Modelling and Forecasting of GDP in Bangladesh: An ARIMA Approach

M. M. Miah¹, Mimma Tabassum², M. Shohel Rana³

¹, ², ³Department of Statistics, Noakhali Science and Technology University, Noakhali – 3814

¹mamunmiah.615@gmail.com, ²tabassum021521@gmail.com, ³ranashohel78@yahoo.com

Corresponding Author: M. M. Miah

https://doi.org/10.26782/jmcms.2019.06.00012

Abstract
This paper aims to model and forecasting on GDP data of Bangladesh for the period of 1960 to 2017. To test the stationarity of the series graphical method, correlogram and unit root test were used. The time series plot of GDP shows a non-stationary pattern and overall this is like exponential curvature shape. 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 (1, 2, 1). The model has been fitted on data to estimate the parameters of autoregressive and moving average components of ARIMA (1, 2, 1) model. For residual diagnostics, correlogram, Q-statistic, histogram, and normality test were used. Also, Chow test was used for stability testing. Using model selection criterion and checking model adequacy, we see that the model is suitable in shape. It is found that the forecast values of GDP in Bangladesh are steadily improving over the next thirteen years.

Keywords: GDP, ARIMA Modeling, Forecasting, Bangladesh.

I. Introduction

Bangladesh is a developing country in South Asia. Its GDP is exponentially increasing after independence. Gross Domestic Product (GDP) is an important indicator of economic activity and is often used by decision-makers to plan economic policy. It is a common measure that’s used to roughly represent the size of a country’s economy. Gross domestic product (GDP) of a country is the monetary value of all the finished goods and services produced within a country's borders in a specific time period. It represents the aggregate statistic of all economic activity. The performance of the economy can be measured with the help of GDP. The issues of GDP has become the most concerned amongst macroeconomic variables and data on GDP is regarded as the important index for assessing the national economic development and for judging the operating status of the macroeconomy as a whole [v]. Forecasts of macroeconomic variables are crucial to many agents in the economy, including economic policymakers. The most important macroeconomic variables to forecast are the Gross Domestic Product (GDP), inflation, and unemployment. As an aggregate measure of total economic production for a country, GDP is one of the primary indicators used to measure the country's economy. Because important economic and
political decisions are based on forecasts of these macroeconomic variables, it is imperative that they are as reliable and accurate as possible. Inaccurate forecasts may result in destabilizing policies and a more volatile business cycle. Gross domestic product (GDP) is one of the most important indicators of national economic activities for countries. For the forecasting of time series, we use models that are based on a methodology that was first developed in Box and Jenkins (1976)[I], known as ARIMA (Auto-Regressive Integrated-Moving-Average) methodology[I]. This approach was based on the World representation theorem, which states that every stationary time series has an infinite moving average (MA) representation, which actually means that its evolution can be expressed as a function of its past developments (Jovanovic and Petrovska 2010) [VII].

II. Sources of Data

Secondary GDP data are taken from the World Bank. The duration of the study period was chosen from the year 1960 to 2017. The data file consists of 59 observations of GDP (in billion USD).

III. Literature Review

Already many studies have been conducted with Gross Domestic Product (GDP). Box and Jenkins (1976)[I] methodology has been used extensively by many researchers in order to highlight the future rates of GDP. Wei and al. (2010)[XIII] use data from Shaanxi GDP for 1952-2007 to forecast the country’s GDP for the following 6 years. Applying the ARIMA (1,2,1) model they find that GDP of Shaanxi present an impressive increasing trend. Maity and Chatterjee (2012)[IX] examine the forecasting of GDP growth rate for India using ARIMA(1,2,2) model and a time period of 60 years. The results of their study showed that predicted values follow an increasing trend for the following years. Zhang Haonan (2013)[XIV] using three models ARIMA, VAR, AR(1) examines the forecasting of per capita GDP for five regions of Sweden for the years 1993 – 2009. The results of the study showed all three models can be used for forecasting in the short run. However, the autoregressive first order model is the best for forecasting the per capita GDP of five regions of Sweden. Shahini and Haderi (2013)[XI] test GDP forecasting for Albania using quarterly data from the first quarter of 2003 until the second quarter of 2013. For the forecasting, they used two model groups ARIMA and VAR. Their results showed that the group of VAR model gives better results on GDP’s forecasting rather than ARIMA model. Zakai (2014)[XIII] investigates forecasting of Gross Domestic Product (GDP) for Pakistan using quarterly data from 1953 until 2012. Choosing an ARIMA (1,1,0) model he finds out the size of the increase for Pakistan’s GDP for the years 2013- 2025. Dr. ChaidoDritsaki (2015)[III] using ARIMA (1,1,1) model showed that Greece’s real GDP rate is steadily improving.

