European Journal of Business and Management
ISSN 2222-1905 (Paper) ISSN 2222-2839 (Online)
Vol.9, No.10, 2017

A Comparative Analysis of the Application of Seasonal ARIMA and Exponential Smoothing methods in short run Forecasting Tourist Arrivals in Tanzania

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Abstract

This paper compared the performance of two forecasting models (Seasonal ARIMA and Exponential smoothing) in an attempt to identify the model that fits properly in forecasting tourist arrivals in a dynamic tourism industry in Tanzania. A two-staged approach to forecasting was carried out using monthly data for the period of 2000 to 2009. The models were assessed in similarly structured setting at the outset, and then best models identified at this level were compared in a differently structured setting. The results show that Seasonal ARIMA$(4,1,4)(3,1,4)_{12}$ and Holt-Winters multiplicative smoothing method are effective in forecasting tourist arrivals in Tanzania in a similarly structured setting. However, when the two models were compared under different structures, the performance of Holt-Winters multiplicative smoothing method outstripped that of Seasonal ARIMA$(4,1,4)(3,1,4)_{12}$. This suggests that Holt-Winters multiplicative smoothing method with Alpha (0.01), Delta (0.11) and Gamma (0.11) is more effective in forecasting tourist arrivals in Tanzania in the short run and it can be used to aid planning processes in the tourism industry. Moreover, the seasonality pattern that characterizes tourist arrivals in Tanzania highlights the need to promote more of local tourism so as to lessen the negative impacts associated with it.

Keywords: Tourist Arrivals, Forecasting, Model, Seasonal ARIMA, Exponential Smoothing, Holt-Winters additive, Holt Winters Multiplicative
JEL: C53

1. Introduction

The tourism sector is recognized as a growing industry playing an important role in trade, economic and social development. A large number of countries worldwide depend on tourism for their economic growth since has been a major sector in foreign exchange earnings via the economic linkages with other sectors. According to the United Nation World Tourism Organization (UNWTO, 2009), visitor expenditure on accommodation, food and drink, local transport, entertainment and shopping is an important pillar of the economies of many destinations. As an internationally traded service, tourism has become one of the major trade categories. The overall export income generated by inbound tourism, including passenger transport exceeded USD 1 trillion in 2009 worldwide (UNWTO, 2010). Tourism exports account for as much as 30 per cent of the world's exports of commercial services and 6 per cent of overall exports of goods and services. Globally, as an export category, tourism ranks fourth after fuels, chemicals and automotive products. The contribution of tourism to economic activity worldwide is estimated to be 5 per cent. For many developing countries, it is one of the main sources of foreign exchange income and the number one export category, creating much needed employment and opportunities for development (Ibid).

International tourist arrivals have continued to grow. For instance in 1990 tourist arrivals were 438 million and continued to grow to 684 million in 2000, and reaching 922 million in 2008

(UNWTO, 2009). In 2006, the sector generated 10.3 per cent of GDP and providing 234 million jobs, the 8.2 percent of total world employment (UNWTO, 2007). In 2008, the GDP of the international tourism reached USD 7.5 trillion, while the capital investment for tourism was USD 682 billion and tax revenue were USD 503 billion (WTTC, 2009). In 2008, 83.2 per cent of all international tourist arrivals took place in Europe and North America. The leading tourism generating countries worldwide include USA, Britain, Germany, France, Canada and Japan, which contribute almost half of the global tourism revenue (WTO, 2010). The World Tourism Organization (2010) forecasts that international arrivals will be up to 1.6 billion in the year 2020 and travelers will spend over USD 2 trillion, making tourism the world's leading industry. These projections are based on annual growth rates of 4.3 percent for arrivals and 6.7 per cent of spending, well above the maximum expected expansion of 3 per cent per year in world GDP. The total tourist arrivals by region shows that by 2020 the top three receiving regions will be Europe (717 million tourists), East Asia and the Pacific (397 million) and the Americas (282 million), followed by Africa, the Middle East and South Asia. Africa achieved positive growth of international tourism, in which the tourist arrivals grew by 3 per cent and reached 5 per cent of the world total in 2009.

In the Tanzania's case, tourism is a good source of foreign exchange and employment as well, as the country enjoys large endowments of world-class tourism assets such as natural, cultural, historic and archeological, that are in high demand in international tourism markets. The contribution of tourism in the country's export has been increasing, for example, in 1995 the number of tourist arrivals was 285,000 and receipts stood at USD 502 million while in 2013 the number of tourist arrivals reached 1,063,000 and tourism receipt was USD 1,939 million. The tourism industry also generates forward and backward linkages with other sectors. The linkages can enhance or reduce the economic returns to tourism and exert an influence on the markets. Hotels, for example, require many inputs which can be produced locally, the extent that these inputs are produced locally can enhance value added and when are imported, they generate leakages of money flowing out of the economy. But the forward linkages exist when products and services are value added outside hotels. Handicrafts and shopping are good examples. In the modern tourism sector, the way in which these opportunities add value, or differentiate the product, has an important impact on tourism's overall success (MIGA, 2006). The reports indicate that the international tourism demand is growing quickly in Tanzania with around 9 percent (2008-2012. The tourist arrivals is characterized by seasonality, whereby certain months register relatively higher number of arrivals than others, for instance in 2014, February and August had the highest number of arrivals (124,264 and 120536) while April and May recorded the lowest (80,519 and 81,421), a period which normally coincides with the main rainy season.

