APPLICATION OF BOX-JENKINS MODELS TO THE TOURIST INFLOW IN BHUTAN

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Abstract

Bhutan has now increasingly become a popular destination for many international tourists. Tourism in Bhutan is considered as one of the largest foreign earning industries. The number of tourist inflow in the country is increasing year by year. Forecasting is very necessary for administration and tourist agent for creating awareness and planning for the future development. It can also predict the future trends as accurately as possible and helps in staying one step ahead of the competition. This study aims to apply mathematical model for forecasting monthly tourist inflow from Malaysia, Singapore, China, USA, England, France, Germany, Thailand, Australia and Japan to Bhutan. The Box-Jenkins model is used to identify the parameters of Autoregressive integrated moving average (ARIMA) model of monthly tourist visited data of above mentioned countries in the period 2011-2015 obtained from Tourism Council of Bhutan. An Akaike's Information Criterion, Schwartz's Bayesian Criterion and estimate variance of white noise are used throughout to test for the identification of best fit model. Further, the periodogram analysis was used to confirm the seasonal period of the model. The results showed ARIMA model for Thai, Chinese, Malaysian and Japanese, while seasonal ARIMA for American, Australian, British, French, Singaporean and German. Further, seasonal ARIMA model was obtained as the best fit model for the overall data. These models are illustrated and could possibly forecast the monthly tourist inflow of one year ahead with acceptable accuracy.

Keywords: *Akaike's information criterion, Box-Jenkins model, Schwartz's Bayesian criterion, variance of white noise*

1. Introduction

Bhutan's tourism industry began in 1974. It was introduced with the primary objective of generating revenue, especially foreign exchange; publicizing the country's unique culture and traditions to the outside world, and to contribute to the country's socio-economic development. Bhutan has now increasingly become a popular destination for many international tourists (Dorji, 2014). The number of tourist inflow in the country is increasing year by year. So forecasting is very necessary for administration and tourist agent for creating awareness and planning for the future development (Honey & Gilpin, 2009). It can also predict the future trends as accurately as possible and helps in staying one step ahead of the competition (Singha, 2012).

In spite of the great importance of tourism in Bhutan's economy, there is an incomprehensible lack of systematic and up to date quantitative research oriented on analyzing the core determinant and patterns of the visitors from different countries in Bhutan. Therefore it is very important to analyze the determinant and the core pattern tourist inflow in Bhutan. Such a study can be used in formulation of future macroeconomic development strategies, pricing strategies and tourism routing strategies in Bhutan as a one of the most popular destination in the world (Mahmood & Ali, 2016).

Given the importance of the tourism industry to Bhutan it is essential to generate the accurate forecast of the future trends of tourist flows from the major origin countries. This research paper aimed is one-period-ahead forecasts of international tourism demand for Bhutan, and to seek provide the best model for forecasting international tourist arrivals to Bhutan for these periods using Box Jenkins Methods with non-seasonal and seasonal modification.The advantages ofBox Jenkins Methodology involve selecting a great quantum of information from the analyzed empirical time series, using a small number of parameters (Nanthakumar & Ibrahim, 2010).

2. Data and methodology

2.1 Data

For the study, we used the monthly tourist inflow series includes data from top ten market sources that is Malaysia, Singapore, China, America, Australia, USA, France, Thailand, Germany and Japan during 2011-2015 obtained from Tourism Council of Bhutan. (Tourism Council of Bhutan, n.d) The series consist of 60 observations where first 54 sample observations are analyzed by using the Box-Jenkins method and the rest 6 observations out of sample are used to compare the forecast in all the nationalities.

2.2 Methodology

In this study, the Box-Jenkins model is used to analyze tourist inflow series which include data from top ten market sources that is Malaysia, Singapore, China, America, Australia, USA, France, Thailand, Germany, Japan and total tourist visitedduring 2011 – 2015.The Box-Jenkins method consists of following steps. (Singh, 2013).

The first step is to identify the all tentative model. Identification consists of specifying appropriate AR, MA or ARMA and order of the model. The identification is done by looking at the ACF and PACF of the interested stationary series.

The second step is to estimate the parameters of the model. Parameters of models can be estimated by least-square method. The estimation of parameter usually requires more complicated iteration procedure but the computer programming automatically generate it.