IV. 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 [II]. Dickey-Fuller (DF) and Augmented Dickey-Fuller (ADF) test are widely used to
check the stationarity. But if the series has no trend and the error terms are auto-
correlated, then we cannot apply DF test because time series data have no trend. That's why we use the ADF test to test the stationarity.
If we plot $\rho_k$ 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:

$$\hat{\gamma}_k = \frac{1}{n} \sum(Y_i - \bar{Y})(Y_{i-k} - \bar{Y})$$

$$\hat{\gamma}_0 = \frac{1}{n} \sum(Y_i - \bar{Y})^2$$

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

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

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 [IV].
The role of ACF is very important at the identification of time series process. It
measures the direction and strength of the statistical relationship between ordered
pairs of observation in a single data series.
The auto-correlation function at lag $k$, denoted by $\rho_k$ is defined as

$$\rho_k = \frac{\gamma_k}{\gamma(0)} = \frac{\text{covariance at lag } k}{\text{variance}}$$

When $k = 0$, then $\rho = 1$, because they are measured with the same units of measurement. $\rho_k$ is unitless, it lies between -1 to +1 as any correlation coefficient does. The exponentially declining natures of the ACF plots were also observed for
taking the final decision about the order of autoregression. The numbers of significant spikes in ACF plots were also observed in taking a decision about the degree of moving average [IV].
The estimated PACF is broadly similar to an estimated ACF. An estimated PACF is
also a graphical representation of the statistical relationship between sets of ordered
pairs drawn from a single time series.
A partial autocorrelation is the amount of correlation between a variable and a lag of
itself that is not explained by correlations at all lower-order-lags. The autocorrelation
of a time series $Y$ at lag 1 is the coefficient of correlation between $Y$ and $Y$, which is
presumably also the correlation between $Y$ and $Y$. But if $Y$ is correlated with $Y$ and
Y is equally correlated with \( Y \), then it appears necessary to find the correlation between \( Y \) and \( Y \). Thus, the correlation at lag 1 “propagates” to lag 2 and presumably to higher order lags. 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 taking the decision about the degree of moving average [4]. The idea of imposing a penalty for adding regressors to the model has been carried further in the AIC criterion, which is defined as:

\[
AIC = e^{\frac{2k}{n}} \sum \frac{u_i^2}{n} = e^{\frac{2k}{n}} \frac{RSS}{n},
\]

(5)

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

\[
\ln AIC = \frac{2k}{n} + \ln \frac{RSS}{n},
\]

(6)

where \( \ln AIC \) is the natural log of \( \frac{RSS}{n} \) 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 [IV].

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 [1]:

\[
y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \ldots + \alpha_p y_{t-p} + \zeta_t
\]

(7)

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 [1]:

\[
y_t = \mu + \beta_1 \zeta_{t-1} + \beta_2 \zeta_{t-2} + \ldots + \beta_q \zeta_{t-q}
\]

(8)

The modeling and forecasting procedure is based on ARIMA models, which is usually known as the Box- Jenkins approach [II]. A major contribution of Box-Jenkins has been to provide a general strategy for time-series forecasting, which emphasizes the importance of identifying an appropriate model in an iterative way.

V. 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 \( q \).
VI. 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.

VII. 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 it is possible that another ARIMA model might do the job well.

VIII. 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 [IV].

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 [V]. 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:

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

(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) [V]. The mean absolute percentage error (MAPE) is computed by finding the absolute error in each period, dividing this by the actual observed value for that period, and then averaging the absolute percentage errors [V]. This approach is useful when the size or magnitude of the forecast variable is important in evaluating the accuracy of the forecast. MAPE provides an indication of how large the forecast errors are in comparison to the actual values of the series. The technique is especially useful when the $Y_t$ values are large. MAPE can also be used to compare the accuracy of the same or different techniques on two entirely different series. MAPE is computed as:
\[ MAPE = \frac{1}{n} \sum_{t=1}^{n} \left| \frac{Y_t - \hat{Y}_t}{Y_t} \right] \] (10)

**IX. Choice of Lag Length**

This is basically 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 57 yearly observations. By this rule, lags 14 and 19 years will do. To save space, we have only shown 20 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).

**X. Result and Discussion**

For any time series analysis, the most important aspect to check is whether the data is stationary or not. If the data is not stationary, our main aspect is to change the data set into stationary. Now for GDP, we will check the stationarity of a time series data. Now at first, we do the line graph of GDP data, and from the time series plot, we observe that the GDP has exponential increasing trend (Figure 2).

