Kruskal- Wallis test for the series D1Y still confirms the existence of seasonality.

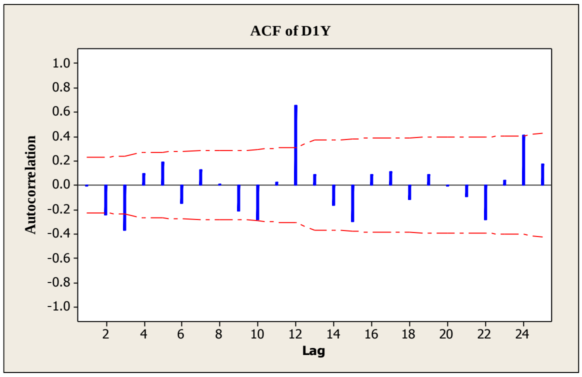

Figure 6. ACF graph of the series D1Y

From the graph of ACF of D1Y in Figure 6, it can be clearly observed that, spikes of 12th and 24th lags are high and not significant. Therefore, it can be assumed that the series D1Y has the seasonality with length 12. To remove this seasonality, the seasonal difference for length 12 is taken and now it is named as D12D1Y.

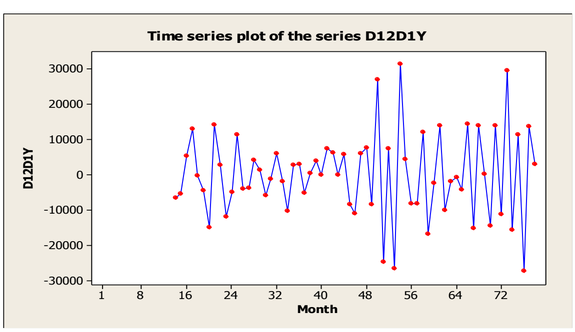

Figure 7. Time series plot of D12D1Y

Time series plot of the series D12D1Y is obtained to observe the behaviour of the 12th differenced series. Time series plot in Figure 7 also suggests that the seasonal differenced series, D12D1Y, with length 12 has no trend. However, it is hard to come to a conclusion about the seasonality. Thus the relevant statistical tests, ADF and Kruskal- Wallis, with ACF and PACF graphs are to be used to make a conclusion on stationary condition of the series D12D1Y.

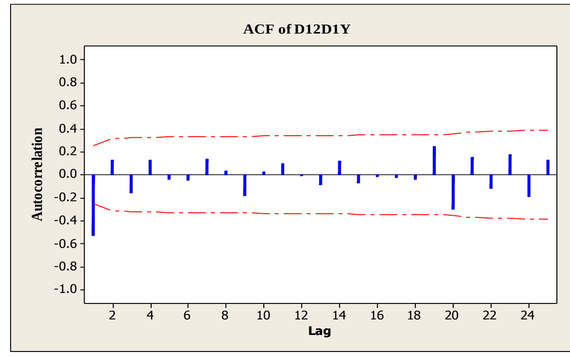

Figure 8. ACF graph of the series D12D1Y

Except at the first lag all the spikes are small and they are significant in the graph of ACF of the series D12D1Y in Figure 8. In addition, all the spikes after first lag are small and significant in the graph of PACF of the series D12D1Y. Both graphs indicate that, the new series D12D1Y is stationary.

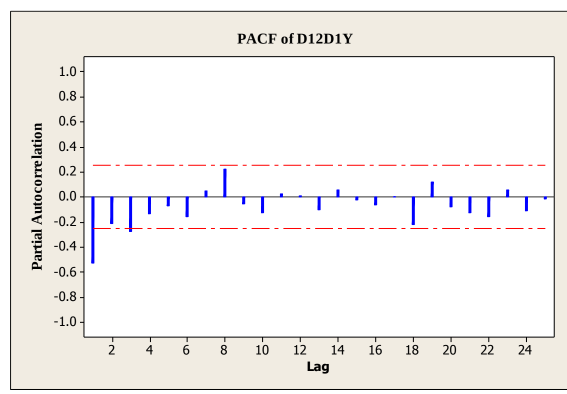

Figure 9. PACF graph of the series D12D1Y

Moreover, the p-value (0.00) of ADF test for D12D1Y shows that, it has no unit root. Therefore it can be concluded with 95% confidence that, D12D1Y has no trend. At the same time, from the p-value (0.37) of Kruskal-Wallis test, it can be concluded that the D12D1Y is now free from the seasonal pattern. Therefore, the new series D12D1Yis stationary and it can be used to fit the dynamic transfer function model.

