Forecasting Foreign Guest Nights in Hill Country of Sri Lanka

Review of Integrative Business & Economics Research

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ABSTRACT

The forecasting occupancy guest nights is an essential discipline in purchase decisions, expansion plans, staffing and maintenance of hotels at Hill Country in Sri Lanka. The high occupancy will increase the demand for accommodation. Therefore, the study was focused on forecasting occupancy guest nights of international tourist in Hill Country. Monthly data of foreign guest nights for the period of January 2008 to December 2016 were obtained from Sri Lanka Tourism Development Authority (SLTDA). The Decomposition, Holt-Winters and Seasonal Autoregressive Integrated Moving Average (SARIMA) models were tested for forecasting. The Anderson–Darling test, Auto-Correlation Function (ACF), and Ljung-Box Q (LBQ)-test were used as the goodness of fit tests in model validation. The best-fitting model was selected by comparing both relative and absolute measurements of errors. The Decomposition and Holt-Winters models dose not satisfy the model validation criterion. Both relative and absolute measurements of errors of the model ARIMA (2,0,1) (2,1,1) are very low in model fitting and verification. The study concluded that SARIMA performs better than other techniques. The SARIMA model is not capable of capturing the cyclical variations. Therefore, it is recommended to test the Circular Model as well.

Keywords: Guest nights, Errors, SARIMA.

1. INTRODUCTION

Over the past years, tourist arrivals to Sri Lanka show increasing trend. Sri Lankan tourism market consist all regions of the world. Patterns of tourist arrival from all the regions of Sri Lanka also show increasing trends (Konarasinghe, 2016). Greater Colombo (Colombo South and North), Colombo city, South Coast, Eastern Coast, Hill Country, Ancient Cities and Northern region are the highly occupied regions by international tourist (SLTDA, 2016). Hill Country is one of the highest occupied regions which are located in the Central province of Sri Lanka. Hill Country consist many UNESCO world heritage sites namely; Kandy city, Knuckles Mountain Range, Adam's Peak and Horton Plains. In addition, so many cultural landscapes, an ancient city, botanical gardens and more than hundreds of waterfalls of the hill country are attractions to the tourists. Natural beauty, the cultural value and various tourism

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categories; Eco, Cultural, Adventure and Religious tourism are leading tourism categories increases the tourism demand for Hill Country in Sri Lanka. It creates demand for accommodation of Classified, Unclassified and Boutique hotels located in the region.

Figure 1: Time Series Plot of Hill Country

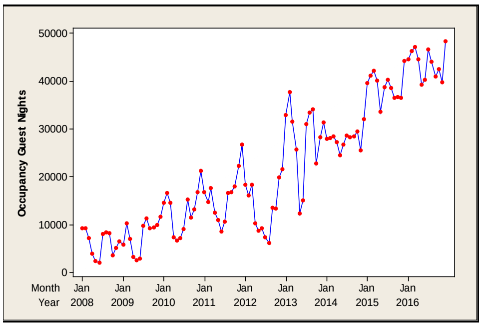

Figure 2: Autocorrelation Function for Hill Country

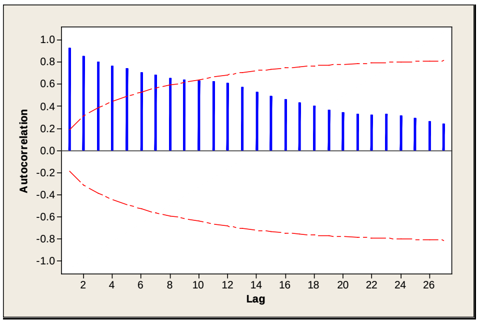

Figure 1 clearly shows an increasing trend of occupancy of international tourist in Hill Country over the years. Figure 2 clearly shows a seasonal behavior of occupancy in Hill Country.

1.1 PROBLEM STATEMENT

An increasing occupancy will increase the demand for accommodation; hence the competition in hotel industry also will increase. Therefore, the hotel industry should adopt various management practices to maximize profits and optimize operations. This can be achieved by accurate forecasting of occupancy by tourist (Schwartz and Hiemstra 1997). It is a well-known fact that accurate forecasting is a critical component in eliminating waste of resources and make industry efficient and effective in their business operations. But it was hard to find attempts of forecasting occupancy guest nights in Hill Country of Sri Lanka. On view of the above, the study was focused on forecasting occupancy guest nights of international tourist in Hill Country of Sri Lanka.

