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Toward Bracketing the Seasonal Export-Import of Bangladesh: A Time Series based Analytical Approach

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Abstract

For any nation, to attain a better growth in business and development, prediction and forecasting is must to confront the gap between export and import. Identifying the trend in export-import as well as predicting the future values of these two sectors, is a major challenge for the national trade policy makers. Hence, to assist in decision making process this article is proposing two time series model based on export and successively on import using export-import data from 2000-2006 in context of Bangladesh, to obtain the information about current export-import trend as well as for future prediction, but still can be developed for any nation. To construct the mathematical export - imports models, different tools of Time series analysis, has been used. Autoregressive (AR) process along with moving average (MA) constitutes autoregressive and moving average (ARMA) process, which is used only to model stationary time series, was considered. In order to extend this model into non-stationary time series model, the concept of autoregressive integrated moving average (ARIMA) has been developed. To identify a perfect ARIMA model for a particular data series, Box and Jenkins methodology that consists of three phases, identification, estimation & diagnostic checking and application was applied. The proposed models also managed to identify the influences of export and imports in past years on export-import in current or future years.

Keywords: *Export-import trend of Bangladesh, Import, Export, Seasonal trend analysis, Export-Import ARIMA model, Autocorrelation, Autocorrelation function, Backward shift operator, Stationary White Noise model*

1. INTRODUCTION

At the beginning of the 1980s, the inefficiencies associated with import substitution policies those were present in Bangladesh for almost two decades coupled with the debt crisis that severely affected the country, prompted a change in economic development strategy. As a consequence, the Bangladesh Government begun to promote the switch from an import substitution strategy of economic development to a strategy based on an outward orientation and export promotion. Bangladesh's import needs are substantial; hence the need to rapidly increase exports is immediate. In order to finance the imports and also to reduce the country's dependence on foreign aid, the Government of Bangladesh has been trying to enhance foreign exchange earnings through planned and increased exports. Industrial and trade policy were focused to promote export. Financial incentives are provided, in the form of tax exemption, on exportable commodities. Exclusive Export Processing Zones (EPZ) are established to attract foreign direct investment and export promotion. Foreign firms, investing in EPZs, get special preference and tax exemption facilities. State owned enterprises, nationalized in the early 1970s, are privatized or are in the process of privatization (Ahmed, 2001). The country has also experienced a change in its export composition- from primary commodities to manufacturing goods (Love and Chandra, 2005). Imports of capital machinery, intermediate goods and industrial raw materials have risen over the years. The export import segments of the country extended largely with a change in pattern so that future forecasting becomes more necessary than ever.

The pace of national economic development poses one of the most essential issues in economic debate. A nation could accelerate the rate of economic growth by promoting exports of goods and services. The volume of imports is negatively related to its relative price and varies positively with aggregate demand (Ahmed et al, 2009). A number studies have showed a strong and positive relationship between export and economic growth including Michaely (1977), Balassa (1978), Tyler (1981), Balassa (1985), Chow (1987), Darrat (1987), Khan and Saqib (1993), Singupta and Espana (1994), McCarville and Nnadozie (1995), Thornton (1996), Panas and Vamvoukas (2002), Abual-Foul (2004) and Awokuse (2004) among others. The results provide evidence in favor of the export-led growth hypothesis for various countries. Similarly effect of import on GDP has been shown in various national and international literatures. So based on yearly export and import this study proposes an ARIMA model for forecasting the future value. ARIMA model has been applied in various sectors in national and international level. In various sectors like, production estimation (Mandal, 2006), price estimation (Raymond, 1997 & Nochai, 2006), Market forecasting (Parish Jr, 2006) etc ARIMA model has been applied.

For any nation, to attain a better growth in business and development, prediction and forecasting is must to confront the gap between export and import. Opinions on forecasting are probably as diverse as views on any set of scientific methods used by decision makers. Forecasting is a necessary input to planning, whether in business, or government. Identifying the trend in export-import as well as predicting the future values of these two sectors, is a major challenge for the national trade policy makers. Hence, to assist in decision making process this article is an attempt to propose two time series model based on export and successively on import using export-import data, to obtain the information about current export-import trend as well as for future prediction, in context of Bangladesh but still can be developed for any nation. The rest of the study is organized as follows. The data and methodology are explained in Section 2. Result Analysis is discussed in Section 3. Concluding remarks are discussed in the last section.

2. DATA AND METHODOLOGY

Annual data on real export and imports from the year 2000 to 2006 are used for this paper. The data have been collected from the Economic Trend of Bangladesh, 2000-2006. To develop the forecasting models based on export and import, monthly export and import statistics have been taken as our variable. The study focuses on to develop an ARIMA model for export and import data. ARIMA method is an extrapolation method for forecasting and, like any other such method, it requires only the historical time series data on the variable under forecasting. Among the extrapolation methods, this is one of the most sophisticated methods, for it incorporates the features of all such methods, does not require the investigator to choose the initial values of any variable and values of various parameters a priori and it is robust to handle any data pattern. As one would expect, this is quite a difficult model to develop and apply as it involves transformation of the variable, identification of the model, estimation through non-linear method, verification of the model and derivation of Forecasts (Mandal, 2006). Autoregressive Integrated Moving Average (ARIMA) model was introduced by Box and Jenkins (hence also known as Box-Jenkins model) in 1960s for forecasting a variable. The applied techniques for the study are as follows:

2.1 Non-seasonal ARIMA Model

Autoregressive (AR) process along with moving average (MA) constitutes autoregressive and moving average (ARMA) process, which is used only to model stationary time series. In order to extend this model into non-stationary time series model, the concept of autoregressive integrated moving average (ARIMA) has been developed. Thus an ARIMA model is a combination of an autoregressive process and moving average (MA) process followed by an integration term, which make the non-stationary time series into stationary time series. The general non-seasonal model is known as ARIMA (p, d, q):

AR: P = order of the auto regression part
I: d = degree of differencing mixed up
MA: q = order of the moving average part

The equation for the ARIMA (P d, q) model is as follows:

$$Y_t = c+\phi_1 Y_{t-1}+\phi_2 Y_{t-2}+.......... +\phi_p Y_{t-p}+ e_t-\theta_1 e_{t-1} -\theta_2 e_{t-2} - .... - \theta_q e_{t-q} \quad (1)$$

Or in back shift notation:

$$(1-\phi_1 B- \phi_2 B^2- ...- \phi_p B^p) Y_t = c + (1--\theta_1 B- -\theta_2 B^2-..........- \theta_q B^q) e_t \quad (2)$$

Where:

C = Constant term
ϕ_i = i the autoregressive parameter
θ_j = j the moving average parameter
e_t = the error term at time t
B^k = the k the order backward shift operator

2.2 Seasonal ARIMA Model

One final complexity to add to AARIMA models is seasonality. In exactly the same way that consecutive data points might exhibit AR, MA, mixed ARMA, or mixed ARIMA properties, so data separated by a whole season (i.e. a year) may exhibit the same properties. The ARIMA notation can be extended readily to handle seasonal aspects, and the general shorthand notation is ARIMA (p, d, q)(P, D, Q)$_s$ where:

(p, d, q) = non-seasonal part of the mode
(P, D, Q)$_S$ = seasonal part of the model
s = number of periods per season