4.3. Fitting dynamic transfer function model

The stationary data D12D1Y feed to SAS program to fit DTF model for univariate time series process. According to its output, the estimated parameter is and p- value of the parameter estimation is less than 0.0001. Therefore it can be concluded with 95% confidence that, the parameter of the model is significant.

Hence, the fitted DTF model to predict international tourist arrivals to Sri Lanka is:

$$\hat{Y}_t = Y_{t-1} + Y_{t-12} - Y_{t-13} + 0.82 * e_{t-1}$$

where $\hat{Y}_t$ is the estimated tourist arrivals at time t

Y_{t-1}, Y_{t-12} and Y_{t-13} are the preceding arrivals at time $t-1$, $t-12$ and $t-13$ respectively

e_{t-1} is the residuals at one preceding period $t-1$

4.4. Residual analysis of the fitted DTF model

The residual analysis to the fitted model to check for the adequacy is carried out as follows:

4.4.1. Normality checking

The probability plot of residuals of fitted DTF model is almost linear in Figure 10 and further the p-value (0.820) of the Anderson Darling test suggests that the residuals follow normal distribution. Thus it can be concluded with 95% confidence that the residuals are normally distributed.

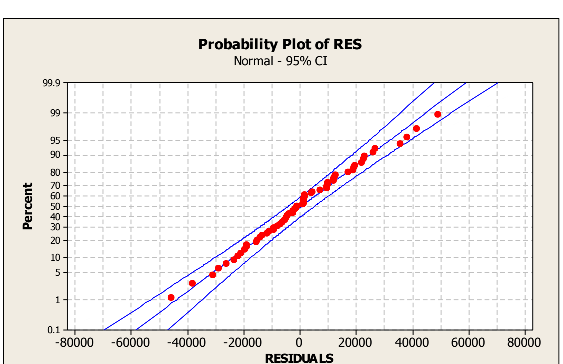

Figure 10. Normal probability plot of residuals

4.4.2. Independency checking

From the plot of residuals versus predicted values in Figure 11, it can be seen that the residuals scatted randomly. Thus it can be stated that the residuals are independently distributed. Further, the p- value (0.62) of Lagrange's Multiplier test confirms that, the residuals of fitted DTF model have no auto correlation.

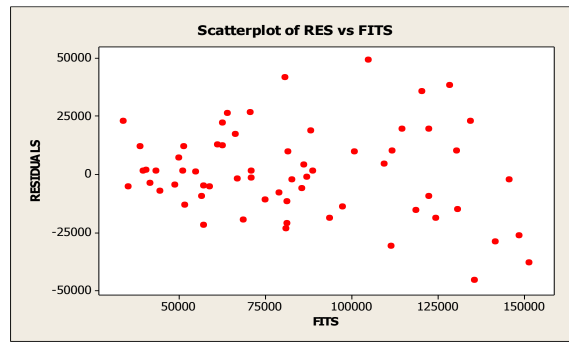

Figure 11. Plot of residuals versus predicted values

4.4.3. Homoscedasticity checking

In addition, the plot of residuals versus observations order in Figure 12 shows that it does not follow any systematic pattern and it is symmetric about 0. Thus it can be claimed that the variance of the residuals is constant throughout. Moreover, the p-value (0.30) of White's general test confirms with 95% confidence that the residuals of fitted DTF model have no heteroscedasticity.

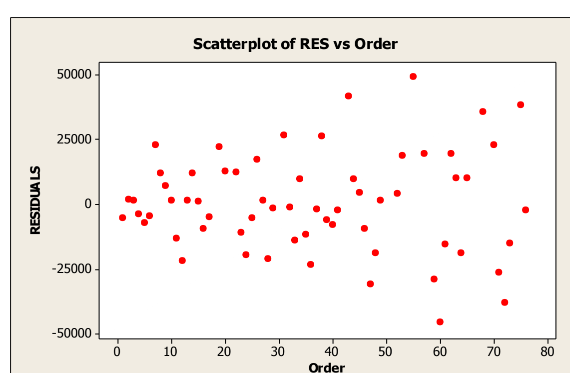

Figure 12. Plot of residuals versus observations order

The residuals of the fitted DTF model satisfy all necessary conditions of the residual analysis. Therefore, it can be concluded that the fitted DTF model is significant. Hence, this model can be recommended for predicting future international tourist arrivals to Sri Lanka.