1.2 OBJECTIVE OF THE STUDY

To Forecast Foreign Guest Nights in Hill Country of Sri Lanka.

1.3 SIGNIFICANCE OF THE STUDY

The results of this study can be used for planning to manage and controlling the business operations of the tourism industry in Hill Country of Sri Lanka. Forecasting occupancy leads to plan their new products and volume of products to create demand by hoteliers and other tourism-related business. For examples; low occupancy for the upcoming period, hoteliers can decide for promotional campaigns for their customers; Operation managers may decide to reduce various offerings such as buffet and, coffee

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shop etc, during low occupancy periods. Business managers can select low cost or high rate channels to yield and sell during high occupancy period. It will be useful for profit maximization. The results of this study will be useful for Financial Controller to estimate cash/ credit flow, multiple expenses that will be generated in different departments such as food and beverages, laundry, transport etc., and including rooms. It will be useful for department financial budgets and can work out requirements of food and beverages, other perishable goods, non-perishable goods and maintenance like laundry sanitary items etc. High occupancy increases higher volume of garbage. Therefore, authorities should plan for efficient and effective solid management practices. In addition, they have to work out safety and security measures during high occupancy period to protect tourist from various forms of threats. Hoteliers can plan for training programs, workshops for their staff and other CSR activities for their stakeholders during low occupancy period. Expansion plans, recruitment plans, hotel maintenance, developments or building of infrastructure and traffic controlling methods can be decided through accurate forecasting of occupancy guest nights. High occupancy increasing high demand for scares resources, such as water, land etc. Therefore, the results of this study provide guidance for various resource management practices. In addition, the results of this study can be used to plan their course of actions in all areas for near future in Hill Country of Sri Lanka. This will provide many benefits to the economy, socio-cultural and environment.

2. 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 in the following:

2.1 Studies based on forecasting guest nights.

2.2 Studies based on forecasting hotel room occupancy rates.

2.1 STUDIES BASED ON FORECASTING GUEST NIGHTS

Brannas, and Nordstrom (2000) model the number of Norwegian guest nights in Swedish hotels and cottages and demand analysis. They model 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. 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 by Lim, Chang, and McAleer (2009). They concluded that the model performance is satisfactory for short-term

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forecasting. In Sri Lanka, SARIMA and Decomposition additive and multiplicative methods used for forecasting foreign guest nights in Colombo and Greater Colombo by Konarasinghe (2017-a). He concluded SARIMA performed better than Decomposition additive and multiplicative models. SARIMA was highly successful in forecasting occupancy of foreign guest nights in Southern Cost and Ancient Cites of Sri Lanka (Konarasinghe, 2017-b) and (Konarasinghe, 2017-c).

2.2 STUDIES BASED ON FORECASTING HOTEL ROOM OCCUPANCY RATES

Pan and Yang (2017) investigate the best modeling technique for forecasting weekly hotel occupancy from big data sources for Charleston, South Carolina in the United States. Autoregressive Integrated Moving Average with External Variables (ARIMAX) and Markov Switching Dynamic Regression (MSDR) model used by them. The results of their study revealed that ARMAX models are superior to MSDR models in forecasting on weekly hotel occupancy. Naive model, the Holt-Winters exponential model and the SARIMA models used to model the net occupancy rates of bed-places in the Croatian hotel industry by Baldigara and Koić (2015). The results show that the Holt-Winters model outperformed the seasonal naive and the seasonal ARIMA model. Andrew, Cranage and Lee (1991) tested the accuracy of Box Jenkins ARMA and Exponential Smoothing models on occupancy forecasts in major center-city hotel USA. Both models show a high level of forecasting accuracy. Chen and Malinda (2015) applied Autoregressive Fractionally Integrated Moving Average and Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity (ARFIMA-FIGARCH) model and the Iterated Cumulative Sums of Squares test (ICCS) method for multiple structural breaks to examine the behavior of room occupancy rates of hotels in Bali Indonesia. They concluded that ARFIMA–FIGARCH model is better in forecasting. Binomial autoregressive model is another approach on forecasting daily number of occupied hotel rooms in three large Swedish cities by Brannas and Nordstrom (2011). The performance of the model is high. New Monte Carlo simulation approach proposed by Zakhary, Atiya, Shishiny, and Gayar (2009) on occupancy forecasting for Plaza Hotel, Alexandria, Egypt. Results of their study concluded that proposed model gives superior results in forecasting. Neural networks are another approach in forecasting hotel occupancy rate in Hong Kong hotel industry by Law (1998). The results concluded that the neural networks approach performs better than multiple regression and naïve extrapolation in forecast room occupancy.