On the other hand, the tourism sector is fraught with some challenges which are related to infrastructural problems such as access roads, poor air transport connectivity; limited support services such as hotels/restaurants facilities; few local and foreign investment in provision of infrastructure and tourist services and shortage of skills of the range of officials and employees with which tourist come into contact. However, according to World Bank report (2013), when compared with other Sub Saharan African countries, Tanzania has placed itself in a position to sustain and deepen tourism sector successes so far achieved; this can be achieved where possible by distributing tourist arrivals more evenly during the calendar year across the country. The report states that the northern circuit is overloaded and the country is trying to create new areas for tourism growth in the south, in Pemba and Mafia Islands, the

Sealous reserve and Zanzibar. Therefore, along with the initiatives in place to augment the performance of the tourism sector, this paper is set to explore the appropriate tourist arrivals forecasting model/tool which would aid planning processes in the tourism industry as the World Bank report (2013) states that the scale of development in the sector will determine the extent of the transformation that the investment can achieve, if the development exceeds the absorptive capacity of the assets and resources available to manage the sector, negative consequences will ensue. Thus, accurate tourist arrivals forecasting is important in order to provide for adequate planning for tourism infrastructure and facilities to capture tourism growth, and avoid shortages or surpluses in tourism goods and services (Grundy, 2011)

2. Literature Review

Various studies have suggested that ARIMA and Exponential Smoothing methods are better forecasting models than either econometric or other time-series models. The studies include, Dharmaratne (1995) who compares a number of ARIMA-type models to forecast tourist arrivals in Barbados. The study concludes that ARIMA-type models are capable of producing valid forecasts, but specifically the ARIMA (2,1,1) is the best performing model. A study by Kulendran and Wong (2005) suggests that ARIMA provides more accurate forecasts for a time series that has fewer seasonal variations, whereas SARIMA provides more accurate forecasts for a time series that has a strong seasonal variation.

Further, Chen (2000) examined different forecasting techniques for domestic tourism demand forecasting, the study concluded that the ARIMA method was more accurate than other approaches to predict the future visitation figures in both annual and seasonal data forms. In addition, Lin et al. (2011) tried to build the forecasting model of visitors in Taiwan using three models which are ARIMA, Artificial Neural Networks (ANNs), and multivariate adaptive regression splines (MARS) methods. Their experimental results demonstrated that ARIMA outperformed ANNs and MARS approaches in terms of RMSE, MAD, and MAPE and provided effective alternatives for forecasting tourism demand. However, Wong et al. (2007) compared the ARIMA models with several other time-series and econometric models, such as the ADLM, ECM and VAR. The authors did not confirm the superiority of the ARIMA models or any other model over the others, for all sample countries instead the authors suggest that in some cases the best forecasting accuracy can be obtained with combined forecast models.

The other popular and widely used forecasting model in time series analysis is exponential smoothing. Ostertagova and Ostertag (2012) argue that exponential smoothing is characterized by simplicity, computational efficiency, ease of adjusting its responsiveness to changes in the process of forecasting, and it is reasonable accuracy. Ravinda (2013) in his study on Forecasting with Exponential Smoothing argues that when there is no trend in the data, simple exponential smoothing will yield a minimum error when α value is small, in the range 0.0 – 0.3. This is true to small series (n=12) as well as large (n=60) and when there is a linear trend in the data, the performance of double exponential smoothing depending on the initial estimates of the level and trend components is good. Dimitrov (2008) explains also the primacy of exponential smoothing in forecasting, as the name suggests the weights attached to past time periods in forming the forecast decline exponentially. That is, the weights decrease rapidly at first and then less and less and so as the time period becomes older. The weight attached to a particular value approaches, but never quite reaches zero. This method generates accurate forecasts for many time series variables, recognizing the decreasing impact of past time periods as they faded further into the past. There are several types of exponential smoothing models which can be applied in forecasting depending on the nature of data in consideration for instance single exponential smoothing smoothes data by computing exponentially weighted averages and provides short-term forecasts. Double exponential smoothing provides short-term forecasts as previous methods. This procedure can work well when a trend is present, but it can also serve as a general smoothing method. This method is found using two dynamic estimates, α and β (with values between 0 and 1). Whereas Winter's 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. Winters' Method calculates dynamic estimates for three components; level, trend and seasonal denoted by α, β and γ (with values between 0 and 1) (Holt, 1957). However, the literature shows that there is no single model that consistently outperforms other models in all situations; therefore, this paper attempts to compare the two approaches in order to arrive to the best method that can be used in forecasting tourist arrivals in Tanzania.

