Modelling and Forecasting Zimbabwe's Tourist Arrivals Using Time Series Method: A Case Study of Victoria Falls Rainforest

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Abstract

Modelling and forecasting of tourist arrivals at one of the Seven Natural Wonders of the World, the Victoria Falls Rainforest, is critical to the tourism industry and economy of Zimbabwe. The aim of this paper is to provide quantitative techniques that will help with accurate tourist arrivals forecasting, shedding light on seasonality and other patterns of tourist arrivals. A time series plot of the monthly tourist arrivals statistics from January 2006 to December 2017 availed by the Zimbabwe Tourism Authority and Zimbabwe Parks and Wildlife Management Authority shows an upward trend in tourist arrivals with large fluctuations. To tame the variance which is increasing with time, a logarithm transformation is done on the data. A SARIMA $(2, 1, 0)(2, 0, 0)_{12}$ model fits well to the data and outperformed other SARIMA models and the naïve, seasonal naïve and Holt-Winters exponential smoothing models. A two-year future out-of-sample forecast is done using this model and gives reasonable forecasts that indicate a general rise in tourist arrivals. Investors, tourism managers and the government can make use of such results in order to find effective and efficient solutions to the investment, foreign currency, accommodation, transport and infrastructure development problems and other tourist-related challenges faced by Zimbabweans.

Keywords: tourist arrivals; seasonality; time series; SARIMA models; Zimbabwe tourism figures

Introduction

Modelling and forecasting of tourist arrivals plays a major role in planning and policy formulation in Zimbabwe. Accurate tourism forecast gives valuable insight into future tourist arrivals and is useful to tourism planners. The World Tourism Organisation (WTO) and the World Travel and Tourism Council (WTTC) recognise the tourism industry as a pivot for economic growth in developing countries (Cortes-Jimenez, Pulina, Prunera and Artis 2009). For a developing country like Zimbabwe, the tourism industry is a major contributor to the country's economic growth as it brings in foreign currency and creates employment, apart from being the major contributor to the country's infrastructure development. The tourism industry surpasses the agriculture and the manufacturing industry in terms of the country's fastest turn around industries (Reserve Bank of Zimbabwe 2016). Accurate forecasts will help the tourism industry maintain its vital role in improving the economic status of the country.

The African tourism industry is expected to grow through the growth of tourism industries in different African countries and Zimbabwe's future tourism industry is bright (UNWTO 2010). Zimbabwe is among the top five tourist destinations in Africa (including Morocco, Egypt, South Africa, and Tunisia), and its tourism industry has the potential to develop further (Africa Tourism Monitor 2015). In terms of natural resources, Zimbabwe ranks 33rd in the world and ranks 114th among most visited destinations (Crotti and Misrahi 2017). There are a wealth of tourist attractions in Zimbabwe, such as the Gonarezhou National Park, Hwange National Park, Great Zimbabwe monuments, Chinhoyi Caves, and the Victoria Falls Rainforest. The Victoria Falls Rainforest is the main tourist destination (Zimbabwe Tourism Authority Report 2015). It is among the Seven Natural Wonders of the World and is surrounded by national parks and a World Heritage Site (Zimbabwe Statistics Report 2014). The Victoria Falls Rainforest attracts a lot of tourists, both local and foreign (Zimbabwe Statistics Report 2015).

The tourism industry is a significant contributor to the gross domestic product (GDP), foreign currency reserves, and tourism receipts of the country. The tourist and hospitality industry contributed 9 per cent towards GDP in 2011 (Chibaya 2013). The WTTC (2017) indicated the tourism industry's total contribution to GDP for the year 2016 as 8.1 per cent. Furthermore, between July 2015 and June 2016, Zimbabwe received revenue amounting to US$800 million from visiting tourists (Zimbabwe Visitor Exit Survey Report 2015/16). The tourism receipts from the Victoria Falls Rainforest play a crucial role in tourism receipts and GDP for the whole country. According to Celik, Ozcan, Topcuoglu and Yildirim (2013), the tourism industry is capable of solving foreign trade deficits and balance of payment problems for developing countries like Zimbabwe. It is evident that the reduction of balance of payment deficits is associated with the tourism revenue increases. Zimbabwe's balance of payment deficit declined from US$269 million in 2008 to US$146 million in 2010 as a result of an increase in tourism revenue contributions (Kaminski and Francis 2011). Therefore, accurate tourist forecasts for the Victoria Falls Rainforest will help in projecting the expected foreign currency likely to be injected into the country by each

tourist destination (Zimbabwe Tourism Authority Report 2014). In Albania, Thano (2015) found a positive relationship between balance of payment and the contributions from the tourism industry, as the industry impacted positively to the balance of payment. Thus, it is important to model and forecast the tourist arrivals as this helps in crafting effective and efficient balance of payment measures.

Tourism income indirectly improves production and results in an increase in national income (Thano 2015). The income from tourists from the Victoria Falls Rainforest as a destination can also increase the country's income as the Victoria Falls Rainforest is a tourist hub (ICAZ 2011), and it is targeted for rebranding as it has proved immune to political events which have plagued the country since 2000. This also justifies the need for forecasting tourists at this destination under the new political dispensation. Furthermore, the availability of adequate information communication technology (ICT) infrastructure in all tourism destination centres', and in the country, depends on accurate tourist arrival forecasts of various tourist destinations.

From 2006 to 2017, mixed tourism patterns have been observed in Zimbabwe, with the Victoria Falls Rainforest contributing the highest number of tourist arrivals of the country's total tourists (Zimbabwe Tourism Authority Report 2014). The removal of Victoria Falls from travel warnings by Japan in April 2009 and the removal of travel warnings by the United States, Germany and other countries to those wanting to visit Zimbabwe resulted in an increase of tourists to the country's major tourist destination (Zimbabwe Statistics Report 2014). Marketing strategies by the Zimbabwe Tourism Authority (ZTA), the recovery of the Zimbabwean economy, the introduction of multiple currencies in August 2009, an improving peaceful political environment, as well as improvement in tourism infrastructure development, all played a major role in boosting visitor numbers (Zimbabwe Statistics Report 2014).

The modelling and forecasting of tourism demand at particular tourism destinations using univariate (non-casual) methods has not been done, to the best of our knowledge, since the introduction of multicurrency system in January 2009, and even after the formation of the government of national unity in February 2009. A few authors (cf. Chigora and Vutete 2015; Karambakuwa et al. 2011; Muchapondwa and Pimhidzai 2011) have researched Zimbabwean tourism demand, but their research concentrated more on identifying tourism demand factors, while ignoring the forecasting aspect, which is very important. Misleading judgmental methods (with little scientific basis) being used to predict future tourist arrivals results in high accommodation costs and few recreation facilities in most tourism resort centres in Zimbabwe. The problems of not getting enough investors, inadequate accommodation, inadequate ICT facilities, and inadequate transport in most tourist destination towns, and in Zimbabwe in general, impact on the Zimbabwean economy as a whole (Zimbabwe Tourism Authority Report 2014). All this can be alleviated once there are tourism models capable of forecasting future tourist arrivals

accurately. Potential investors, tourism managers and tourism policy makers depend on accurate tourism forecasts.