The algebra is simple but can get lengthy, so for illustrative purposes consider the following general ARIMA (1, 1, 1) (1, 1, I)$_{12}$ model:

$$(1-\phi_1 B)(1-\Phi_1 B^{12})(1-B)(1-B^{12})Y_t = (1-\theta_1 B)(1-\vartheta_2 B^{12})e_t \quad (3)$$

Where:

ϕ_1 = non-seasonal AR (1)
Φ_1 = seasonal AR (1)
1-B = non-seasonal difference
B^{12} = seasonal difference
θ_1 = non-seasonal MA (1)
ϑ_2 = Seasonal MA (1)

All the factors can be multiplied out and the general model written as follows:

$$Y_t = (1+\phi_1)Y_{t-1} - \phi_1 Y_{t-2} + (1+\Phi_1)Y_{t-12} - (1+\phi_1+\Phi_1+\phi_1\Phi_1)Y_{t-13} + (\phi_1+\phi_1\Phi_1)Y_{t-14} - \Phi_1 Y_{t-16}$$
$$+ (\Phi_1+\phi_1\Phi_1)Y_{t-17} - \phi_1\Phi_1 Y_{t-18} + e_t - \theta_1 e_{t-1} - \theta_1\vartheta_1 e_{t-13} \quad (4)$$

In this form, once the coefficients $\phi_1, \Phi_1, \theta_1 and\, \vartheta_1$ have been estimated from the data.

2.3The Box-Jenkins (BJ) Methodology

To identify a perfect ARIMA model for a particular data series, Box and Jenkins proposed a methodology that consists of three phases is known as Box-Jenkins methodology, or in short BJ methodology. The total process of selecting a model is nothing but an iteration procedure that contains the following phases, namely Identification, Estimation & Diagnostic Checking and Application.

3. RESULT ANALYSIS

3.1 Analysis of the amount of export

The data set consists of 72 observations on monthly export of Bangladesh from July 2000 through June 2006.We divide the whole set of observation into two segments, namely "the training segment" used to fit the model and "the test segment" used to test the model. The training segment contains the first 60 observations and the test segment contains the remaining 12 observations.

3.1.1 Choosing an ARIMA Model

A visual plot of monthly export data of Bangladesh is plotted in Figure 1.The data shows seasonality over time periods. Moreover, it seems that the data are non-stationary in the mean only.

Figure 1: Time plot of export data

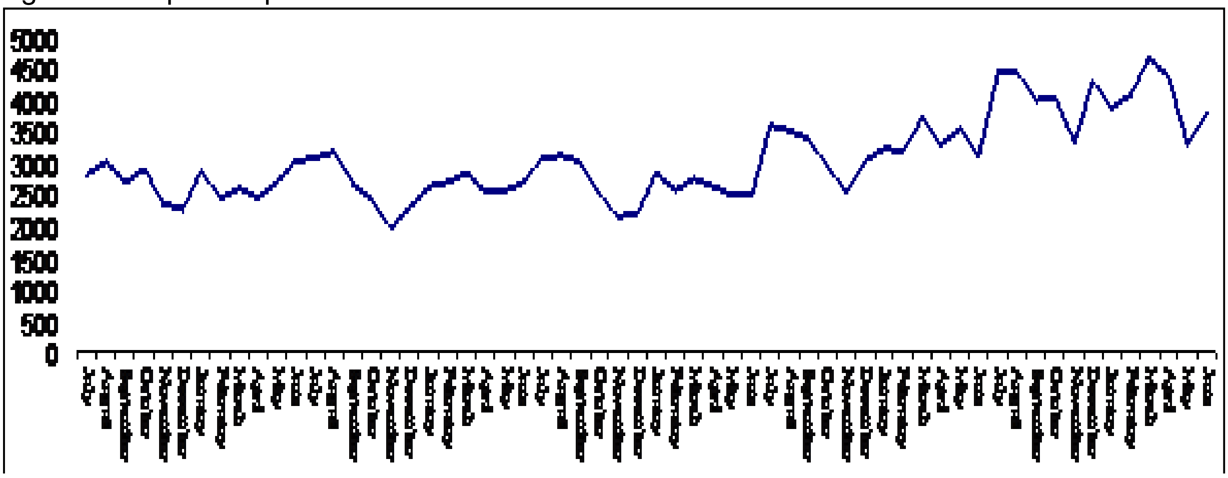


Figure 2: ACF of export

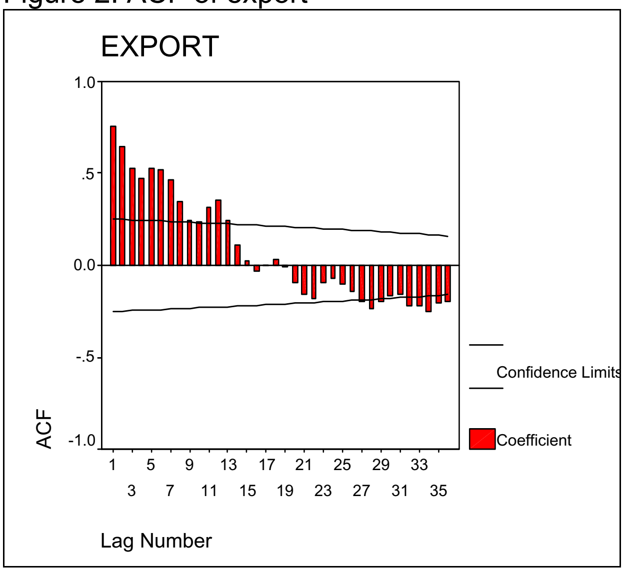
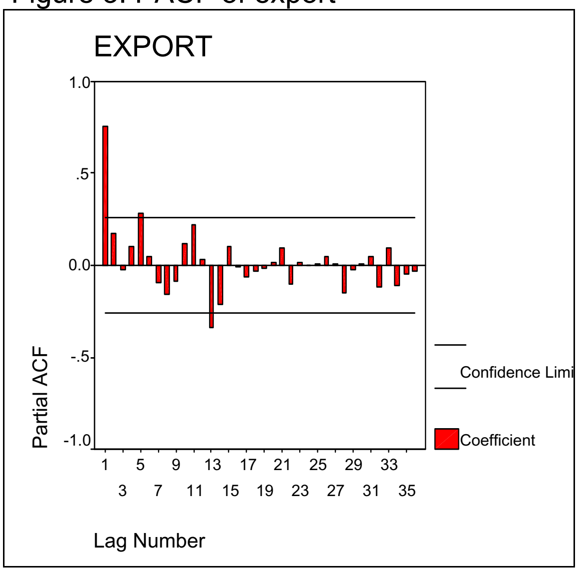


Figure 3: PACF of export



3.1.2 Testing Stationarity

From the Correlogram (ACF or PACF plot), Figure 2 and Figure 3, we observe that the autocorrelation are decaying exponentially and most of the spikes fall outside the two standard error limit. It indicates that the data set is non-stationary also seasonality is present in the data.

3.1.3 White Noise test

For the autocorrelation values r_i, the Box-Pierce Q statistic is equal to199.647, comparing this value to chi-square distribution with 36 degrees of freedom; we can conclude that the values are significantly different from a null set. The Ljung-box test also indicates that the data set does not follow a white noise series.

Figure 4: Time plot of seasonally differenced export data.

