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Forecasting Tourism Revenue in Bangladesh Using ARIMA Approach: The Case of Bangladesh

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The Tourism industry is considered as one of the fastest-growing industries in the world. The main objective of this paper is to provide a short-run estimation of tourism receipts for Bangladesh. Considering the annual tourist receipts from 1973 to 2017 and following the Box-Jenkins approach, the Autoregressive Integrated Moving Average (ARIMA) model has been applied for the short-term forecasting of tourism receipts in Bangladesh. Different ARIMA models are analyzed, and the best fitting ARIMA (0,1,1) model is constructed based on the Akaike Information Criterion (AIC). Our results reveal that a 76% increase in tourism receipts in 2021 than in 2017 and a 188%increase in 2025.

Keywords: Forecasting and Prediction Methods,Tourismand DevelopmentPolicy.

JEL Classification: C53,Z32, Z38

1. Introduction

Tourism can play a vital role in any economy by generating private revenues, increased employment opportunities, and government revenues. Tourism is also considered as an instrument for export diversification and contribute to the balance of payments. Tourism's contribution to GDP is significant for many countries, whereas it has a low contribution to several other countries. Bangladesh is such a country where tourism contribution to GDP is small compared to other countries, which is established by the Travel and Tourism Council Report of 2019 about Bangladesh. It shows that travel and tourism's total contribution to GDP in Bangladesh is about4.4%,whereas the worldaverage is 10.4%, and the South Asian average is 8.8%. Nevertheless, tourism still is an essential factor for a country's economy.

Since in the case of Bangladesh entire export basket is concentrated mainly in the readymade garment (RMG) sectors (around 80% of the total export earnings). Due to the dominance of this sector in the overall economy, any vulnerability in the RMG sector can have huge repercussions on the economy of Bangladesh. So, rather than only focusing our undivided attention on this sector, we can also initiate the promotion of other potential sectors. The development of the tourism sector can play a crucial role in this aspect. Proper policy is necessary regarding the development of

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the future economic security of Bangladesh. Forecasting of tourism volume is particularly crucial as it is an indicator of future demand, will providethe required direction for ensuing planning and policymaking (Chu, 2009). It will also facilitate policymakers and planners to predict infrastructural development needs. (Chu, 2008). Moreover, precise forecasting of future tourist flow is vital to determine effective investment in the tourism industry for both the public and private sectors. To ensure efficient use of transportation and resources, the approximation of tourism demand is very important in the public sector (Coshall, 2006).For the hospitality and tourism industry, it is necessary for the managers to have the plan to curtail the risk, and forecasting plays a crucial role in this aspect. (Archer, 1994, p. 105).

Though the consensus on the need to develop accurate forecasts of tourism, to our knowledge, there are no previous studies from the perspective of Bangladesh. Many studies have been directedto forecast tourism demand (Akal, 2004; Saayman& Saayman,2008; Torra and Claveria,2014; Yılmaz*et al.*, 2015; Apergis*et al.* ,2017; Petrevska, 2017), but none of the previous papers have dealt with theforecasting of tourism revenue in the context of Bangladesh. This motivates us to fill out this research gap.

To understand the dynamics of tourism demand over the period, it is of immense importance to forecast the volume of tourism revenue from the perspective of Bangladesh. So, this paper focused on the forecasting of the growth of tourism revenue in Bangladesh using Auto-Regressive Integrated Moving Average (ARIMA) model. ARIMA model traditionally estimated using Box-Jenkins methodology, named after George Box and Gwilym Jenkins. This method first estimates the order of ARIMA that best fitted for that particular time series process. Then this procedure estimates the result and applies diagnostic tests on the residuals. However, another alternative to Box-Jenkins methodology, finding the orders of ARIMA using different information criteria such as Akaike Information Criteria(AIC) or Bayesian Information Criteria(BIC).

This paper is structured as follows: following the introduction, Section 2 provides the literature review on tourism demand forecasting. In section 3, the method, model, and data used in this paper have been discussed. Section 4 focuses on the main findings and analysis of the results. The forecasting accuracy of the selected specifications is given in Section 5, while the conclusions and some future scopes of this paper are presented in the final section.

2. Literature Review

There are numerous pieces of literature associated with modeling and forecasting tourism. The literature of the modeling and forecasting tourism demand can be categorized into two key methods, the causal econometric approach and the time-series approach (Song & Li, 2008). From the studies of Witt and Witt (1995) and Kulendran and King (1997) have shown that univariate time series models tend to perform better than the causal econometric approach. Though tourist arrival isthe most widely used measure of tourism demand, some papers have employed tourist expenditure in the destination (Li *et al*., 2006a) or tourism revenues (Akal, 2004).

