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*Original Research Article*

# Forecasting Ability of Univariate Time Series Approach in Foreign Guest Nights in the Southern Coast of Sri Lanka

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## ABSTRACT

The South Coast of Sri has been an attraction to the tourists for centuries. Even today, the international tourism demand to the region is in the uptrend, resulting high occupancy in the region. The high occupancy increases the demand for accommodation. Hence, the hotel industry should adopt various management practices to maximize profits and optimize operations by accurate forecasting. Therefore, this study was focused on identifying suitable forecasting techniques for occupancy guest nights of international tourism in the South Coast of Sri Lanka. Monthly data of foreign guest nights for the period of January 2008 to December 2016 were obtained from annual reports of 2008 -2016 published by Sri Lanka Tourism Development Authority (SLTDA). Time series plots used for pattern identification. The Decomposition techniques, SARIMA, and Holt-Winters models were tested for forecasting. The Anderson–Darling test, Auto-Correlation Function (ACF), and Ljung-Box Q (LBQ)-test were used to model validation. Forecasting ability of the models was assessed by relative and absolute measurements. Except for ARIMA $(1,0,1)(1,2,1)_6$ all other techniques do not meet the model validation criterion. Therefore, future night occupancy by the foreign guest in the Southern Coast can be forecasted by past night occupancy by foreign guest, past errors and seasonal components. The study concluded that SARIMA performs better than Decomposition and Holt-Winters in forecasting occupancy guest nights. However, the SARIMA model is not capable of capturing the cyclical variations. Therefore, it is recommended to test the Circular Model for de-trended series.

***Key Words:*** Occupancy, Measurement of errors, SARIMA

## INTRODUCTION

Forecasting plays a vital role in business; leads to minimize the risk and maximize the benefits. Forecasting can be divided into scientific and non-scientific approaches. Using the judgment and intuition is known as non-scientific; whereas applying mathematical and statistical modeling known as a scientific approach. The Sri Lankan tourism market consists all the regions of the world. Patterns of tourist arrival from all the regions to Sri Lanka show increasing trends, [1] especially after the year 2009. Tourists are highly occupied in Greater Colombo region (Colombo South and North), Colombo city, Southern Coast, Eastern Coast, Hill Country, Ancient Cities and Northern regions. The increase of tourist arrivals leads to increases tourism demand for accommodation capacity of Classified, Unclassified and Boutique Hotels located in tourist occupied areas. The Southern Coast of Sri Lanka is the second highest occupancy region among others. [2] Figure 1 highlighted the Southern Coast of Sri Lanka, whilst Figure 2 shows a scenic rocky area of the Southern Coast.

Hikkaduwa, Unawatuna, Bentota, Mirissa, Kogalla, and Tangalle are the famous beaches in the Southern Coast area. Sunbathing, water sports activities, boat rides, scuba diving, snorkeling, surfing are the famous leisure activities on the Southern Coast. The gorgeous reef and coral gardens, natural swimming pools, witness whales, and dolphins are some other attractions to tourist. The old town of Galle and its fortifications is one of the UNESCO World Heritage sites, located in the Southern Coast.

Figure 3 is the time series plot of occupancy in the Southern Coast and figure 4 is the autocorrelation function for occupancy in the Sothern Coast. Figure 3 clearly shows a growth of occupancy and figure 4 shows a seasonal pattern.

