Sustainable Technology and Entrepreneurship 2 (2023) 100027

Sustainable Technology and Entrepreneurship

https://www.journals.elsevier.com/sustainable-technology-and-entrepreneurship

Full Length Article

International tourist arrivals modelling and forecasting: A case of Zimbabwe

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ARTICLE INFO

Article History:
Received 16 June 2022
Accepted 2 September 2022

Keywords:
International tourist arrivals
Forecasting
ARIMA
SARIMA

ABSTRACT

Zimbabwe is blessed with tourist attractions that draw visitors from all over the world. However, there are no quantitative models available for tourism stakeholders to utilize in decision-making and planning. The country is experiencing foreign currency shortages, which may be alleviated if the tourism industry, which has the power to generate foreign currency, adopted quantitative forecasting techniques that can provide reliable estimates. For planning reasons, resource mobilization, and allocation, accurate tourist projections are critical to the government and other tourism stakeholders. The goal of this research is to model international tourist arrivals in Zimbabwe and develop a quantitative statistical model that can be used to forecast future international tourist visitors. The Zimbabwe National Statistics Agency (ZIMSTAT) provided monthly foreign tourist arrivals data for the period January 2000 to December 2018. After the data revealed non-stationarity and seasonality, a time series technique in the form of the Box-Jenkins approach is applied to the data. The autocorrelation function (ACF), partial autocorrelation function (PACF), and root mean square error (RMSE) revealed that a seasonal autoregressive integrated moving average (SARIMA) model suited well to the data. The model predicted a gradual and seasonal increase in international tourist arrivals. The results of this model could be used by those in charge of tourism marketing to develop effective and efficient marketing strategies so that the country can receive a significant increase in international tourists, which will bring in much-needed foreign currency. It is important for tourism stakeholders and service providers to guarantee the availability of enough transport and accommodation facilities, especially during peak seasons.

Introduction

One of the key economic areas that is expanding quickly around the world is tourism, which offers employment and investment opportunities (Chang *et al.*, 2011). According to Mitchell and Ashley (2006) and the World Bank (2006), it is one of the important sectors that can reduce poverty and boost economic growth in African nations. The tourist industry contributes 12% of Zimbabwe's GDP. Tourism is one of the most diverse industries in the world due to its integrating effect that spans practically all sectors of the economy (Meschede, 2020). It is recognized as the largest industry in the planet (Li et al., 2022). Tourism has been reckoned to be one of the most developed as a major global industry reflected by an annual average growth of 4-5% contributing to 8% of the Global GDP and 10 % in global employment (World Tourism Organisation, 2020; Valtolina, Barricelli, and Di Gaetano, 2020; Nyagadza et al., 2022). According to WTTC (2019) the tourism industry witnessed a growth of 3.9% and contributed $8.8 trillion in revenue and created 319 million jobs to the global economy. This shows how tourism can influence global turnaround of economies, if it is supported with proper investment in marketing and provided with systems that amend any likely mishaps. Tourism reckoned as one of the most developed industries globally (Nyagadza *et al.*, 2022). This is reflected by the industries annual average growth of 4-5%, its 8% contribution to the Global GDP and 10 % contribution in global employment (Nyagadza, Mazuruse, Muposhi & Chigora, 2022).

Because it directly adds to the country's gross domestic product (GDP), generates employment, and boosts foreign exchange reserves in addition to drawing in foreign direct investment (FDI), Zimbabwe's tourist sector is crucial to the country's economic development (Chikobvu & Makoni, 2019). The majority of Zimbabwe's economic

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https://doi.org/10.1016/j.stae.2022.100027

sectors are associated with the travel and tourism sector, and they greatly profit from foreign visitors (Woyo & Slabbert, 2021; Makoni and Chikobvu, 2018; Chikobvu & Makoni, 2019; Makoni & Chikobvu, 2017). Therefore, successful international tourism demand forecasting in Zimbabwe offers tourism decision-makers a useful planning tool.