While evaluating non-linear approaches in forecasting South African tourist arrivals, Saayman and Botha (2015) acknowledged that the univariate time series models like the autoregressive integrated moving average (ARIMA) and seasonal ARIMA (SARIMA) give better forecasts when compared to seasonal naïve forecasts. The aim of this paper is to come up with an informative univariate time series model (SARIMA) that can be used to predict tourist arrivals at the Victoria Falls Rainforest destination. The gap of unavailability of informative time series models and scientific methods in predicting tourist arrivals for specific tourist destinations for rebranding, resource allocation, investment and policy formulation purposes under the new political dispensation is being filled. By new political dispensation, we are referring to a period of new political and favourable economic recovery policies. The new dispensation is friendlier towards Western countries whose tourists contribute significantly towards Zimbabwe's tourism. The tug of war between former president Mugabe and Western countries is no secret. SARIMA models have higher forecasting power and are suitable for short-term forecasting (Etuk 2012; Ismail and Mahpol 2005; Junttila 2001; Omane-Adjepong et al. 2013; Pufnik and Kunovac 2006; Saayman and Saayman 2010; Schulz and Prinz 2009; Suleman and Sarpong 2012), hence, the SARIMA model is adopted in this paper. Major objectives of the paper are: determining tourism patterns; postulating possible reasons for the patterns; the identification of seasonal months, since tourist arrivals are assumed to be seasonal; and to forecast future tourist arrivals. This will help visualise the behaviour of tourist arrivals for planning purposes and resources allocation. Knowing the seasonal month helps in pricing strategies, ensuring accommodation availability and transport facilities.

Dritsakis (2004), Dogru and Sirakaya-Turk (2016), and Kusni, Kadir and Nayan (2013) carried out case studies in Greece, Turkey, and Malaysia, respectively. These studies used panel cointegration approaches, and a cointegration relationship was observed in the models. Furthermore, relative pricing, word of mouth, and income were found to significantly affect tourism demand in these countries. In addition, their findings emphasised the importance of case studies in tourism studies and pointed out that case studies help in identifying individual characteristics of a destination, destination branding as well as logically linking data to a specific study and its conclusion. All this has motivated the adoption of univariate approach to the Victoria Falls Rainforest, unlike the cointegration approach used in other studies.

The research paper is organised as follows: the following section is a review of the literature; thereafter, the following section describes the methods used for data analysis. The subsequent section gives the time series modelling process and results, and, finally, the last section presents the conclusions.

Literature Review

The time series and regression analysis are the common approaches used in modelling tourist arrivals. A few tourism studies on Africa or on developing countries, like Zimbabwe, exist; however, most of the studies in Africa concentrated more on the determinants of tourist arrivals (Bentum-Ennin 2014; Eja et al. 2012; Fourie and Santana-Gallego 2011; Naudé and Saayman 2004; Okon 2014).

Chigora and Vutete (2015), Muchapondwa and Pimhidzai (2011), and Karambakuwa et al. (2011) are some of the few authors who have researched identifying tourism demand factors in developing countries, like Zimbabwe. Their models did not address the forecasting aspect addressed in this paper and did not use the widely used ARIMA and SARIMA models adopted in this paper and other international studies. In modelling South African tourism demand, Saayman and Saayman (2010) used different models—i.e. naïve, ARIMA, SARIMA, and exponential smoothing. Their SARIMA model outperformed other models—naïve, ARIMA, and exponential smoothing. It was later used to forecast future arrivals, and they noted the accuracy of the SARIMA models. Ndiege (2015) used quarterly data in modelling international tourism demand in Tanzania and fitted ARIMA and SARIMA models that estimated a low growth of the Tanzanian's tourist rate per year. The studies justify the superiority of SARIMA models in terms of popularity and forecasting accuracy.

In Catalonia, Claveria and Torra (2014) compared forecasting performance of ARIMA models, self-exciting threshold autoregressions (SETAR) and artificial neural network (ANN) models during forecasting tourism demand at regional level. ARIMA models outperformed SETAR and ANN models for shorter horizons. Chu (2009) modified the ARIMA model and came up with the ARMA-based models (fractionally integrated autoregressive moving average (ARFIMA)) which performed very well for the Asia-Pacific tourist destinations. Lee, Song and Mjelde (2008) forecasted South Korea's international tourism expo using both qualitative techniques and quantitative forecasting models (SARIMA and regression). The Delphi method adopted by the authors gave more conservative forecasts than those obtained using a combination of qualitative techniques and willingness to visit (WTV) and SARIMA models. Univariate volatility models (generalised autoregressive conditional heteroscedasticity (GARCH)) and exponential GARCH (EGARCH)) were used in modelling UK tourism demand and produced highly accurate tourism forecasts (Coshall 2009).

In Hong Kong, Wong, Song and Witt (2007) used single and combined forecast of ARIMA, autoregressive distributed lag model (ADLM), error correction model (ECM) and vector autoregressive (VAR) model, and they noted that the accuracy of the tourism forecasts varies according to tourist destination or origin flow. The authors concluded that combined tourism forecasts were preferred over single tourism forecasts. Chen (2006) investigated US tourism flows intervention impact and the accuracy of various forecasting techniques (naïve 1, naïve 2, Holt-

Winters, SARIMA, and ANN models). The SARIMA model was considered the best model among all the models according to mean absolute percentage error results. Yeung and Law (2005) used time series forecasting techniques (SARIMA and ARIMA) in predicting US air travellers to Europe, the Caribbean, and Asia and noted the superiority of SARIMA model. Akal (2004) adopted an autoregressive integrated moving average with explanatory variable (ARMAX) model in forecasting Turkey's international tourism revenue and obtained reliable revenue forecasts. Most of the above-mentioned studies acknowledge the accuracy of ARIMA and SARIMA models, hence, they are adopted in this study.

Çuhadar (2014) used the SARIMA $(2,0,0)(1,1,0)_{12}$ model that presented best forecast accuracy for modelling international tourist arrivals in Istanbul. Baldigara and Mamula (2015) proposed a useful SARIMA $(0,0,0,)(1,1,3)_4$ model for German tourists to Croatia. Chu (2014) adopted a logistic growth regression model in modelling Las Vegas tourism demand, while Song, Kjetil and Fabrizio (2011) used a time series approach in China. All their models gave valuable insights on tourism. Tularam, Wong and Nejad (2012) adopted the ARIMA (2,2,2) model in modelling Australian tourism demand and produced reasonable forecasts. Bonham, Gangnes and Zhou (2009) used a vector error correction model (VECM) in modelling Hawaii tourism, and the model fitted well to the data. Wong, Song and Witt (2007) suggested that the vector autoregressive (VAR) performed better than the autoregressive distributed lag model (ADLM), ARIMA in modelling Hong Kong's tourism demand. Smeral and Wüger (2005) concentrated on the determinants of Australian tourism, hence they used econometric methods that fitted well to their data.

Loganathan and Ibrahim (2010) studied Malaysian tourism demand, and their SARIMA model suggested the growth of the tourism demand in the country. Shen, Li and Song (2011) implemented five econometrics models (reduced autoregressive distributed lag model (READLM)); Wickens-Breusch (1988) implemented the error correction model (WB-ECM), and Johansen (1988) implemented the maximum likelihood error correction model (JML-ECM), VAR model and time-varying parameter (TVP) model, and two time series models (naïve and SARIMA) in coming up with individual UK international tourism demand forecasts. The authors also adopted six forecasts combination methods (simple average combination method, variance-covariance method, Granger and Ramanthan regression method, discounted mean square forecast error method, shrinkage method and time-varying-parameter combination method with the Kalman filter) in this study, and the results indicated that the combination forecasts outperformed individual forecasts.

Saayman and Botha (2015) mentioned that univariate time-series methods produce accurate forecasts and acknowledge their popularity as a better method though with shortcomings of not explaining influential external forces. Seasonal exponential smoothing models were used by Çuhadar (2014) to model and forecast tourism demand for Istanbul. They produced good results. Chu (2008) forecasted tourism demand in the Asia-Pacific region using an ARIMA model and produced sensible short-term tourism forecasts using both the monthly and quarterly data. Chu

(2008) recommended the use of ARIMA models in modelling tourist arrivals. Lim and McAleer (2002) adopted an ARIMA model that produced meaningful forecast for Australia's tourist arrivals in 2002.