On the contrary, the most popular techniques in non-causal time series forecasting are the ARIMA (autoregressive integrated moving average) methods (Goh and Law, 2002) and the exponential smoothing (ES) models (Cho, 2003).Akal (2004) has applied the ARMAX (Autoregressive–moving-average model with exogenous inputs) model to predict international tourism revenue for Turkey. Song and Witt (2008) have used VAR (vector autoregressive) method to forecast tourist flows to Macau from eight major origin countries during the period 2003–2008. Athanasopoulos and Hyndman (2008) have forecasted Australian domestic tourism demand by utilizing innovation state-space models with exogenous variables.Saayman&Saayman (2008) have forecasted the monthly tourist arrivals in South Africa by using standard ARIMA, Holt-Winters exponential smoothing, and SARIMA models and found that the SARIMA model outperformed other models. To forecast tourism demand in the nine major tourist destinations in the Asian-Pacific region, Chu (2008) has shown that ARFIMA (autoregressive fractionally integrated moving average model) exhibits the highest forecasting accuracy in both short-run and long-run. This paper has also shown that SARIMA is the best performing model in the medium-run.Comparing three univariate ARMA-based models (SARIMA, ARAR (autoregressions of AR), and ARFIMA) to forecast tourism demand, Chu(2009)has found that the ARFIMA model performed better than the rest of the models. Using the monthly datasets of tourist arrivals for Croatia, Apergis*et al.(*2017) have tested the performance of four alternative univariate time series forecasting models (SARIMA, SARIMA with Fourier transformation, ARAR, and ARFIMA) and found that SARIMA model with Fourier transformation outperforms the other univariate time series forecasting models across the corresponding regions investigated. Torra and Claveria (2014) have evaluatedthe forecasting accuracy of the different methods (ARIMA, SETAR, and ANN) for modeling tourist arrivals to Catalonia and have concluded that ARIMA models outperformed SETAR (self-exciting threshold autoregressions) and ANN (artificial neural network) models, especially for shorter horizons. Usingthe seasonal ARIMA model, Petrevska (2017) has provided a short-run estimation of international tourism demand in Macedonia from 1956-2013 by using the Box-Jenkins methodology and found that ARIMA (1,1,1) as most suitable for forecasting.Kumar *et al.* (2015) have utilized the ARIMA model to forecast international tourism demand for Malaysia and suggested ARIMA (1,0,1) with seasonal effects as the best-fitted model. Topredict the tourist arrivals in Turkey using monthly data for the period 2002-2013, Ergüven*et al.*(2015)haveemployed the SARIMA and the structural time series model.In this paper,theSARIMA model produces more accurate short-term forecasts than the structural time series model. Chang & Liao (2010) have forecasted the monthly outbound tourism departures of three significantdestinations from Taiwan using SARIMA models. Aslanargun*et al.*(2007) have used ARIMA, linear ANN, multilayer perceptron (MLP), and radial basis function network (RBFN) models along with various combinations of these models for forecasting tourist arrivals to Turkey.

To capture seasonality and trends in forecasting tourism flows to Macau, Chu (2011) hasapplied piecewise linear regression and showed that the piecewise linear method performed the best in forecasting tourist arrivals in Macau. Chu(2014) has employed logistic regression to predict tourism demand in Las Vegas and found that the logistic growth model performed better than SARIMA and Naïve 1 in tourism demand forecasting.Saayman and Botha (2015) have applied the STAR (smooth transition AR) model to forecast tourist arrivals in South Africa and compared the STAR model with several other time series models and showed that the STAR model outperformed the linear models.To forecast tourism demand in Mozambique using the monthly datasets from the period January 2004 to December 2013, Constantino *et al.* (2016) have used ANN methods. Álvarez-Díaz *et al.* (2019) have forecasted the tourism demand in Spainand found that ANN and genetic programmingperformed slightly better than the SARIMA approach. Most recently, Lin & Law (2020) have predicted monthly tourist arrivals from nine countries to Hong Kong by employing decomposed search engine data to improve the forecasting accuracy of tourism demand.

In the context of the economy of Bangladesh, the tourism sector has immense potentialities, and therefore accurate forecasting and good comprehensibility are crucial for policymakers in the tourism industry. However, there is no previous literature related to forecasting tourism indicators for Bangladesh. This paper will surely fill the existing gap regarding forecasting tourism revenue from the perspective of Bangladesh.