The growth and promise of this global giant would have transcended into the current and future periods but was curtailed by the catastrophic surge of the COVID-19 pandemic (Gössling et al., 2020). This pandemic has negatively impacted economies globally killing many lives (Rezapouraghdam & Karatepe, 2020; Guo *et al.*, 2020). It caused a downturn in the world economy which was never experienced in the past decades (World Economic Forum, 2020). It forced businesses to close and restricted both inbound and outbound movement of people for pleasure and business. According to Bahar & Celik Ilal (2020) the upsurge of COVID-19 has negatively impacted the global tourism business which had made large investments in the building of hotels, setting up of tour operators and airline companies. They also said that the surge affected the employees and clients of this industry as it came as a destruction in doing business and supporting progress in the global socio-economy wellbeing (Don Chi Wai Wu et al., 2021; Nyagadza, Chuchu & Chigora, 2022). Furthermore, Fernandes (2020) announced that the consequences brought by COVID-19 on the global economy are worse than those experienced in the Great Depression of the 1930s and even those of the global financial crisis (GFC) of 2008.

However, many countries, like Zimbabwe, have reaped significant benefits from tourism since the host country can obtain foreign currency, which helps to enhance the country's GDP. According to the World Travel and Tourism Council (WTTC), tourism accounts for 10% of worldwide GDP (Adhikari and Agrawal, 2013; Ghalehkhondabi *et al.*, 2019). Accurate tourism demand is important for investors, the government, and tourism managers since it aids in planning and decision-making (Li *et al.*, 2022, Makoni & Chikobvu, 2021). According to Makoni and Chikobvu (2018), accurate tourism projections enable the sector to continue playing a crucial role in raising the nation's economic standing. These forecasts are mainly obtained through using scientific statistical techniques (Makoni & Chikobvu, 2021, Chang, 2011). The forecasting performance of statistical forecasting methods is superior to judgmental methods, claim Athanasopoulos *et al.* (2009).

According to Salinas Fernández *et al.* (2022), the Covid-19 global pandemic is having a detrimental impact on the tourism business activities and the economies of countries that heavily rely on the sector. Zimbabwe is not exceptional. In addition to agriculture and mining, Zimbabwe's economy depends heavily on the tourism industry, which the Covid-19 outbreak affected severely. For things to return to normal in Zimbabwe, the nation must make the tourism industry competitive. Rebranding and ensuring that the nation's tourist sector is competitive, will be achieved through the use of accurate tourism projections emanating from statistical models (Nyagadza *et al.*, 2022).

Tourism time series and forecasting studies will be vital if the country is to expand economically, monetarily, and socially. It is quite difficult to accurately predict the expected quantity of tourists within a certain time frame because there are some unplanned changes that can disrupt activity (Hao et al., 2020). As a result, it is vital to precisely anticipate the number of tourists at any given time. Accurate tourist demand projections are essential to design policy. Zimbabwe is one of the world's most tourist-dependent countries. International tourist arrivals in Zimbabwe should be taken seriously because they vary year to year owing to unforeseeable reasons like COVID-19 and drought (Ugur and Akb ıyık, 2020). Accurate forecasting assists government and industry actors in making key decisions, minimizing waste and inefficiency of tourist resources, and thereby decreasing risk and uncertainty (Chen *et al.*, 2014).

This study aims at predicting Zimbabwe's international tourist arrivals using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. In Africa and Zimbabwe in particular, statistical time-series tourist prediction models are lacking. More wealthy nations than emerging ones use the models. The lack of scientific methodologies and informative time series models for forecasting international visitor arrivals for planning and decision-making purposes is being filled. The study adds to the body of knowledge regarding the significance of SARIMA models in the tourism sector. Consequently, effective demand forecasting for international tourism in Zimbabwe and beyond provides decision-makers in the tourism industry with a useful planning tool. The most widely used and well-known statistical time series forecasting models is the Autoregressive Integrated Moving Average (ARIMA) or a seasonal ARIMA (SARIMA). The Box-Jenkins methodology is employed in fitting the ARIMA/SARIMA models, it is well-known for its high forecasting accuracy and efficiency in modeling a variety of time series in a basic manner (Khandlwal *et al.*, 2015; Nyagadza & Chigora, 2022).

Literature review

According to Song and Li (2008), there are primarily three model groups (time series, econometric, and artificial intelligence-based models) used to anticipate tourism demand using historical data.