Univariate methods produce superior forecasts as compared to econometric methods. This was confirmed by Athanasopoulos, Rob, Song and Wu (2011) when they compared forecasting accuracy of different models. Goh and Law (2002) used the Holt-Winters exponential smoothing method to model tourist arrivals in Hong Kong and acknowledged the superiority of ARIMA models over naïve and exponential smoothing techniques. During a study in Catalonia, the ARIMA model outperformed nonlinear methods such as ANN models and STAR models (Claveria and Torra 2014). Lin, Chen and Lee (2011) noted that ARIMA models outperformed the artificial neural networks models and the multivariate adaptive regression splines in forecasting tourism demand in Taiwan. In Australia, Brierley (2011) noted that seasonal time series methods (the enhanced transmission system (ETS), the seasonal naïve, SARIMA and damped Holt-Winters) performed equally in terms of accuracy.

Kamel, Ftiti and Chaibi (2015) adopted a vector autoregression error correction model in modelling Tunisian tourism and concluded that a favourable real exchange rate allows more overnight stays in the country. The unavailability of useful tourism data (foreign currency exchange rate, tourism receipts and tourism expenditure) and adoption of the multiple currency system in Zimbabwe make this method inapplicable. Baldigara and Koić (2015) used a second order polynomial regression to model German international tourism demand to Croatia. Annual arrival and overnight-stays tourism data were used, and the models fitted well to the data. This modelling approach cannot be used in this research because of unavailability of overnight-stays data. Li, Song and Witt (2005) and Song and Li (2008) used regression models in modelling tourist arrivals that gave good forecasts, though Song, Li and Witt (2010) noted forecasting failure from these models. Furthermore, Shen, Li and Song (2009) stated that the time-varying parameter (TVP) model, the autoregressive distributed lag (ADL) model, the error correction model (ECM) and the vector autoregressive (VAR) model are not good for seasonal data. Hence, based on the unsuitability of the VAR models on seasonal data, they were not considered in this study. Tourism data exhibit seasonality, therefore SARIMA models suit most arrivals' data and they produce accurate forecasts (Saayman and Botha 2015).

Lin and Lee (2013) used the multivariate adaptive regression splines (MARS), the support vector regression (SVR) and the artificial neural network (ANN) in modelling monthly tourist arrivals for Taiwan and noted that the SVR outperformed the rest. Constantino, Fernandes and Teixeira (2016) came up with a good ANN model for Mozambique. Econometric models are good at determining the relationship between tourism factors and tourist demand. They make use of econometric variables such as transport costs, country of origin's income, GDP, tourism receipts, tourism expenses, exchange rate, accommodation fees, and travel expenses, among others, which

are difficult to find in Zimbabwe because of the now abandoned unstable local currency that has since been replaced by multiple international currencies.

A naïve 1 model was adopted by Smeral and Wüger (2005) in modelling tourist arrivals, and the model outperformed the ARIMA and SARIMA model results. Lim and McAleer (2002) used Holt-Winters exponential smoothing method in modelling Australia's tourism demand, and the method outclassed other smoothing techniques. Naïve and seasonal naïve models are normally used as baseline models (Saayman and Botha 2015).

Methodology

Time series models (naïve, seasonal naïve, Holt-Winters and ARIMA/SARIMA) are adopted in this paper based on their ability to produce accurate forecasts, as supported by Lim and McAleer (2000). Furthermore, Song and Li (2008) acknowledged the popularity of the ARIMA/SARIMA models in modelling and forecasting tourism demand since they help in identifying the patterns and seasonality on tourist arrivals.

Stationary Processes and ARIMA Models

The Argumented Dicky-Fuller (ADF) test is used to check stationarity. An ARIMA/SARIMA model is fitted once data is stationary, hence, certain transformations are done if the series are not stationary. ARIMA models were initiated by Box and Jenkins in the 1970s. According to Musundi et al. (2016), a Box-Jenkins method is an iterative process that involves four stages: identification, estimation, diagnostic checking and forecasting of time series. A non-seasonal ARIMA model can be written as $ARIMA(p, d, q)$, where p, d and q represent the number of autoregressive terms, non-seasonal differences and moving-average terms, respectively. The general model can be expressed as follows:

$$\phi(B)Z_t = \Theta(B)a_t \tag{1}$$

where Z_t is the tourist arrivals series being modelled, a_t is a white noise process, ϕ and Θ are unknown model parameters to be estimated by the least-squares method, or the maximum likelihood estimation method, and B is a backward difference operator. Seasonal ARIMA models exist for seasonal time series data, like tourism data, which exhibit seasonal components.

A SARIMA model for tourist arrivals Z_t is written as:

$$\phi_p\phi_{Ps}(B^s)\nabla^d\nabla^{Ds}Z_t = \theta_q\Theta_{Qs}(B^s)a_t \tag{2}$$

where, s is the seasonal lag, B is the backward shift operator, B^s is the seasonal backshift operator, ∇^d is the differencing operator, and ∇^{Ds} is the seasonal differencing operator.

The autocorrelation functions (ACF) and partial correlation functions (PACF) are useful in the identification of an appropriate ARIMA model (Çuhadar 2014). Furthermore, Adhikari and Agrawal (2013) highlighted the need for carrying out ACF and PACF analysis in order to come up with an appropriate time series model. The ACF determines the order of the MA term, while

the PACF determines the order of the AR term (Box and Jenkins 1970). An indication of an MA(q) is seen if the ACF cuts off after lag q and the AR(p) is identified if the PACF cutting off after lag p (Box and Jenkins 1970). The best ARIMA or SARIMA model is one with statistically significant coefficients, uncorrelated residuals and smallest Akaike information criterion (AIC) and Schwarz Bayesian information criterion (BIC). The maximum likelihood estimation (MLE) is a technique used in estimating the model parameters (Hamilton 1994). MLE selects the set of values of the model parameters that maximises the likelihood function and will be adopted in this study.

Naïve and Seasonal Naïve Models

Baseline forecasts are produced by the naïve and seasonal naïve models (Athanasopoulos, Rob, Song and Wu 2011). According to Gelažanskas and Gamage (2015), simple forecasting methods are useful for performance comparison purposes with advanced methods. The naïve forecasting method, in simple terms, makes use of the recently available observations to predict future values (Makridakis, Wheelwright and Hyndman 1998). The naïve method only produces baseline forecasts mainly used for comparison purposes (Bakker and Pechenizkiy 2009). There is seasonality in tourism data since tourists usually have habits, hence, the seasonal naïve model is adopted. The seasonal naïve model assumes that tourist arrivals are a stochastic process for which it is difficult to predict the trends (Goh and Law 2002). With monthly tourist arrival data, last month's tourist arrival will be the next month's forecast, hence, can be given by the formula:

$$\hat{Z}_{t+1} = Z_t \tag{3}$$

where t and $t + 1$ represent the current and next month periods respectively. Forecasts from the benchmark seasonal naïve model will be compared with the fitted SARIMA model.

Exponential Smoothing

With the simple moving average models (SMA), the future forecasts are obtained by averaging a specified number of recent observations, with each observation receiving the same weight (Nau 2014). The exponential smoothing technique depends only on current and past values of the series and may be used to forecast future values (Gardner Jr. 2005). The method uses a constant smoothing parameter α (weight) that lies between 0 and 1. Sharpe, De Vaux and Velleman (2010) indicated that the exponential smoothing method allocates heavier weights to current values than to old values. Furthermore, the weights will decay exponentially. The method reduces fluctuations in the time series data as it smooths coefficients. Holt-Winters smoothing method deals with a time series that has a de-seasonalised demand ($\tilde{Y}_t$), a linear trend ($\tilde{B}_t$), and a multiplicative seasonal variation (S_t) (Saayman and Saayman 2010).