3. Method, Model, and Data

In a general autoregressive time series, a variable is regressed by its lag values. That means variability of the present variable depends on the variability of the previous values of that variable.

$$y_t = c + \phi_1 y_{(t-1)} + \phi_2 y_{(t-2)} + \cdots + \phi_p y_{(t-p)} + \epsilon_t \tag{1}$$

Here, c is constant, and this is an $AR(p)$ model as lags $(1, \dots, p)$ can explain the variation in y_t.

In moving average models, the present value of a variable depends on the past error values, that is

$$y_t = c + \theta_1 \epsilon_{(t-1)} + \theta_2 \epsilon_{(t-2)} + \cdots + \theta_q \epsilon_{(t-q)} + \epsilon_t \tag{2}$$

Here, ϵ_t is white noise and this is a $MA(q)$ model as error of the $(t-q)$ can also explain the variation of y_t. The consolidation of above mentioned two models is known as generalized $ARMA(p,q)$ model.

$$y_t = c + \phi_1 y_{(t-1)} + \cdots + \phi_p y_{(t-p)} + \theta_1 \epsilon_{(t-1)} + \cdots + \theta_q \epsilon_{(t-q)} + \epsilon_t \tag{3}$$

Where, ϵ_t is a white noise term. The main limitation of $ARMA(p,q)$ model is that it assumes y_t is stationary over time, which is not true in most of the cases. Therefore, a more generalized model is needed. A $ARMA(p,q)$ model, which is integrated to order d, is called $ARIMA(p,d,q)$. So, time series integrated to order 1 can be called as $ARIMA(p,1,q)$ model and can be written as,

$$y_t' = c + \phi_1 y_{(t-1)} + \cdots + \phi_p y_{(t-p)} + \theta_1 \epsilon_{(t-1)} + \cdots + \theta_q \epsilon_{(t-q)} + \epsilon_t \tag{4}$$

Where, $y_t' = y_t - y_{(t-1)}$ which is the first difference of y_t. Using backshift notation this equation can be written as

$$\left(1-\phi_1 B-\cdots-\phi_p B^p\right)(1-B)y_t=c+\left(1+\theta_1 B+\cdots+\theta_q B^q\right)\epsilon_t \tag{5}$$

This equation can be generalized by order of integration d by the following method,

$$\left(1-\phi_1 B-\cdots-\phi_p B^p\right)(1-B)^d y_t=c+\left(1+\theta_1 B+\cdots+\theta_q B^q\right)\epsilon_t \tag{6}$$

Drift over the time can be included in this ARIMA model by the following method,

$$\left(1-\phi_1 B-\cdots-\phi_p B^p\right)\left(y_t'-\mu\right)=c+\left(1+\theta_1 B+\cdots+\theta_q B^q\right)\epsilon_t \tag{7}$$

Where, $y_t'=(1-B)^d y_t$ and $c=\mu\left(1-\phi_1-\cdots-\phi_p\right)$ and $\mu=mean\ \ of(1-B)^d y_t$

Therefore μ can be interpreted as a drift coefficient.