The ARIMA/SARIMA models are the widely used in tourism demand forecasting Wu et al. (2021). Athanasopoulos *et al.* (2011) compared univariate and multivariate time series approaches, econometric models using 66 monthly series, 427 quarterly series, and 518 annual series, and came to the conclusion that pure time series-based approaches like ARIMA models are superior to the models with explanatory variables. Forecasts using univariate models like the ARIMA or SARIMA are accurate. In Macau, a special administrative region (SAR) of China, Wu *et al.* (2021) forecast a need for tourists. The authors proposed a brand-new hybrid strategy that combines the SARIMA model with long short-term memory (LSTM) (SARIMA + LSTM). The proposed model fared better than the ARIMA, SARIMA, and naive models.

A SARIMA $(2, 1, 0)(2, 0, 0)_{12}$ model, according to Makoni and Chikobvu (2018), fit the Victoria Falls Rainforest, one of Zimbabwe's most well-known tourist destinations, well. The SARIMA model was shown to have the highest predicting accuracy by Makoni and Chikobvu (2018) when they compared it to the naive, seasonal naive, and Holt-Winters exponential smoothing models. A similar method will be applied to Zimbabwe as a country rather than just one particular tourist attraction site. In Spain, seasonality was taken into account in Martín Martín and Salinas Fernández's (2022) analysis of the implications of technological advancements in the train network on tourism sustainability. They suggested models that account for the seasonality in tourist arrivals; thus, this study uses a SARIMA model that does so.

As recommended by Salinas Fernández *et al.* (2022) as recovery plans for the tourism sector, Zimbabwean tourism stakeholders must ensure the availability of information and communication technologies, the destination's openness to travelers from around the world, and the availability of adequate transportation and accommodation infrastructures and tourist services. This is possible with the help of insightful, accurate tourism projections. In their study, Li *et al.* (2022) found a positive correlation between a recovery employee's physical beauty and tourists' perceptions of the recovery employee and the company (Arasli et al., 2021; Mao et al., 2021). In order to develop effective and efficient recovery measures that go beyond the COVID-19 outbreak, the current study's major objective is to use time series models to model international arrivals, regardless of their gender and employee's physical beauty (Bartik et al., 2020; Sam et al., 2020).

Li *et al.* (2022) forecast the medium-term performance of restructured tourism enterprises using a new adaptive integrated predictor.

The SARIMA models will be used in this study rather than the adaptive integrated predictor since they are more flexible and straightforward to employ for predicting tourism demand (Brito *et al.*, 2021; Siami-Namini *et al.*, 2018). Two alternative univariate-time-series methodologies and one artificial intelligence (AI) methodology were used by Diunugala and Mombeuil (2020) to forecast the number of tourists arriving in Sri Lanka from the top 10 tourist-producing nations (India, China, the UK, France, Japan, the Maldives, Germany, the USA, Russia, and Australia). They came to the conclusion that ARIMA and Winter's exponential smoothing were the two most effective models for predicting foreign traveler arrivals (FTAs) in Sri Lanka.

Msofe and Mbago (2019) used the Box-Jenkins (1970) approach to predict the arrival of foreign tourists in Zanzibar and discovered that the SARIMA $(1, 1, 1)(1, 1, 2)_{12}$ model best fit the monthly data as indicated by the Akaike's Information Criterion (AIC). The forecasts revealed a rise in seasonality and future foreign tourist arrivals. In their projection for Indonesia's foreign tourism demand, Nurhasanah *et al.* (2022) used the Box-Jenkins (1971) methodology. The best model, according to the authors, was a SARIMA one because it took into account the seasonality of tourist demand. The predictions revealed a rise in incoming foreign tourists. The authors suggested using the methodology, therefore it will be used in this study to forecast tourist demand.

Methods

The Box-Jenkins (1970) technique has a good performance in forecasting, according to the literature (Nadal-De Simone *et al.*, 2000), hence it is adopted in this study. The proposed container throughput forecasting methodology includes the following steps: (i) time series characteristics, (ii) Augmented Dickey-Fuller Test for stationarity, (iii) model identification and estimation, (iv) diagnostic checking, (v) accuracy measures, and (vi) forecasting and forecast evaluation.