De-seasonalised demand: $\qquad \tilde{Y}_t = \alpha\left(\frac{Y_t}{S_{t-s}}\right) + (1 - \alpha)(\tilde{Y}_{t-1} + \tilde{B}_{t-1})$

$\qquad$ (4)

Linear trend: $\qquad \tilde{B}_t = \beta\left(\tilde{Y}_t - \tilde{Y}_{t-1}\right) + (1 - \beta)\tilde{B}_{t-1}$ $\qquad$ (5)

Multiplicative seasonal variation: $\quad S_t = \gamma\left(\frac{Y_t}{\tilde{Y}_t}\right) + (1 - \gamma)S_{t-s}$ $\qquad$ (6)

Forecast equation:
$$F_{t+n} = (\tilde{Y}_t + \tilde{B}_t n)S_{t-s+m} \tag{7}$$
where α, β and γ are the smoothing coefficients that range from 0 to 1, s is the seasonality length, $\tilde{Y}_t$ denotes the smoothed tourist arrivals at time t, and F_{t+n} are the n period future forecasts.

Model Adequacy

The mean absolute percentage error (MAPE), mean absolute error (MAE), root mean squared error (RMSE) and the mean absolute scaled error (MASE) are used to check the adequacy of the model in this study. MAPE and MASE are the most common in evaluating tourism models (Loganathan and Ibrahim 2010; Saayman and Botha 2015; Saayman and Saayman 2010; Song et al. 2011; Yeung and Law 2005). The RMSE, MAPE, MAE and MASE are presented in equations, (8), (9), (10) and (11), respectively.

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{8}$$

$$MAPE = \left(\frac{1}{n}\sum_{t=1}^{n}\frac{|A_t - F_t|}{|A_t|}\right) * 100 \tag{9}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \tag{10}$$

$$MASE = \frac{1}{n}\sum_{t=1}^{n}\left(\frac{|A_t - F_t|}{\frac{1}{n-1}\sum_{t=2}^{n}|A_t - A_{t-1}|}\right) \tag{11}$$

where A_t is the actual tourist arrival statistics, F_t is the corresponding forecasted tourist arrival statistic, and n is the total number of years in the forecasting period.

Data Characteristics and Analysis

Analysis of the tourist arrivals data is done using the R and Minitab software packages. Monthly tourist arrivals statistics for the Victoria Falls Rainforest from January 2006 to December 2017 are used and were availed by the ZTA and ZPWMA. Data for the period January 2006 to December 2016 is used as the development sample, and data from January 2016 to December 2017 is used for testing forecasting accuracy. Figure 1 shows the time series plot of the original tourist data (Y_t).
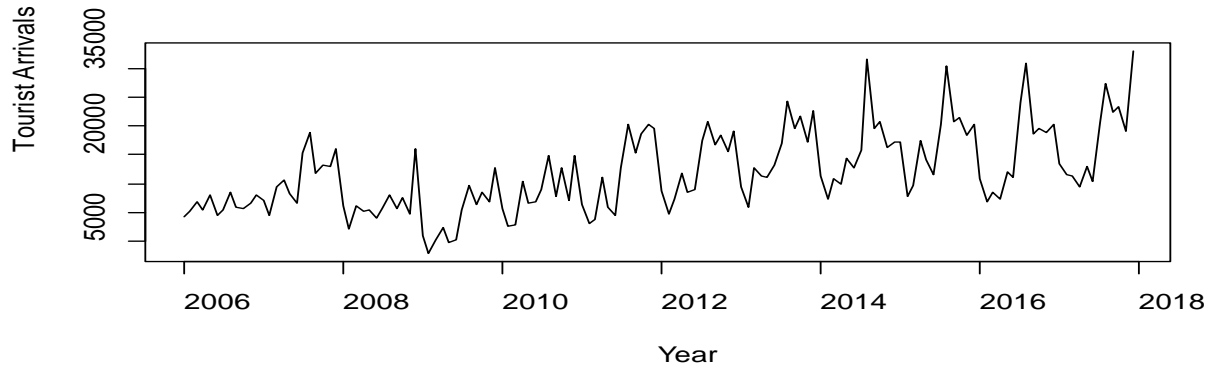
Figure 1: Time series plot of the original tourist arrivals data (Y_t)

Figure 1 shows tourist arrivals at Victoria Falls Rainforest for the 12-year period 2006 to 2018. Statistics from 2008 were affected by presidential elections held in the country, and the financial crisis that occurred in America and affected countries whose citizens visit Zimbabwe as tourists. There is more variation in the plot as the variance increase with time, especially from mid-2009 to 2017. This may be due to the introduction of multiple currencies by the Reserve Bank of Zimbabwe Governor in August 2009. A major decrease of arrivals in early 2009 may be due to lack of confidence by tourists soon after the presidential elections held in mid-2008. Political instability was an influential factor in tourist arrivals and movements. The general increasing trend noticed in Figure 1 after the year 2012 may be because of the political stability together with zero cases of infectious diseases such as cholera and Ebola. It should be pointed out that there was no Ebola outbreak in Zimbabwe, but cholera was reported (Cuneo et al. 2017; Dube 2017; Mukandavire et al. 2011). Ebola was, however, recorded in a few countries in West Africa (Dube 2017; European Centre for Disease Prevention and Control 2015). The outbreak in West Africa may have been enough to discourage visitors to Africa in general during the years. Soon after March 2014, West Africa experienced the largest outbreak of Ebola in history, with multiple countries affected. The outbreak was, however, contained. December 2017 recorded a high number of tourist arrivals possibly due to a new political dispensation and the announcement by the new president, Emmerson Dambudzo Mnangagwa, that Zimbabwe is now open for business and available for investment.

Since the volatile graph indicates non-stationarity series, and the data is logarithm transformed to smooth the variance, the resulting series is denoted as Z_t.

$$Z_t = \log(Y_t) \tag{9}$$

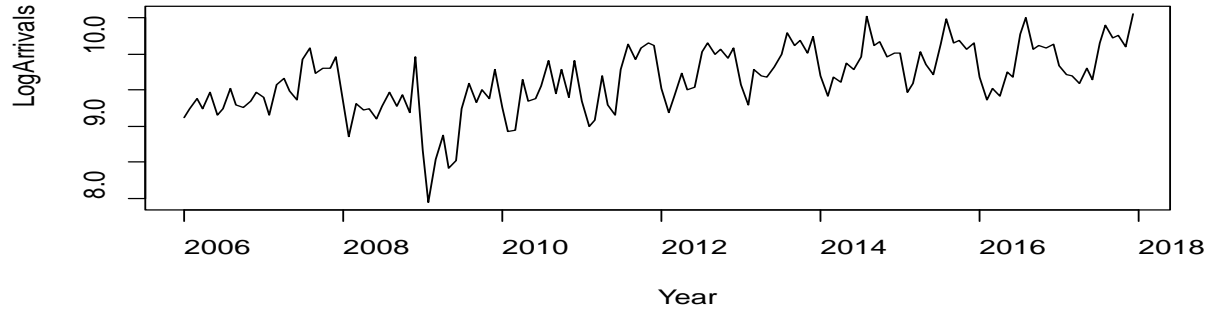A time series plot for log transformed (Z_t) is constructed.

Figure 2: Time series plot of log transformed tourist arrivals data (Z_t)

An almost uniform variation is now being exhibited in Figure 2, though it is not stationary. An ADF test is conducted under the null hypothesis that the first difference of Z_t is not stationary against the alternative hypothesis that states that the first difference of Z_t is stationary.