The third step is to check the model. This step is also called diagnostic checking or verification. Two important elements in checking are to ensure that the residuals of the model are random and white noise i.e. uncorrelated and constant variance $\hat{\sigma}_a{}^2$, and also to make sure that the estimated parameters are strictly significant (Newbold, 2013).

The fourth step is to elect the best model from the various ARIMA models which might be suitable for the series. Thus we use Akaike's Information Criteria (AIC) and Schwarz's Bayesian Criterion (SBC) for model selection to find the best model of the monthly tourist inflow in Bhutan.

2.2.1 ARIMA model

If the process is not stationary, we have to take differencing term $(1-B)^d$ in the process. When model ARMA (*p, q)* model on a time series which has been differenced *d* times we call this an ARIMA (*p*, *d*, *q*) model [4].Thus the general ARIMA (*p*, *d*, *q*) written using backshift operator as:

$$f_p(B)(1-\ B)^d X_t = q_0 + q_q(B)a_t$$

where $\phi_p(B) = 1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_p B^p$ is the stationary AR operator,

$\theta_q(B) = 1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q$ is the invertible MA operator

and $\theta_0 = \mu(1 - \phi_1 - \phi_2 - \cdots - \phi_p)$ which is known as deterministic trend term.(Ekpenyong, 2016)

2.2.2 Seasonal ARIMA

The Seasonal ARIMA model includes both seasonal and non-seasonal factors in multiplicative model called ARIMA $(p, d, q) \times (P, Q, D)_S$ where p is non-seasonal AR order, d is non-seasonal differencing,q is non-seasonal MA order,P is seasonal AR order,D is seasonal differencing,Q is seasonal MA orderand$S$ is seasonal periodwhere the general equation of the model is

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D X_t = \theta_q(B)\Theta_Q(B)^s a_t$$

(Baldigara & Mumula, 2015) where $\phi_p(B)$ is the non-seasonal autoregression component of order *p*, $\Phi_p(B^s)$ is the seasonal autoregression of order *s*, X_t is the current value of the time series examined, *B* is the backward shift operator $X_t(B^i) = X_{t-i}$, $(1-B)^d$ is non-seasonal difference term, $(1-B^s)^D$ is the seasonal difference term, $\theta_q(B)$ is the non-seasonal moving average of order *q* and $\Theta_Q(B)^s$ is the seasonal moving average of order *Q* (1990, p. 106)

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2.2.3 Periodogram analysis

To confirm the seasonality, we perform periodogram analysis. Periodogram help us to find the hidden periodicities. If model contains a single periodic component at frequency ω, the periodogram $I(\omega_k)$ at Fourier frequency ω_k closest to ω will be maximum. Thus the maximum periodogram ordinate will be

$$I^{(1)}(\omega_{(1)}) = \max\{I(\omega_k)\}$$

where $\omega_{(1)}$ is to indicate the maximum periodogram ordinate of the Fourier frequency.

Under the nul1 hypothesis H_0, including a period in a time series, an exact test statistic of $I^{(1)}(\omega_{(1)})$ is known as Fisher's test which is based on the equation below

$$T = \frac{I^{(1)}(\omega_{(1)})}{\sum_{k=1}^{[n\ 2]} I(\omega_k)}.$$

3. Results

The monthly tourist visited from top ten market source during 2011 – 2015 is analyzed by using Box – Jenkins's model. Out of which we will present only one nationality with all the process and rest will be presented with best fit models. The Box-Jenkins model consist of following steps: model identification, parameter estimation, diagnostic checking and model forecasting.

3.1.1 Model identification.

1. To use Box - Jenkins methodology, the series should be stationary. In this study, the graphical methods have been used to check the stationary of the series. In graphical method, graph and correlogram have been used. Figure 1 shows the graph of monthly American tourist visited

during 2011 – 2015. The data set suggests that the series is not stationary in variance. To stabilize the variance, we used Box-Cox transformation (Buthmann, n.d.). The preliminary residual mean square errors are calculated using the power transformation by SAS system software version 9.1 and we need logarithm transformation. Figure 2 shows the graph of monthly logarithm transformed American tourist visited which is stationary in the mean and variance. (Sample ACF and Properties of AR(1) Model. n.d.).