3.0 Data and Methodology

This paper uses monthly tourist arrivals data from January, 2000 to December, 2009 due to data availability. The data were sourced from Tanzania Tourist Board (TTB) and the Ministry of Natural Resources and Tourism (MNT).

3.1 Methodology

3.1.1 Seasonal ARIMA

ARIMA models depend on a statistical modeling theory known as the Box–Jenkins methodology. This methodology is concerned with iteratively building a parsimonious model that accurately represents the past and future patterns of a time series (Louvieris, 2002). The ARIMA modeling approach expresses the current time series value as a linear function of past time series values (AR) and current lagged values of a white noise process (MA). The ARIMA model, which can be fitted to seasonal time series (quarterly or monthly observations), consists of seasonal and non seasonal parts; the seasonal part of the model has its own autoregressive and moving average parameters with orders P and Q while the non seasonal part has orders p and q (Kulendran and Shan, 2002). The AR, MA, or ARMA models are often viewed as stationary processes, that is, their means and covariances are stationary with respect to time. Since we are using monthly data with seasonal pattern we use ARIMA (p,d,q), (P,D,Q)s.

Where

(p,d,q) = Non-seasonal part of the model

(P,D,Q) = Seasonal part of the model

(S)= Number of period per season

$$(1-B^r)(1-B^s)\mathrm{Y}_t f_p(B^p) = c + e_t q_{q(}B^q{}_) + Q_Q(B^Q)$$

Where

$(1-B^r)$ = The regular difference of order r

$(1-B^s)$ = The tourist arrival data

$f_{p(B^P)}$ = The regular autoregressive terms

$F_{P(B^P)}$ = The seasonal autoregressive terms

C= Constant term

ε_t = The error of residuals

$q_{q(B^q)}$ = The regular moving average terms

$Q_{Q(B^Q)}$ = The seasonal moving average terms

Then, we create a catalog of autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) to determine whether or not seasonal difference is needed. The graph of the sample of autocorrelation function (ACF) and partial autocorrelation function (PACF) are drawn. The ACF measures the amount of linear dependence between observations in a time series that are separated by a lag q. The PACF helps to determine how many autoregressive terms in p are necessary (Chang, 2012). The general features of theoretical ACFs and PACFs are shown in table 1.

Table 1: Characteristics of ACF and PACF in Seasonal ARIMA Model

Model	ACF	PACF
AR	Spikes decay towards zero	Spikes cutoff to zero
MA	Spikes cutoff to zero	Spikes decay to zero
ARMA	Spikes decay to zero	Spikes decay to zero

Source: Pankratz (1983)

Seasonal ARIMA model requires diagnostic checking (or modal validation); before can be used for forecasting application. This is done by checking for normality of the residuals or by using a quantile-quantile (Q-Q) plot. The check of model adequacy is provided by the Ljung-Box Q statistic. The test statistic Q is given by

$$Q' = T(T+2)\sum_{K=1}^{P}\left(\frac{pk^2}{T-k}\right)$$

Where *pk* is the sample autocorrelation at lag k

3.1.2 Exponential Smoothing

While in seasonal ARIMA the past observations are weighted equally, on the other hand, exponential smoothing produces a smoothed time series. Exponential Smoothing assigns exponentially decreasing weights as the observation get older where as there are one or more smoothing parameters to be determined (or estimated) and these choices determine the weights assigned to the observations (Dimitrov, 2008). With regard to exponential smoothing, this paper uses two exponential smoothing techniques which are Holt-Winters additive and Holt-Winters multiplicative exponential smoothing to determine the appropriate forecasting model. Holt (1957 and Winters (1960) extended Holt's method to capture seasonality. The holt-winters seasonal method comprises the forecast equation and three smoothing equations, one for the level, one for trend and the other for the seasonal component. There are two variations to this method that differ in the nature of the seasonal component. The additive method is preferred when the seasonal variations are roughly constant through the series while the multiplicative method is preferred when the seasonal variations are changing proportional to the level of the series. With additive method, the seasonal component is expressed in absolute terms in the scale of the of the observed series and in the level of equation, the series is seasonally adjusted by subtracting the seasonal component. With multiplicative method, the seasonal component will add up to approximately zero. The seasonal component is expressed in relative terms (percentage) and the series is seasonally adjusted by dividing through by the seasonal component. According to Hyndman and Athanasopoulos (2013), both multiplicative and additive models give the same point forecasts with varying prediction intervals. Here we report the most favorable results for ETS by evaluating between point forecasts and prediction intervals.

(i) Holt-Winters Additive Method

The Holt-Winters methods include estimates of the seasonal factors for periods (denoted by S). The parameters p, states the number of seasonal periods in a year. For example, p = 12 would correspond to monthly seasonal adjustments and p = 4 would correspond to quarterly seasonal adjustments. In the additive version, the forecast for period t+n (n periods after the current period) is given by

$$E_t = \alpha (A_t - S_{t-p}) + (1-\alpha)(E_{t-1} + T_{t-1})$$

$$T_t = \beta (E_t - E_{t-1}) + (1-\beta)T_{t-1}$$

$$S_t = \gamma (A_t - E_t) + (1-\gamma)S_{t-p}$$

$$F_{t+n} = E_t + nT_t + S_{t+n-p}$$

α and β smooth base and trend while the parameter γ ($0 < \gamma < 1$) is used to smooth trend.