Table 1: Augmented Dickey-Fuller test results of first difference of Z_t

Augmented Dickey-Fuller test		
Test Statistic = -1.7936	Lag order = 12,	p-value = 0.0446

Table 1 supports the rejection of the null hypothesis at the 5% significance level as evidenced by a small p-value (0.0446), which is less than 0.05. ACF and PACF of first difference of Z_t are done to visualise the appropriate p, d and q, as well as seasonality lag for the model.
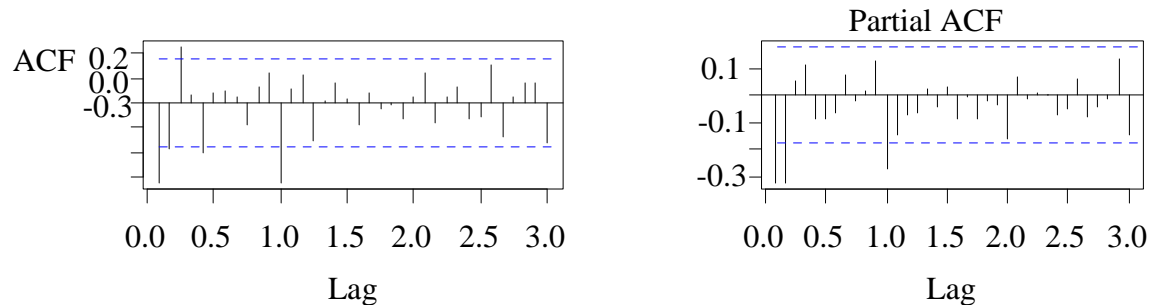

Figure 3: ACF and PACF of first difference of Z_t

Figure 3 shows decaying spikes on the ACF, suggesting an AR model. Significant spikes at lag 1 and lag 2 in the PACF and decaying spikes on the ACF suggest a non-seasonal AR(2) model, and the significant spike at lag 12 and lag 24 on the PACF suggests a seasonal AR(2) component. The extended autocorrelation functions (EACF) are used further to help in identifying the exact AR(p) and MA(q) and results are shown below.

12

Table 2: EACF of Z_t

AR/MA	0 1 2 3 4 5 6 7 8 9 10 11 12 13
0	x x x x x o x x x x x x x x
1	o x o x o x o x o o o x o x
2	o x o o o x o x o o o x x o
3	x x o o o x o o o o o x x x
4	o x x o o o o o o o o x o x
5	x x x o o o o o o o o x o x
6	x x o o o o o o o o o x o x
7	x x o o o o o o o o x x o o

The EACF pattern in Table 2 suggests an ARMA (2,0) model. Consequently, we will start with a seasonal $ARI(2)$ model with a period of 12 that incorporates autocorrelations shown at lag 1 and 2 then lag 12 and 24 and the model can be written as $SARIMA(2,1,0)(2,0,0)_{12}$ model, although, different models may be fitted and tested.

Model Fitting

The identification of a tentative model allows us to do parameter estimation. Parameters for the selected seasonal ARIMA models will be estimated using maximum likelihood estimation (MLE) method. The following are parameter results from estimated competing models.

Table 3: Results of estimated SARIMA models

SARIMA (2,1,0)(2,0,0)₁₂				
Type	**Coef**	**SE Coef**	**T**	**p-value**
AR 1	-0.4387	0.0815	-5.38	0.000
AR 2	-0.3157	0.0815	-3.87	0.000
SAR 12	0.5557	0.0819	6.78	0.000
SAR 24	0.2908	0.0856	3.40	0.001
AIC=-26.13 AICc=-25.69 BIC=-11.32				
Modified Box-Pierce (Ljung-Box) Chi-Square statistic				
Lag	12	24	36	48
Chi-Square	8.12	12.9	24.9	30.5
DF	8	20	32	44
p-value	0.423	0.881	0.811	0.938
SARIMA (1,1,0)(1,1,0)₁₂				
Type	**Coef**	**SE Coef**	**T**	**p-value**
AR 1	-0.3724	0.0821	-4.54	0.000
SAR 12	-0.4411	0.0803	-5.50	0.000
AIC=-27.98 AICc=-27.79 BIC=15.64				

Modified Box-Pierce (Ljung-Box) Chi-Square statistic				
Lag	12	24	36	48
Chi-Square	23.5	35.7	52.8	58.5
DF	10	22	34	46
p-value	0.009	0.033	0.021	0.102

Results from Table 3 suggest a SARIMA $(2,1,0)(2,0,0)_{12}$ as the best model because all coefficients are significant, the modified Box-Pierce (Ljung-Box) statistic shows the nonexistence of autocorrelation and this is the model with the lowest AIC and BIC value.

Furthermore, all the three conditions of an AR model are satisfied, that is $\phi_2 - \phi_1 < 1, |\phi_2|<1$ and $\phi_1 + \phi_2 < 1$. The parameters of the SARIMA $(1,1,0)(1,1,0)_{12}$ are significant but the modified Box-Pierce (Ljung-Box) statistic is indicating the presence of autocorrelation. The model seems suitable since the Box-Ljung test suggest that the residuals are uncorrelated (chi-square = 14.307 and p-value = 0.8146) and, according to the Jarque Bera test, (chi-square = 12.3841 and p-value = 0.05084), residuals are normally distributed.

Holt-Winters Exponential Smoothing Model

The AIC is used to select the best model after fitting original tourist arrival data. An exponential smoothing (ETS) model with additive errors, no seasonality and additive trend (A, N, A) is selected. The smoothing parameters for the model are $\alpha = 0.53945, \beta = 0$ and $\gamma = 0$ and they seemed to be superior than the (multiplicative, multiplicative, multiplicative) MMM model as indicated by smaller log-likelihood value; AIC value and RMSE values.

Naïve and Seasonal Naïve forecasts

The normal naïve and seasonal naïve models are used to come up with the baseline forecast for tourist arrivals. The normal naïve is a bit noisy, while the seasonal naïve follow a seasonal pattern. These models are compared against the Holt-Winters model and SARIMA models.

Forecast Accuracy

Measures of forecast accuracy such as the mean absolute percent error (MAPE), mean absolute error (MAE), root mean squared error (RMSE) and the mean absolute scaled error (MASE) are employed in assessing the forecasting accuracy of the estimated models.

Table 4: Forecasting accuracy measures results

Model	RMSE	MAPE	MAE	MASE
Holt-Winters	0.331764	1.696841	0.192163	0.635258
SARIMA $(2,1,0)(2,0,0)_{12}$	0.2048788	1.582456	0.1505642	0.6287068
SARIMA $(1,1,0)(1,1,0)_{12}$	0.2169942	1.640062	0.1563917	0.6530407
Seasonal naïve	0.3746250	1.936148	0.1842723	0.6613594
Naïve	0.6936952	1.366057	0.1948634	0.45472635

Table 4 shows that the SARIMA $(2,1,0)(2,0,0)_{12}$ model's forecasting accuracy outperformed the other SARIMA model, the Holt-Winters exponential smoothing model, and naïve and seasonal naïve models as supported by its lower RMSE, MAE, MAPE and MASE values. The SARIMA $(1,1,0)(1,1,0)_{12}$ model seems to be the second best. The SARIMA $(2,1,0)(2,0,0)_{12}$ model is being confirmed to be the model that fits well to the Victoria Falls Rainforest tourist arrival data, hence, it can be used for forecasting purposes. This result is similar to that of Saayman and Saayman (2010), which showed that SARIMA models outperformed all the other different models (naïve, ARIMA and exponential smoothing).