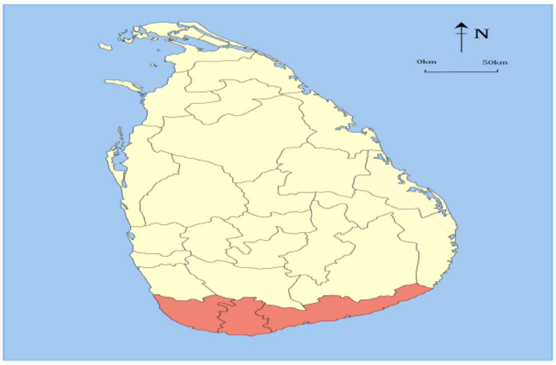


**Figure 1: Southern Coast of Sri Lanka**
**Source: Wikipedia Map**

**Figure 2: Rocky Southern Coast of Sri Lanka**
**Source: Wikipedia Map**

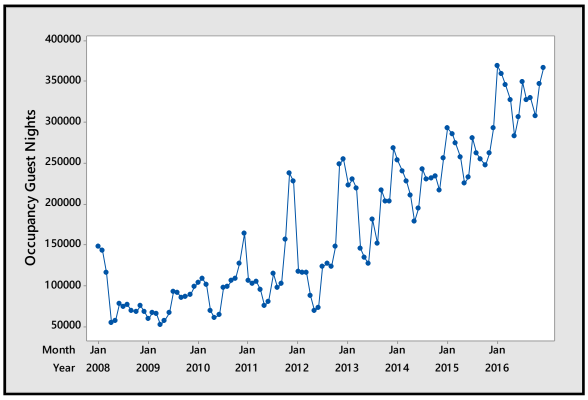


**Figure 3: Time Series plot of occupancy in the Southern Coast**

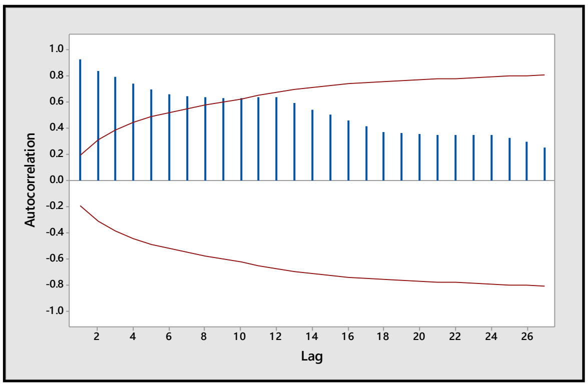


**Figure 4: Autocorrelation function for occupancy in the Southern Coast**

## Problem Statement

The high occupancy will increase the demand for accommodation. Therefore the hotel industry should adopt various management practices to maximize profits and optimize business operations. This can be achieved by accurate forecasting of occupancy by tourist. [3] Literature revealed that the Univariate time series approaches were successful in forecasting occupancy in some of the areas. Hence, this study was focused on identifying suitable univariate time series technique on forecasting occupancy guest nights of international tourism in the Southern Coast of Sri Lanka.

## The significance of the Study

The results of the study will be very helpful for strategy developments, decision making, and various planning in both macro and micro level of the tourism industry in the Sothern Coast of Sri Lanka. Further, the results of this study will be a lighthouse for the sustainable development of the tourism industry.

## The objective of the Study

To forecast foreign guest nights in the Southern Coast of Sri Lanka

## LITERATURE REVIEW

The literature review is focused on forecasting hotel room occupancy rates and guest nights. Both multivariate and univariate models were used on forecasting hotel room occupancy rates and guest nights. In addition, soft computing techniques; Artificial Neural Network (ANN) also used for the purpose. The literature review consists of;

- Studies based on forecasting guest nights
- Studies based on forecasting hotel room occupancy rates

**Studies Based on Forecasting Guest Nights**

Brannas, and Nordstrom (2000) [4] model the number of Norwegian guest nights in Swedish hotels and cottages and demand analysis. They model a number of hotel and cottage visitors for a region at a certain day. The study used Integer-valued autoregressive model and monthly arrival data from Norway. They concluded that most of the explanatory variables are significant and the estimation power is high. The Autoregressive Moving Average (ARMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) used to examine and forecast tourist accommodation demand in New Zealand using hotel-motel room nights. [5] The respective study concluded that the model performance is satisfactory for short-term forecasting. In Sri Lanka, the SARIMA and the Decomposition methods used for forecasting foreign guest nights in Colombo and Greater Colombo. The SARIMA performed better than Decomposition models. [6] The SARIMA was highly successful in forecasting occupancy of foreign guest nights in the Ancient Cites of Sri Lanka. [7]