Characteristics of time series data

The monthly international tourist arrivals statistics (Y_t) for Zimbabwe for the period January 2000 to December 2018 were used in this study. The time-series data is initially examined for inconsistencies. To stabilize the variance, a variety of transformation strategies (Hill *et al.*, 2006; Nyagadza, Chigora & Chuchu, 2022) might be used. An autocorrelation function (ACF) can be used to visualize the modified time series and display a seasonal trend. There is a need to examine seasonality in the series if the ACF and partial correlation function (PACF) show considerable rises with a repeated and persistent pattern over the complete lag period.

Test for stationarity (the augmented Dickey-Fuller t statistic)

The mean, variance, and covariance are the key features to look for when determining whether or not the data is stationary. The Augmented Dickey-Fuller (ADF) test is the regularly used method for testing stationarity of data, and it will be applied in this study. It will be carried out under the null hypothesis that the monthly international tourist data series has a unit root. The ADF test statistic will be computed and compared to the relevant critical value. The ADF test is based on the following expression proposed by Banerjee *et al.* (1993).

$$\Delta y_t - \alpha + \beta t + (\mathrm{p}-1)y_{t-1} + \delta_1 \Delta y_{t-1} + \ldots + \delta_{p-1}\Delta y_{t-p+1} + \varepsilon_t, \tag{1}$$

where α is a constant, β the coefficient of a simple time trend, Δ is the first difference operator, δ_i are parameters and p the lag order of the autoregressive process. The decision on whether to include the intercept and/or the time trend should be determined ahead of time. The lagged differenced variables are used to account for any serial correlation that might emerge in the error term e_t, which is assumed to be a white noise process (Banerjee *et al.*, 1993).

Box-Jenkins method

The Box-Jenkins (1970) methodology is a combination of the autoregressive (AR) and moving average (MA) method (Shen, 2009). The approach accommodates both stationary and non-stationary time series. The approach include:

(i) *Identification*- ACF and PACF are used to determine the model's order using time series graphs of the data.

(ii) *Parameter estimation.* Applying the maximum likelihood estimation (MLE) method in estimating the model parameters of the tentative model.

(iii) *Diagnostic Checking.* The suitability of the fitted model in terms of forecasting accuracy is being checked.

ARMA

Once the data is stationary and the tentative model has been identified, an appropriate model can be fitted. Box *et al.* (2011) propose an *ARMA* model that reduces the number of parameters by combining both the *AR* and *MA* models. The *ARMA* (*p*,*q*) is a combination of an AR(p) and MA(q) components. Both p and q are integers and represent the orders of the *AR* and the *MA* components, respectively. An *ARMA (p,q)* model can be expressed as:

$$\mathrm{yt} = \mu + \sum_{i=1}^{p} \emptyset_i \mathrm{Yt-i} - \sum_{i=1}^{q} \theta_i \varepsilon \mathrm{t-i}\varepsilon_t, \tag{2}$$

where μ is the mean, $\emptyset_i$ represents the AR parameters, θ_i represents the MA parameters, ε_t is a white noise series with mean zero and variance σ^2 denoted as $\varepsilon_t \sim N(0, \sigma^2)$.

After applying the backward shift operator, the resultant model will be:

$$(1 - \emptyset_1 B - \emptyset_2 B - \ldots \emptyset_1 B^2 - \ldots - \emptyset_p B^p)Y_t$$
$$= \mu + (1 - \theta_1 B - \theta_2 B - \ldots \theta_1 B^2 - \ldots - \theta_q B^q)\varepsilon_t, \tag{4}$$

where the first component 1 - $\emptyset_1 B - \emptyset_2 B - \ldots \emptyset_1 B^2 - \ldots - \emptyset_p B^p$ represents the AR(p) and the second component 1 - $\theta_1 B - \theta_2 B - \ldots \theta_1 B^2 - \ldots - \theta_q B^q$ represents the MA(q).

ARIMA

SARIMA model

The Seasonal ARIMA (SARIMA) is formed by adding seasonal terms in the ARIMA models. SARIMA Models are written as:

SARIMA (p, d, q) (P, D, Q) $_s$ where p is the non-seasonal AR order, d is the non-seasonal difference, q is the non-seasonal MA order, P is the seasonal AR order, D is the seasonal difference, Q is the non-seasonal MA order and s denotes the seasonality period. The SARIMA model can be written as:

$$\varphi_p(W)\emptyset_P(W^s)\nabla^d \nabla_s^D Y_t = \theta_q(W) * \theta *_Q(W^s)\varepsilon_t \tag{5}$$

where $\varphi p, \emptyset_P, \theta_q, *\theta*_Q$ are model parameters and $\nabla_s^D = (1 - W^s)^D$

The ACF and PACF plots are used to identify the tentative orders of the model. Table 1 summarizes the behavior of ACF and PACF; it was adopted from Aidoo (2011) who also adopted it from Shumway and Stoffer (2006).

