A Time Series Analysis of RMG Export of Bangladesh

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Abstract- Readymade Garment (RMG) industry is one of the export-oriented business sectors in Bangladesh. This paper aims to build an appropriate model and to forecast using that estimated model. The secondary data used for this research obtained from Bangladesh Garment Manufacturers and Exporters Association (BGMEA). Using 36 financial years (FY 1983-84 to FY 2018-19) observations an attempt is made to build an ARIMA model to forecast exports of RMG of Bangladesh. Forecasts are obtained for the next ten (FY 2019-20 to FY 2028-29) financial years. To test the stationarity of the RMG export series graphical method, correlogram and unit root test were used. The time series plot of RMG export shows a non-stationary pattern. Hence the data have been differenced twice to convert the data from non-stationary to stationary. From the autocorrelation function (ACF) and partial autocorrelation function (PACF) we obtain the order of the time series model. The chosen model was Autoregressive Integrated Moving Average ARIMA (2, 2, 5). The model has been fitted on data to estimate the parameters of autoregressive and moving average components of ARIMA (2, 2, 5) model. For residual diagnostics, correlogram, Q-statistic, histogram, and normality test were used. Using model selection criterion and checking model adequacy, we see that the model is suitable in shape. It is found that the forecast of RMG exports values of Bangladesh is steadily increasing over the next ten financial years.

Index Terms- *RMG, ARIMA, Bangladesh*

I. INTRODUCTION

The readymade garment (RMG) sector plays a pivotal role in the economy of Bangladesh. About more than 84 percent of the country's exports and contributing approximately 16 percent to the GDP. RMG sector has raised as the biggest earner of foreign currency. In over three decades, Bangladesh has witnessed substantial growth in its export of goods and services. In Bangladesh, the RMG sector is considered as the lifeline of the economy. After China Bangladesh has become the world's second-largest garment exporter. According to Export Promotion Bureau (EPB), country's export earnings from the readymade garment sector went up by 15.65% to $17.08 billion in July-December period of the fiscal year 2018-19. Bangladesh, to emerge as a middle-income country by 2021, has to achieve its 2021 goal of manufacturing, which represents 90 percent of exports; it would have to increase its output substantially and secure a 28 percent share of the GDP up from roughly 20 percent. This is only possible if RMG production continues to achieve double-digit growth annually.

The role of the RMG sector in Bangladesh is remarkable. About 84.2% of total export earnings come from this sector. From BGMEA statistics it's known that in FY 2013-14 the value was US$ 24.49billion, in FY 2014-15 the value was US$ 25.49billion, in FY 2015-16 the value was US$ 28.09billionand finally in FY 2018-19the value stands at US$ 34.13billion. There are many authors(Ahmed & Barua, 2015), (Halder, Karmaker, Kundu, & Daniel, 2018), (Islam & Chowdhuri, 2014), (Rakib & Adnan, 2016), (Shimu & Islam, 2018)worked on covering the RMG sector of Bangladesh. They discussed socio-economic factors, factors affecting the productivity, workplace safety compliance, impacts of macroeconomic variables and challenges towards development of RMG sector. But a few numbers of authors (Mamun & Nath, 2017), (Chawla, 2001) worked time series related work on the RMG sector in Bangladesh. In our previously published article (M. M. Miah, Tabassum, & Rana, 2019), (M. Miah & Rahman, 2016), (Mamun Miah, Majumder, & Rahman, 2015)we estimated time series model and forecasted using the estimated model. For the forecasting of time series, we use models that are based on a methodology that was first developed in (Box & Jenkins 1976), known as ARIMA (Auto-Regressive Integrated-Moving-Average) methodology. This approach was based on the World representation theorem, which states that every stationary time series has an infinite moving average (MA) representation, which means that its evolution can be expressed as a function of its past developments (Jovanovic&Petrovska, 2010).

II. SOURCES OF DATA

Secondary data are taken from the Bangladesh Garment Manufacturers and Exporters Association (BGMEA). The duration of the study period was chosen from the financial year FY1983-84 to FY2018-19. The data file consists of 36financial year observations of RMG Exports (in million US$).