**Studies Based on Forecasting Hotel Room Occupancy Rates**

Pan and Yang (2017) [8] used Autoregressive Integrated Moving Average with External Variables (ARIMAX) and Markov Switching Dynamic Regression (MSDR) model for forecasting weekly hotel occupancy from big data sources for Charleston, South Carolina in the United States. They concluded that ARMAX models are superior to MSDR models in forecasting on weekly hotel occupancy. Baldigara and Koić (2015) [9] used Naive model, the Holt-Winters exponential model and the SARIMA models in forecasting net occupancy rates of bed-places in the Croatian hotel industry. The study concluded that the Holt-Winters model outperformed the seasonal naive and the seasonal ARIMA model. An occupancy forecasts in major center-city hotel in the USA [10] with the application of Box Jenkins ARMA and Exponential Smoothing models. Both models show a high level of forecasting accuracy. The Autoregressive Fractionally Integrated Moving Average and the Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (ARFIMA-FIGARCH) model is another successful approach in forecasting the behavior of room occupancy rates of hotels in Bali Indonesia. [11] A Binomial Autoregressive model is an approach to forecasting daily number of occupied hotel rooms in three large Swedish cities. [12] The new Monte Carlo simulation approach, proposed by Zakhary, Atiya, Shishiny, and Gayar (2009) [13] used on occupancy forecasting of Plaza Hotel, Alexandria, Egypt. The results of their study concluded that the performance of the proposed model is very high in forecasting. The Neural Network performs better than Multiple Regression and naïve extrapolation in forecasting room occupancy rate in the Hong Kong hotel industry. [14] Most of the researcher's concern on multivariate time series. Brannas and Nordstrom (2000), [4] Lim, Chan, and McAleer (2009) [5] confirmed that ARMA and SARIMA models are suitable for forecasting guest nights. Pan and Yang (2017) [8] says that ARIMAX is suitable for forecasting on weekly hotel room occupancy rates. Holt-Winters exponential model is superior to SARIMA in forecasting hotel room occupancy rates. [9] The ARFIMA–FIGARCH and Neural Networks also tested by researchers for forecasting occupancy rates. The SARIMA performed extremely well in forecasting occupancy in Sri Lanka. [6,7]

## MATERIALS AND METHODS

Monthly data of foreign guest nights for the period of January 2008 to December

2016 were obtained from annual reports of 2008 -2016 published by SLTDA. Time series plots used for pattern identification. Time series plot of occupancy guest nights (Figure 3), shows a trend and figure 4 is the Auto-Correlation Function (ACF) of occupancy guest nights shows a seasonal behavior. The trend and seasonal pattern can be captured by Decomposition, SARIMA, and Holt-Winters models. Therefore, Decomposition additive and multiplicative models, SARIMA and Holt-Winters additive and multiplicative models were tested on forecasting. The Anderson–Darling test, ACF, and Ljung-Box Q (LBQ)-test were used to test the validation criterion and fit the model. Forecasting ability of the models was assessed by two measurements of errors; Mean Absolute Percentage Error (MAPE) and Mean Absolute Deviation (MAD) in both model fitting and verification process.

**Statistical Methods**

Statistical methods used in the study are as follows;

**Decomposition Techniques**

In Decomposition, a time series is described using a multifactor model. The model is:

$$Y_t = f(T, C, S, e) \quad (1)$$

Where;

$Y_t$ = Actual value of time series at time $t$

$f$ = Mathematical function of

$T$ = Trend

$C$ = Cyclical influences

$S$ = Seasonal influences

$e$ = Error

There are two general types of decomposition models; Additive and Multiplicative models. Multiplicative models can be used when the size of the seasonal pattern depends on the level of the data. This model assumes that as the data increase so does the seasonal pattern. The multiplicative model is:

$$Y = T \times C \times S \times e \quad (2)$$

The additive model uses when the size of the seasonal pattern does not depend on the level of the data. In this model, the trend, seasonal, and error components are added. Model is as follows:

$$Y = T + C + S + e \quad (3)$$

**Autoregressive Integrated Moving Average (ARIMA)**

ARIMA modeling can be used to model many different time series, with or without trend or seasonal components, and to provide forecasts. The forecast profile depends upon the model that is fit. The model as follows;

An ARIMA model is given by:

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t$$

Where; $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 \ldots \phi_p B^p$ (4)

$$\theta(B) - 1 - \theta_1 B - \theta_2 B^2 \ldots\ldots \theta_P B^q$$

$\varepsilon_t$ = Error term

D = Differencing term

B = Backshift operator ( $B^a Y_t = Y_{t-a}$ )

Analogous to the simple SARIMA parameters, these are:

Seasonal Autoregressive - (Ps)

Seasonal Differencing - (Ds)

Seasonal Moving average parameters - (Qs)

Seasonal models are summarized as ARIMA (p, d, q) (P, D, Q)$_s$

$$(1 - \emptyset B)(1 - \varphi B^s)(1 - B)(1 - B^s)Y_t \quad = (1 - \theta_1)B\,(1 - \theta_1\, B^s)\varepsilon_t$$
(5)

An ARIMA model is given by:

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \quad (6)$$

Where; $\phi(B) = 1 - \phi_1 B - \phi_2 B^2 \ldots \phi_p B^p$

$$\theta(B) - 1 - \theta_1 B - \theta_2 B^2 \ldots\ldots \theta_P B^q$$

$\varepsilon_t$ = Error term

D = Differencing term

B = Backshift operator ( $B^a Y_t = Y_{t-a}$ )

**Holt's Winter's three parameter Models**

This Method smoothes data by Holt-Winters exponential smoothing and provides short to medium-range forecasting. This can be used when both trend and seasonality are present, with these two components being either additive or multiplicative. [15] Winter's multiplicative model is;

$$L_t = \alpha\left(Y_t \big/ S_{t-p}\right) + (1-\alpha)[L_{t-1} + T_{t-1}] \quad (7\text{-}1)$$

$$T_t = \beta[L_t - L_{t-1}] + (1-\beta)T_{t-1} \quad (7\text{-}2)$$

$$S_t = \gamma\left(Y_t \big/ L_t\right) + (1-\gamma)S_{t-p} \quad (7\text{-}3)$$

$$\hat{Y}_t = (L_{t-1} + T_{t-1})S_{t-p} \quad (7\text{-}4)$$

Where,

$L_t$ = is the level at time t, α is the weight for the level,

$T_t$ = is the trend at time t, β is the weight of the trend,

$S_t$ = is the seasonal component at time t,

γ is the weight of the seasonal component,

p = is the seasonal period,

$Y_t$ = is the data value at time t,

$\hat{Y}_t$ = is the fitted value, or one-period-ahead forecast, at time t.

Formulae of Winter's additive model is ;

$$L_t = \alpha(Y_t - S_{t-p}) + (1-\alpha)[L_{t-1} + T_{t-1}] \quad (8\text{-}1)$$

$$T_t = \beta[L_t - L_{t-1}] + (1-\beta)T_{t-1} \quad (8\text{-}2)$$

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-p} \quad (8\text{-}3)$$

$$\hat{Y}_t = L_{t-1} + T_{t-1} + S_{t-p} \quad (8\text{-}4)$$

Where,

$L_t$ = is the level at time t, α is the weight for the level,

$T_t$ = is the trend at time t,

β is the weight of the trend,

$S_t$ = is the seasonal component at time t,

γ is the weight of the seasonal component,

p = is the seasonal period,

$Y_t$ = is the data value at time t,

$\hat{Y}_t$ = is the fitted value, or one-period-ahead forecast, at time t.

## RESULTS

Data analysis is organized as follows;

1. Forecasting by Decomposition Techniques
2. Forecasting by Holt's Winter's three parameter Models
3. Forecasting by Seasonal Autoregressive Integrated Moving Average (SARIMA)

### Forecasting by decomposition techniques

The Decomposition multiplicative and additive models run for night occupancy by the foreign guest in the Southern Coast with six seasons; season 1 is January – February, Season 2 is March –April, Season 3 is May -June, Season 4 is July –August, Season 5 is September – October, Season 6 November – December. Figure 5 and 6 are the plots for the seasonal analysis of multiplicative and additive models. According to the Figure 5; night occupancy of seasons 1, 2 and 3 are below the average, while the night occupancy of the other three seasons is above the average. The same results can be seen in figure 6.