Table 1
ACF and PACF behaviour for seasonal and non-seasonal *ARMA* (p,q) models

		AR(p)	MA(q)	ARMA(p,q)
Non-seasonal ARMA(p,q)	ACF	tails off at lag k k = 1, 2, 3, . . .	cuts off after lag q	Tails off
	PACF	cuts off after lag p AR(P)s	Tails off at lags k k = 1, 2, 3, . . . MA(Q)s	Tails off ARMA(P,Q)s
pure-seasonal ARMA(p,q)	ACF	tails off at lag ks k = 1, 2, 3, . . .	cuts off after lag Qs	Tails off at ks
	PACF	cuts off after lag Ps	Tails off at lags ks k = 1, 2, 3, . . .	Tails off at ks

Source: Data analysis (2022)

Table 2
Descriptive statistics for Y_t.

Mean	Standard Deviation	Minimum	Maximum	Skewness	Kurtosis
175881	60055.3	15511	485900	1.24	4.33

Source: Data analysis (2022)

Model selection and validation

The Akaike's Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used for model selection whereby a lower AIC or BIC imply a better model. The AIC and BIC are computed as follows:

$$\mathrm{AIC} = 2\mathrm{k} - 2\log(\mathrm{L}) = 2\mathrm{k} - \mathrm{n}\log\left(\frac{RSS}{n}\right), \tag{6}$$

$$\mathrm{BIC} = (\sigma e2) \ + \frac{k}{n}\log(\mathrm{n}), \tag{7}$$

where k is the number of parameters in the statistical model, *RSS* is the residual sum of squares for the estimated model, n is the number of observations and σ_e^2 is the variance of the residuals.

They are used to evaluate the forecasting accuracy of a model. The RMSE and MAPE can be given by the following equations.

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

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

where n is the number of observations, is the actual and the estimated tourism series, respectively. A model with lower RMSE or MAPE suggest a better model and will be used for prediction purposes.

Results and discussion

Data characteristics and analysis

The monthly international tourist arrivals data (Y_t) for Zimbabwe for the period January 2000 to December 2018 obtained from the Zimbabwe National Statistics Agency (ZIMSTAT) are used. The in-sample data is from January 2000 to December 2017 and out of sample data is from January 2018 to December 2018. R software is used for data analysis. The descriptive statistics for the data are presented in Table 2.

The average number of international tourists is 175881. The data is positively skewed because of the positive skewness value. The distribution of the data is leptokurtic because of the kurtosis value that exceed 3. The distribution is not normally distributed. To visualise some of the characteristics of the data, a time series plot for Y_t was constructed. Figure 1 is a time series of the data.

Figure 1 shows a significant decline in international tourist arrivals around the year 2008 probably due to the presidential elections that were held during that year. The noticed spike around the year 2009 was due to the introduction of multiple currencies and the formation of the government of national unity (GNU). There is minimum variation in the series but a stationarity test (ADF test) is conducted. The null hypothesis of the presence of unit root on Y_t is examined. Table 3 presents the results.

At the 5% level of significance, the null hypothesis is being rejected and it can be concluded that the data is stationary. To identify the tentative model, the ACF and PACF of Y_t are constructed and presented in Figure 2.

Table 3
Augmented Dickey-Fuller Test of Y_t.