(ii) Holt-Winters Multiplicative method

The multiplicative version of the Holt-Winters method uses seasonal factors as multipliers rather than additive constants. The forecast for period t+n is given by

$$E_t = \alpha \frac{A_t}{S_{t-p}} + (1-\alpha)(E_{t-1} + T_{t-1})$$

$$T_t = \beta (E_t - E_{t-1}) + (1-\beta)T_{t-1}$$

$$F_{t+n} = (E_t + nT_t)\, S_{t+n-p}$$

3.2 Comparative Analysis between Seasonal ARIMA and Exponential Smoothing Models

When making comparison between Seasonal ARIMA and Exponential smoothing methods, forecasting was carried out for a period of 6 months. We use Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), the Bayesian Information Criterion (BIC), and Mean Absolute Deviation (MAD) to determine the most effective model in forecasting tourist arrivals. While MAPE is useful for purposes of reporting, it expresses accuracy as a percentage of the error, RMSE's value is minimized during the parameter estimation process, and it is the statistic that determines the width of the confidence interval for prediction. On the other hand, MAD gives the relative measure of error that is applicable to time series data, it expresses accuracy in the same unit as the data, which becomes easier to conceptualize the amount of error and BIC is preferred by statisticians because it has the feature that if there is a true underlying model, then with enough data BIC will select that model. We use the following measures of accuracy to identify the best model

(i) MAPE

$$\frac{1}{n}\sum_{t=1}^{n}\frac{e_t}{A_t}*100$$

(ii) RMSE

$$\sqrt{\frac{1}{n}\sum_{t=1}^{n}e_t^{\,2}}$$

(iii) MAD

$$MAD = \frac{1}{n}\sum_{t=1}^{n}\left|A_t - F_t\right|$$

(iv) BIC

$$BIC = -2\ln(L) + \ln(N)k$$

Where

e_t Is the forecast error and it is calculated by subtracting the forecast value from the actual value in the series. A_t and F_t represent actual and forecast values respectively. L is the value of the likelihood function evaluated at the parameter estimates, N is the number of observations, and k is the number of estimated parameters. Minimum values of these accuracy measures provide best fitting models.

4. Data Analysis and Results Presentation

Figure 1 below presents the time series plot of tourist arrivals in Tanzania from January, 2000 to December, 2009. According to Song and Li (2010), seasonality is a notable characteristic of tourism demand and cannot be ignored in the modeling process when monthly or quarterly data are used. In determining whether tourist arrivals data portrays some seasonality features or not, we use time series plot, descriptive statistics and seasonal factors to examine the pattern of data.

Figure 1: Plot of Monthly Time series Data from January, 2000 to December, 2009

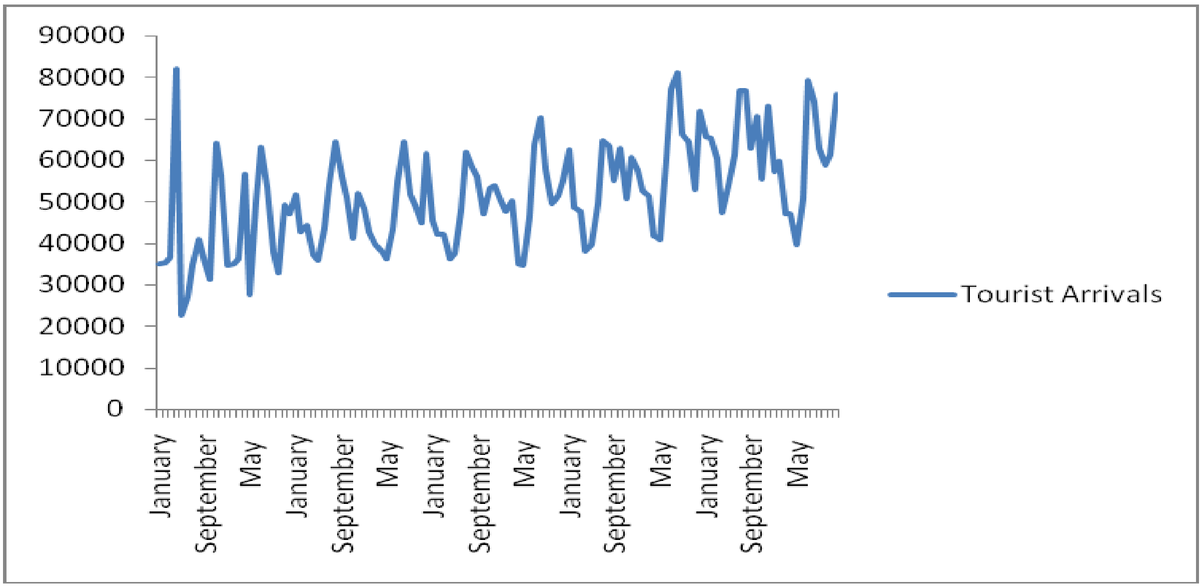


Table 2: Descriptive Statistics of tourist arrivals (January, 2000 to December, 2009)