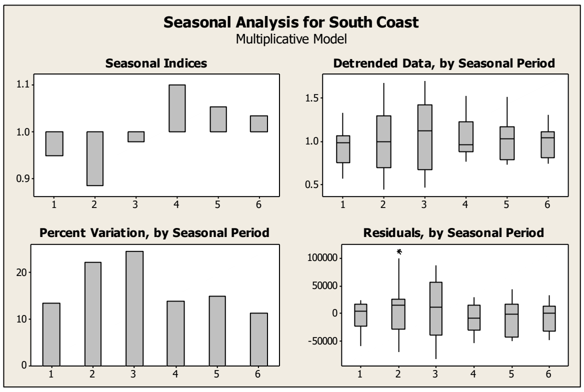


**Figure 5: Seasonal Analysis-Multiplicative Model**

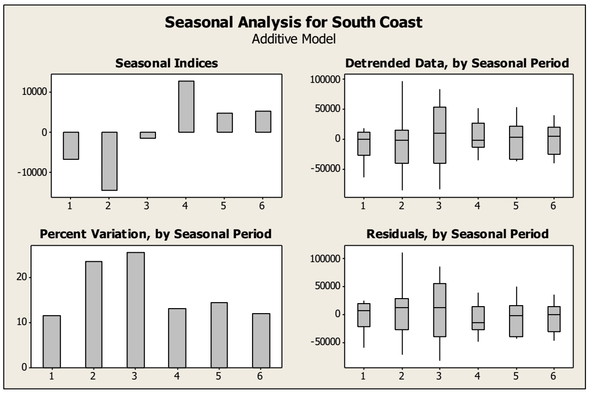


**Figure 6: Seasonal Analysis- Additive Model**

Table 1 is the summary results of seasonal indices in both Decomposition multiplicative and additive models.

**Table 1: Summary Results of Seasonal Indices for Southern Coast**

| Multiplicative Model | | | Additive Model | | |
|---|---|---|---|---|---|
| Trend Model | Season | Index | Trend Model | Season | Index |
| $Y_t$ = 39142.9 + 2345.49$t$ | 1 | 0.94869 | $Y_t$ = 39447.3 + 2325.00$t$ | 1 | -6768.8 |
| | 2 | 0.88504 | | 2 | -14405.7 |
| | 3 | 0.97815 | | 3 | -1540.5 |
| | 4 | 1.10029 | | 4 | 12692.7 |
| | 5 | 1.05254 | | 5 | 4839.9 |
| | 6 | 1.03529 | | 6 | 5182.3 |

According to the table 1, seasonal indices for the periods of 1, 2, 3, 4, 5 and 6 of the multiplicative model are 0.94869, 0.88504, 0.97815, 1.10029, 1.05254 and 1.03529. Seasons 1, 2 and 3 are below the average, while the night occupancy of the other three seasons is above the average. It means the number of night occupancy for the periods of 1, 2 and 3 are below the average, while the night occupancy of the other three seasons is above the average by the foreign guest in the Southern Coast. Seasonal indices for the periods of 1, 2, 3, 4, 5 and 6 of the additive model are -6768.8, -14405.7, -1540.5, 12692.7, 4839.9 and 5182.3. The results are similar to the multiplicative model. The summary measures of the model fitting of both multiplicative and additive models are given in Table 2.

**Table 2: Model Summary**

| Model | Model Fitting | |
|---|---|---|
| Multiplicative Model | MAPE | 24 |
| | MAD | 28393 |
| | Normality | P = 0.057 |
| | Independence | h=1 |
| Additive Model | MAPE | 24 |
| | MAD | 28593 |
| | Normality | P = 0.143 |
| | Independence | h=1 |

Both relative and absolute measurements of errors are not satisfactorily low in model fitting. The Anderson-Darling test revealed that the residuals of both multiplicative and additive models follow the normal distribution. The LBQ test and ACF did not confirm the independence of residuals (h=1). It confirms that the models do not meet the validation criterion. The results of Decomposition multiplicative and additive models confirmed that they are not suitable for forecasting the occupancy guest nights in the Southern Coast of Sri Lanka.

**Forecasting by Holt's Winter's three parameter models**

The Holt's Winter's three parameter multiplicative and additive models were tested for various α (level), γ (trend) and δ (seasonal) values using trial and error methods. The seasonal length is taken as 6.