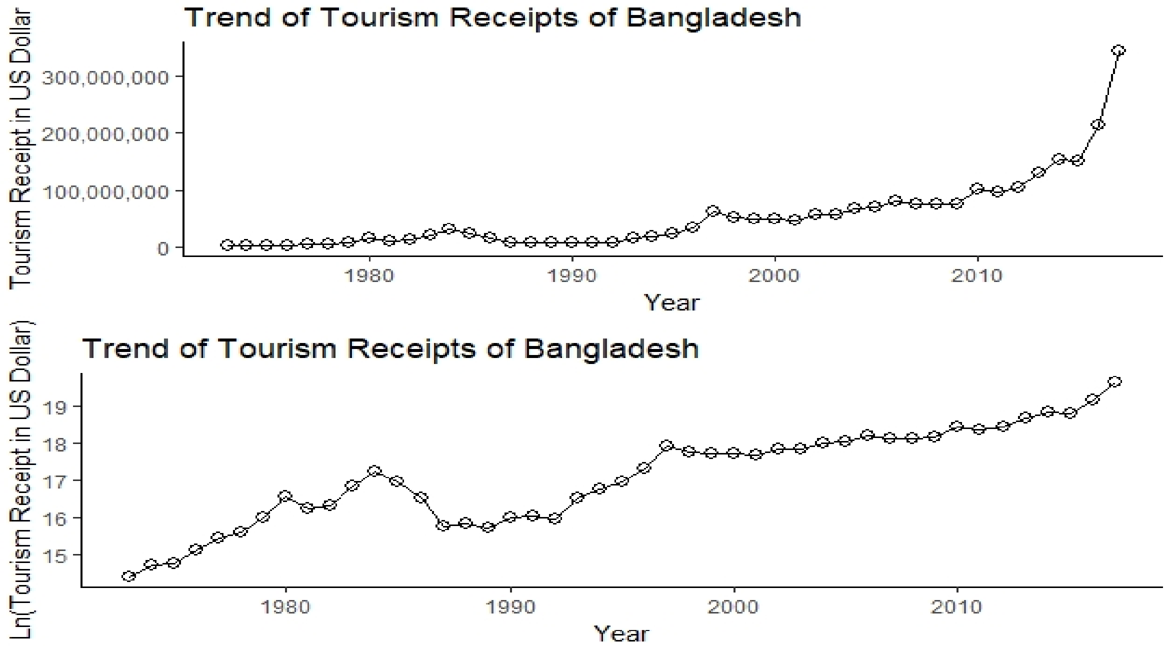
1.1 Description of the Data

This paper used time-series data of tourism receipts from 1973 to 2017 for a total of 45 years. The data from 1973 to 2006 is collected from the Bangladesh Police. The data from 2006 to 2017 are collected from the world bank databank. If the unit of tourism receipt is other than the US dollar, it is converted to US dollars using the respective year's exchange rate. The tourism receipt is mainly defined as money spent by international inbound visitors.

1.2 Detecting Order of $\boldsymbol{ARIMA(p,d,q)}$ Using Traditional Box-Jenkins Methodology

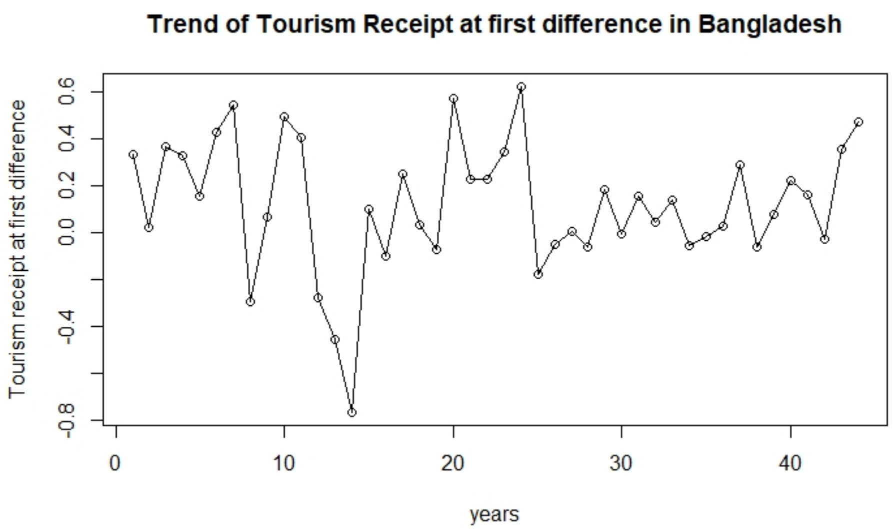
Traditionally it is custom to use Box-Jenkins methodology for estimating correct ARIMA to describe time series processes. This methodology is derived from George Box and Gwilym Jenkins's work on time series methodology. In this method, there are mainly three steps for defining the best $ARIMA$ method. The first step is the identification of $ARIMA$ model where appropriate values of p, d, and q, is determined. The next step is using this appropriate $ARIMA$ method results are estimated, which uses maximum likelihood methods. The last step is the verification of the model, where autocorrelation of the residuals is checked for the best fitting $ARIMA$ model.

Figure 1: Time Plot of International Tourist Receipt in Bangladesh



Now from this data on tourism receipt, from Figure-1,the tourism receiptis not stationary over time. Therefore, this data needs to be transformed. At first natural logarithm of tourismreceipt is taken as this will reduce the variability of trend and seasonality over time. From Figure-1,the logarithm of the tourism receipt is still not stationary over time. Therefore, this paper has taken one-time differenced data ($y_t' = y_t - y_{t-1}$), and from the Figure-2, it seems this data is stationary over time.