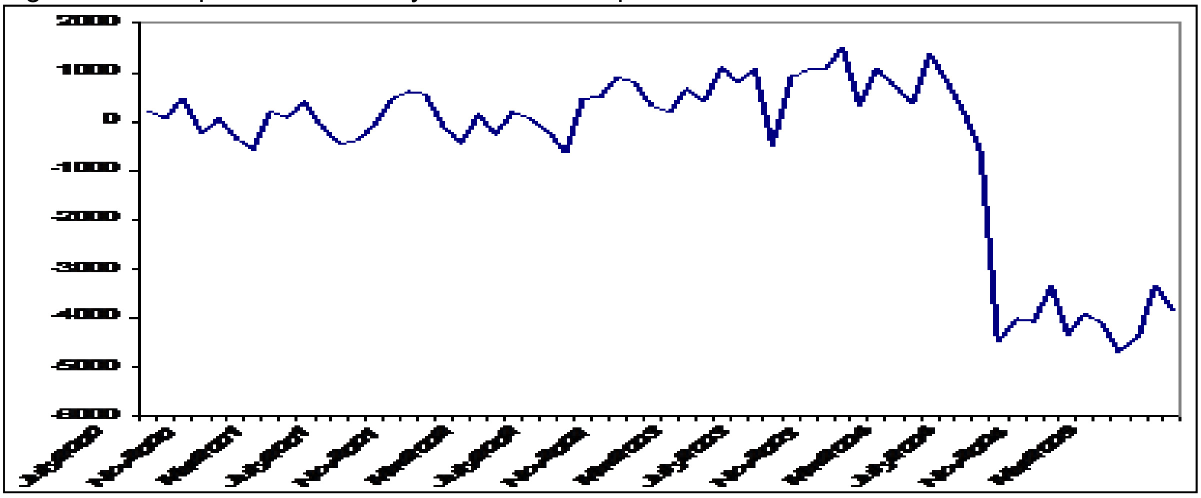


Figure 5: ACF of first seasonal difference of export

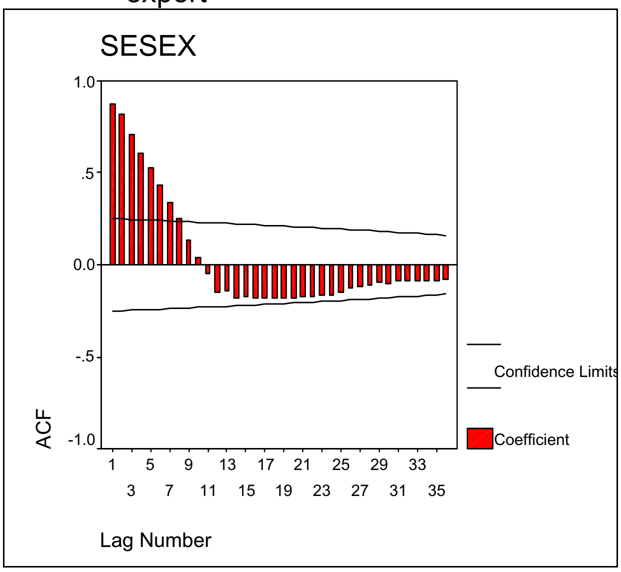
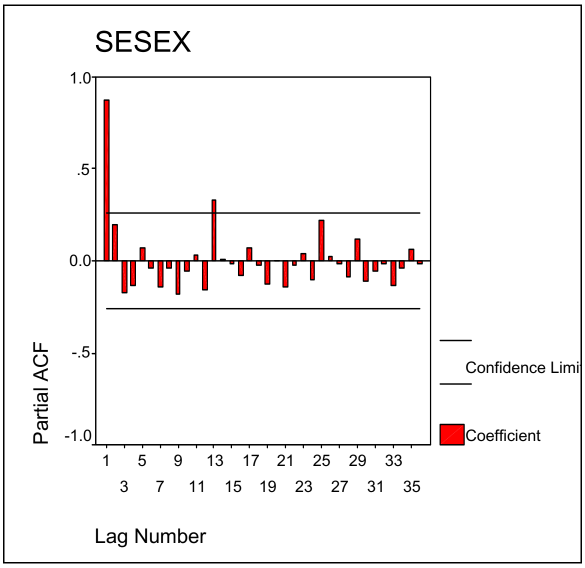


Figure 6: PACF of first of first seasonal difference of export



3.1.4 Obtaining stationarity

The time plot of the first seasonal differenced series is given in Figure 4, which shows that the values differ around a constant mean. The graphical representation of ACF and PACF of the first seasonal differenced data are given in Figure 5 and Figure 6. The Box-pierce statistic and the Ljung-box Q statistic show that neither of these is significant. Then we take the first difference of the first seasonal data. The time plot of the first difference first seasonal difference of export data is plotted in Figure 7, which shows that the data has become stationary. The graphical representation of ACF and PACF of the first difference first seasonal differenced data are given in Figure 8 and Figure 9. The Box-pierce statistic takes the value 199.647 and the Ljung-box Q statistic is equal to 256.348 for these data and comparing to a chi-square distribution with 36 degrees of freedom neither of these is insignificant. So, the data follows white noise model.