Univariate and Multivariate time series techniques are used in hotel room occupancy rates and guest nights forecasting the horizon. Soft computing techniques like neural networks also used in forecasting occupancy. Most of the researcher's concern on multivariate time series. Brannas and Nordstrom (2000), Lim and Chan (2009) confirmed that the Integer-valued autoregressive, ARMA and SARIMA models are suitable for forecasting guest nights. Pan and Yang (2017) says that ARIMAX is suitable for forecasting on weekly hotel room occupancy rates. Baldigara and Koić (2015) confirmed that the Holt-Winters exponential model is superior to SARIMA in

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forecasting hotel room occupancy rates. In addition, ARFIMA–FIGARCH and Neural Networks tested by researchers for forecasting occupancy rates. In Sri Lankan context SARIMA performed extremely well in forecasting occupancy. It was confirmed by Konarasinghe (2017-a), (2017-b) and (2017-c). The suitable models were ARMA and SARIMA, ARIMAX , Holt-Winters exponential models in forecasting occupancy Neural networks also suitable soft computing technique in forecasting occupancy.

3. METHODOLOGY

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 and Auto-Correlation Function (ACF) were used for pattern identification. The 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 three measurements of errors; Mean Absolute Percentage Error (MAPE), Mean Square Error (MSE) and Mean Absolute Deviation (MAD) in both model fitting and verification process.

3.1 DECOMPOSITION TECHNIQUES

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

$$Y_t = f(T, C, S, e) \tag{1}$$

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

Decomposition is to separate the time series into linear trend and seasonal components, as well as error, and provide forecasts. 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. Most time series plots exhibit such a pattern. The multiplicative model is:

$$Y = T \times C \times S \times e \tag{2}$$

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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:

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

3.2 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 advantage of ARIMA modeling compared to the simple forecasting and smoothing methods is that it is more flexible in fitting the data. However, identifying and fitting a model may be time-consuming, and ARIMA modeling is not easily automated. The model as follows:

An ARIMA model is given by:

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

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

$$\theta(B) - 1 - \theta_1 B - \theta_2 B^2 \ldots\ldots\theta_P B^q \quad (4)$$

$\varepsilon_t =$ 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

$$(1-\phi_1 B)(1-\varphi_1 B^s)(1-B)(1-B^s)Y_t = (1-\theta_1 B)(1-\theta_1 B^s)\varepsilon_t \quad (5)$$

3.3 HOLT'S WINTER'S THREE PARAMETER MODELS

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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 (Holt,1957). Winter's multiplicative model is:

$$L_t = \alpha\left(Y_t \big/ S_{t-p} \right) + (1-\alpha)\left[L_{t-1} + T_{t-1}\right] \tag{6-1}$$

$$T_t = \beta\left[L_t - L_{t-1}\right] + (1-\beta)T_{t-1} \tag{6-2}$$

$$S_t = \gamma\left(Y_t \big/ L_t \right) + (1-\gamma)S_{t-p} \tag{6-3}$$

$$\hat{Y}_t = (L_{t-1} + T_{t-1})S_{t-p} \tag{6-4}$$

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 :

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

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

$$S_t = \gamma(Y_t - L_t) + (1-\gamma)S_{t-p} \tag{7-3}$$

$$\hat{Y}_t = L_{t-1} + T_{t-1} + S_{t-p} \tag{7-4}$$

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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.

4. RESULTS

Data analysis is organized as follows:

4.1. Forecasting by Decomposition Techniques.
4.2. Forecasting by Holt's Winter's three parameter Models.
4.3. Forecasting by Seasonal Autoregressive Integrated Moving Average (SARIMA).

4.1. FORECASTING BY DECOMPOSITION TECHNIQUES

The Decomposition multiplicative and additive models run for night occupancy by the foreign guest in Hill Country with four seasons; season 1 is January - March, Season 2 is April - June, season 3 is July - September and season 4 is October - December. Figure 3 and 4 are the plots for the seasonal analysis of multiplicative and additive models. According to the Figure 3; night occupancy of seasons 1 and 2 are below the average, while the night occupancy of the other two seasons is above the average. The same results can be seen from figure 4.