Figure 2: Time Plot of the Natural Logarithm of Tourism Receipt in Bangladesh at the First Difference



To make sure that the first difference form of tourism receipt is stationary,the Augmented Dicky-Fuller test is conducted. Here, three versions of the ADF test is used, which are mainly unit root tests. The first one has no drift and trend over time, the second one has drift, but no linear trend, and the third version has both linear trends and drift over time.

$$y_t^{'} = \gamma y_{(t-1)} + \sigma_1 y_{(t-1)}^{'} + \sigma_2 y_{(t-2)}^{'} + \cdots + \sigma_n y_{(t-n)}^{'} + \epsilon_t \tag{8}$$

$$y_t^{'} = \alpha + \gamma y_{(t-1)} + \sigma_1 y_{(t-1)}^{'} + \sigma_2 y_{(t-2)}^{'} + \cdots + \sigma_n y_{(t-n)}^{'} + \epsilon_t \tag{9}$$

$$y_t^{'} = \alpha + \beta t + \gamma y_{(t-1)} + \sigma_1 y_{(t-1)}^{'} + \sigma_2 y_{(t-2)}^{'} + \cdots + \sigma_n y_{(t-n)}^{'} + \epsilon t \tag{10}$$

Here, α shows drift, βt shows trend with time, and the null hypothesis of this test is to test is nonstationary or $\gamma = 0$. ADF tests allow higher-order autoregressive processes to the $lag\ n$ and lastly ϵ_t is the white noise term.

Also, Phillips–Perron (PP) test and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests are conducted to check the stationarity of this transformed data. Phillips-Perron is also a unit root test like the ADF test, where the null hypothesis is non-stationarity. However, KPSS has a null hypothesis of stationarity over time.

Table 1: Different Types of Stationarity Test for Tourism Receipt

Number of Differenced	ADF test			PP Test			KPSS Test			Comments
	No Drift No Trend	With Drift No Trend	With Drift and Trend	No Drift No Trend	With Drift No Trend	With Drift and Trend	No Drift No Trend	With Drift No Trend	With Drift and Trend	
1	P < 0.01	P < 0.01	P < 0.01	P < 0.01	P < 0.01	P < 0.01	P > 0.1	P > 0.1	P > 0.1	Stationary Process

From Table 1 and Figure 2, this data is now stationary over time. Therefore, from these tests, it can be sure that the tourism receipt is stationary if it is differenced at least one time. Therefore, $d = 1$ and order of $ARIMA$ model should be $(p, 1, q)$.

To find the value of autoregressive order, p and moving average order, q this paper used ACF and $PACF$. ACF shows autocorrelation function that means correlation of the variable with its lag variable

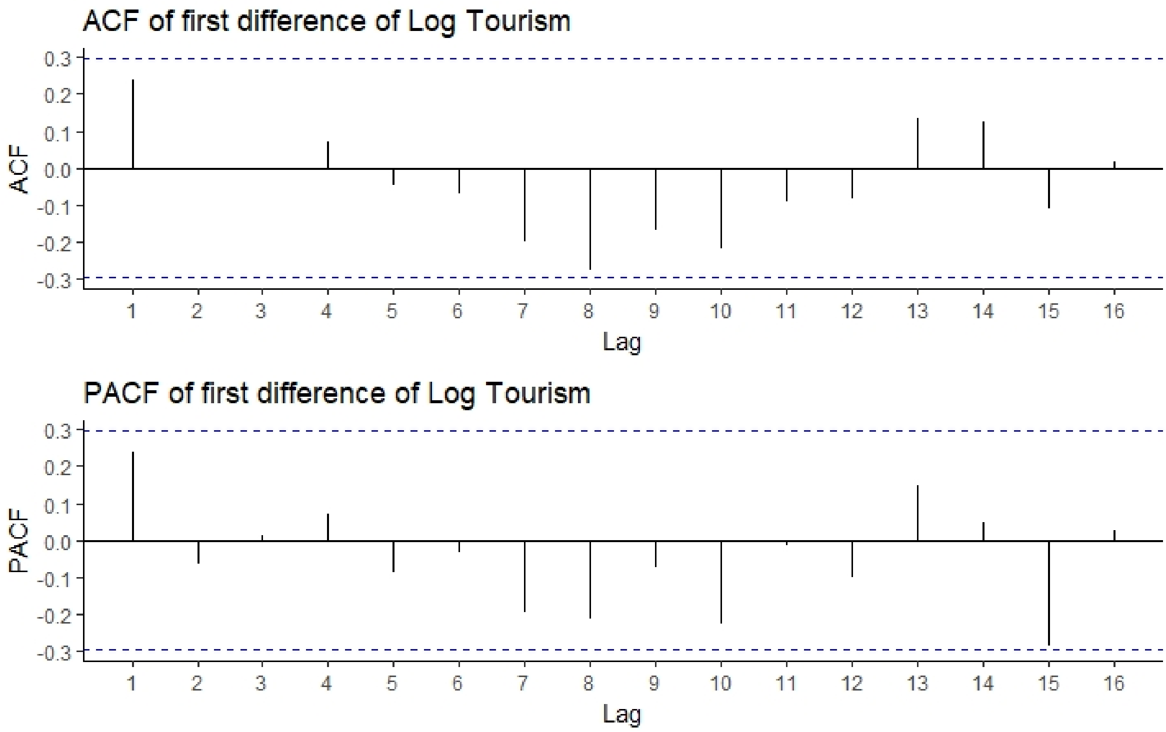
$$r_k = \frac{\sum_{t=k+1}^{T}(y_t - \bar{y})(y_{t-k} - \bar{y})}{\sum_{t=k+1}^{n}(y_t - \bar{y})^2}$$