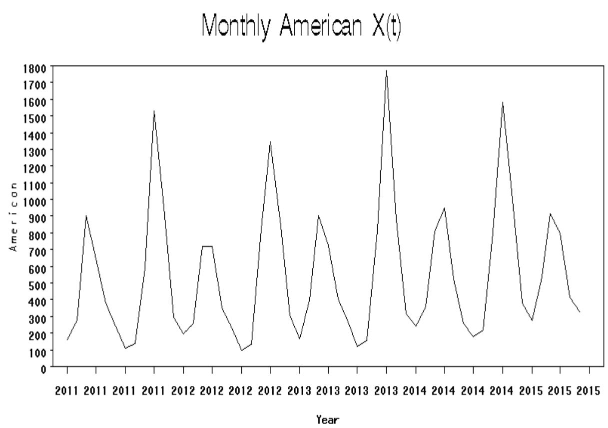

Fig. 1 The monthly American tourist visited during 2011 -2015

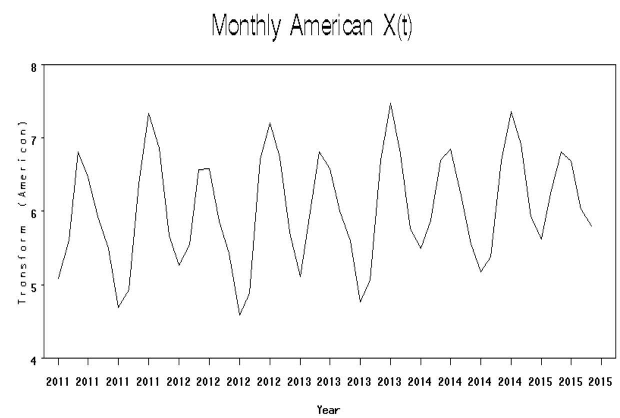

Fig. 2 The monthly logarithm transformed American tourist visited during 2011 -2015

Autocorrelations

Lag	Covariance	Correlation	Std Error
0	0.561199	1.00000	0
1	0.275484	0.49088	0.136083
2	-0.211709	-.37724	0.165660
3	-0.403305	-.71865	0.180870
4	-0.201307	-.35871	0.227689
5	0.182113	0.32451	0.237924
6	0.369330	0.65811	0.245984
7	0.166376	0.29647	0.276675
8	-0.205447	-.36608	0.282496
9	-0.370559	-.66030	0.291149
10	-0.163669	-.29164	0.317672
11	0.232442	0.41419	0.322593
12	0.422760	0.75332	0.332295
13	0.196771	0.35063	0.362543
14	-0.181317	-.32309	0.368769
15	-0.315143	-.56155	0.373975
16	-0.144071	-.25672	0.389277
17	0.141215	0.25163	0.392399
18	0.270134	0.48135	0.395376
19	0.104389	0.18601	0.406084
20	-0.169342	-.30175	0.407658
21	-0.271148	-.48316	0.411774
22	-0.117488	-.20935	0.422142
23	0.158044	0.28162	0.424060
24	0.281238	0.50114	0.427509
25	0.115719	0.20620	0.438253
26	-0.134712	-.24004	0.440046
27	-0.216128	-.38512	0.442464
28	-0.098576	-.17565	0.448629
29	0.087099	0.15520	0.449901
30	0.166823	0.29726	0.450891
31	0.055755	0.09935	0.454506
32	-0.119651	-.21321	0.454908
33	-0.170948	-.30461	0.456754
34	-0.062858	-.11201	0.460501
35	0.083772	0.14927	0.461005
36	0.136559	0.24333	0.461900
37	0.050700	0.09034	0.464267
38	-0.078288	-.13950	0.464593
39	-0.109674	-.19543	0.465368
40	-0.038594	-.06877	0.466885
41	0.044261	0.07887	0.467073
42	0.066537	0.11856	0.467319
43	0.014848	0.02646	0.467876
44	-0.050552	-.09008	0.467904
45	-0.060831	-.10839	0.468225

Partial Autocorrelations

Lag	Correlation
1	0.49088
2	-0.81447
3	0.06720
4	-0.16551
5	0.40795
6	-0.11096
7	-0.04343
8	-0.21393
9	-0.08071
10	0.11430
11	0.29950
12	0.15104
13	-0.03529
14	0.26627
15	0.11914
16	-0.16907
17	0.00811
18	-0.17551
19	0.04048
20	-0.00685
21	-0.05333
22	-0.09942
23	0.04321
24	-0.10964
25	-0.05546
26	0.04109
27	-0.11091
28	0.00272
29	-0.05802
30	-0.04405
31	-0.02622
32	0.00633
33	0.03281
34	0.00397
35	-0.20075
36	0.03751
37	-0.03745
38	-0.05589
39	0.04150
40	0.01359
41	-0.04034
42	0.02825
43	0.08096
44	-0.02458
45	0.03890

Figure 3 Sample ACF and PACF of monthly logarithm transformation of American tourist visited (Nau, n.d.).