Augmented Dickey-Fuller Test		
Test Statistic = -5.777	Lag order = 6,	p-value = 0.01

Source: Data analysis (2022)

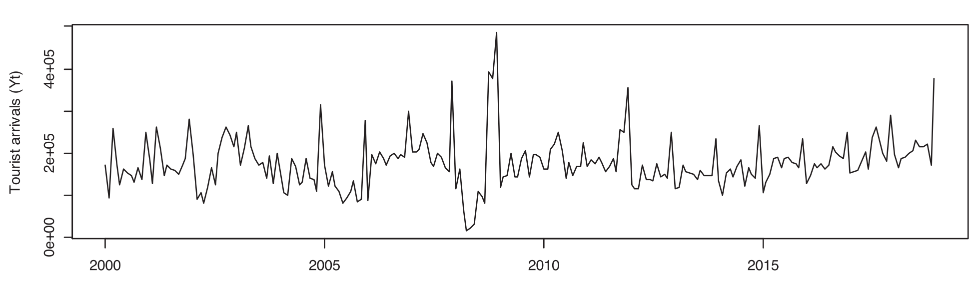

Fig. 1. Time series plot of original tourist arrivals data (Y_t). Source: Data analysis (2022)

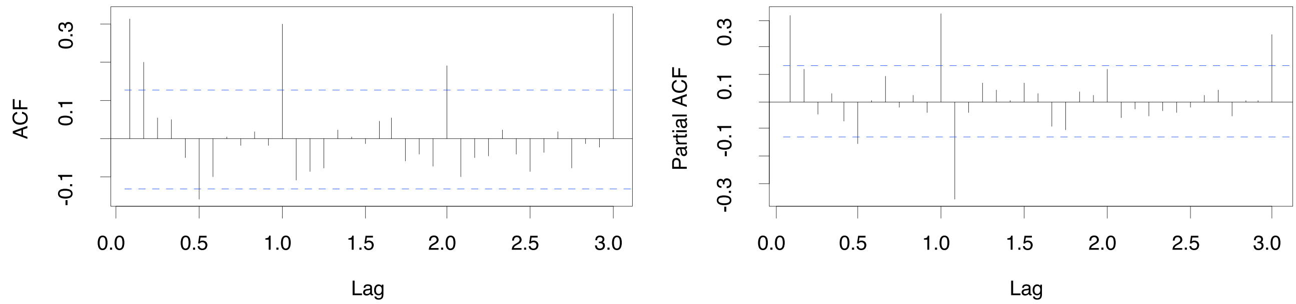

Fig. 2. ACF and PACF of Y_t. Source: Data analysis (2022)

Table 4
AIC values for fitted models

Model specification	AIC value
SARIMA(1,0,0)(1,0,0)$_{12}$ model with non-zero mean	5591.42
SARIMA(1,0,0)(1,0,0)$_{12}$ model with zero mean	5631.69
SARIMA(1,0,0)(0,0,1)$_{12}$ model with non-zero mean	5606.37
SARIMA(1,0,0)(0,0,1)$_{12}$ model with zero mean	5663.4
SARIMA(1,0,0)(1,0,1)$_{12}$ model with non-zero mean	5561.62
SARIMA(1,0,0)(1,0,1)$_{12}$ model with zero mean	5580.25

Source: Data analysis (2022)

Table 5
SARIMA (1,0,0)(1,0,1)$_{12}$ model parameters.

	μ	θ_1	Θ_1	$\emptyset_1$
Coefficient	177589.04	0.491	0.9872	-0.8647
S.E	21662.31	0.060	0.0240	0.1261
T-statistic	8.1981	8.1833	41.1333	-6.8573

Source: Data analysis (2022)

Figure 2 shows decaying spikes on the ACF and the first spike that cutting of at lag 1 on the PACF suggest an AR(1) model. Significant spikes at lag 1 and lag 12, lag 24 and lag 36 in the ACF and PACF suggests the need for a seasonal component. The possible models being suggested are the $SARIMA(1,0,0)(1,0,1)_{12}$ and $SARIMA(1,0,0)(1,0,0)_{12}$. The suggested model will be fitted together with other specifications and the best model will be the one with a lower AIC value. The AIC for the fitted models are presented in Table 4.

The results in Table 4 suggest that the SARIMA (1,0,0)(1,0,1)$_{12}$ model with non-zero mean is the best for the data because of the lowest AIC value.

The Maximum Likelihood Estimation (MLE) method was used in the estimation of the SARIMA (1,0,0)(1,0,1)$_{12}$ model with non-zero mean parameters. The model parameters are summarised in Table 5.

Table 5 results shows that all the model parameters are statistically significant as indicated by the t-statistic (t > = 2.00) values. Since the model residuals are significant, the next is to examine if the model residuals are correlated and normally distributed. The QQ and ACF plots are used to assess normality and autocorrelation, respectively. The results are presented in Figure 3.