However, y_t and y_{t-2} maybe correlated because they are both correlated to y_{t-1}. To solve this problem, partial autocorrelation function can be used which measures the relationship between y_t and y_{t-k} after removing the effects of lag that are between these two. Using the graphs of ACF and $PACF$, the value of p and q can be found by the following rule.

Table 2: Detection of ARIMA Models using ACF and PACF

ARIMA Model	ACF	PACF
ARIMA(p,d,0)	Decaying Exponentially or Sinusoidal	The significant spike at lag p and after that no significant lag or pattern
ARIMA(0,d,q)	The significant spike at lag q and after that no significant lag or pattern	Decaying Exponentially or Sinusoidal

Figure 3: ACF and PACF of the First Difference of Log Tourism



From the Figure-3, it seems that the value of p and q is zero. That means there is no autoregressive component or moving average component in this $ARIMA(0,1,0)$ model. However, as the first ACF component is very close to the significant level and this significant level depends on the length of the series, T and calculated as $\pm 2/\sqrt{T}$,which in this case, would be ± 2.98. So, this value depends on the length of the series. Therefore, if the length of the series were greater than 45, we would see a lower value of a significant level, and there might be ACF or $PACF$ component in the model. Therefore, this paper used information criteria for detecting the order of $ARIMA$ model.

1.3 Detecting Order of $ARIMA(p,d,q)$ Using Information Criterion

When a statistical model is used to model the data process, it is rarely correct, and there are some information get missing. However, it is the objective of the model to reduce this loss of information as much as possible. Akaike's Information Criterion (AIC) or Bayesian Information Criterion (BIC) shows how much information is lost due to a model.

Akaike's Information Criterion (AIC) can be calculated for $ARIMA(p,d,q)$ model using the following formula

$$AIC = -2lag(L) + 2(p + q + k + 1)$$

Here, the likelihood of the data is shown by L, and the value of k depends on the value of c. For a small number of T, AIC can give a biased estimation. Therefore, we should use the Corrected Akaike's Information Criterion(AICc), which can be calculated as follows

$$AIC_c = AIC + \frac{2(p + q + k + 1)(p + q + k + 2)}{T - p - q - k - 2}$$

Here, T is the length of the time series. Also, AIC can be corrected by BIC which is as follows

$$BIC = AIC + [log(T) - 2](p + q + k + 1)$$

Keeping $d = 1$ fixed different versions of $ARIMA(p, 1, q)$ are compared in Table 3, using various information criteria. Also, the ARIMA model with drift is considered in all these models.

Table 3: Akaike Information Criteria(AIC), Corrected Akaike Information Criteria (AICc) and Bayesian Information Criteria for Different Types of ARIMA Models

ARIMA model	AIC	AICc	BIC
ARIMA (0,1,0)	20.21	20.3	21.99
ARIMA (0,1,0) with drift	14.39	14.68	17.96
ARIMA (0,1,1)	17.15	17.45	20.72
ARIMA (0,1,1) with drift	**13.64**	**14.24**	**18.99**
ARIMA (0,1,2)	18.64	19.24	23.99
ARIMA (0,1,2) with drift	15.63	16.65	22.76
ARIMA (1,1,0)	16.44	16.73	20.01
ARIMA (1,1,0) with drift	13.78	14.38	19.14
ARIMA (1,1,1)	18.37	18.97	23.72
ARIMA (1,1,1) with drift	15.63	16.65	22.77
ARIMA (1,1,2)	20.4	21.43	27.54
ARIMA (1,1,2) with drift	17.38	18.96	26.3

FromTable 3, it can be shown that $ARIMA(0,1,1)$ with drift has a lower value of AIC, AICc, and BIC. Therefore, it is the best fitting model for the tourism receipt of Bangladesh.