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Figure 3: Seasonal Analysis- Multiplicative Model

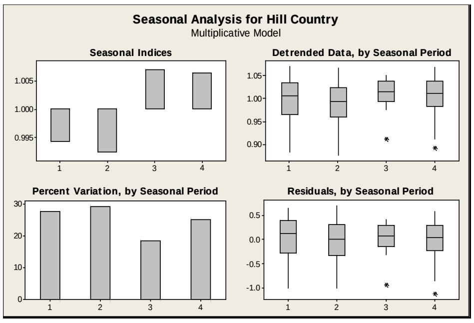

Figure 4: Seasonal Analysis- Additive Model

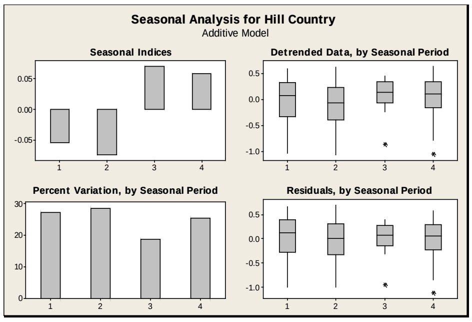

Table 1 is the Summary Results of Seasonal Indices in both Decomposition multiplicative and additive models.

Table 1: Summary Results of Seasonal Indices for Hill Country

Multiplicative Model			Additive Model		
Trend Model	Season	Index	Trend Model	Season	Index
$lnY_t = 8.51203 + 0.0226558t$	1	0.99421	$lnY_t = 8.51257 + 0.0226473t$	1	-0.05426
	2	0.99239		2	-0.07407
	3	1.00701		3	0.06989
	4	1.00639		4	0.05844

According to the table 1, seasonal indices for the periods of 1, 2, 3 and 4 of the multiplicative model are 0.99421, 0.99239, 1.00701 and 1.00639. Seasons 1 and 2 are below the average, while the night occupancy of other two seasons is above the average by the foreign guest in Hill Country. Seasonal indices for the periods of 1, 2, 3 and 4 of the additive model are -0.05426, -0.07407, 0.06989 and 0.05844. 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.

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Table 2: Model Summary

Model	Model Fitting	
Multiplicative Model	MAPE	3.59255
	MAD	0.32762
	MSE	0.17317
	Normality	P = 0.005
	Independence	h=1
Additive Model	MAPE	3.59007
	MAD	0.32743
	MSE	0.17284
	Normality	P = 0.006
	Independence	h=1

Both relative and absolute measurements are very low in model fitting. But those are not sufficient for model verification. The Anderson-Darling test revealed that the residuals of both multiplicative and additive models do not follow a normal distribution. The LBQ test 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 Hill Country of Sri Lanka.

4.2. 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 4.

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

Models			MAPE	MAD	MSE	Normality (P–value)	Independence of Residuals
Level (α)	Trend (γ)	Seasonal (δ)					
0.2	0.2	0.2	4.551	0.421	0.296	0.172	No

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0.28	0.2	0.28	4.281	0.397	0.269	0.125	No
0.34	0.34	0.34	4.328	0.402	0.283	0.094	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 satisfactory low. The residuals of the models were normally distributed but 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	MSE	Normality (P–value)	Independence of Residuals
Level (α)	Trend (γ)	Seasonal (δ)					
0.2	0.2	0.2	4.539	0.420	0.294	0.170	No
0.28	0.2	0.28	4.261	0.395	0.267	0.119	No
0.34	0.34	0.34	4.293	0.399	0.279	0.070	No

Table 4 shows the results of additive models. Measurements of errors are satisfactory low. The residuals of the models were normally distributed but not independent (Correlated). It is clear that Holt's Winters three-parameter multiplicative and additive models do not meet all model validation criterion. Therefore, Holt's Winters three-parameter models cannot forecast the occupancy guest nights in Hill Country of Sri Lanka.

4.3. FORECASTING BY SEASONAL AUTOREGRESSIVE INTEGRATED MOVING AVERAGE (SARIMA)

The SARIMA model runs for night occupancy by the foreign guest in Hill Country with four seasons.