III. METHODS AND MATERIALS

To test the stationarity of the time series data, we used some tests such as graphical analysis, correlogram and unit root test. The most frequently used method for the test of a unit root in a parametric framework is the Dickey-Fuller (DF) test (Dickey DA & Fuller, 1979). Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) test are widely used to check the stationarity.

If we plot ρ_k against lag, the graph we obtain is known as the population correlogram. In a practical situation, we can only compute the sample autocorrelation function (SACF), $\hat{\rho}_K$.

To compute this, we must first compute the sample covariance at lag K $\hat{\gamma}_k$, and the sample variance $\hat{\gamma}_0$ which is defined as:

$$\hat{\gamma}_k = \frac{1}{n}\sum\left(Y_t - \bar{Y}\right)\left(Y_{t+k} - \bar{Y}\right) \tag{1}$$

$$\hat{\gamma}_0 = \frac{1}{n}\sum\left(Y_t - \bar{Y}\right)^2 \tag{2}$$

where n is the sample size and $\bar{Y}$ is the sample mean. Therefore, the sample autocorrelation function at lag k is

$$\hat{\rho}_k = \frac{\hat{\gamma}_k}{\hat{\gamma}_0} \tag{3}$$

This is simply the ratio of sample covariance (at lag k) to sample variance. If we plot $\hat{\rho}_K$ against the lag then we get sample correlogram. For any stationary time series, the auto-correlation of various lags remains around zero. Otherwise, the series is non-stationary (Gujrati DN & Potter, 2003).

The partial autocorrelation at lag 2 and the expected correlation due to the propagation of correlation at lag 1 and exponential declining nature of PACF plots also helps in deciding on the degree of moving average (Gujrati DN & Potter, 2003). The idea of imposing a penalty for adding regressors to the model has been carried further in the AIC criterion, which is defined as:

$$AIC = e^{2k/n}\frac{\sum\hat{u}_i^2}{n} = e^{2k/n}\frac{RSS}{n} \quad , \tag{4}$$

Where, k is the number of regressors and n is the number of observations. For mathematical convenience, (1) is written as

$$\ln AIC = \frac{2k}{n} + \ln\frac{RSS}{n} \quad , \tag{5}$$

Where $\ln AIC$ is the natural log of AIC $\frac{2k}{n}$ and is the penalty factor?

In comparing two or more models, the model with the lowest value AIC is preferred. One advantage of AIC is that it is useful for not only in-sample but also out of sample forecasting performance of a regression model. Also, it is useful for both nested and non-nested models. It has been used to determine the lag length in a $AR(p)$ model (Gujrati DN & Potter, 2003).

In the autoregressive (AR) process of order, P the current observation y_t is generated by a weighted average of past observations going back p periods, together with a random disturbance in the current period. We denote this process as $AR(p)$ and write the equation as (Box GEP, Gwilum& Gregory, 1994):

$$Y_t = c + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \ \dots \ + \alpha_p Y_{t-p} + \zeta_t \tag{6}$$

In the moving average (MA) process of order q, each observation y_t is generated by a weighted average of the random disturbance going back to q periods. We denote this process as $MA(q)$ and write the equation as (Box GEP, Gwilum& Gregory, 1994):

$$Y_t = \mu + \zeta_t + \beta_1\zeta_{t-1} + \beta_2\zeta_{t-2} + \ \dots + \beta_q\zeta_{t-q} \tag{7}$$

The modeling and forecasting procedure is based on ARIMA models, which is usually known as the Box- Jenkins approach (Dickey DA &Fukker, 1979).

ARIMA models have shown the efficient capability to generate short-term forecasts. It constantly outperformed complex structural models in short-term prediction (Meyler A., Kenny &Quinn). An ARIMA(p, d, q) model, the future value of a variable is a linear combination of past values and past errors, expressed as follows:

$$\Delta^d Y_t = \phi_0 + \phi_1 \Delta^d Y_{t-1} + \phi_2 \Delta^d Y_{t-2} + \ldots + \phi_p \Delta^d Y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \ldots + \theta_q \varepsilon_{t-q} \quad (8)$$

Where Y_t are the actual value and ε is the random error at t, d refers to the number of differencing transformations required by the time series to get stationary. ϕ_i and θ_j are the coefficients, p and q are integers that are often referred to as autoregressive and moving average, respectively.