Figure 7: Time plot of first difference of seasonally differenced of export data

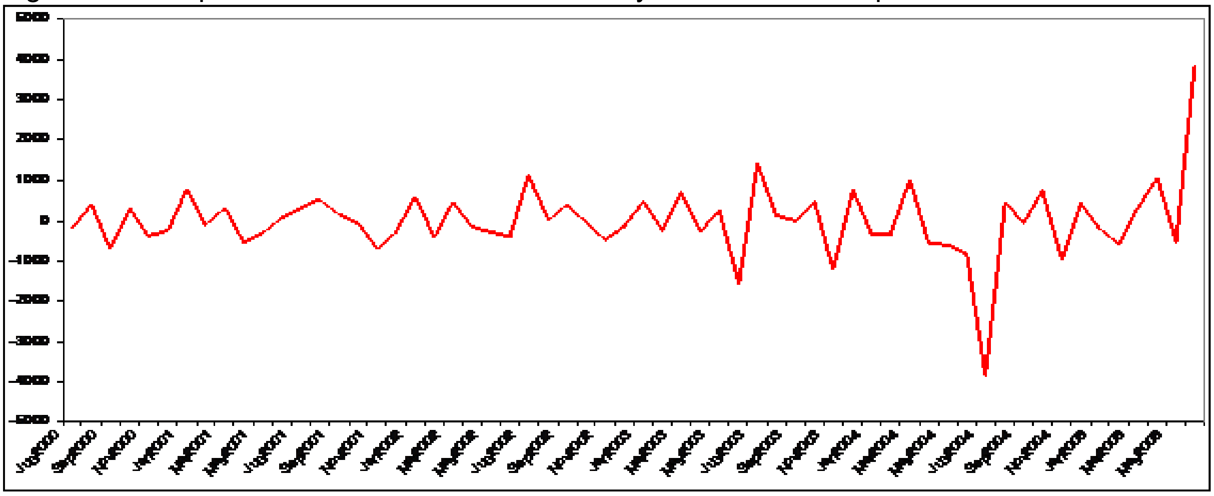


Figure 8: ACF of first difference of seasonally differenced export data

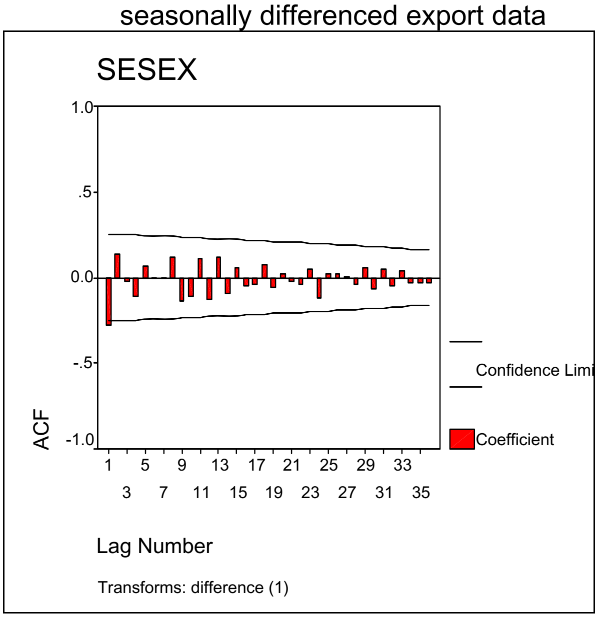
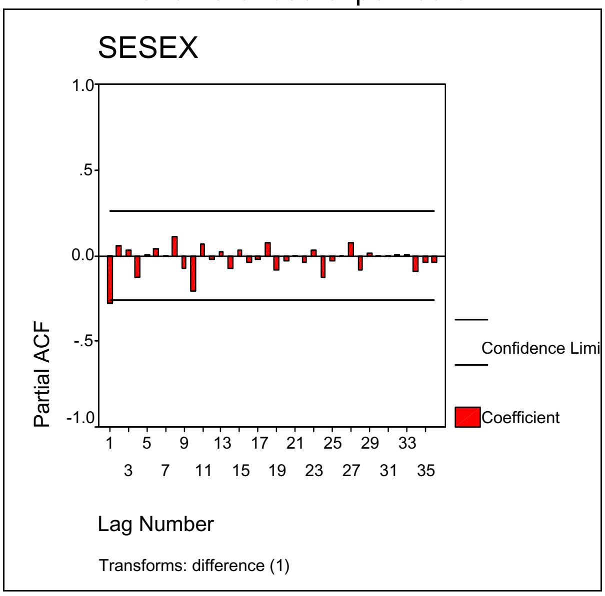


Figure 9: PACF of first difference of differenced export data



3.1.5 Model selection

We use the Akaike information criterion (AIC criterion) to choose the best model among the plausible models. The model, which has minimum Akaike information criteria estimates (MAICE), is our model of interest. For different values of p and q, we find the AIC value using computer program namely R. It gives the minimum AIC values for different p and q values for ARIMA (p, 1, q) (P, I, Q) 12 are given in Table 1:

Table 1: AIC values

Model	AIC	Model	AIC
ARIMA $(0,1,0)(1,1,0)_{12}$	695.44	ARIMA $(2,1,3)(1,1,0)_{12}$	688.33
ARIMA $(0,1,1)(1,1,0)_{12}$	686.33	ARIMA $(3,1,2)(1,1,0)_{12}$	690.07
ARIMA $(1,1,0)(1,1,0)_{12}$	692.05	ARIMA $(3,1,3)(1,1,0)_{12}$	689.41
ARIMA $(1,1,1)(1,1,0)_{12}$	687.46	ARIMA $(0,1,4)(1,1,0)_{12}$	688.31
ARIMA $(0,1,2)(1,1,0)_{12}$	687.03	ARIMA $(4,1,0)(1,1,0)_{12}$	687.43
ARIMA $(2,1,0)(1,1,0)_{12}$	688.07	ARIMA $(4,1,1)(1,1,0)_{12}$	687.92
ARIMA $(1,1,2)(1,1,0)_{12}$	698.1	ARIMA $(1,1,4)(1,1,0)_{12}$	689.95
ARIMA $(2,1,2)(1,1,0)_{12}$	687.15	ARIMA $(4,1,2)(1,1,0)_{12}$	683.4
ARIMA $(0,1,3)(1,1,0)_{12}$	698.02	ARIMA $(2,1,4)(1,1,0)_{12}$	688.72
ARIMA $(3,1,0)(1,1,0)_{12}$	687.35	ARIMA $(4,1,3)(1,1,0)_{12}$	684.12
ARIMA $(3,1,1)(1,1,0)_{12}$	689.97	ARIMA $(3,1,4)(1,1,0)_{12}$	693.4
ARIMA $(1,1,3)(1,1,0)_{12}$	690.55	ARIMA $(4,1,4)(1,1,0)_{12}$	685.09

From the Table 1, we found that ARIMA $(4, 1, 2)(1,1,0)_{12}$ model initially selected the lowest AIC value. Whereas, ARIMA $(4,1,2)(1,1,0)_{12}$, ARIMA $(4,1,3)(1,1,0)_{12}$, ARIMA $(4,1,4)(1,1,0)_{12}$, and ARIMA $(0,1,1)(1,1,0)_{12}$ have almost nearest AIC values, So we have considered all of them in our diagnostic checking.

3.1.6 Estimation and Diagnostic Checking

We have measured the forecasting accuracy by comparing the mean squared error. The mean squared error of ARIMA $(4,1,2)(1,1,0)_{12}$, ARIMA $(4,1,3)(1,1,0)_{12}$, ARIMA $(4,1,4)(1,1,0)_{12}$ and ARIMA $(0,1,1)(1,1,0)_{12}$ are 603712.3, 643580.1, 749037.3, and 848670.3 respectively. Also from the Table 1 this model shows the minimum AIC values in model selection. This model indicates that one non-seasonal moving average part, seasonal autoregressive part and one non-seasonal autoregressive part:

$$\left(1-\phi_1 B-\phi_2 B^2-\phi_3 B^3-\phi_4 B^4\right)\left(1-\Phi_1 B^{12}\right)\left(1-B\right)\left(1-B^{12}\right)Y_t=\left(1-\theta_1 B-\theta_2 B^2\right)e_t \qquad (5)$$

The coefficients of ARIMA $(4, 1, 2)(1,1,0)_{12}$ with their estimated value and corresponding value of z-statistic are given in the following Table 2:

Table 2: The significance test of the parameter of ARIMA $(4,1,2)(1,1,0)_{12}$

Coefficient	Parameter	Standard error	z-value	p-value	Comment
ϕ_1	0.7911	0.1395	5.06709	0.00001	Significant
ϕ_2	-0.5371	0.1800	-2.98	0.001	Significant
ϕ_3	0.0110	0.1801	0.06	0.4761	Insignificant
ϕ_4	-0.3872	0.1516	-1.445	0.0749	Insignificant
θ_1	-1.6055	0.0995	16.135	0.0001	Significant
θ_2	1.0000	0.1041	9.606	0.0001	Significant
Φ_1	-0.2851	0.1973	-2.554	0.0054	Significant