Mean	51847.2583
N	120
Std. Deviation	12754.80275
Maximum	82048.00
Minimum	22722.00
Skewness	0.229
Kurtosis	-.416
Sum	6221671.00

Table 3: Seasonal Factors

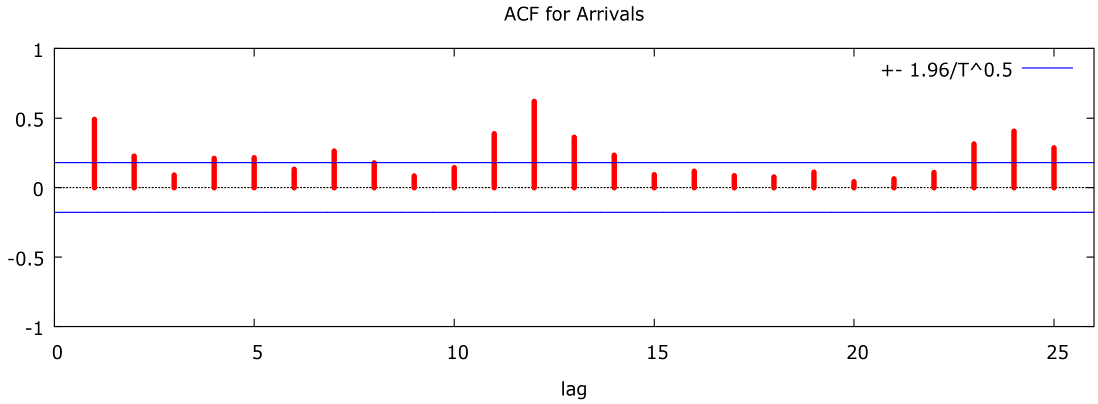
Period (Months)	Seasonal Factor (%)
1	103.1
2	94.1
3	89.9
4	76.8
5	73.3
6	95.7
7	123.6
8	126.8
9	104.7
10	99.7
11	97.8
12	114.5

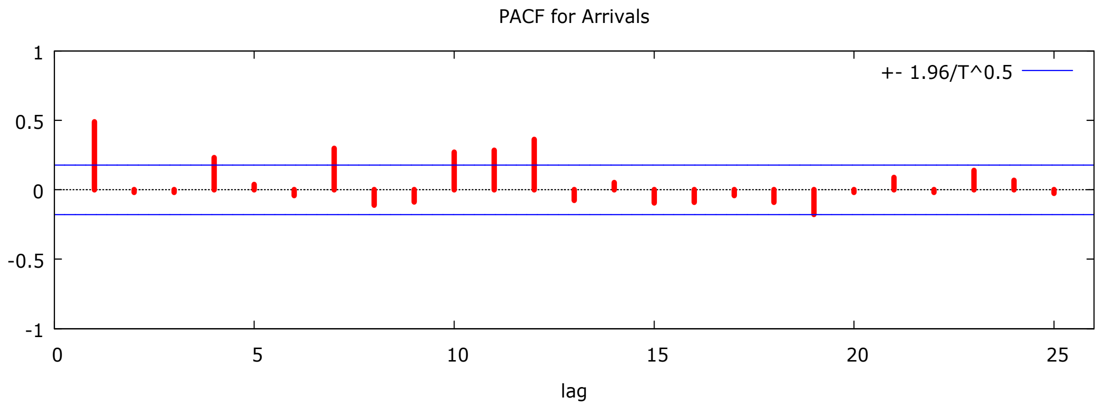
According to time series plot, descriptive statistics and seasonal factors results, there is the presence of seasonal effects on the tourist arrivals data. Seasonal factors are expressed in percentage, from table 2, it is clear that July, August, December and January recorded relatively higher factors (123.6%, 126.8%, 114.5% and 103.1%), while March, April and May recorded relatively lower factors (89.9%, 76.8%, and 73.3%). This suggests that July, August, December and January are months of high tourism demand while months of March, April and May record relatively lower demand.

4.1 ARIMA Models

The Box-Jenkins methodology was used in the selection of the appropriate Seasonal ARIMA model. The first stage of the Seasonal ARIMA model building is to identify whether the variable which is being forecasted is stationary in time series or not. By stationary we mean, the values of variables over time varies around a constant mean and variance. The time plot of the tourist arrivals data in figure1 above clearly shows that the data is not stationary. We further, examine the Auto correlation Function (ACF) and Partial Autocorrelation Function (PACF).

Figure 2: Plots for Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF)





The plots for ACF and PACF show the presence of spikes outside the insignificant zones. ACF shows higher spikes at lag 1, 12 and 24 while PACF indicates spikes at lag 1 and 12. This suggests the seasonal structure of the data and its non-stationarity. Hence, differencing of the data was carried out in order to make the data stationary.