IV. MODEL IDENTIFICATION

Examine the data to see which member of the class of ARIMA process appears to be most appropriate. That is, find out the appropriate values of *p*, *d*, and *q*.

V. ESTIMATION

Having identified the appropriate p and q values, the next stage is to estimate the parameters of autoregressive and moving average terms included in the model. Sometimes, this calculation can be done by simple least-squares but sometimes, we will have to resort to nonlinear estimation method.

VI. DIAGNOSTIC CHECKING

Having chosen a particular ARIMA model and having estimated its parameters, next we see whether the chosen model fits the data reasonably well, for another ARIMA model might do the job well.

VII. FORECASTING

One of the reasons for the popularity of ARIMA modeling is its success in forecasting. In more cases, the forecasts obtained by this method are more reliable than those obtained from the traditional econometric modeling, particularly for short-term forecasts (Gujrati DN & Potter, 2003).
Therefore procedure for Box-Jenkins methods involves four general steps, namely: model identification, model estimation, diagnostic checking and use of the fitted model to forecast future values. The first three steps are repeated until an adequate and satisfactory model is formed.
The mean square error (MSE) is another method for evaluating a forecasting technique (Hanke JE &Wichern, 2005). Each error or residual is squared; these are then summed and divided by the number of observations. This approach penalizes large forecasting errors because the errors are squared, which is important; a technique that produces moderate errors may well be preferable to one that usually has small errors but occasionally yields extremely large ones. The MSE is given by:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(Y_t - \hat{Y}_t)^2 \quad (9)$$

Sometimes it is more useful to compute the forecasting errors in terms of percentage rather than amounts. Root mean square error (RMSE) is simply the square root of mean square error (MSE) (Hanke JE &Wichern, 2005).

VIII. CHOICE OF LAG LENGTH

This is an empirical question. A rule of thumb is to compute ACF up to one-third to one-quarter the length of the time series. Since for our time series data, we have 36 yearly observations. By this rule, lags 9 and 12 years will do. To save space, we have only shown lags in the ACF graph. The best practical advice is to start with sufficiently large lags and then reduce them according to some statistical criterion, such as the Akaike information criterion (AIC).

IX. RESULTS AND DISCUSSION

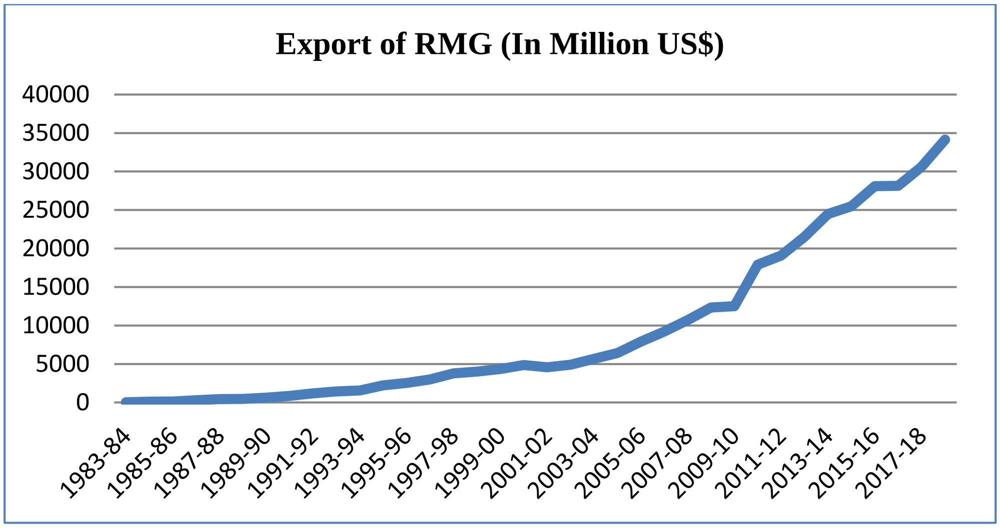


Figure 1: Time series plot of RMG Export (In Million US$) from the financial year 1983-84 to 2018-19 in Bangladesh.