Forecasting

Forecasts of future tourist arrivals for the Victoria Falls Rainforest are important for the government, investors and tourism managers. The SARIMA $(2,1,0)(2,0,0)_{12}$ model seems to be good, and, as shown by various statistical checks can now be used to estimate future tourist arrivals. Forecasted (out of sample forecasts) tourist arrivals for the 24 months ahead are summarised in Table 5. These forecasts were done under the assumption that the economic environment and new political dispensation in Zimbabwe remains in place for the near future.

Table 5: 24-period ahead out of sample tourist forecasts

Month	Forecast	Lo 95	Hi 95	Month	Forecast	Lo 95	Hi 95
Jan-18	24885	16536	37448	Jan-19	29796	11180	79408
Feb-18	20188	12609	32321	Feb-19	25939	9149	73543
Mar-18	22367	13499	37061	Mar-19	27173	9112	81028
Apr-18	20380	11556	35939	Apr-19	25137	7940	79577
May-18	24472	13210	45337	May-19	29303	8767	97941
Jun-18	22444	11640	43277	Jun-19	26846	7643	94300
Jul-18	34320	17072	68993	Jul-19	38343	10389	141508
Aug-18	40985	19602	85690	Aug-19	44854	11589	173607
Sep-18	33522	15464	72670	Sep-19	38682	9549	156689
Oct-18	34510	15371	77479	Oct-19	39625	9358	167777
Nov-18	31462	13549	73055	Nov-19	36117	8171	159649
Dec-18	40330	16818	96714	Dec-19	46548	10100	214520

It is evident from Table 5 that tourist arrivals at the Victoria Falls Rainforest will increase slowly with high numbers expected in the second half of each year. This means accommodation facilities need to be increased to accommodate the high number of tourist arrivals in the destination town, so as to ease accommodation problems. December seems to be a seasonal month with the highest number of tourist arrivals. Transportation and accommodation must be in place in this month. Forecasts of this SARIMA $(2,1,0)(2,0,0)_{12}$ model compare relatively well to the SARIMA $(1,0,1)(1,0,1)_4$ model fitted by Ndiege (2015) for Tanzania which predicted an increase in tourist arrivals. Tanzania and Zimbabwe are the same region and often compete for tourists.

Conclusions

The paper used raw data in plotting a time series plot that exhibited the behaviour of tourist arrivals. An increasing variance with time and non-stationary series was observed from the plot. December is noted to be the seasonal month that receives a significant number of arrivals. Political turmoil and economic meltdown, especially around 2008 may have impacted negatively on tourist arrivals. A logarithm transformation to smooth the variations was done. A regular difference was done to make the series stationary. A SARIMA$(2,1,0)(2,0,0)_{12}$ model is suggested by the ACF, PACF and EACF plots and fits well to the tourist arrivals data. AIC, BIC and forecasting accuracy measures supported the SARIMA$(2,1,0)(2,0,0)_{12}$ model over the widely used SARIMA $(1,1,0)(1,1,0)_{12}$ and other considered models. Short term (year 2018) out of sample future tourist arrivals forecasts from the model indicated a positive upward trend, hence, the ZTA may start planning to have enough facilities (accommodation, transport, ICT, etc.) to cater for increased arrivals. The expected increase in tourist arrivals under the new political dispensation has the possibility of luring investors, and these predictions are of great use to tourism investors. Furthermore, marketing strategies and friendly policies must be put in place in the country in order to record even more arrivals in the next few years as this will ease foreign currency shortages and result in employment creation. Accommodation, ICT infrastructure and transportation problems can be eased through planning. The results from this paper are similar to the results of previous studies of Baldigara and Mamula (2015), Saayman and Saayman (2010), and Goh and Law (2002) which suggest that SARIMA models fit well to tourism data and produce accurate forecasts that are useful for marketing and planning purposes.

Future Work

The SARIMA model considered above assumes homoscedasticity which is not always a true assumption. Heteroscedasticity may be present leading to GARCH modelling of the variance terms. Adjustments of tourism policies and the changes in the currency will have a greater impact on the number of tourist arrivals in the country. Improvement of tourism resort sites can help attract more visitors. Marketing strategies help increasing arrivals in Zimbabwe and casual methods like the VAR and regression methods help in marketing. Nonlinear bass diffusion models can be used to model arrivals since they capture effectiveness of marketing strategies.

References

Adhikari, R., and R. K. Agrawal. 2013. "An Introductory Study on Time Series Modelling and Forecasting." arXiv:1302.6613.

Africa Tourism Monitor. 2015. "Unlocking Africa's Tourism Potential." African Development Bank, the Africa House at New York University and the Africa Travel Association. Accessed January 8, 2018. https://www.afdb.org/en/knowledge/publications/africa-tourism-monitor/africa-tourism-monitor-2015/.

Akal, M. 2004. "Forecasting Turkey's Tourism Revenues by ARMAX Model." *Tourism Management* 25 (5): 565–580. https://doi.org/10.1016/j.tourman.2003.08.001.

Athanasopoulos, G., J. H. Rob, H. Song, and D. Wu. 2011. "The Tourism Forecasting Competition." *International Journal of Forecasting* 27 (3): 822–845. https://doi.org/10.1016/j.ijforecast.2010.04.009.

Bakker, J., and M. Pechenizkiy. 2009. "Food Wholesales Prediction: What is Your Baseline?" In *18th International Symposium on Foundations of Intelligent Systems*, edited by J. Rauch, Z. W. Ras, P. Berka, and T. Elomaa, 493–502. Berlin: Springer. https://doi.org/10.1007/978-3-642-04125-9_52.

Baldigara, T., and M. Koić. 2015. "Modelling the International Tourism Demand in Croatia Using a Polynomial Regression Analysis." *The Business of Tourism* 15: 29–38.

Baldigara, T., and M. Mamula. 2015. "Modelling international Tourism Demand Using Seasonal ARIMA Models." *Tourism and Hospitality Management* 21 (1): 19–31.

Bentum-Ennin, I. 2014. "Modelling International Tourism Demand in Ghana." *Global Business and Economics Research Journal* 3 (12): 1–22.

Bonham, C., B. Gangnes, and T. Zhou. 2009. "Modelling Tourism: A Fully Identified VECM Approach." *International Journal of Forecasting* 25 (3): 531–549. https://doi.org/10.1016/j.ijforecast.2008.11.014.

Box, G. E. P., and G. M. Jenkins. 1970. *Time Series Analysis: Forecasting and Control.* San Francisco: Holden-Day.

Brierley, P. 2011. "Winning Methods for Forecasting Seasonal Tourism Time Series." *International Journal of Forecasting* 27 (3): 853–854. https://doi.org/10.1016/j.ijforecast.2011.03.004.

Celik, K. A., S. Ozcan, A. Topcuoglu, and E. K. Yildirim. 2013. "Effects of the Tourism Industry on the Balance of Payments Deficit." *An International Journal of Tourism and Hospitality Research* 24 (1): 86–90.

Chen, R. J. C. 2006. "Before and after the Inclusion of Intervention Events. An Evaluation of Alternative Forecasting Methods for Tourist Flows." *Tourism Analysis* 10 (3): 269–276. https://doi.org/10.3727/108354205775322907.

Chibaya, T. 2013. "From 'Zimbabwe Africa's Paradise to Zimbabwe a World of Wonders': Benefits and Challenges of Rebranding Zimbabwe as A Tourist Destination." *Developing Country Studies* 3 (5): 84–92.

Chigora, F., and C. Vutete. 2015. "Comprehending Determinants of Demand: Zimbabwe Tourism Destination Scenario." *International and Business* 1 (2): 17–19.

Chu, F. L. 2008. "Analyzing and Forecasting Tourism Demand with ARAR Algorithm." *Tourism Management* 29 (6): 1185–1196. https://doi.org/10.1016/j.tourman.2008.02.020.