Figure 3: Plot of Differenced Tourist Arrivals Data

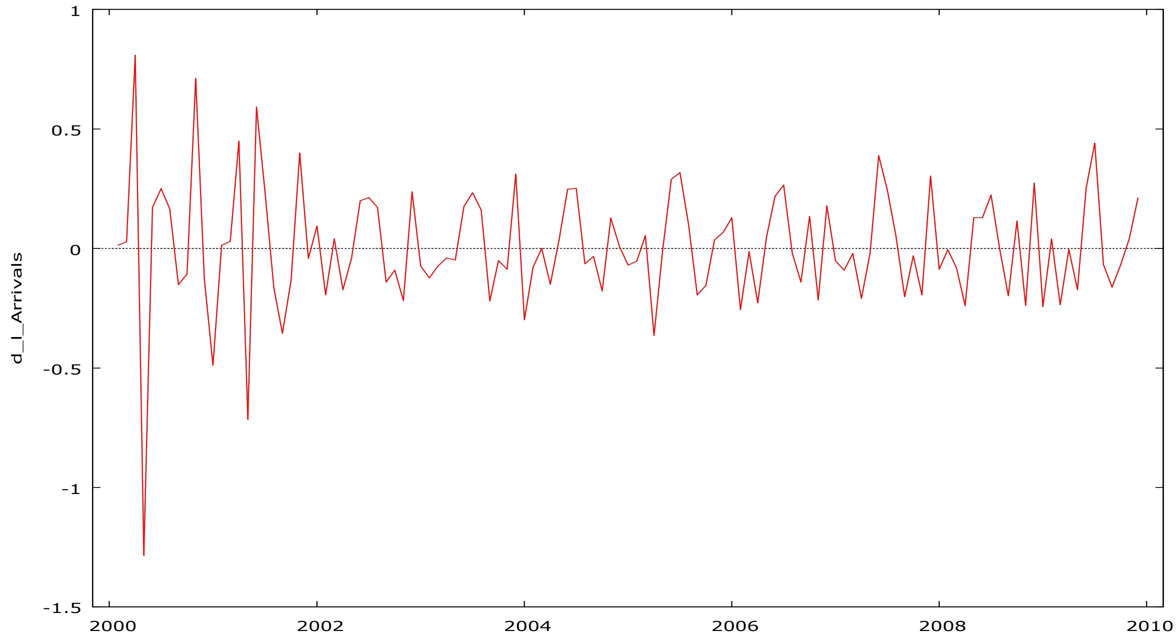


Figure 3 above indicates the differenced tourist arrivals data, after introducing the first difference of monthly tourist arrivals data it became stationary. The next step is to identify the non-seasonal and seasonal values in form of (p,d,q) (P,D,Q) and then the selection of best ARIMA model using measures of the accuracy. Only those models with all significant parameters of estimates and with no serial correlation were selected.

Table 4: The Results of MAPE, RMSE, BIC and MAD values of fitted Seasonal ARIMA

ARIMA Models	MAPE	RMSE	BIC	MAD
ARIMA (3,13) (3,1,3)	12.686	9541.222	18.894	6457.106
ARIMA (4,1,4) (3,1,4)	11.037	8138.441	18.707	5562.089
ARIMA (3,1,3) (4,1,3)	11.383	8555.550	18.720	5833.759
ARIMA (3,1,4) (3,1,3)	12.556	9595.836	18.950	6393.920
ARIMA (3,1,2) (4,1,3)	11.878	8838.017	18.741	6027.864
ARIMA (2,1,3) (2,1,3)	11.343	8226.648	18.511	5774.019
ARIMA (3,1,3) (2,1,3)	11.603	8348.704	18.584	5913.829
ARIMA (3,1,3) (2,1,2)	11.860	8414.080	18.556	6069.586
ARIMA (2,1,3) (2,1,2)	11.792	8330.152	18.492	6031.634

Table 3 above, shows the performance of Seasonal ARIMA, several seasonal models were identified. It was observed that out four measures of accuracy, the performance of ARIMA(4,1,4)(3,1,4)$_{12}$ was relatively better in three measures of accuracy which are MAPE (11.037), RMSE (8138.441) and MAD (5562.089) when compared with other ARIMA models. The Ljung-Box (*Q*) statistics were computed for checking residuals in seasonal lags of 12, 24, and 36. The Ljung-Box *Q* statistics is a diagnostic measure of white noise for a time series, assessing whether there are patterns in a group of autocorrelations under the hypotheses with (kp-q-P-Q) degree of freedom (Çuhadar, 2014).