To test the stationarity of the data, we use correlogram. We use correlogram with lag length 20 as follows (Table 1).

*Fig. 1. Time series plot for GDP (billion USD) from the year 1960 to 2017 of Bangladesh.*

From the above time series plot, we observe that over the period of study the time series data seems to be trending, suggesting perhaps that the mean and variance has been changing. That is the GDP series showing exponential curve and does not follow the stationary pattern.
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 20 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 GDP series is non-stationary.

Table 1: Correlogram for GDP (in billion USD) of Bangladesh.

| Autocorrelation | Partial Correlation | AC     | PAC    | Q-Stat | Prob |
|-----------------|---------------------|--------|--------|--------|------|
| 1               | 0.875               | 0.875  | 46.690 | 0.000  |      |
| 2               | 0.763               | -0.006 | 02.500 | 0.000  |      |
| 3               | 0.666               | 0.005  | 111.12 | 0.000  |      |
| 4               | 0.584               | 0.001  | 134.13 | 0.000  |      |
| 5               | 0.516               | 0.020  | 150.62 | 0.000  |      |
| 6               | 0.458               | 0.007  | 164.64 | 0.000  |      |
| 7               | 0.395               | -0.044 | 173.30 | 0.000  |      |
| 8               | 0.340               | -0.066 | 183.34 | 0.000  |      |
| 9               | 0.292               | 0.000  | 189.39 | 0.000  |      |
| 10              | 0.251               | 0.000  | 193.96 | 0.000  |      |
| 11              | 0.219               | 0.012  | 197.49 | 0.000  |      |
| 12              | 0.191               | 0.003  | 200.25 | 0.000  |      |
| 13              | 0.162               | -0.19  | 202.31 | 0.000  |      |
| 14              | 0.136               | -0.09  | 203.76 | 0.000  |      |
| 15              | 0.113               | -0.002 | 204.79 | 0.000  |      |
| 16              | 0.095               | 0.005  | 205.63 | 0.000  |      |
| 17              | 0.073               | -0.029 | 205.98 | 0.000  |      |
| 18              | 0.050               | -0.025 | 206.20 | 0.000  |      |
| 19              | 0.027               | -0.017 | 206.26 | 0.000  |      |
| 20              | 0.003               | -0.024 | 206.26 | 0.000  |      |
| 21              | -0.021              | -0.025 | 206.30 | 0.000  |      |
| 22              | -0.046              | -0.031 | 206.51 | 0.000  |      |
| 23              | -0.064              | 0.003  | 206.91 | 0.000  |      |
| 24              | -0.072              | -0.009 | 207.64 | 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 20 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 GDP series is non-stationary.

Table 2: Unit root test for GDP of Bangladesh

| Null Hypothesis: GDP has a unit root |
|-------------------------------------|
| Exogenous: Constant                 |
| Lag Length: 0 (Automatic- based on SIC, maxlag=10) |
| Augmented Dickey-Fuller test statistic | 14.83170 | 1.000 |
| Test critical values:               |
| 1% level                            | -3.50396 |
| 5% level                            | -2.913549 |
| 10% level                           | -2.594521 |

From the above unit root test, the null hypothesis states that the GDP series of Bangladesh doesn’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 GDP (in billion USD) series of Bangladesh is not stationary. Taking the second difference in the Line graph, Correlogram, Unit root test, ACF and PACF are given below:
Fig 2. Time series plot for second difference series of GDP (billion USD) from the year 1960 to 2017 of Bangladesh.

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

Table 3: Correlogram for second difference series of GDP (in billion USD) in Bangladesh.

| Year | GDP (Second Difference) |
|------|-------------------------|
| 1970 |                         |
| 1980 |                         |
| 1990 |                         |
| 2000 |                         |
| 2010 |                         |