Now, the revised model becomes:

$$\left(1-\phi_1 B-\phi_2 B^2\right)\left(1-\Phi_1 B^{12}\right)\left(1-B\right)\left(1-B^{12}\right)Y_t=\left(1-\theta_1 B-\theta_2 B^2\right)e_t$$
$$\Rightarrow Y_t = Y_{t-1}+\phi_1 Y_{t-1}+\phi_2 Y_{t-2}-\phi_1 Y_{t-2}-\phi_2 Y_{t-3}+\Phi_1 Y_{t-12}-\Phi_1\phi_1 Y_{t-13}-\Phi_1\phi_2 Y_{t-14}-\Phi_1 Y_{t-13}$$
$$+\Phi_1\phi_1 Y_{t-14}+\Phi_1\phi_2 Y_{t-15}+e_t-\theta_1 e_{t-1}-\theta_2 e_{t-2} \tag{6}$$

$$\Rightarrow Y_t = Y_{t-1}+0.7911Y_{t-1}-0.5371Y_{t-2}-0.7911Y_{t-2}+0.5371Y_{t-3}-0.3872Y_{t-12}+(0.7911)(0.3872)Y_{t-13}$$
$$+(0.5371)(0.3872)Y_{t-14}+0.3872Y_{t-13}-(0.7911)(0.3872)Y_{t-14}-(0.5371)(0.3872)Y_{t-15}$$
$$+1.6055e_{t-1}-e_{t-2}+e_t \tag{7}$$

Hence, this is our suggested ARIMA model to select the forecasting the monthly export data of Bangladesh.

3.1.7 Sample Forecast for the period July 2005-June 2006

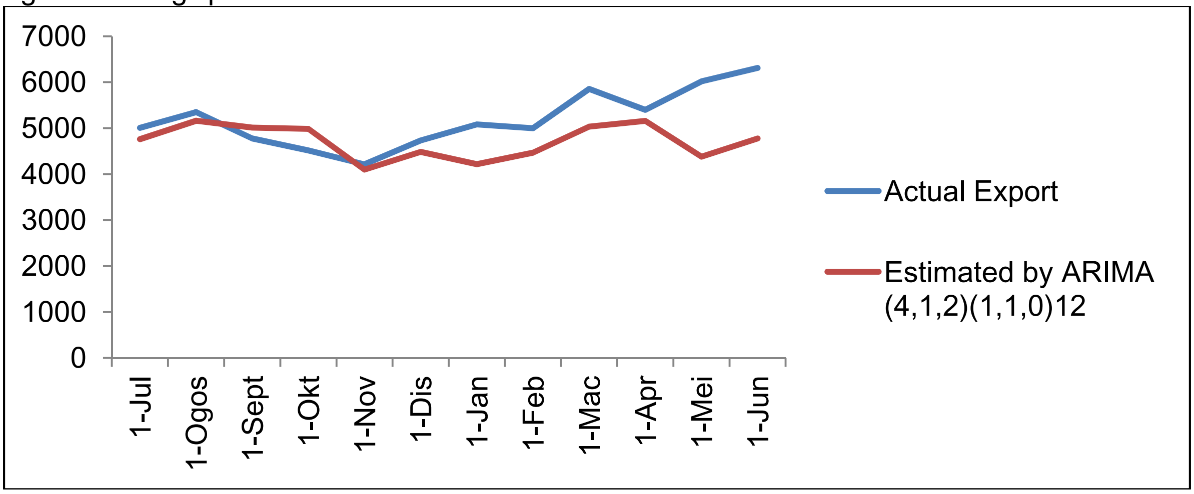
Now to see the performance of this model in the out-of-sample forecasting, the forecasted value of the monthly export data for the period July 2000-June 2005 will be derived using this model. Then we compare the forecasted value with the actual value, which is available from July 2005 – June 2006. The following table gives the forecasted value obtained by models ARIMA $(4,1,2)(1,1,0)_{12}$ and along with the actual data.

Table 3: The comparison of actual data and forecast data of Export

Name of months	Actual export	Estimated by ARIMA (4,1,2)(1,1,0)12
Jul-05	5006	4761.452
Aug-05	5349	5161.511
Sep-05	4775	5012.844
Oct-05	4514	4985.905
Nov-05	4212	4099.094
Dec-05	4731	4484.226
Jan-06	5081	4215.654
Feb-06	4999	4465.987
Mar-06	5852	5031.771
Apr-06	5397	5157.237
May-06	6018	4379.834
Jun-06	6309	4776.068

The forecasted values are calculated by using R computer programming and the graphs are produced by MS-Excel as shown in Figure 10. We clearly see that the forecasted values are most close to the actual values for our finally suggested model. As the forecasted values go upward then go downward and then again go upward as compared to the actual value, which indicates that forecasting model weights all the observations equally.

Figure-10: The graph of actual value and forecasted value



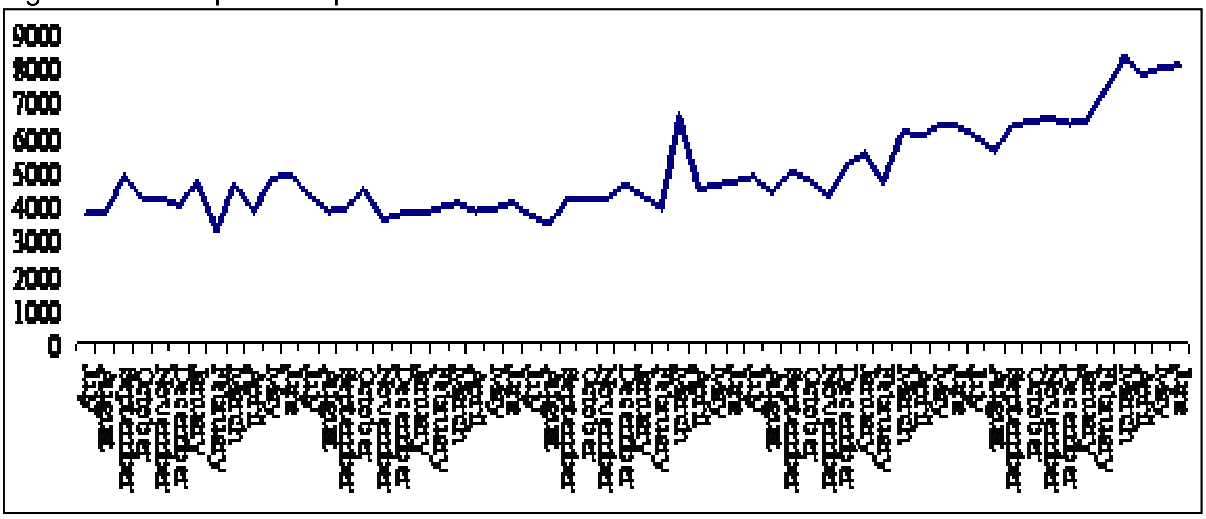
3.2 Analysis of the amount of import

The data set consists of 72 observations on monthly export of Bangladesh from July 2000 through June 2006.We divide the whole set of observation into two segments, namely "the training segment" used to fit the model and "the test segment" used to test the model. The training segment contains the first 60 observations and the test segment contains the remaining 12 observations.

3.2.1 Choosing an ARIMA Model

A visual plot of monthly import data of Bangladesh is plotted in Figure 11. The data shows seasonality over time periods. Moreover, it seems that the data are non-stationary in the mean only.

Figure 11: Time plot of import data



3.2.2 Testing stationarity

From the correlogram (ACF or PACF plot), Figure 12 and Figure 13, we observe that the autocorrelation are decaying exponentially and most of the spikes fall outside the two standard error limit. It indicates that the data set is non-stationary also the seasonality is present in our data.