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Table 5: Model Summary of SARIMA

Model	Model Fitting		Verification	
ARIMA(2,0,1)(2,1,1)$_4$	MAPE	2.329	MAPE	1.566
	MSE	0.078	MSE	0.041
	MAD	0.215	MAD	0.166
	Normality	P= 0.594		
	Independence of Residuals	h=0		

The results of SARIMA are given in Table 5. The model ARIMA(2,0,1)(2,1,1)$_4$ describes a model that includes 2 autoregressive parameter, 1 regular moving average parameter,2 seasonal autoregressive parameters and 1 seasonal moving average parameter and these parameters were computed for the series after no differenced with, and one seasonally differenced. Both relative and absolute measurements of errors of the model are very low in model fitting. The Anderson-Darling normality test confirmed the normality of residuals; the LBQ- test confirmed the independence of residuals (h=0). Under the verification also the measurements of errors were very low. Therefore, future night occupancy by the foreign guest in Hill Country can be forecasted by past night occupancy by foreign guest, past errors and seasonal components. Figure 5 and 6 are the Time Series Plot of actual vs fits and actual vs forecast of the ARIMA (2,0,1)(2,1,1)$_4$ model. The fitted line in Figure 5 follows the similar pattern of the series. Actual and fitted are closer to each other. The deviation of the actual and forecast is very less (Figure 6).

Figure 5: Time Series Plot of Actual Vs Fits

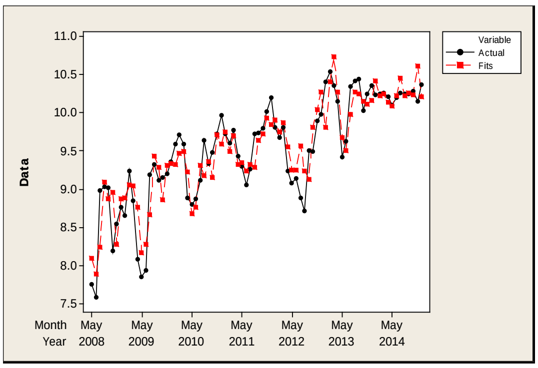
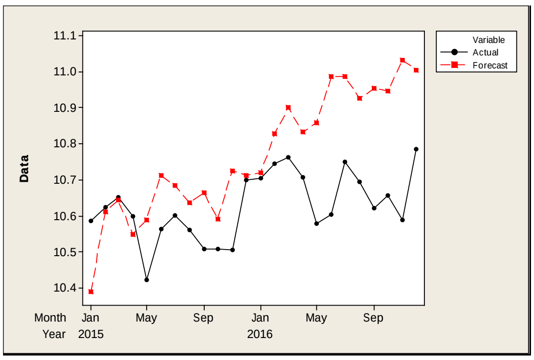


Figure 6: Time Series Plot of Actual Vs Forecast



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The study tested Decomposition additive and multiplicative models, Holt's Winters three parameter additive and multiplicative models and SARIMA models on night occupancy by the foreign guest in Hill Country. According to the results shown in Table 6, Decomposition additive and multiplicative models and Holt's Winters three-parameter models were not fitted, as models do not satisfy the model validation criterion. But the residuals of SARIMA satisfied the model validation criterion. The relative measurement of SARIMA is very low in fitting and verification. Absolute measurements are same in fitting and verification.

Table 6: Model Comparison of Hill Country

Model	Model Fitting					Verification		
	MAPE	MSE	MAD	Normality	Correlation of residuals	MAPE	MSE	MAD
ARIMA $(2,0,1)(2,1,1)_4$	2.329	0.078	0.215	0.594	h=0	1.566	0.041	0.166
Decomposition Multiplicative	3.592	0.173	0.327	0.005	h=1	Not Fitted		
Decomposition Additive	3.590	0.172	0.327	0.006	h =1	Not Fitted		
Holt's Winters Multiplicative	4.281	0.269	0.397	0.125	h =1	Not Fitted		
Holt's Winters Additive	4.261	0.267	0.395	0.119	h =1	Not Fitted		

Estimated Foreign Guest Nights in Hill Country of Sri Lanka for the period of January 2017 to December 2018 shown in Table 7.

Table 7: Estimated Night Occupancy of Hill Country

Year	Month	Number of Estimated Hill Country
2017	January	32542
	February	40603
	March	41925

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	April	38122
	May	39698
	June	44907
	July	43656
	August	41632
	September	42805
	October	39791
	November	45467
	December	44919
2018	January	45244
	February	50473
	March	54227
	April	50620
	May	51968
	June	59122
	July	59043
	August	55659
	September	57228
	October	56819
	November	61848
	December	60209

5. CONCLUSION AND RECOMMENDATION

Hill Country is one of the highest occupied regions by international tourist. It provides many benefits to the hotels and tourism-related businesses in Hill Country of Sri Lanka. However, there exists a knowledge gap in forecasting occupancy guest nights in Hill Country of Sri Lanka. The study tested Decomposition additive and multiplicative models, Holt's Winters three parameter additive and multiplicative models and SARIMA models on night occupancy by the foreign guest in Hill Country. The results of the study revealed that SARIMA is suitable for forecasting occupancy guest nights in Hill Country of Sri Lanka. The results of the study agree with the studies of Lim, Chang and McAleer (2009), Konarasinghe (2017-a), (2017-b) and (2017-c) in forecasting guest nights.