| Auto-correlation | Partial Correlation | AC | FAC | Q-Stat | Prob |
|------------------|---------------------|----|-----|--------|------|
| 1                | -0.246              | 5.674 | 0.059 |        |      |
| 2                | -0.246              | 7.2618 | 0.026 |        |      |
| 3                | 0.105               | 7.9338 | 0.047 |        |      |
| 4                | 0.026               | 9.7576 | 0.092 |        |      |
| 5                | -0.002              | 8.1505 | 0.148 |        |      |
| 6                | 0.167               | 9.9570 | 0.126 |        |      |
| 7                | 0.013               | 9.9987 | 0.190 |        |      |
| 8                | -0.029              | 10.026 | 0.263 |        |      |
| 9                | -0.064              | 10.228 | 0.332 |        |      |
| 10               | 0.083               | 10.716 | 0.398 |        |      |
| 11               | 0.003               | 10.716 | 0.457 |        |      |
| 12               | 0.024               | 10.759 | 0.550 |        |      |
| 13               | -0.038              | 10.869 | 0.622 |        |      |
| 14               | -0.041              | 10.998 | 0.888 |        |      |
| 15               | 0.182               | 13.623 | 0.554 |        |      |
| 16               | -0.171              | 15.998 | 0.453 |        |      |
| 17               | -0.064              | 16.593 | 0.482 |        |      |
| 18               | 0.173               | 19.153 | 0.362 |        |      |
| 19               | -0.066              | 19.532 | 0.423 |        |      |
| 20               | -0.122              | 20.877 | 0.494 |        |      |
| 21               | 0.181               | 23.903 | 0.298 |        |      |
| 22               | -0.059              | 24.239 | 0.335 |        |      |
| 23               | 0.018               | 24.268 | 0.389 |        |      |
| 24               | -0.052              | 24.546 | 0.431 |        |      |
Table 4: Unit root test for second difference series of GDP (in billion USD) in Bangladesh

| Null Hypothesis: Second difference in GDP has a unit root | t-statistic | P-value |
|----------------------------------------------------------|-------------|---------|
| Exogenous: Constant                                      |             |         |
| Lag Length: 1 (Automatic- based on SIC, maxlag=10)        |             |         |
| Augmented Dickey-Fuller test statistic                   | -7.930981   | 0.0000  |
| Test critical values:                                     |             |         |
| 1% level                                                 | -3.557472   |         |
| 5% level                                                 | -2.916566   |         |
| 10% level                                                | -2.596116   |         |

From the above unit root test, the null hypothesis states that the GDP 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 GDP (in billion USD) series of Bangladesh is stationary.
Fig. 3. ACF and PACF for second difference series of GDP (billion USD) of Bangladesh.

From the above ACF and PACF, we observe that one period lag is statistically significant for autocorrelation function and partial autocorrelation function.

Table 5: Summary of ARIMA(1,2,1) Model

| Variable   | Coefficient | Std. Error | t-Statistic | Prob.  |
|------------|-------------|------------|-------------|--------|
| C          | 9.781199    | 10.45962   | 0.935139    | 0.3540 |
| AR(1)      | 0.976072    | 0.054404   | 17.04118    | 0.0000 |
| MA(1)      | -0.365438   | 0.123080   | -2.969106   | 0.0046 |
| SIGMASQ    | 14.26712    | 1.948151   | 7.318651    | 0.0000 |

R-squared 0.713346  Mean dependent var 4.305702
Adjusted R-squared 0.697120  S.D. dependent var 7.117579
S.E. of regression 3.917127  Akaike info criterion 5.076759
Sum squared resid 813.2259  Schwarz criterion 5.820131
Log likelihood -157.7876  Hannan-Quinn criter. 5.732478
F-statistic 43.96387  Durbin-Watson stat 1.867384
Prob(F-statistic) 0.000000

Inverted AR Roots .98
Inverted MA Roots .37

Copyright reserved © J. Mech. Cont.& Math. Sci.
M. M. Miah et al
The chosen model is summarized in the above table and is given by
\[ \Delta^2 Y_t = 9.781199 + 0.976072\Delta^2 Y_{t-1} - 0.365438\epsilon_{t-1} + \epsilon_t \]
On the following diagram, the inverse roots of AR and MA characteristic polynomials for the stability of the ARIMA model are presented.

![Inverse Roots of AR/MA Polynomial(s)](image)

**Fig. 4.** The inverse roots of AR and MA characteristic polynomials.

The following diagram shows the Gradients of the Objective Function

![Gradients of the Objective Function](image)

**Fig. 5.** Gradients of the Objective Function.

From the above diagram, we observe that the ARIMA model is stable since the corresponding inverse roots of the characteristic polynomials are in the unit circle.
XI. Diagnostic Checking of the Model