4.5. Model validation

The plot in Figure 13 clearly shows that the predicted value from the first six months in 2016 period is very closer to the actual observations that of in the same periods in 2016. It is noted that, in the first three months the predicted values under estimate and however in the last there months they over estimate. Geometric representation of model validation in Figure 13 indicates that the predicted values are closer to the observed values. However, it has to be justified by using statistical method.

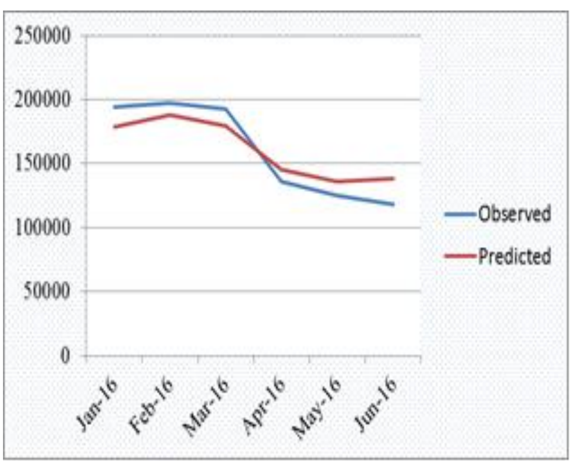

Figure 13. Plot of observed and predicted values

To check the accuracy of fitted model as model validation, MAPE statistic is calculated from the period from January 2016 to June 2016. The predicted arrivals with the observed arrivals in that particular period are summarized in Table 2.

According to the MAPE value (8.63) in Table 2, it can be concluded that, the fitted DTF model explains over 90% accuracy in terms of forecasting. This model can be strongly recommended to forecast future tourist arrival to Sri Lanka.

Table 2. Observed and predicted arrivals in 2016

Month in 2016	**Observed**	**Predicted**
January	194280	179003
February	197697	188298
March	192841	179808
April	136367	144974
May	125044	136286
June	118038	138224
MAPE	**8.63**	

4.6. Forecasting future arrivals in 2016

The future arrivals for last six months in the year 2016 are forecasted and reported in Table 3.

Table 3. Forecasted arrivals in 2016

Month in 2016	**Predicted Arrivals**
July	198,561
August	189,367
September	166,131
October	155,037
November	166,904
December	228,871
Total Arrivals	**1,104,871**

Based on the monthly wise forecasted arrivals from July 2016 to December 2016 in Table 3, it can be expected that over 1.105 million tourists will come to Sri Lanka in the last six months in 2016. It is approximately 14% increase in the tourist arrivals over the last six months in the year 2015.

5. CONCLUSIONS

Based on this study, here we provide some recommendations which can be made to improve the tourism industry in Sri Lanka.

5.1. Pattern of tourist arrivals to Sri Lanka

Since the tourist arrivals have been dramatically increased in recent past, particularly after the internal conflict in Sri Lanka, it is recommended for more attention on this industry is needed in the country. Since the seasonal patterns are very clearly observed, it is recommended to promote some activities to attract the tourists especially in off periods.

5.2 Fitted DTF model

The fitted DTF model to predict the international tourist arrivals to Sri Lanka is $\hat{Y}_t = Y_{t-1} + Y_{t-12} - Y_{t-13} + 0.82 * e_{t-1}$

where $\hat{Y}_t$ is the estimated tourist arrivals at time t

Y_{t-1}, Y_{t-12} and Y_{t-13} are the preceding arrivals at time $t-1$, $t-12$ and $t-13$ respectively

e_{t-1} is the residuals at one preceding period $t-1$

5.3. Prediction of future arrivals

Over 1.1 million international tourists can be expected in the last six months of the year 2016 and it will be 14% increase with the year 2015. Therefore it is better to be ready to facilitate the needs of those visitors in future.

5.4. Further Work

Since tourism contributes to national revenue of Sri Lanka in a large scale, it is better to carry out a causal relation study of international tourist arrivals to Sri Lanka versus gross domestic product (GDP) and then it would be useful to fit a dynamic transfer function (DTF) model by considering GDP as the dependent variable and tourist arrivals as the independent variable.

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