Figure 12: ACF of import data

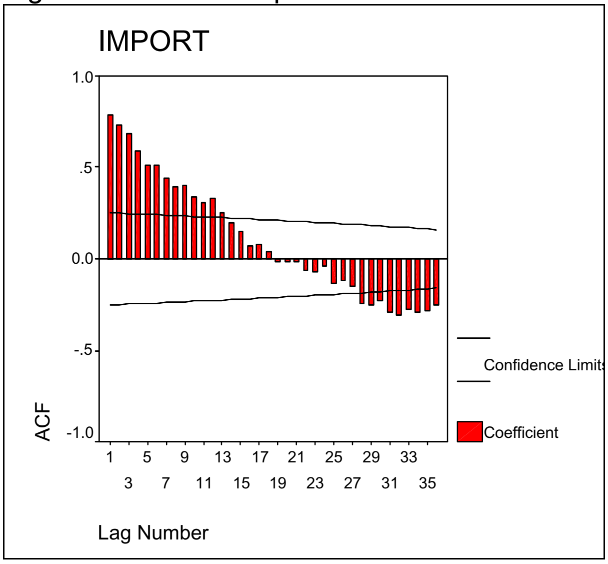
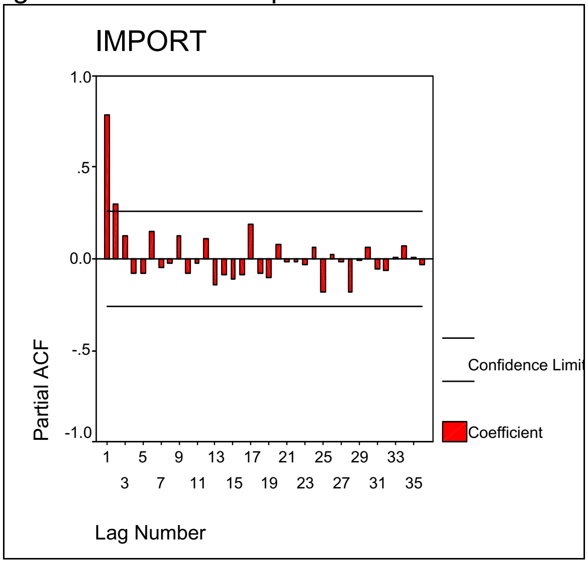


Figure13: PACF of import data



3.2.3 White Noise test

For the autocorrelation values , the Box-Pierce Q statistic is equal to 247.1346, comparing this value to chi-square distribution with 36 degrees of freedom; we can conclude that the values are significantly different from a null set. The Ljung-Box test also indicates that the data set does not follow a white noise series.

3.2.4 Obtaining stationarity

The time plot of the first seasonal differenced series is given in Figure 14, which shows that the values differ around a constant mean. The graphical representation of ACF and PACF of the first seasonal differenced data are given in Figure 15 and Figure 16. The Box-pierce statistic and the Ljung-box Q statistic show that neither of these is significant. Then we take the first difference of the first seasonal data. The time plot of the first difference first seasonal difference of export data is plotted in Figure 17, which shows that the data has become stationary. The graphical representation of ACF and PACF of the first difference first seasonal differenced data are given in Figure 18 and Figure 19. The Box-pierce statistic takes the value 247.1346 and the Ljung-box Q statistic is equal to 329.859 for these data and comparing to a chi-square distribution with 36 degrees of freedom neither of these is insignificant. So, the data follows white noise model.

Figure 14: The time plot of seasonally differenced Import data

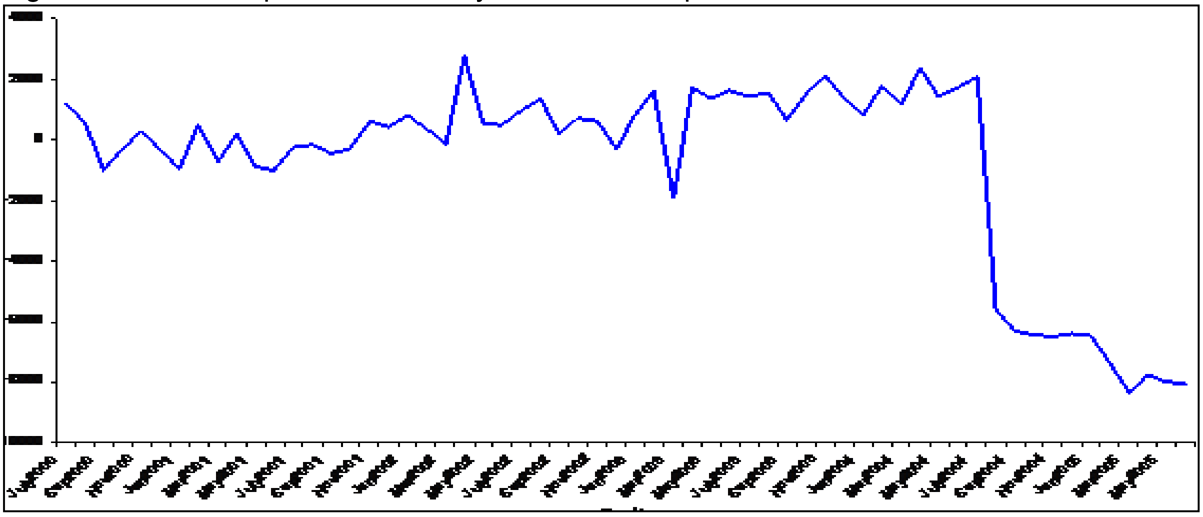


Figure 15: ACF of first seasonal difference of import data

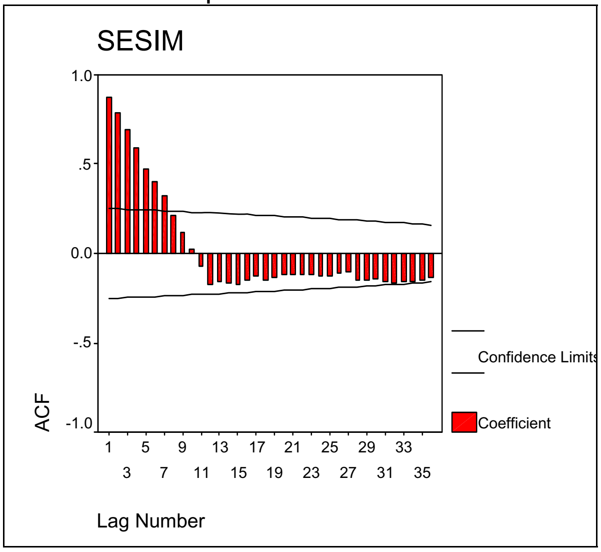


Figure 16: The PACF of first seasonal difference of Import data.