Figure 3 shows sample ACF and PACF with 95% confidence limits. (Adhikari & Agrawal, 2013, pp. 1–3) The ACF shows damp sine cosine wave and slow decaying of the spikes indicates cyclic or seasonal movement of the correlation (Keshvani, 2013). Therefore to confirm the seasonality, we perform periodogram analysis. The periodogram analysis of the logarithm of monthly American tourist visited is clearly dominated by a very large peak at frequency, 1.04720. This frequency corresponds to a period of Pequals 6. It indicates that the data exhibit an approximate of 6 months cycle. So we need first seasonal differencing of period 6 months. Figure 4 shows sample ACF and PACF of monthly logarithm transformation of American tourist visited for first seasonal differencing at period 6 months. The sample ACF shows spike at lag 1, 6 and 12 and PACF cuts off after lag 6. Therefore, the tentative models are ARIMA (1, 0, 0) × (0, 1, 1)6, ARIMA (1, 0, 0) × (0, 1, 2)6, ARIMA (4, 0, 0) × (0, 1, 2)6, ARIMA (5, 0, 0) × (0, 1, 1)6 ,ARIMA (5, 0, 0) × (0, 1, 2)6 ARIMA (0, 0, 1) × (1, 1, 1)6, ARIMA (0, 0, 1) × (1, 1, 0)6 , ARIMA (0, 0, 0) × (1, 1, 0)6 and ARIMA (0, 0, 0) × (0, 1, 1)6..

Autocorrelations

Lag	Covariance	Correlation	Std Error
0	0.357732	1.00000	0
1	0.201891	0.56436	0.144338
2	0.0092044	0.02573	0.184674
3	-0.018725	-.05234	0.184749
4	-0.039448	-.11027	0.185057
5	-0.182859	-.51116	0.186421
6	-0.293355	-.82004	0.213635
7	-0.170188	-.47574	0.271403
8	-0.0097719	-.02732	0.288253
9	0.0065530	0.01832	0.288307
10	0.031425	0.08785	0.288331
11	0.161116	0.45038	0.288888
12	0.250237	0.69951	0.303164
13	0.150897	0.42182	0.335107
14	0.0055975	0.01565	0.345992
15	-0.0093078	-.02602	0.346006
16	-0.020716	-.05791	0.346047
17	-0.136318	-.38106	0.346249
18	-0.216742	-.60588	0.354878
19	-0.122262	-.34177	0.375811
20	0.0010921	0.00305	0.382232
21	0.011954	0.03342	0.382232
22	0.020158	0.05635	0.382293
23	0.109253	0.30541	0.382466
24	0.169620	0.47415	0.387513
25	0.093110	0.26028	0.399417
26	0.00033299	0.00093	0.402935
27	-0.013350	-.03732	0.402935
28	-0.025505	-.07130	0.403007
29	-0.082702	-.23119	0.403270
30	-0.117947	-.32971	0.406022
31	-0.070402	-.19680	0.411562
32	-0.0042451	-.01187	0.413518
33	0.011790	0.03296	0.413525
34	0.019678	0.05501	0.413580
35	0.056141	0.15694	0.413732
36	0.080204	0.22420	0.414970
37	0.046529	0.13007	0.417486
38	-0.0040485	-.01132	0.418330
39	-0.012743	-.03562	0.418336
40	-0.012317	-.03443	0.418399
41	-0.034025	-.09511	0.418458
42	-0.047445	-.13263	0.418908
43	-0.021173	-.05919	0.419782
44	0.015799	0.04416	0.419956
45	0.021811	0.06097	0.420053

Partial Autocorrelations

Lag	Correlation
1	0.56436
2	-0.42961
3	0.30475
4	-0.42808
5	-0.53541
6	-0.50208
7	0.17642
8	-0.31660
9	-0.19094
10	-0.05022
11	-0.10420
12	-0.02229
13	-0.07101
14	-0.16395
15	0.02260
16	-0.00795
17	-0.09217
18	-0.05581
19	0.17701
20	-0.17726
21	0.18563
22	0.01350
23	-0.14269
24	0.03465
25	0.03964
26	-0.02390
27	-0.16242
28	0.08731
29	0.00532
30	0.05098
31	-0.08999
32	-0.01030
33	0.06146
34	-0.12512
35	-0.00061
36	-0.05129
37	-0.11818
38	-0.09584
39	-0.00343
40	-0.10230
41	-0.13557
42	0.03022
43	-0.08023
44	0.09951
45	-0.03340

Figure 4 Sample ACF and PACF of monthly logarithm transformation of American tourist visited for first seasonal differencing at period 6 months.