Chu, F. L. 2009. "Forecasting Tourism Demand with ARMA-based Methods." *Tourism Management* 30 (5): 740–751. https://doi.org/10.1016/j.tourman.2008.10.016.

Chu, F. L. 2014. "Using a Logistic Growth Regression Model to Forecast the Demand for Tourism in Las Vegas." *Tourism Management Perspectives* 12: 62–67. https://doi.org/10.1016/j.tmp.2014.08.003.

Claveria, O., and Torra, S. 2014. "Forecasting Tourism Demand to Catalonia: Neural Networks vs. Time Series Models." *Economic Modelling* 36: 220–228. https://doi.org/10.1016/j.econmod.2013.09.024.

Constantino, H., P. O. Fernandes, and J. O. Teixeira. 2016. "Tourism Demand Modelling and Forecasting with Artificial Neural Network Models: The Mozambique Case Study." *Tékhne* 14 (2): 113–124. https://doi.org/10.1016/j.tekhne.2016.04.006.

Cortes-Jimenez, I., M. Pulina, C. R. Prunera, and M. Artis. 2009. "Tourism and Exports as a Means of Growth." *Research Institute of Applied Economics Working Papers 2009/10.*

Coshall, J. T. 2009. "Combining Volatility and Smoothing Forecasts of UK Demand for International Tourism." *Tourism Management* 30 (4): 495–511. https://doi.org/10.1016/j.tourman.2008.10.010.

Crotti, R., and T. Misrahi. 2017. "The Travel and Tourism Competitiveness Index: Travel and Tourism as an Enabler of Inclusive and Sustainable Growth." In *The Travel and Tourism Competitiveness Report 2017: Paving the Way for a More Sustainable and Inclusive Future*, edited by R. Crotti and T. Misrahi, 3–29. Geneva: World Economic Forum.

Çuhadar, M. 2014. "Modelling and Forecasting Inbound Tourism Demand to Istanbul: A Comparative Analysis." *European Journal of Business and Social Sciences* 2 (12): 101–119.

Cuneo, C. N., R. Sollom, and C. Beyrer. 2017. "The Cholera Epidemic in Zimbabwe, 2008-2009: A Review and Critique of the Evidence." *Health and Human Rights* 19 (2): 249.

Dogru, T., and E. Sirakaya-Turk. 2016. "Modelling Turkish Outbound Tourism Demand using a Dynamic Panel Data Approach." *Tourism and Hospitality Research* 18 (4): 411–414. https://doi.org/10.1177/1467358416663822.

Dritsakis, N. 2004. "Cointegration Analysis of German and British Tourism Demand for Greece." *Tourism Management* 25 (1): 111–119. https://doi.org/10.1016/S0261-5177(03)00061-X.

Dube, C. 2017. "An Investigation into Level of Preparedness to Ebola Virus Disease in Zimbabwe: A Case Study of Tsholotsho District Hospital." B.Ed project: Midlands State University.

Eja, E. I., J. K. Ukwayi, and F. E. Ojong. 2012. "Success Factors Determining Nigeria as a Tourist Destination." *Journal of Emerging Trends in Educational Research and Policy Studies* 3 (4): 426–432.

Etuk, E. H. 2012. "Predicting Inflation Rates of Nigeria Using a Seasonal Box-Jenkins Model." *Journal of Statistical and Econometric Methods* 1 (3): 27–37.

European Centre for Disease Prevention and Control. 2015. "Outbreak of Ebola Virus Disease in West Africa." Stockholm: ECDC.

Fourie, J., and M. Santana-Gallego. 2011. "The Impact of Mega-sport Events on Tourist Arrivals." *Tourism Management* 32 (6): 1364–1370. https://doi.org/10.1016/j.tourman.2011.01.011.

Gardner Jr., E. S. 2006. "Exponential Smoothing: The State of the Art-Part II." *International Journal of Forecasting* 22 (4): 637–666. https://doi.org/10.1016/j.ijforecast.2006.03.005.

Gelažanskas, L., and K. A. A. Gamage. 2015. "Forecasting Hot Water Consumption in Residential Houses." *Energies* 8 (11): 12702–12717. https://doi.org/10.3390/en81112336.

Goh, C., and R. Law. 2002. "Modelling and Forecasting Tourism Demand for Arrivals with Stochastic Non-stationary Seasonality and Intervention." *Tourism Management* 23 (5): 499–510. https://doi.org/10.1016/S0261-5177(02)00009-2.

Hamilton, J. D. 1994. *Time Series Analysis*. Princeton: Princeton University Press.

Institute of Chartered Accountants of Zimbabwe (ICAZ). 2011. "The Significance of a Vibrant Hospitality Industry towards Economic Transformation." Paper presented at the Institute of Chartered Accountants of Zimbabwe Winter School, Victoria Falls, August 26–29, 2010.

Ismail, Z., and K. A. Mahpol. 2005. "SARIMA Model for Forecasting Malaysian Electricity Generated." *Matematika* 21: 143–152.

Johansen, S. 1988. "Statistical Analysis of Cointegration Vectors." *Journal of Economic Dynamics and Control* 12 (2): 231–254. https://doi.org/10.1016/0165-1889(88)90041-3.

Junttila, J. 2001. "Structural Breaks, ARIMA Model and Finnish Inflation Forecasts." *International Journal of Forecasting* 17 (2): 203–230. https://doi.org/10.1016/S0169-2070(00)00080-7.

Kamel, J., Z. Ftiti, and H. Chaibi. 2015. "The Tunisian Tourism Business: What We Learn about the European Demand?" *The Journal of Applied Business Research* 31 (6): 2079–2090. https://doi.org/10.19030/jabr.v31i6.9476.

Kaminski, B., and N. Francis. 2011. "Zimbabwe's Foreign Trade Performance During the Decade of Economic Turmoil: Will Exports Recover? A Revised Version of a Background Paper Prepared for Zimbabwe's Diagnostic Trade Integration Study in Africa Region (AFTP1)." Accessed August 30, 2018. http://siteresources.worldbank.org/INTRANETTRADE/Resources/239054-1239120299171/5998577-1254498644362/6461208-1300202947570/Zimbabwe_Trade_Diagnostic.pdf.

Karambakuwa, R. T., T. Shonhiwa, L. Murombo, F. N. Mauchi, N. R. Gopo, W. Denhere, F. Tafirei, A. Chingarande, and V. Mudavahu. 2011. "The impact of Zimbabwe Tourism Authorsity Initiatives on Tourist Arrivals in Zimbabwe (2008–2009)." *Journal of Sustainable Development in Africa* 13 (6): 68–77.

Kusni, A., N. Kadir, and S. Nayan. 2013. "International Tourism Demand in Malaysia by Tourists from OECD Countries: A Panel Data Econometric Analysis." *Procedia Economics and Finance* 7: 28–34. https://doi.org/10.1016/S2212-5671(13)00214-1.

Lee, C. K., H. J. Song, and J. W. Mjelde. 2008. "The Forecasting of International Expo Tourism Using Quantitative and Qualitative Techniques." *Tourism Management* 29 (6): 1084–1098. https://doi.org/10.1016/j.tourman.2008.02.007.

Li, G., H. Song, and S. F. Witt. 2005. "Recent Developments in Econometric Modelling and Forecasting." *Journal of Travel Research* 44 (1): 82–99. https://doi.org/10.1177/0047287505276594.

Lim, C., and M. McAleer. 2000. "A Seasonal Analysis of Asian Tourist Arrivals to Australia." *Applied Economics* 32 (4): 499–509. https://doi.org/10.1080/000368400322660.

Lim, C., and M. McAleer. 2002. "Time Series Forecast of International Travel Demand for Australia." *Tourism Management* 23 (4): 389–396. https://doi.org/10.1016/S0261-5177(01)00098-X.