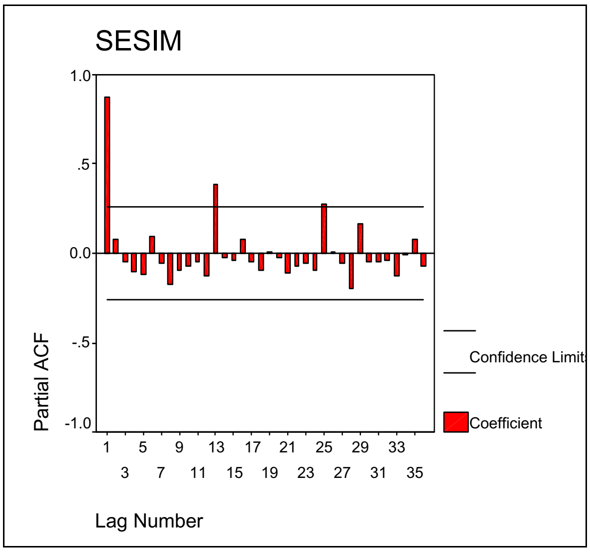


Figure 17: Time plot of first difference of seasonally differenced import data

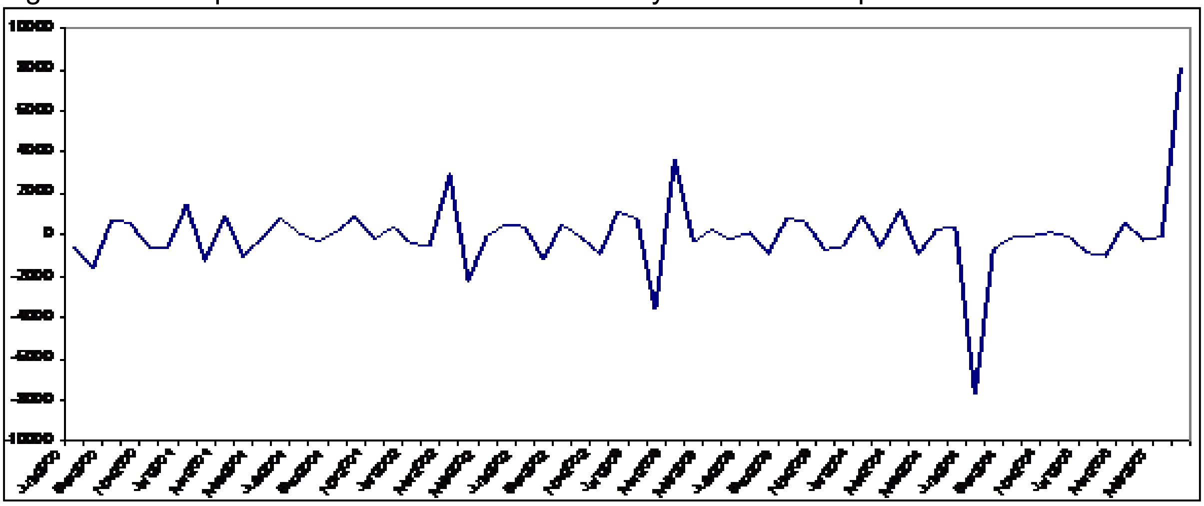


Figure 18: ACF of first difference of seasonally differenced Import data

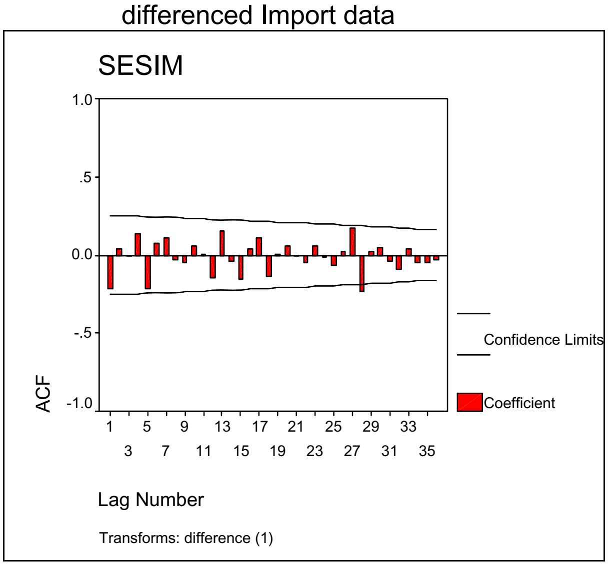
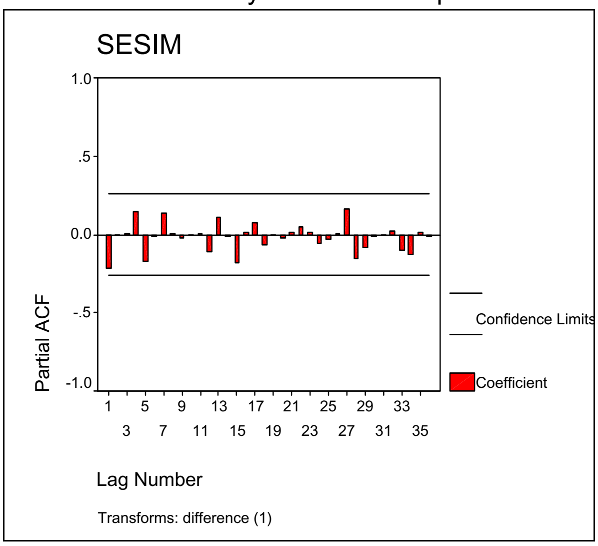


Figure 19: PACF of first difference of seasonally differenced Import data



3.2.5 Model selection

We use the Akaike information criterion (AIC criterion) to choose the best model among the plausible models. The model, which has minimum Akaike information criteria estimates (MAICE), is our model of interest. For different values of p and q, we find the AIC value using computer program namely R.I t gives the minimum AIC values for different p and q values for ARIMA (p, 1, q) $(P, I, Q)_{12}$ are given in Table 4:

Table 4: AIC values of import

Model	AIC	Model	AIC
ARIMA $(0,1,0)(1,1,0)_{12}$	701.55	ARIMA $(2,1,3)(1,1,0)_{12}$	688.21
ARIMA $(0,1,1)(1,1,0)_{12}$	688.36	ARIMA $(3,1,2)(1,1,0)_{12}$	690.03
ARIMA $(1,1,0)(1,1,0)_{12}$	689.51	ARIMA $(3,1,3)(1,1,0)_{12}$	690.17
ARIMA $(1,1,1)(1,1,0)_{12}$	688.31	ARIMA $(0,1,4)(1,1,0)_{12}$	694.07
ARIMA $(0,1,2)(1,1,0)_{12}$	687.14	ARIMA $(4,1,0)(1,1,0)_{12}$	690.01
ARIMA $(2,1,0)(1,1,0)_{12}$	688.27	ARIMA $(4,1,1)(1,1,0)_{12}$	691.23
ARIMA $(1,1,2)(1,1,0)_{12}$	689.9	ARIMA $(1,1,4)(1,1,0)_{12}$	689.73
ARIMA $(2,1,2)(1,1,0)_{12}$	688.13	ARIMA $(4,1,2)(1,1,0)_{12}$	691.93
ARIMA $(0,1,3)(1,1,0)_{12}$	690.76	ARIMA $(2,1,4)(1,1,0)_{12}$	691.57
ARIMA $(3,1,0)(1,1,0)_{12}$	688.36	ARIMA $(4,1,3)(1,1,0)_{12}$	689.74
ARIMA $(3,1,1)(1,1,0)_{12}$	689.57	ARIMA $(3,1,4)(1,1,0)_{12}$	693.5
ARIMA $(1,1,3)(1,1,0)_{12}$	691.39	ARIMA $(4,1,4)(1,1,0)_{12}$	693.4

From the Table 4, we found that ARIMA $(0,1,2)(0,1,1)_{12}$ model initially selected the lowest AIC value. Whereas, ARIMA $(0,1,2)(0,1,1)_{12}$, ARIMA $(2,1,0)(0,1,1)_{12}$, ARIMA $(1,1,2)(0,1,1)_{12}$ and ARIMA $(1,1,3)(0,1,1)_{12}$ have almost nearest AIC values. So we have considered all of them in our diagnostic checking.