From the above time series plot, we observe that throughout the study the time series data seems to be trending, suggesting perhaps that the mean and variance has
been changing. That is, the RMG Export series is not a stationary pattern. Visually, the mean and variance do not remain constant from time to time, so we can say that the original Export data series is not stationary. Again, the second not the first difference of RMG Exportdata series shows more stable variance than the original series. That is, our difference order is 2 to make the RMG Export series as stationary.

Table 1: Correlogram of RMG Export data series

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.895	0.895	31.308	0.000
		2	0.802	0.007	57.215	0.000
		3	0.713	-0.034	78.268	0.000
		4	0.610	-0.118	94.151	0.000
		5	0.514	-0.032	105.82	0.000
		6	0.411	-0.099	113.53	0.000
		7	0.321	-0.010	118.38	0.000
		8	0.236	-0.035	121.11	0.000
		9	0.150	-0.066	122.26	0.000
		10	0.097	0.083	122.75	0.000
		11	0.038	-0.065	122.83	0.000
		12	-0.013	-0.020	122.84	0.000
		13	-0.057	-0.042	123.03	0.000
		14	-0.096	-0.015	123.60	0.000
		15	-0.127	-0.024	124.65	0.000
		16	-0.155	-0.023	126.29	0.000

From the above table of correlogram, we observe that the coefficients of autocorrelation (ACF) starts with a high value and declines slowly, indicating that the series is non-stationary. Also the Q-statistic of Ljung-Box (1978) [at the 16 lags has a probability value of 0.0000 which is smaller than 0.05 that indicates not the rejection of the null hypothesis that is the RMG Export data series is non-stationary.

Table 2: Unit root test for RMG Export data series of Bangladesh

Null Hypothesis: RMG Export has a unit root			
Exogenous: Constant			
Lag Length: 0 (Automatic- based on SIC, maxlag = 9)			
		t-statistic	P-value
Augmented Dickey-Fuller test statistic		4.550340	1.000
Test critical values:	1% level	-3.632900	
	5% level	-2.948404	
	10% level	-2.612874	

From the above unit root test, the null hypothesis states that the RMG Exports data series of Bangladesh don't have a unit root. This means that the data is non-stationary. Since P-value is greater than the level of significance we don't reject the null hypothesis. That is the RMG Exports (In Million US$) data series of Bangladesh is not stationary.

Taking the second difference in the Line graph, Correlogram, Unit root test, ACF and PACF are given below:

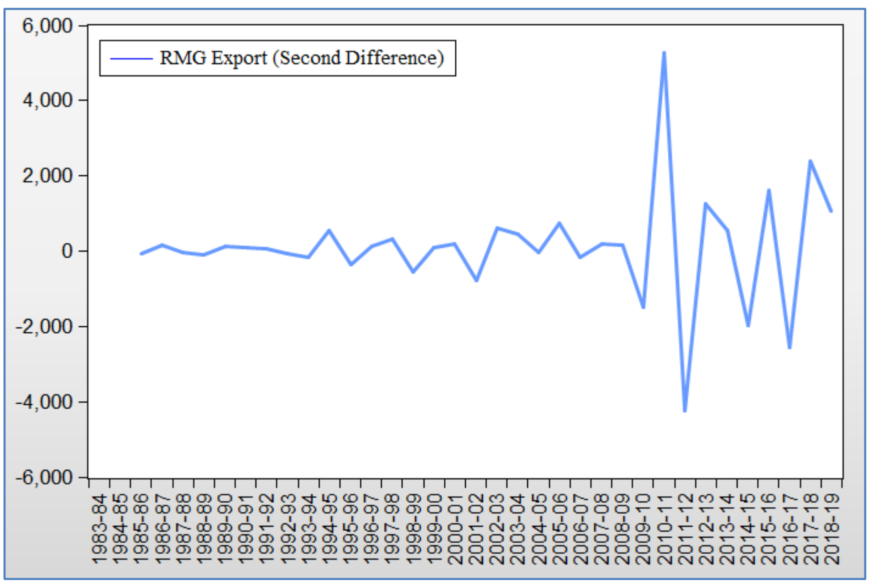
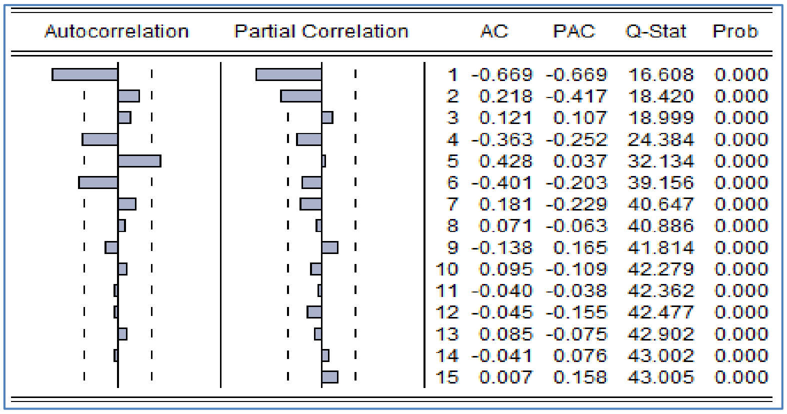