**Table 3: Model Summary of Holt's Winters three parameter multiplicative models**

| Models | | | MAPE | MAD | Normality (P–value) | Independence of Residuals |
|---|---|---|---|---|---|---|
| Level (α ) | Trend (γ) | Seasonal (δ) | | | | |
| 0.2 | 0.2 | 0.2 | 25 | 31413 | 0.012 | No |
| 0.38 | 0,25 | 0.25 | 23 | 30712 | 0.030 | No |
| 0.38 | 0.25 | 0.38 | 24 | 31761 | 0.017 | No |

Table 3 shows the summary of output results of Holt's Winters three parameter multiplicative models. The residuals of each model were tested for normality and independence by Anderson-Darling test, LBQ test, and ACF respectively. Measurements of errors are not satisfactorily low. The residuals of the models do not follow the normal distribution and not independent (Correlated). Winter's additive models were tested after multiplicative models.

**Table 4: Model Summary of Holt's Winters three parameter additive models**

| Models | | | MAPE | MAD | Normality (P–value) | Independence of Residuals |
|---|---|---|---|---|---|---|
| Level (α ) | Trend (γ) | Seasonal (δ) | | | | |
| 0.2 | 0.2 | 0.2 | 25 | 31413 | 0.012 | No |
| 0.38 | 0.25 | 0.25 | 24 | 31232 | 0.058 | No |
| 0.38 | 0.28 | 0.25 | 24 | 31936 | 0.073 | No |

Table 4 shows the results of additive models. Measurements of errors are not satisfactorily low as a multiplicative model. The residuals of the models follow normally distribution except the model $\alpha$ = 0.2, $\gamma$ =0.2, $\delta$ = 0.2. But the residuals of all three models are not independent (Correlated). It is clear that Holt's Winters three-parameter multiplicative and additive models do not meet the model validation criterion. Therefore, Holt's Winters three-parameter models cannot forecast the occupancy guest nights in the Southern Coast of Sri Lanka.

**Forecasting by Seasonal Autoregressive Integrated Moving Average (SARIMA)**

The SARIMA model runs for night occupancy by the foreign guest in the Southern Coast with six seasons.

**Table 5: Model Summary of SARIMA**

| Model | Model Fitting | | Verification | |
|---|---|---|---|---|
| ARIMA $(1,0,1)(1,2,1)_6$ | MAPE | 14.8279 | MAPE | 8.5686 |
| | MAD | 2.0289e+04 | MAD | 2.5019e+04 |
| | Normality | P = 0.082 | | |
| | Independence of Residuals | h=0 | | |

The results of SARIMA are given in Table 5. The model ARIMA$(1,0,1)(1,2,1)_6$ describes a model that includes 1 autoregressive parameter, 1 regular moving average parameter,1 seasonal autoregressive parameters and 1 seasonal moving average parameter and these parameters were computed for the series after no differenced with, and two seasonally differenced. Both relative and absolute measurements of errors of the model are satisfactorily low in model fitting. The Anderson-Darling Normality test confirmed the normality of residuals; the LBQ- test, and ACF confirmed the independence of residuals (h=0). Under the verification also the measurements of errors were low. Therefore, future night occupancy by the foreign guest in the Southern Coast can be forecasted by past night occupancy by foreign guest, past errors and seasonal components.

Figure 7 is the time series plot of actual vs. fits of the above model. Fits almost follow the pattern of actual behavior. Both are close to each other. Figure 8 is the time series plot of actual vs. forecast. The deviation between actual and forecast is very less. Hence, the selected model is suitable for forecasting night occupancy by the foreign guest in the Southern Coast of Sri Lanka.