3.1.2 Model estimation and Evaluation

To check model adequacy, we consider whether the residuals of the model are white noise by using a Q statistic test with k = 12. The values of the Q statistic and p-values are given in Table 1. Procedure of choosing the models depends on the value of AIC and SBC (EKPENYONG, 2016). The model with the minimum values is considered as the best model for the data set (Scott, 2019). The models are presented in Table 2. From Table 2 the least AIC and SBC is ARIMA (0, 0, 1) × (1, 1, 0)6 that indicates the ARIMA (0, 0, 1) × (1, 1, 0)6 is the best model for forecasting the monthly American tourist visited during 2011 – 2015. (Yong & Brook, 2014).

Table 1 The Q statistic test for k=12 of the tentative models for monthly American tourist visited.

Model	Q statistic	p-value
1. ARIMA $(1, 0, 0) \times (0, 1, 1)_6$	40.23	<.0001
2. ARIMA $(1, 0, 0) \times (0, 1, 2)_6$	31.25	0.0005
3. ARIMA $(4, 0, 0) \times (0, 1, 2)_6$	25.47	0.0006
4. ARIMA $(5, 0, 0) \times (0, 1, 1)_6$	47.51	<.0001
5. ARIMA $(5, 0, 0) \times (0, 1, 2)_6$	31.26	0.0005
6. ARIMA $(0, 0, 1) \times (1, 1, 1)_6$	**12.51**	**0.1862**
7. ARIMA $(0, 0, 1) \times (1, 1, 0)_6$	**9.7**	**0.4676**
8. ARIMA $(0, 0, 0) \times (1, 1, 0)_6$	**14.77**	**0.1934**
9. ARIMA $(0, 0, 0) \times (0, 1, 1)_6$	50.71	<.0001

Table 2 The summary of AIC and SBC for American visited.

Model	AIC	SBC
6. ARIMA $(0, 0, 1) \times (1, 1, 1)_6$	7.997593	13.6112
7. ARIMA $(0, 0, 1) \times (1, 1, 0)_6$	**7.056717**	**10.79912**
8. ARIMA $(0, 0, 0) \times (1, 1, 0)_6$	20.17794	22.04914

3.1.3 Diagnostic checking

In time series modeling the selection of best fit model is directly related to how well the residual analysis is performed. One of the assumptions of ARIMA model is that for a good model the residual should be white noise (Pelgrin, 2011).

Form the Figure 5 the sample ACF and PACF of the model shows that the autocorrelation of the residual are all close to zero which mean they are uncorrelated, hence the residual assume mean of zero and constant variance. Finally the p-value (0.4676) for the Ljung-Box statistic clearly exceeds 5% for all lag orders. Thus the selected model ARIMA $(0, 0, 1) \times (1, 1, 0)_6$ satisfies all the model assumptions.