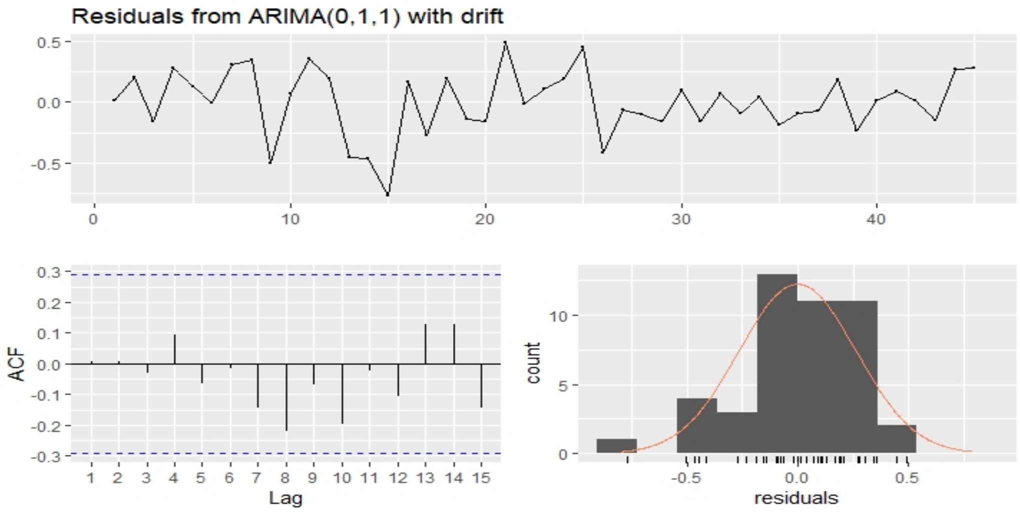
4. Analysis of Results

$ARIMA(0,1,1)$model for the log of tourism receipt(y_t) can be written as

$$y_t^{'} = .1232 + .2530\epsilon_{t-1} + \epsilon_t$$

As here AR order is 0, in other words, there is $c = \mu = .1232$, and ϵ_t is white noise whose standard deviation is $\sqrt{0.07286} = .2699$.
This paper used a graphical test of residuals, which included time plot of residuals, ACF of residuals, and histogram of residuals.

Figure 4 : Diagnostic Check for the Residuals of the ARIMA(0,1,1) Model

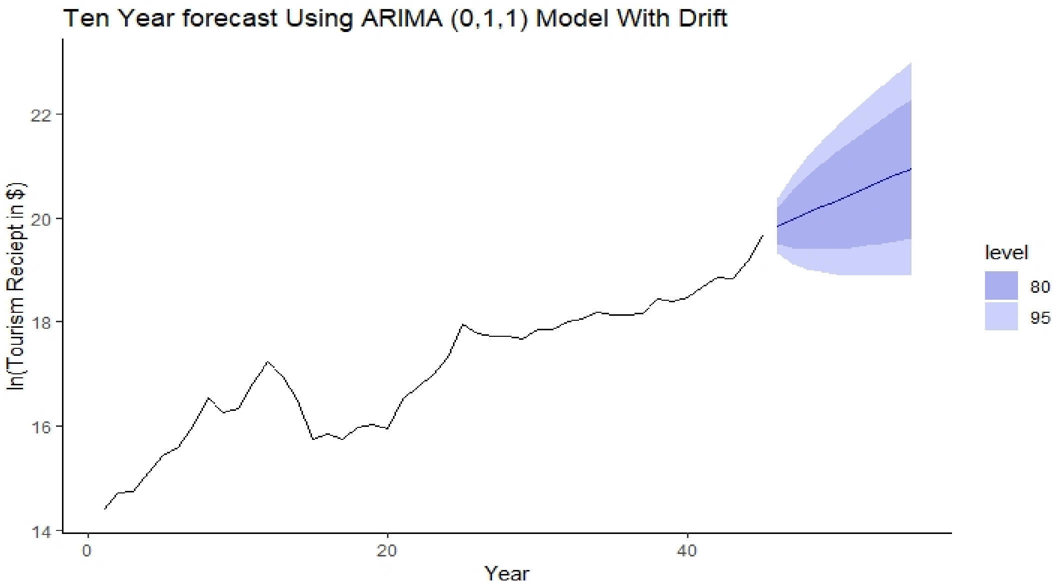


From Figure 4, residuals have a mean of zero, and their ACFs are not significant. That means residuals of $ARIMA(0,1,1)$ model seems white noise. Also, from the Ljung-Box test, results are not significant due to high p values. Therefore, residuals are not different from white noise series. That means this $ARIMA(0,1,1)$ model can explain the variation of tourism receipt.