Figure 2: Time series plot for second difference series of RMG Export (In Million US$) from FY 1983-84 to FY 2018-19 of Bangladesh.

From the above time series plot, we observe that throughout the study the second difference time series data seems to be a stationary pattern.

Table 3: Correlogram for second difference series of RMG Exports (in million US$) in Bangladesh.



Lag	AC	PAC	Q-Stat	Prob
1	-0.669	-0.669	16.608	0.000
2	0.218	-0.417	18.420	0.000
3	0.121	0.107	18.999	0.000
4	-0.363	-0.252	24.384	0.000
5	0.428	0.037	32.134	0.000
6	-0.401	-0.203	39.156	0.000
7	0.181	-0.229	40.647	0.000
8	0.071	-0.063	40.886	0.000
9	-0.138	0.165	41.814	0.000
10	0.095	-0.109	42.279	0.000
11	-0.040	-0.038	42.362	0.000
12	-0.045	-0.155	42.477	0.000
13	0.085	-0.075	42.902	0.000
14	-0.041	0.076	43.002	0.000
15	0.007	0.158	43.005	0.000

Table 4: Unit root test for second difference series of RMG Exports (in million US$) in Bangladesh

Null Hypothesis: Second difference in RMG Export has a unit root			
Exogenous: Constant			
Lag Length: 1 (Automatic- based on SIC, maxlag = 9)			
		t-statistic	P-value
Augmented Dickey-Fuller test statistic		-8.363444	0.0000
Test critical values:	1% level	-3.653730	
	5% level	-2.957110	
	10% level	-2.617434	

From the above unit root test, the null hypothesis states that the second difference RMG Exports data series of Bangladesh has a unit root. This means that the data is stationary. Since P-value is less than the level of significance we may reject the null hypothesis. That is the RMG Exports (in million US$) data series of Bangladesh is stationary.