Table 3 Parameter estimation of appropriate ARIMA $(0, 0, 1) \times (1, 1, 0)_6$

Model	MA1	SAR1
Parameter	0.87445	0.7458
SE	0.09300	0.10328

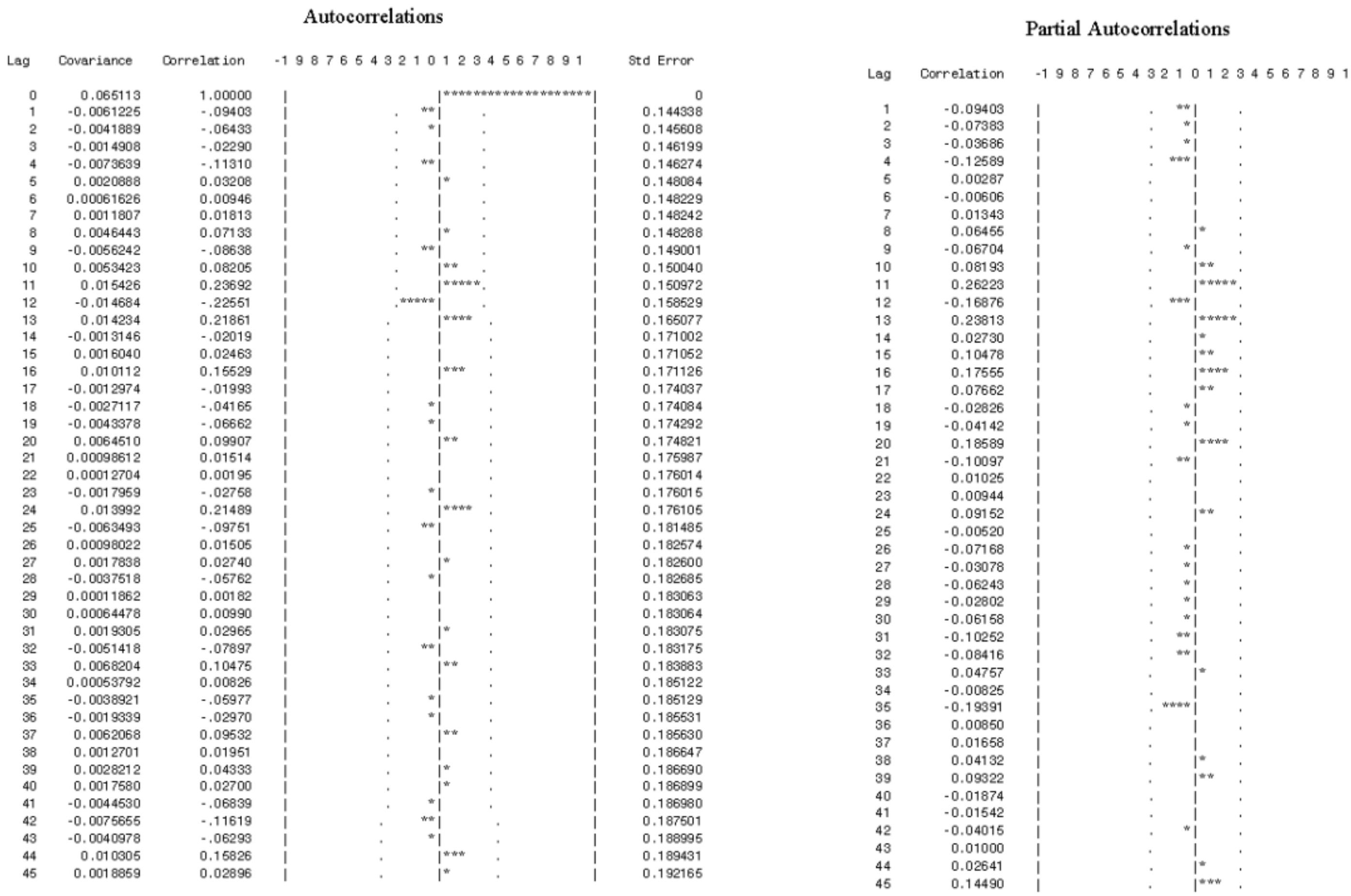

Figure 5 Sample ACF and PACF of the residual of ARIMA (0, 0, 1) × (1, 1, 0)$_6$

3.1.4 Forecasting

The forecast values with 95 percent forecast limit of the ARIMA (0, 0, 1) × (1, 1, 0)$_6$of model for monthly American tourist are shown in Table 4 with standard error, lower and upper limit (Ekpenyong, 2016).

Table 4 Forecasted value for 6 months American tourist visited for 2015

Date	Tourist visited	Forecasted value	95% confidence limit		Error
			Lower	Upper	
Jul-15	131	244.6	148.4	403.4	-113.6
Aug-15	198	242.0	129.8	451.4	-44
Sep-15	681	813.3	436.1	1386.2	-132.3
Oct-15	1514	1449.4	777.1	2702.9	65.6
Nov-15	1020	897.3	481.2	1673.4	122.7
De-15	323	371.6	199.3	693.0	-48.6

3.2 The best fitted model for each nationality

By considering all the steps in Box-Jenkins methodology the best fit model with t-ratio and variance of white noise forall the nationalities are shown in Table 5.