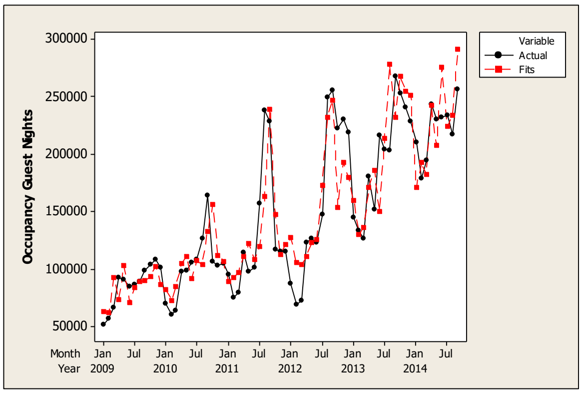


**Figure 7: Actual Vs Fits**

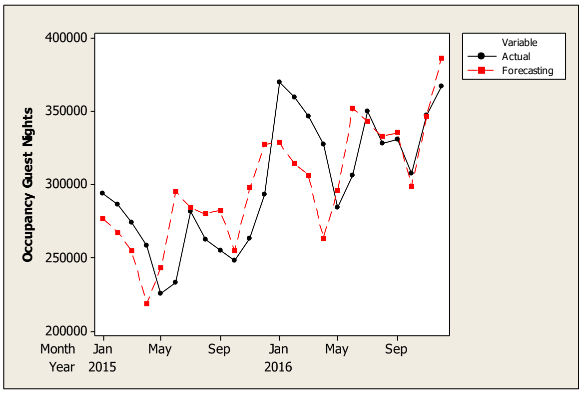


**Figure 8: Actual Vs Forecast**

## DISCUSSION

The SAIRMA performs better in previous studies on forecasting guest nights. The results of the study agree with few studies in the literature [5-7]. The results of this study can be used for planning and control the business operations of the tourism industry in the South Coast of Sri Lanka. Controlling business operations can be done by controlling physical resources namely: inventory management, quality control, and equipment control. Human resources namely: selection and placement, training and development, performance appraisal, and compensation. Information resources namely: sales and marketing, and production scheduling. Financial resources namely: managing capital funds and cash flow, collection and payment of debts. Forecasting occupancy provides high and low occupancy periods. It directs hoteliers and other tourism-related business to increase or decreases their production volume and product differentiation. During high occupancy, there will be high demand for shopping malls, restaurants, banks etc. Due to high demand, product and process layouts should be adjusted to meet the requirements of tourists. It can be decided based on the results of forecasting occupancy. High occupancy increase higher volume of garbage and various forms of threats. Therefore, authorities should plan for efficient and effective solid management practices and work out safety and security measures during high occupancy period to protect tourist. Increasing traffic will be another critical issue during high occupancy period. Therefore, authorities should plan ahead for smooth functions with the guidance of forecasting. The damage to the natural environment of the South Coast could be possible. Then there should be environmental protection measures to be implemented. Wastage of scares resources electricity, water, and food etc, could exist during high occupancy period. Then the business managers should be implemented and practice various resource management practices to minimize the wastage. Promotional campaigns for the products of hotels and other tourism-related business can be done by observing the occupancy behavior. The revision of prices can implement by observing the occupancy behavior. The prices can be reduced during low and increase during high occupancy period. And also the various offerings for products can be reduced during low occupancy period. Varieties of buffet and coffee shops can be taken as examples. Hoteliers can plan for training programs, workshops for their staff and CSR activities for their stakeholders during low occupancy period.

The results of this study will be useful for the financial department to estimate cash/ credit flow, expenses that will be generated in different departments such as food and beverages, laundry, transport, accommodation and other maintenance. It is useful for planning a financial budget, work out requirements of food and beverages, other perishable goods, non-perishable goods, and maintenance etc. In addition, recruitment plans, hotel maintenance, structural changes of hotels and establishing emergency services can be decided through accurate forecasting of occupancy guest nights in the Sothern Coast of Sri Lanka.

The decomposition and Holt's Winters three parameter approaches were not successful in this study, while, the SARIMA was highly successful. The data series of occupancy follows the wave-like pattern. A wave-like pattern may contain both seasonal and cyclical variation, but the SARIMA is unable to separate them. The Circular Model is a recently developed univariate forecasting technique, which can be used to capture both seasonal and cyclical patterns. [16] Therefore, it is recommended to test the Circular Model for de-trended data, in order to see whether it improves the forecasting ability.

## CONCLUSION

The study tested Decomposition, SARIMA, and Holt-Winters models. Decomposition multiplicative and additive models and Holt-Winters additive and multiplicative models do not meet the validation criterion. Those models are not suitable for forecasting the occupancy guest nights in the Southern Coast of Sri Lanka. Results of the study revealed that the model ARIMA $(1,0,1)(1,2,1)_6$ model satisfied the validation criterion. Therefore, it is suitable for forecasting the occupancy guest nights in the Southern Coast of Sri Lanka. Future night occupancy by the foreign guest in the Southern Coast can be forecasted by past night occupancy by foreign guest, past errors and seasonal components.

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