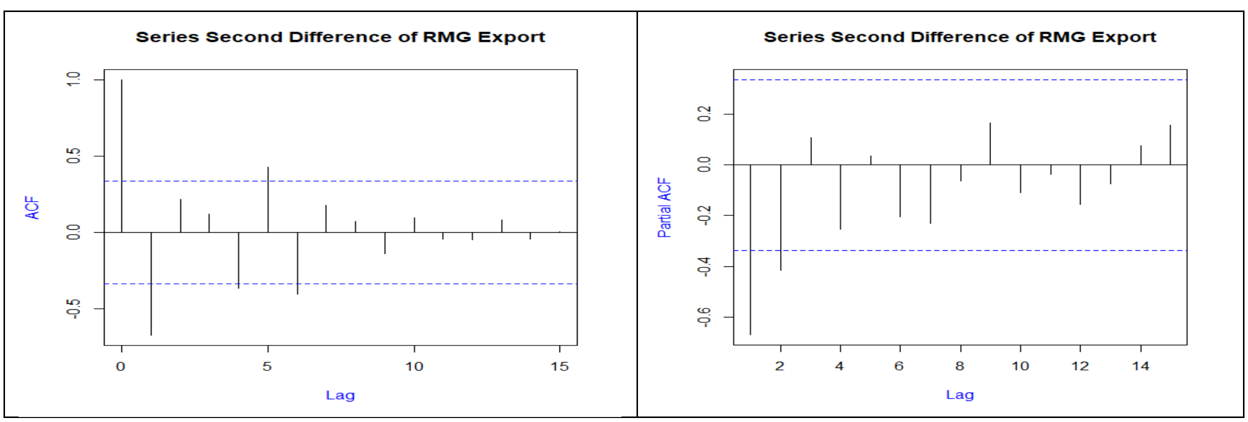


Figure 3: ACF and PACF for the second difference series of RMG Exports (in million US$) of Bangladesh.

From the above ACF and PACF, we observe that one period lag is statistically significant for autocorrelation function and partial autocorrelation function. Also, it is clear from the above ACF and PACF that our expected model is $ARIMA(p,d,q) = ARIMA(2,2,5)$

Table 5: Summary of ARIMA (2,2,5) Model

Parameter	Estimates	Standard Error	Estimated σ^2	log-likelihood
$AR(1)$	0.4887	0.3198		
$AR(2)$	0.3743	0.3392		

$MA(1)$	-1.5563	0.3101	749122	-279.56
$MA(2)$	0.6436	0.4961		
$MA(3)$	0.3556	0.3811		
$MA(4)$	-0.9117	0.2850		
$MA(5)$	0.5462	0.1785		

The functional form of the model is

$$\Delta^2 Y_t = 0.4887Y^2{}_{t-1} + 0.3743Y^2{}_{t-2} + \varepsilon_t - 1.5563\varepsilon_{t-1} + 0.6436\varepsilon_{t-2} + 0.3556\varepsilon_{t-3} - 0.9117\varepsilon_{t-4} + 0.5462\varepsilon_{t-5}$$