3.2.6 Estimation and Diagnostic Checking

We have measured the forecasting accuracy by comparing the mean squared error. The mean squared error of ARIMA $(0,1,2)(0,1,1)_{12}$, ARIMA $(2,1,0)(0,1,1)_{12}$, ARIMA $(1,1,2)(0,1,1)_{12}$ and ARIMA $(1,1,3)(0,1,1)_{12}$ are 1036627.5, 1236668.16, 1574300.08, and 3724075 respectively. Also from the Table 4 this model shows the minimum AIC values in model selection. This model indicates that one seasonal moving average part, and one non-seasonal autoregressive part.

$$\left(1-\phi_1 B-\phi_2 B^2\right)\left(1-\Phi_1 B^{12}\right)\left(1-B\right)\left(1-B^{12}\right)Y_t=\left(1-\theta_1 B^{12}\right)e_t \tag{8}$$

The coefficients of ARIMA $(0,1,2)(0,1,1)_{12}$ with their estimated value and corresponding value of z-statistic are given in the following Table 5:

Table 5: The significance test of the parameter of ARIMA $(0,1,2)(0,1,1)_{12}$

Coefficient	Parameter	Standard error	z-value	p-value	Comment
ϕ_1	-0.7054	0.1562	-4.516	0.00001	Significant
ϕ_2	-0.2734	0.1085	-2.641	0.0058	Significant
θ_1	-0.5573	0.2229	-2.5	0.0062	Significant

So, the revised model becomes:

$$\left(1-\phi_1 B-\phi_2 B^2\right)\left(1-\Phi_1 B^{12}\right)(1-B)\left(1-B^{12}\right)Y_t=\left(1-\theta_1 B^{12}\right)e_t$$

$$\Rightarrow Y_t = Y_{t-1}+\phi_1 Y_{t-1}+\phi_2 Y_{t-2}-\phi_1 Y_{t-2}-\phi_2 Y_{t-3}+Y_{t-12}-\phi_1 Y_{t-13}-\phi_2 Y_{t-14}-Y_{t-13}$$
$$+\phi_1 Y_{t-14}+\phi_2 Y_{t-15}+e_t-\theta_1 e_{t-12} \quad (9)$$

$$\Rightarrow Y_t = Y_{t-1}-0.7054Y_{t-1}-0.2734Y_{t-2}+0.7054Y_{t-2}+0.2734Y_{t-3}+Y_{t-12}+0.7054Y_{t-13}+0.2734Y_{t-14}-Y_{t-13}$$
$$-0.7054Y_{t-14}-0.2734Y_{t-15}+e_t+0.5573e_{t-12} \quad (10)$$

Hence, ARIMA $(2,1,0)(0,1,1)_{12}$ is our suggested model to select the forecasting the monthly import data of Bangladesh.

3.2.7 Sample Forecast for the period January 2006-December 2007

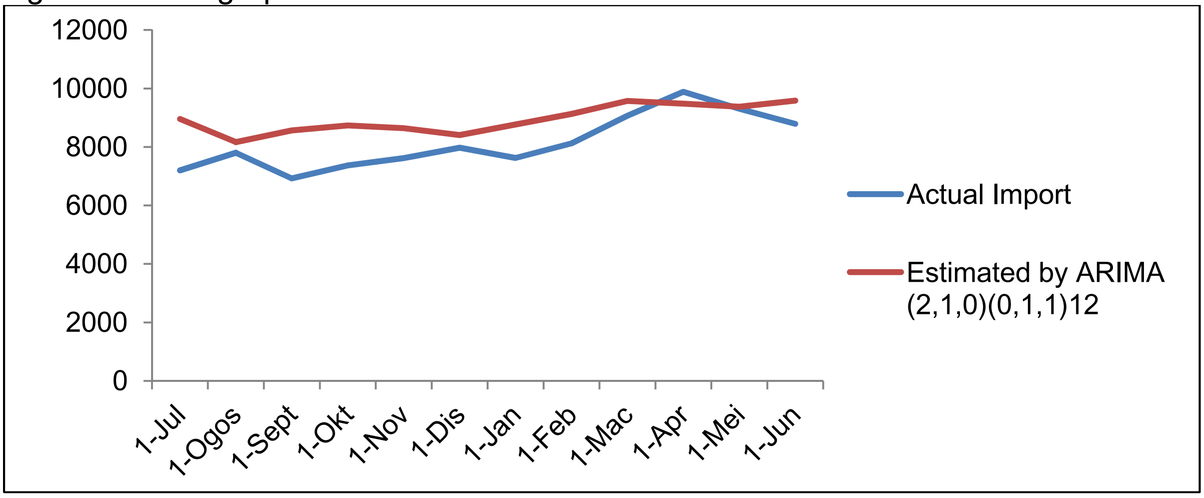
Now to see the performance of this model in the out-of-sample forecasting, the forecasted value of the monthly import data for the period July 2000-June 2005 will be derived using this model. Then we compare the forecasted value with the actual value, which is available from July 2005 – June 2006. The following table gives the forecasted value obtained by models ARIMA $(2,1,0)(0,1,1)_{12}$ and with the actual data.

Table 6: The comparison table of actual data and forecast data of import

Name of Months	Actual Import	Estimated by ARIMA $(2,1,0)(0,1,1)_{12}$
Jul-05	7200	8956.306
Aug-05	7800	8166.609
Sep-05	6922	8568.237
Oct-05	7364	8738.292
Nov-05	7621	8643.791
Dec-05	7977	8406.738
Jan-06	7625	8771.1
Feb-06	8121	9131.566
Mar-06	9068	9575.672
Apr-06	9886	9481.044
May-06	9306	9376.623
Jun-06	8789	9584.121

We clearly see that the forecasted values are most close to the actual values for our finally suggested model. As the forecasted values go upward then go downward and then again go upward as compared to the actual value, which indicates that forecasting model weights all the observations equally.

Figure 20: The graph of actual value and forecasted value



4. CONCLUSION

The basic aim of the study was to select models for forecasting export and import of Bangladesh. In this context we took our interest on ARIMA with respect to our data. It was found that AIC based model selection procedures gave ARIMA models with order $(4,1,2)(1,1,0)_{12}$ and order $(2,1,0)(0,1,1)_{12}$ for export and import respectively were appropriate for the data. We obtained the forecast error for both the models, which are listed in Table 3, and 6 in chapter five. It shows that the forecasting performance of ARIMA $(4,1,2)(1,1,0)_{12}$ and ARIMA $(2,1,0)(0,1,1)_{12}$ models are better. On the basis of the above discussion, we can conclude that, to forecast monthly export and import data, one can easily use ARIMA model. From the pattern of the graphical representation of the models (Figure 4 and 17) we can conclude that on the whole the trend of export and import rose through all around the years.
It should also be borne in mind that a good forecasting technique for a situation may become inappropriate technique for a different situation. The validation of particular model must be examined as time changes.

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