According to the QQ plot, the model residuals seem normally distributed and the ACF plots suggest that the absence of autocorrelation on the residuals besides one significant spike exhibited which is outside the boundaries.

Accuracy measures

The Root Mean Squared Error (RMSE) and Mean Absolute Percent Error (MAPE) were used to examine the forecasting accuracy of the model. Table 6 presents the results.

The SARIMA (1,0,0)(1,0,1)$_{12}$ model with non-zero mean's forecasting accuracy outperformed the other fitted SARIMA models because of both lower RMSE and MAPE values. The model is used to project future international tourist arrivals for the next 4 years. The forecasts are besides the Covid-19 period. Table 7 presents the results.

Table 7 shows a slow decline in future tourist arrivals. There is seasonality in the arrivals with more tourists being expected around December. This is probably due to the fact that most tourists from European countries visit Zimbabwe during their winter season (around December). Enough accommodation, transport facilities and enough tour guides have to be in place during the seasonal months. Furthermore, the Zimbabwe Tourism Authority (ZTA) could embark on effective marketing strategies and market all the tourism resorts in Zimbabwe to all the possible visitors. This will result in significant increase in international tourist arrivals; hence increase in foreign currency earnings, employment opportunities. Figure 4 is a graphical presentation of the forecasted international tourist arrivals.

According to the estimates, the number of international visitor arrivals will gradually increase. Those in charge of marketing might use this model to develop effective and efficient marketing tactics so

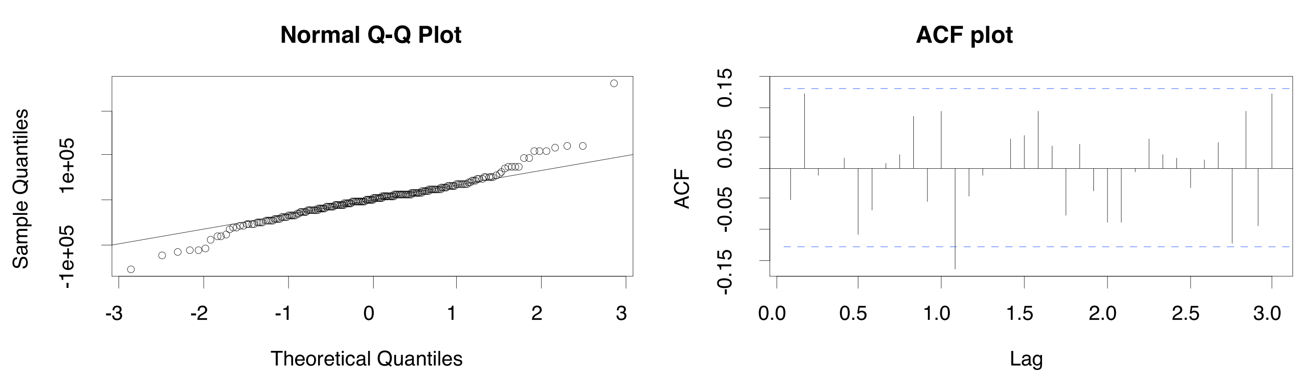

Fig. 3. QQ and ACF plots of SARIMA (1,0,0)(1,0,1)$_{12}$ model residuals. Source: Data analysis (2022)

Table 6
Accuracy measures.

Model	RMSE	MAPE
SARIMA(1,0,0)(1,0,0)$_{12}$ model with non-zero mean	54138.74	24.15696
SARIMA(1,0,0)(1,0,0)$_{12}$ model with zero mean	49863.24	26.61991
SARIMA(1,0,0)(1,0,1)$_{12}$ model with non-zero mean	45410.89	23.89017
SARIMA(1,0,0)(1,0,1)$_{12}$ model with zero mean	45603.11	22.87933

Source: Data analysis (2022)

Table 7
60-period ahead out of sample tourist forecasts

Month	Year				
	2019	2020	2021	2022	2023
January	210186	153570	153168	152850	152532
February	178250	145277	144927	144626	144325
March	183504	164203	163834	163493	163153
April	185105	173741	173363	173003	172643
May	174531	167796	167438	167089	166741
June	161282	157249	156916	156590	156264
July	174387	171879	171518	171161	170805
August	185436	183805	183420	183039	182658
September	171469	170389	170034	169680	169327
October	188194	187383	186993	186603	186215
November	173084	172480	172121	171763	171405
December	280466	279741	279159	278578	277998