The decomposition and Holt's Winters three parameter approaches were not successful in this study, while, the SARIMA was highly successful. However, 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 (Konarasinghe,

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Abeynayake, and Gunaratne, 2016). Therefore, it is recommended to test the Circular Model for de-trended data, in order to see whether it improves the forecasting.

REFERENCES

[1] Andrew, W.P., Cranage, D.A., Lee, C.K. (1991), "Forecasting Hotel Occupancy Rates with Time Series Models: An Empirical Analysis", *Hospitality Research Journal*.

[2] Baldigara, T., Koić, M. (2015), "Modeling Occupancy Rates in Croatian Hotel Industry", *International Journal of Business Administration,* 6(3).

[3] Brannas, K., Nordstrom, J. (2011), "The Number of Occupied Hotel Rooms a Time Series Model that Accounts for Constrained Capacity and Prices", Umea Economics Studies 559.

[4] Brannas, K., Nordstrom, J. (2000), "A Bivariate Integer Value Allocation Model for Guest Nights in Hotels and Cottages", Umea Economic Studies. Sweden.

[5] Chen, J., Malinda, M. (2015), "Room Occupancy Rates of Hotels in Bali: Testing for Long Memory and Multiple Structural Breaks", *Journal of International and Global Economic Studies*, 8(1), 51-67.

[6] Holt, C.C. (1957), "Forecasting seasonal and trends by exponentially weighted moving average", *Office of Navel Research*, Research memorandum, 52.

[7] Konarasinghe, K.M.U.B. (2017a), "Forecasting Foreign Guest Nights in Colombo and Greater Colombo of Sri Lanka", *Conference Proceedings of the 14th International Research Conference on Business Management (ICBM) – 2017,* Faculty of Management Studies and Commerce, University of Sri Jayawardanapura, Sri Lanka.

[8] Konarasinghe, K.M.U.B.(2017b), " Forecasting Foreign Guest Nights in Southern Coast of Sri Lanka", *Conference Proceedings of the Peradeniya University International Research Sessions (iPURSE) -2017,* University of Peradeniya, Sri Lanka, 21, 40.

[9] Konarasinghe,K.M.U.B.(2017c), "Forecasting Foreign Guest Nights in Ancient Cities of Sri Lanka", *Conference Proceedings of the 22nd International Forestry and Environment Symposium 2017,* Department of Forestry and Environmental Science, University of Sri Jayewardenepura, Sri Lanka. 114.

[10] Konarasinghe, K.M.U.B. (2016), "Time Series Patterns of Tourist Arrivals to Sri Lanka", *Review of Integrative Business and Economics Research,* 5(3), 161-172.

[11] Konarasinghe, W.G.S., Abeynayake, N.R., Gunaratne, L.H.P. (2016), "Circular Model on Forecasting Returns of Sri Lankan Share Market", *International Journal of Novel Research in Physics, Chemistry and Mathematics,* 3(1), 49-56.

[12] Lim,C., Chang, C., McAleer, M. (2009). "Forecasting h(m)otel guest nights in New Zealand", *International Journal of Hospitality Management*, 28(2), 228-235.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)

[13] Law, R. (1998), “Room Occupancy Rate Forecasting: A Neural Network Approach”, *International Journal of Contemporary Hospitality Management*, 10(6), 234–239.

[14] Pan, B., Yang, Y. (2017), “Forecasting Destination Weekly Hotel Occupancy with Big Data”, *Journal of Travel Research January 2017*.

[15] Sri Lanka Tourism Development Authority (SLTDA). (2016), “Summary report 2016”, Online at http://www.sltda.lk/statistics.

[16] Schwartz, Z., Hiemstra, S. (1997), “Improving the accuracy of hotel reservations forecasting: Curves Similarity Approach”, *Journal of Travel Research*, 36(1), 3-14.

[17] Zakhary, A., Atiya, A.F., Shishiny, H., Gayar., N. E.(2009), “Forecasting Hotel Arrivals and Occupancy Using Monte Carlo Simulation”, *International Journal of Information Technology*.

ISSN: 2304-1013 (Online); 2304-1269 (CDROM); 2414-6722 (Print)