Table 5 The best fitted model for each nationality

Nationality/model	Parameters estimated $\hat{\sigma}_a^{\ 2}$
1. American ARIMA (0, 0, 1) × $(1, 1, 0)_6$	$(1+0.87445B^6)\ln X_t = (1+0.74358B)a_t$ 0.065113 (0.09300) (0.10328)
2. British ARIMA (0, 0, 1) × $(1, 1, 2)_6$	$(1+0.99004B^6)\sqrt{X_t} = (1+0.39654B)(1-0.43849B^6)a_t$ 7.374285 (0.07764) (0.12700) (0.14988)
3. Australian ARIMA (0, 0, 0) × $(1, 1, 0)_6$	$(1+0.83277B^6)\ln X_t = a_t$ 0.120644 (0.10493)
4. Singaporean ARIMA (1, 1, 0) × $(1, 1, 0)_6$	$(1+0.54467B)(1+0.31214B^6)\sqrt{X_t} = a_t$ 6.467712 (0.11637) (0.12178)
5. French ARIMA (0, 0, 0) × $(1, 1, 0)_6$	$(1+0.94419B^6)\sqrt{X_t} = a_t$ 6.232704 (0.07173)
6. German ARIMA (0, 0, 0) × $(1, 1, 0)_6$	$(1+0.95822B^6)\sqrt{X_t} = a_t$ 19.81132 (0.09604)
7. Chinese ARIMA (4, 1, 0) × (0, 0, 0)	$(1+0.50235B+0.29826B^2+0.81347B^3+0.65127B^4)X_t = a_t$ 24169.85 (0.12606) (0.11889) (0.11812) (0.15240)
8. Thai ARIMA (1, 1, 1) × (0, 0, 0)	$(1+B)\sqrt{X_t} = (1+0.83645B)a_t$ 0.692335 (0.03225) (0.11171)
9. Malaysian ARIMA (5, 1, 1) × (0, 0, 0)	9.524783 $(1+0.23876B+0.80638B^2+0.70042B^3+0.57061B^4+0.43780B^5)\sqrt{X_t} = (1+0.77508B)a_t$ (0.17488) (0.22156) (0.23070) (0.21658) (0.14701)(0.17466)
10. Japanese ARIMA (3, 1, 1) × (0, 0, 0)	$(1+0.38389B^3)X_t = (1-0.52109B)a_t$ 31153.39 (0.13307) (0.11981)
Total ARIMA (0, 0,1) × $(1, 1, 0)_6$	$(1+0.79357B^6)\sqrt{X_t} = 2.24357-(1+0.47057B)a_t$ 68.71606 (0.13374) (0.97511) (0.14447)

4. Conclusion

In this study, a univariate time series models are selected by using the data of the past monthly tourist visited from top ten market sources during 2011 – 2015 obtained from Tourism Council of Bhutan. We applied Box-Jenkins model for forecasting the monthly tourist inflow in Bhutan. The graph, correlogram and periodogram of data show that some of nationalities data sets have seasonality at the period 6. From Table 5 we see that the best model for each nationality is divided into 2 groups. In the first group the model is ARIMA model which consist of Chinese - ARIMA (4 ,1, 0) × (0, 0, 0), Thai - ARIMA (1, 1, 1) × (0, 0, 0), Malaysian - ARIMA (5, 1, 1) × (0, 0, 0) and Japanese - ARIMA (3, 1, 0) × (0, 0, 0) and in the second group it is seasonal ARIMA model which consist of Australian-ARIMA (0, 0, 0) × (1, 1, 0)6, British - ARIMA (0, 0, 1) × $(1, 1, 2)_6$, American- ARIMA (0, 0, 1) × $(1, 1, 0)_6$, Singaporean - ARIMA (0, 1, 1) × $(1, 1, 0)_6$, French - (0, 0, 0) × $(1, 1, 0)_6$, German - ARIMA (0, 0, 0) × $(1, 1, 0)_6$ and overall data - ARIMA (0, 0, 1) × $(1, 1, 0)_{6.}$Among the visitors, Chinese, Thai, Malaysian and Japanese doesn't show seasonality. [Otieno, Mung'ta & Orwa, 2014).] The main purpose of visitors from these four countries is to experience culture and tradition, and for spiritual and wellness activities which happen throughout the year so the season doesn't hinders the interest of their visit. But for American, Australian, British, Singaporean, French, and Germany shows seasonality as most of them preferred for adventurous tourism. The spring and autumn weather is basically warm and less rainfallwhich makes it favorable for the visitors those who are interested in (Tourism council of Bhutan, n.d.).

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