Loganathan, N., and Y. Ibrahim. 2010. "Forecasting International Tourism Demand in Malaysia Using Box Jenkins SARIMA Application." *South Asian Journal of Tourism and Heritage* 3 (2): 50–60.

Makridakis, S., S. C. Wheelwright, and R. J. Hyndman. 1998. *Forecasting: Methods and Applications* 3rd ed. New York: John Wiley & Sons.

Muchapondwa, E., and O. Pimhidzai. 2011. "Modelling International Tourism Demand for Zimbabwe." *International Journal of Business and Social Science* 2 (2): 71–81.

Mukandavire, Z., S. Liao, J. Wang, H. Gaff, D. L. Smith, and J. G. Morris. 2011. "Estimating the Reproductive Numbers for the 2008–2009 Cholera Outbreaks in Zimbabwe." *Proceedings of the National Academy of Sciences* 108 (21): 8767–8772. https://doi.org/10.1073/pnas.1019712108.

Musundi, S.W., P. M. M'mukiira, and F. Mungai. 2016. "Modelling and Forecasting Kenyan GDP using Autoregressive Integrated Moving Average (ARIMA) Models." *Science Journal of Applied Mathematics and Statistics* 4 (2): 64–73. https://doi.org/10.11648/j.sjams.20160402.18.

Nau, R. 2014. "Forecasting with Moving Averages." *Fuqua School of Business, Duke University*. Accessed September 25, 2018. http://people.duke.edu/~rnau/411home.htm.

Naudé, W. A., and A. Saayman. 2004. "The Determinants of Tourist Arrivals in Africa: A Panel Data Regression Analysis." Paper presented at the International Conference—Centre for the Study of African Economies, University of Oxford, March 21–22.

Ndiege, B. O. 2015. "An Analysis of the Performance of International Tourism Demand in Tanzania." *ARA Journal* 5 (1): 53–62.

Okon, E. O. 2014. "Inbound Tourism and Social Factors in Nigeria: Evidence from an Ardl-Ecm Model." *Asian Journal of Economics and Empirical Research* 1 (2): 4–47.

Omane-Adjepong, M., F. T. Oduro, and S. D. Oduro. 2013. "Determining the Better Approach for Short-term Forecasting of Ghana's Inflation: Seasonal ARIMA vs Holt-winters." *International Journal of Business, Humanities and Technology* 3 (1): 69–79.

Pufnik, A., and D. Kunovac. 2006. "Short-term Forecasting of Inflation in Croatia with Seasonal ARIMA Processes." Working Paper, W-16, Croatia National Bank, Croatia. https://ideas.repec.org/p/hnb/wpaper/16.html.

Reserve Bank of Zimbabwe. 2016. *Zimbabwe Mid-Year Fiscal Policy*. Printflow: Harare. Accessed January 8, 2018. https://www.dpcorp.co.zw/assets/zimbabwe-mid-year-fiscal-policy-8-september-2016.pdf

Saayman, A., and I. Botha. 2015. "Evaluating Non-linear Approaches in Forecasting Tourist Arrivals." ERSA Working Paper 492. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.667.741&rep=rep1&type=pdf.

Saayman, A., and M. Saayman. 2010. "Forecasting Tourist Arrivals in South Africa." *Acta Commercii* 10 (1): 281–293. https://doi.org/10.4102/ac.v10i1.141.

Schulz, P. M, and A. Prinz. 2009. "Forecasting Container Transhipment in Germany." *Applied Economics* 41 (22): 2809–2815. https://doi.org/10.1080/00036840802260932.

Sharpe, R. N., R. De Vaux, and P. F. Velleman. 2010. *Business Statistics* 2nd edn. Boston: Pearson Education.

Shen, S., G. Li, and H. Song. 2009. "Effect of Seasonality Treatment on the Forecasting Performance of Tourism Demand Models." *Tourism Economics* 15 (4): 693–708. https://doi.org/10.5367/000000009789955116.

Shen, S., G. Li, and H. Song. 2011. "Combination Forecasts of International Tourism Demand." *Annals of Tourism Research* 38 (1): 72–89. https://doi.org/10.1016/j.annals.2010.05.003.

Smeral, E., and M. Wüger. 2005. "Does Complexity Matter? Methods for Improving Forecasting Accuracy in Tourism: The Case of Australia." *Journal of Travel Research* 44 (1): 100–110. https://doi.org/10.1177/0047287505276596.

Song, H., and G. Li. 2008. "Tourism Demand Modelling and Forecasting. A Review of Recent Research." *Tourism Management* 29 (2): 203–220. https://doi.org/10.1016/j.tourman.2007.07.016.

Song, H., G. Li, and S. F. Witt. 2010. "Tourism Demand Modelling and Forecasting: How Should Demand Be Measured?" *Tourism Economics* 16 (1): 63–81. https://doi.org/10.5367/000000010790872213.

Song, Z., S. Kjetil, and Z. Fabrizio. 2011. "Growing Like China." *American Economic Review* 101 (1): 196–233. https://doi.org/10.1257/aer.101.1.196.

Suleman, N., and S. Sarpong. 2012. "Forecasting Milled Rice Production in Ghana Using Box-Jenkins Approach." *International Journal of Agricultural Management and Development* 2: 79–84.

Thano, R. 2015. "The Impact of Tourism on the Balance of Payments." *American Journal of Economics, Finance and Management* 1 (5): 529–536.

Tularam, G. A., V. S. H. Wong, and S. Nejad. 2012. "Modelling Tourist Arrivals Using Time Series Analysis: Evidence from Australia." *Journal of Mathematics and Statistics* 8 (3): 348–360. https://doi.org/10.3844/jmssp.2012.348.360.

United Nations World Tourism Organisation (UNWTO). 2010. "World Tourism Barometer." Accessed February 5, 2018. https://www.e-unwto.org/doi/pdf/10.18111/wtobarometereng.2010.08.5.1.

Wickens, M. R., and T. S. Breusch. 1988. "Dynamic Specification, the Long-run and the Estimation of Transformed Regression Model." *Economic Journal* 98 (390): 189–205. https://doi.org/10.2307/2233314.

Wong, K., H. Song, S. F. Witt, and D. C. Wu. 2007. "Tourism Forecasting: To Combine or Not to Combine?" *Tourism Management* 28 (4): 1068–1078. https://doi.org/10.1016/j.tourman.2006.08.003.

World Travel and Tourism Council. 2017. "Travel and Tourism Economic Impact 2017 Zimbabwe." Accessed January 8, 2018. https://www.wttc.org/-/media/files/reports/economic-impact-research/countries-2017/zimbabwe2017.pdf

Yeung, M., and A. Law. 2005. "Forecasting US Air Travellers to Europe, Caribbean and Asia." *Asia Pacific Journal of Tourism Research* 10 (2): 137–149. https://doi.org/10.1080/10941660500135852.

Zimbabwe Statistics Report. 2014. Government of Zimbabwe. Printflow: Harare. Accessed January 8, 2018. http://www.zimstat.co.zw/

Zimbabwe Statistics Report. 2015. Government of Zimbabwe. Printflow: Harare. Accessed January 8, 2018. http://www.zimstat.co.zw/

Zimbabwe Tourism Authority Report. 2014. Government of Zimbabwe. Printflow: Harare. Accessed January 8, 2018. https://www.zimbabwetourism.net/tourism-trends-statistics/

Zimbabwe Tourism Authority Report. 2015. Government of Zimbabwe. Printflow: Harare. Accessed January 8, 2018. https://www.zimbabwetourism.net/tourism-trends-statistics/

Zimbabwe Visitor Exit Survey (VES) Report. 2015/16. Government of Zimbabwe. Printflow: Harare. Accessed January 8, 2018. http://www.zimstat.co.zw/