X. DIAGNOSTIC CHECKING OF THE MODEL

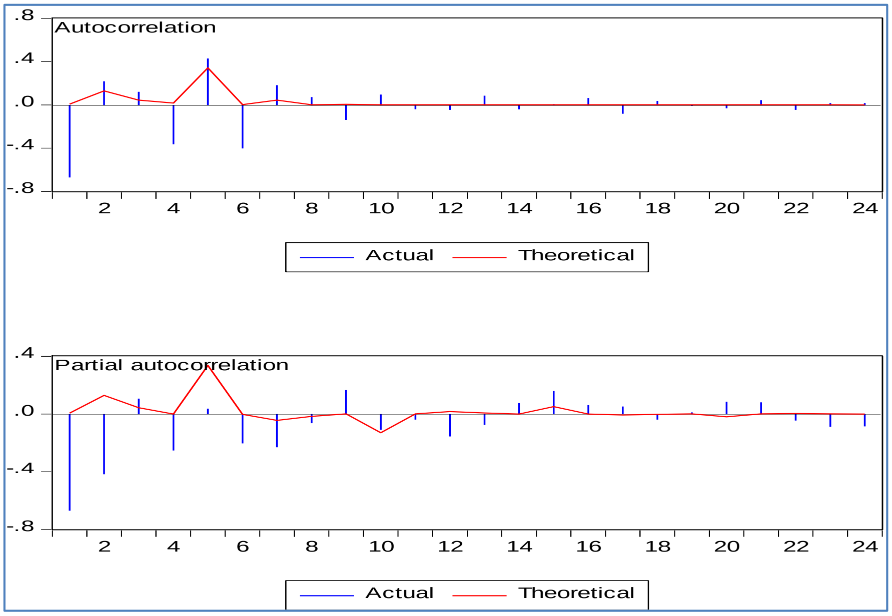


Figure 4: Correlogram of ARIMA (2, 2, 5) Model

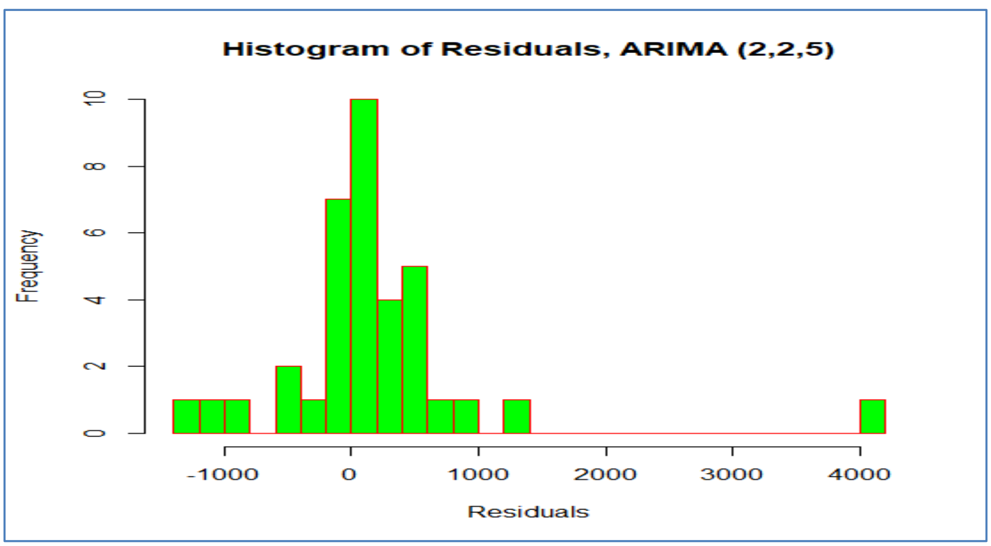


Figure 5: Histogram of Residuals for ARIMA (2,2,5) Model.

The histogram of the residuals shows that the variance of the residuals seems to be roughly constant over time. The histogram of the time series shows that the residuals are roughly normally distributed and the mean seems to be close to zero. Therefore, it is plausible that the residuals are normally distributed with mean zero and constant variance.

Since successive residuals do not seem to be correlated, and the residuals seem to be normally distributed with mean zero and constant variance, the ARIMA(2,2,5) does seem to provide an adequate predictive model for the Exports of RMG in Bangladesh.

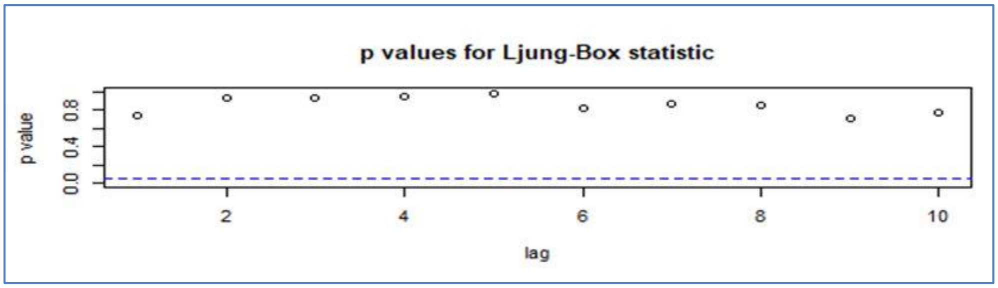


Figure 6: P values for Ljung-Box statistic

From the results of figure 5 and figure 6, we observe that the residuals of the ARIMA(2,2,5) model follows approximately a normal distribution. Moreover, the results from table 3 indicate that the Q statistic of Ljung-Box for all the 10 lags has values greater than 0.05 that indicates the null hypothesis cannot be rejected. That means, there is no autocorrelation for the examined residuals of the RMG Exports data series.

XI. FORECASTING

We have estimated the model using the data covered from FY 1983-84 to FY 2018-19. Here we have forecasted for the next ten financial year as from FY 2019-20 to FY 2028-29.