Source: Data analysis (2022)

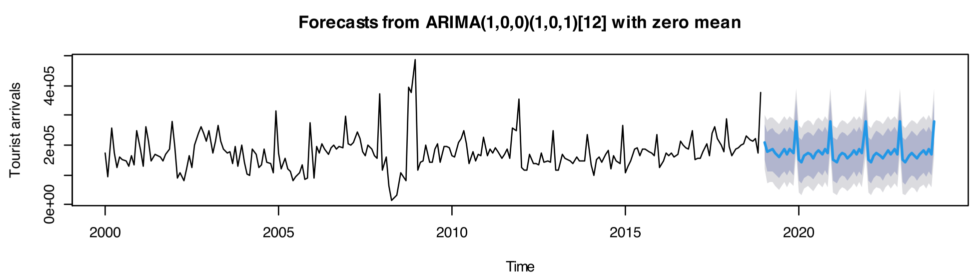

Fig. 4. Forecasted international tourist arrivals. Source: Data analysis (2022)

that the country can see a big increase in international tourists, bringing in much-needed foreign currency. They can strive to promote all of the country's tourist attractions. International tourist arrivals are expected to be seasonal, thus tourism stakeholders should keep this in mind while arranging transportation, lodging, and food and beverage services.

Conclusion

Predicting future foreign visitor arrivals is critical for tourism planning and marketing purposes since it is currently one of Zimbabwe's key areas for economic growth. The Box-Jenkins method was used in this study to analyze data on monthly foreign visitor arrivals in Zimbabwe. The SARIMA(1,0,0)(1,0,1)$_{12}$ model, which was used to provide monthly projections from January 2019 to December 2023, is the model that fits the data the best, according to the results. The predictions show that the number of foreign visitors to Zimbabwe is anticipated to keep rising, following a seasonal trend that is similar to that of the first statistics. The results from this paper are similar to the results of previous studies of Msofe and Mbago (2019), Makoni and Chikobvu (2018), Baldigara and Mamula (2015) and Saayman and Saayman (2010), who used the Box-Jenkins (1970) approach to predict the arrival of tourist arrivals, fitted the SARIMA models that revealed a rise in seasonality and future tourist arrivals. The purpose of this study is to attempt to add to the body of knowledge about the importance of SARIMA models in the tourism industry. Forecasters and government decision-makers can both profit from this work in different ways. It serves as a manual for improving sample predictions in the prediction context. These findings assist government decision-makers in developing appropriate policies, planning and providing resources to society, and making investment decisions.

Study implications

According to the predicted values, there is a moderate but steady increase in the number of foreign visitors arriving. Therefore, in order to draw more foreign visitors from all areas of the world, the Zimbabwe Tourism Authority and other tourism stakeholders in Zimbabwe should continually keep improving the quality of tourism services and products as well as tourism marketing methods. This study also found evidence of seasonal changes, indicating the need for appropriate action to address the problem of declining numbers of foreign visitors and tourism revenue during low season. For instance, the government should run tourism campaigns, ease international traveler visa requirements, create welcoming travel policies, introduce direct flights to cut down on the number of tourists arriving by road, and appoint tourism ambassadors to market the nation's tourist destinations abroad as well as promote domestic tourism. The government has to create better marketing and advertising campaigns, such as using digital tourism marketing, to promote international tourist arrivals. Additionally, they must make greater investments in sustainable infrastructure facilities that satisfy high international standards. The government is urged to create policies that promote domestic travel as well, especially when there are fewer foreign visitors.

Declaration

Ethics

Ethical recommendations were followed during the conduction of this research.

Consent for publication

All authors consent publication of the article with *Sustainable Technology & Entrepreneurship (STE).*

Availability of data and materials

Not Applicable.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial or not-for-profit sectors.

Disclaimer

The views and opinions expressed in this article are those of the authors and do not necessarily reflect the official policy or position of any affiliated agency of the authors.

Authors' contributions

All authors contributed equally in the development of the article.

Declaration of Competing Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Acknowledgements

Not Applicable.

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