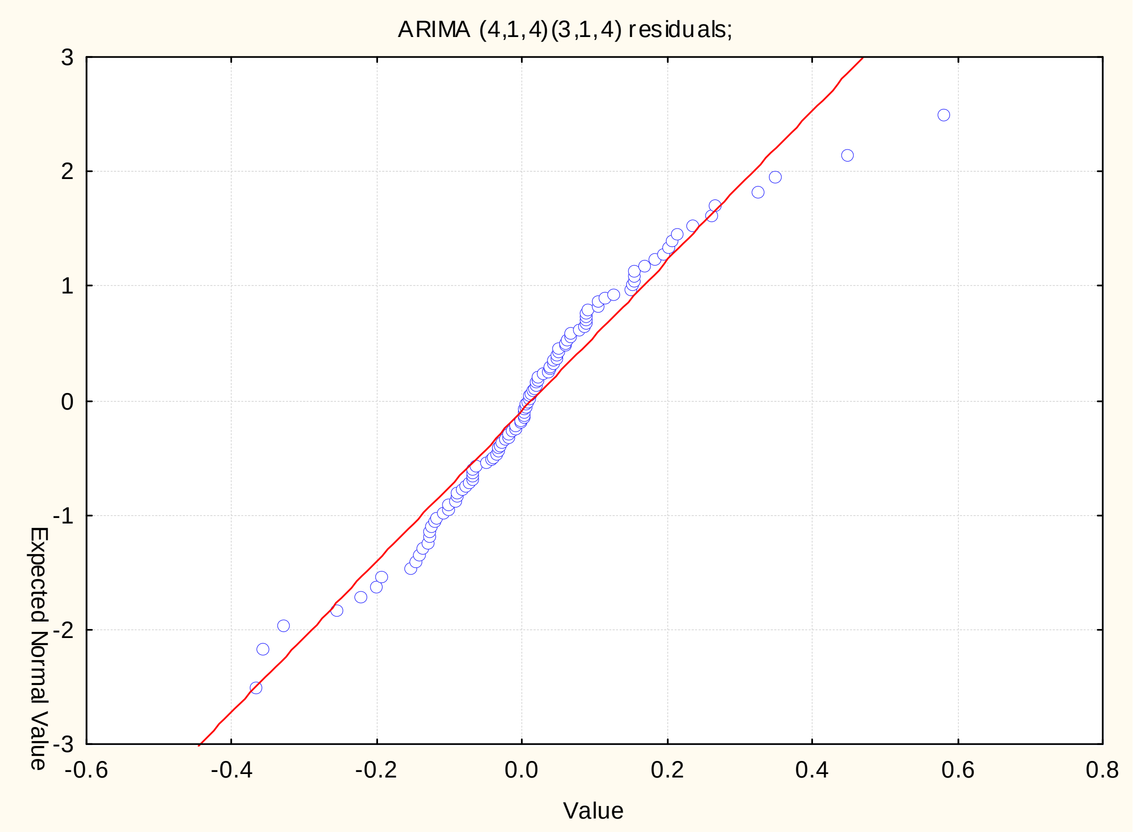
H0: ACFs are not significantly different than white noise ACFs (i.e., ACFs = 0).
H1: ACFs are statistically different than white noise ACFs (i.e., ACFs ≠ 0).

Table 5: Box-Ljung Test Statistics

Lag	ACF (k)	SE	X^2 (α=0.005)	Df	Q	Sign
12	-0.012001	0.090252	36.38	7	16.05990	0.188577
24	0.013399	0.084359	66.77	19	30.14704	0.180051
36	-0.024394	0.078023	79.40	31	34.73165	0.528865

Table 5 above shows Box-Ljung test statistics, since Q is less than chi-square ($Q < X^2$) at the seasonal lags (12, 24 and 36) the null hypothesis is accepted at the 5% level of significance. The Ljung-Box (Q) statistics for diagnosing white noise confirms that the residual ACFs are not significantly different than white noise ACFs.

Figure 4: Normal Q-Q Plot of Residuals (Forecast Errors)



Based on the Ljung-Box (*Q*) statistics results and normal Q-Q Plot, we can conclude that ARIMA $(4,1,4)(3,1,4)_{12}$ is fit for forecasting tourist arrivals in Tanzania having passed the diagnostic checking tests.

4.2 Exponential Smoothing Models

In examining exponential smoothing models we use the Sum of the Squared Error (SSE) and the Mean Squared Error (MSE). The minimum values of SSE and MSE are preferred. The parameters of Alpha (**α**), Gamma (**β**) and Delta (**γ**) which minimizes the values of SSE and MSE were identified through an iteration process.