Table 6: Forecasted RMG Exports of Bangladesh using ARIMA (2,2,5) Model

FY	Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2019-20	35666.93	34557.19	36776.67	33969.73	37364.13
2020-21	38874.45	37356.59	40392.31	36553.08	41195.82
2021-22	42075.20	39933.00	44217.41	38798.99	45351.42
2022-23	44573.54	41496.98	47650.10	39868.35	49278.73
2023-24	47467.97	43681.90	51254.04	41677.67	53258.26
2024-25	50293.05	45727.03	54859.07	43309.93	57276.17
2025-26	53232.50	47873.02	58591.98	45035.88	61429.12
2026-27	56201.87	49987.43	62416.32	46697.70	65706.04
2027-28	59228.68	52100.12	66357.23	48326.49	70130.86
2028-29	62294.74	54181.18	70408.30	49886.13	74703.36

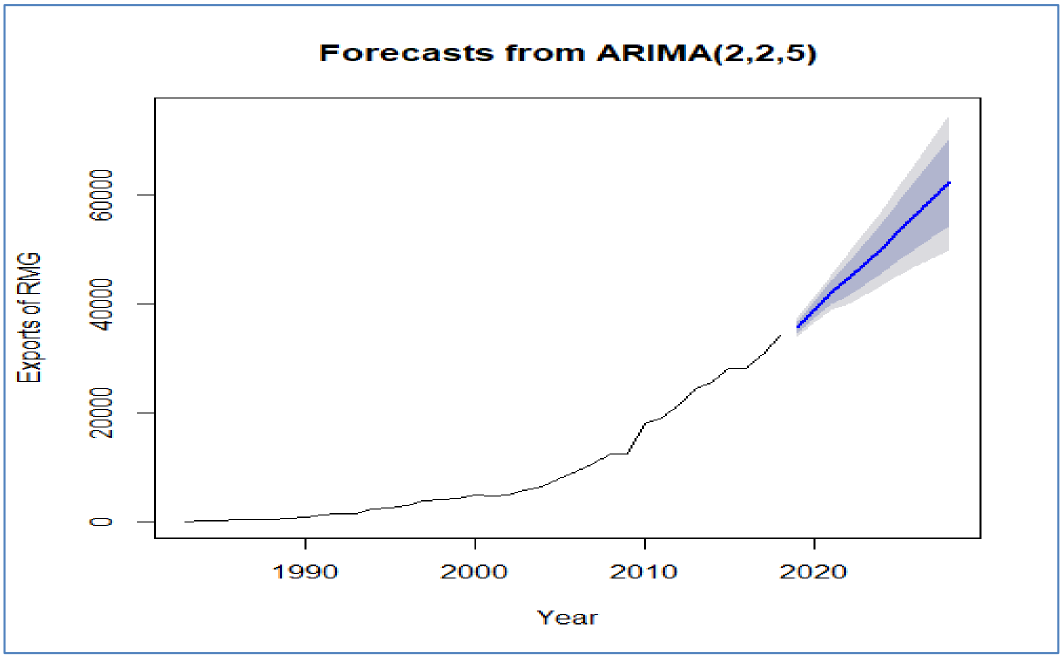


Figure 7: Original and next ten years (FY 2019-20 to 2028-29) forecasted Exports of RMG in Bangladesh.

The original time series is for the Exports of RMG in Bangladesh for the last 36 financial years. The above table gives a forecast for the RMG Exports of the next ten financial years (FY 2018-20 to FY 2028-29), as well as 80% and 95% prediction intervals for those predictions.

XII. CONCLUSION

In this paper, we are trying to model and forecast the Export of RMG in Bangladesh for the next ten financial years. It is shown that the time series ARIMA model can be used to model and forecast the Export of RMG (in million US$) in Bangladesh. After checking the stationarity of the data series, we find the appropriate $ARIMA(p,d,q)$ process. The ACF and PACF helped in choosing the appropriate p q and for the data series. The identified $ARIMA(2,2,5)$ model has proved to be adequate in forecasting exports of RMG for the financial years up-to FY 2028-29. This model will also help the researchers, policymakers, businessmen, and government for future planning. Also, it is clear from the graph that the forecasted exports of RMG are sharply increasing. Despite the unequivocal success story, the RMG sector has got several drastic challenges for future growth. Hope the Government of Bangladesh will take necessary steps to continue the growth of exports of RMG sectors.

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