5. Forecasting Tourism Receipt Using ARIMA (0,1,1)

As this paper reveals that ARIMA (0,1,1) with the drift model is the most fitted method to describe the trend of tourism receipt over time, now this paper will use this model to forecast tourism data for 2018 to 2027. It is assumed that the historical trend of tourism receipts will continue in these ten years of the forecasting period. These forecast points areobtained by expanding this model for future periods. Also, a confidence interval is given for 80% and 95% confidence level.

Figure 5: Ten-year Forecast for Tourism Receipt Using the ARIMA(0,1,1) Model with Drift



Now using antilog, we can generate the values of tourism receipt in US dollars, which is given in Table 4. From the table, we can see that at 2021 tourism receipts would be more than 604 million US dollars per year, which is 75% growth from 2017's tourism receipt. In 2025 tourism receipt would grow by 188% than that of 2017.

Table 4: Ten-year Forecast of Tourism Receipt of Bangladesh, with 80% and 90% Confidence Level

Year	Point Forecast of Tourism Receipt in US dollars	Lower bound of 80% confidence level	Higher bound of 80% confidence level	Lower bound of 95% confidence level	Higher bound of 95% confidence level
2018	417840358.5	295647965.9	590535316.7	246176668.3	709208416.7
2019	472600036.5	271425972.8	822879226.5	202374399	1103651429
2020	534536193.1	264420183.5	1080586731	182171662.3	1568475554
2021	**604589334.8**	**264525972.7**	**1381837538**	**170777141.8**	**2140403073**
2022	683823225.5	268899967.4	1739006830	164062826.4	2850242741
2023	773448774.4	276375221.9	2164510336	160290764.2	3732074193
2024	874812381.3	286388546.2	2672205504	158575281.4	4826029901
2025	**989460101.2**	**298667060.2**	**3278002238**	**158418369.5**	**6180036410**
2026	1119132871	313083347.8	4000399228	159515236.1	7851653630
2027	1265799784	329606474.7	4861097148	161676826.1	9910196366

6. Conclusion

Bangladesh has achieved remarkable progress since 2009, and the country plans to achieve sustainable development goals and become a developed country by 2041. The tourism sector can play a dominating role in the future to achieve this target.The tourism industry contributes to the generation of income, creation of jobs, earnings of foreign exchange, the betterment of the living standards, and reduction of poverty for the developing and emerging countries (Amin & Rahman, 2019). The trend of international tourism has shown persistent growth during the last few decades. So, to understand the dynamics of tourism revenue is very crucial for preparing sustainable tourism policy and creating a harmonious environment of tourism within this country. The Box-Jenkins methodology has been used in this paper, and the ARIMA (0,1,1) model is the best-suited model for the short-run forecasting of international tourism revenue in Bangladesh based on annual data. The paper forecasts that the upward trend of the tourism revenue will continue in the near future.So, the tourism sector is one of the potential industries from the perspective of Bangladesh in the upcoming decades.

Seasonality is one of the most crucial features of tourism time series (Koc&Altinay, 2007). This paper has used the ARIMA process instead of SARIMA due to the unavailability of monthly or quarterly datasets of tourism revenue in the context of Bangladesh. Tourism demand forecasting has constantly beenattractingthe attention of researchers, and the forecasting techniques (Time series, econometric, AI, and combination models) will continue to dominate the tourism demand forecasting (Jiao, 2019). However, there is no single model that outperforms the others in every circumstance (Li et al., 2005).The future aspect of this research may address the application and modeling of the models such as hybrid models, artificial neural network (ANN) models, conditional volatility models, Holt-Winter additive models, Holt-Winter multiplicative models and VAR models, that may provide forecasts that are closer to actual time series and greater accuracy. Moreover, there is also a future scope to understand the dynamics of tourism in the South Asian regions and how the South Asian regions can be mutually benefitted through the promotion of tourism.

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