Table 6: Exponential Smoothing Parameters

Model	α (level)	β (Growth)	γ (Seasonal)	SSE	MSE
Holt-Winter's Multiplicative model	0.01	0.11	0.11	3.476E+09	3.218E+07
Holt-Winter's Additive model	0.10	0.12	0.11	3.537E+09	3.275E+07

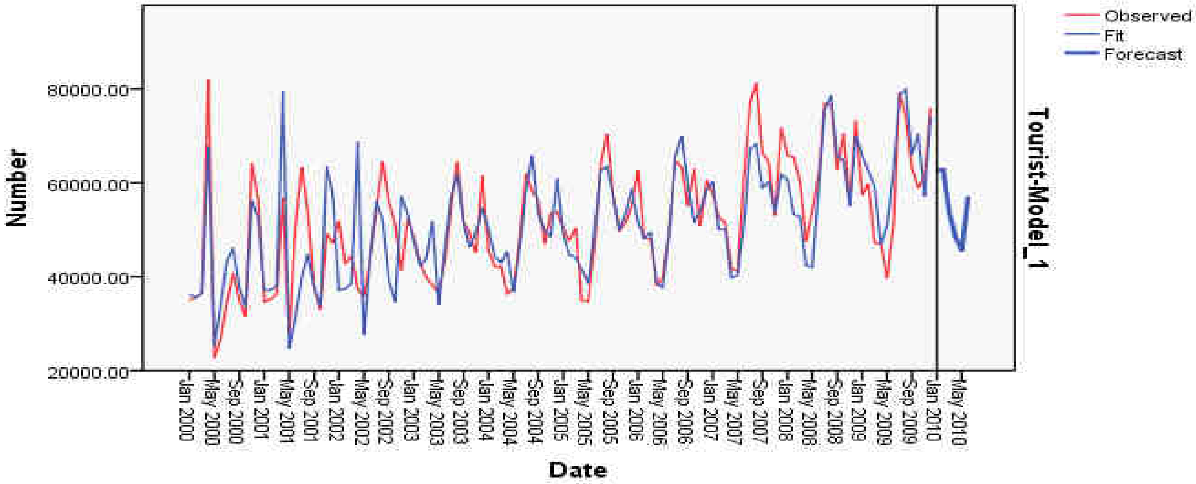
Table 6 above shows that Holt-Winter's Multiplicative exponential smoothing recorded relatively lower SSE and MSE values, this suggests that Holt-Winter's Multiplicative exponential smoothing is appropriate for forecasting tourist arrivals in similar structure model setting (exponential smoothing models). However, to identify the best model, the performance of Holt-Winter's Multiplicative was compared with that of ARIMA$(4,1,4)(3,1,4)_{12}$ using the results of MAPE, RMSE, BIC and MAD.

Table 7: Comparative Analysis of Seasonal ARIMA$(4,1,4)(3,1,4)_{12}$ and Holt-Winter's Multiplicative Exponential Smoothing

Models	MAPE	RMSE	BIC	MAD
Holt-Winter's Multiplicative	9.0	3973.528	-60	4529.42
ARIMA (4,1,4) (3,1,4)	11.037	8138.441	18.707	5562.089

In comparative analysis between Seasonal ARIMA and exponential smoothing models, the results in table 7 indicate that Holt-Winter's Multiplicative exponential smoothing model recorded relatively lower values in terms of MAPE (9.0), RMSE (3973.528), BIC(-60) and MAD (4529.42). This shows that Holt-Winter's Multiplicative has outperformed other Seasonal ARIMA models. Based on these results, we can conclude that Holt-Winter's Multiplicative model is the best model for forecasting tourist arrivals in the short run.

Figure 5: Tourist Arrivals Fitted with Holt-Winters Multiplicative (January, 2000 to June, 2010)



5. Discussion and Conclusion

The objective of this paper was to compare the appropriateness of two models in forecasting tourist arrivals in the short run in Tanzania. In order to capture the seasonality pattern of the data, the performance of Seasonal ARIMA, Holt-Winters Additive and Holt-Winters multiplicative exponential smoothing were examined. The findings show that Holt–Winters' multiplicative exponential smoothing model with alpha (0.01), Delta (0.11) and Gamma (0.11) is the more accurate model for forecasting tourist arrivals in the short run when a comparative analysis was carried out using measures of accuracy such as MAPE, RMSE, BIC and MAD. This finding suggests that the seasonal variations of the tourist arrivals data are changing in proportional to the level of the series in Tanzania. This result corroborates with the study of Nisantha and Lelwala who concluded that Holt–Winter's Exponential Smoothing model with multiplicative seasonality is the more accurate model for forecasting six – month – ahead tourist arrivals to SriLanka. Similarly, studies of Law (2000), Burger *et* al., (2001), Lim and McAleer (2001) and Cho (2001, 2003) have confirmed the superiority of exponential smoothing methods in forecasting tourism demand. However, Cuhadar (2014), reported that forecasts by the seasonal exponential smoothing models have provided quite good results but SARIMA $(2,0,0)(1,1,0)_{12}$ model has showed best forecast accuracy with lowest deviation (MAPE 3.42%) among the all applied models in forecasting inbound tourism demand in Istanbul. Further, Cho (2003) investigated three different techniques (exponential smoothing, univariate ARIMA and artificial neural networks) to forecast tourist arrivals in Hong Kong, the findings show that artificial neural networks forecasts to be the most accurate. In the context of Tanzania, it would therefore be interesting if future research explores more the effectiveness of new and emerging models in forecasting such as Artificial Neural Network, Singular Spectrum Analysis (SSA), and Time Varying Parameter (TVP) etc.

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