Table 6: Correlogram of ARIMA (1,2,1) Model

| Autocorrelation | Partial Correlation | AC    | PAC    | Q-Stat | Prob |
|-----------------|---------------------|-------|--------|--------|------|
| 1               | 0.157               | 0.157 | 1.4791 | 0.224  |
| 2               | 0.134               | 0.112 | 2.5775 | 0.275  |
| 3               | -0.042              | -0.081| 2.6862 | 0.442  |
| 4               | -0.005              | -0.003| 2.6997 | 0.611  |
| 5               | -0.027              | -0.011| 2.7379 | 0.740  |
| 6               | 0.031               | 0.036 | 2.8024 | 0.833  |
| 7               | -0.070              | -0.079| 3.1234 | 0.873  |
| 8               | 0.074               | -0.057| 3.5088 | 0.899  |
| 9               | -0.078              | -0.037| 3.9394 | 0.915  |
| 10              | -0.053              | -0.028| 4.1934 | 0.941  |
| 11              | -0.061              | -0.045| 4.4099 | 0.956  |
| 12              | -0.056              | -0.038| 4.8021 | 0.955  |
| 13              | 0.080               | 0.057 | 5.8987 | 0.953  |
| 14              | -0.102              | -0.071| 6.6257 | 0.948  |
| 15              | -0.013              | 0.011 | 6.6395 | 0.967  |
| 16              | 0.012               | -0.017| 6.6507 | 0.979  |
| 17              | 0.012               | -0.012| 6.6635 | 0.983  |
| 18              | -0.007              | -0.019| 6.6674 | 0.993  |
| 19              | -0.005              | -0.024| 6.6693 | 0.995  |
| 20              | 0.043               | 0.032 | 6.8407 | 0.997  |
| 21              | 0.041               | -0.002| 6.9949 | 0.998  |
| 22              | -0.029              | -0.077| 7.0731 | 0.999  |
| 23              | -0.040              | -0.056| 7.2352 | 0.999  |
| 24              | -0.065              | -0.062| 7.6858 | 0.999  |

Fig. 6. Histogram and Normality Test for ARIMA(1,2,1) Model
From the results of figure 5 and figure 6, we observe that the residuals of the ARIMA(1,2,1) model follow a normal distribution. Moreover, the results from table 3 indicate that the Q statistic of Ljung-Box for all the 20 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 GDP series.

XII. Forecasting

We have estimated the model using the data covered the period from 1960 to 2017. Now we will forecast between the observations 1960 to 2017 and then 1960 to 2030.
Here, for Chow's breakpoint test, we took the breakpoint sample 1980 and for Chow's forecast test we took the forecast sample from 1960 to 2017. From the above Table 6, we can see that both Chow’s tests support the hypothesis that there is no structural break in the model. Thus the model is fully specified.

**Fig. 8.** In-Sample Forecast of GDP in Bangladesh from the year 1960 to 2017.

Using the appropriate model, we forecast the up-to-the year 2030.

**Fig. 9.** Forecast of GDP (in billion USD) from the year 1960 to 2030.
Line graph of GDP of Bangladesh is shown below (Figure 10):

![GDP graph](image)

**Fig. 10.** Linear Trend line of forecasted GDP series from the year 2018 to 2030 in Bangladesh.

From the above Figure, we see that the Gross Domestic Product (GDP in billion USD) is increasing steadily.

![Real and Forecasted GDP graph](image)

**Fig. 11.** Linear Trend line of Real and Forecasted GDP (in billion USD)

From the above figure, we observe that all of the forecasts' real GDP trends are upwards.
XIII. Conclusion

In this paper, we are trying to model and forecast the GDP in Bangladesh for the next thirteen years. It is shown that the time series ARIMA model can be used to model and forecast the GDP (in billion USD) 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 and q for the data series. The identified ARIMA(1,2,1) model has proved to be adequate in forecasting GDP up to the year 2030. Results of the study will be helpful for the policymakers to formulate effective policies for attracting foreign direct investment. Here, we found that the GDP of Bangladesh is increasing yearly.

References

I. Box GEP, Gwilym MJ, Gregory CR. Time Series Analysis: Time Series Analysis Forecasting & Control. New Jersey: Prentice Hall, Englewood Cliffs; 1994.

II. Dickey DA, Fuller WA. Distributions of the Estimators for Autoregressive Time Series with a Unit Root. J Am Stat Assoc. 1979; 74(366),pp:427–481.

III. Dr. ChaidoDritsaki (2015). Forecasting Real GDP rate through Econometric Models: An Empirical Study from Greece. J of Internal Business and Economics, 3(1), pp: 13-19.

IV. Gujarati DN, Porter DC, Gunasekar S. Econometric Modeling: Specification and Diagnostic Testing. Basic Econometrics. 4th Edn. McGraw Hill International; 2003.

V. Hanke JE, Wichern DW. Business Forecasting. 8th Edn. Int J Forecast. 2005; 22(4), pp: 823–824.

VI. Imon AHMR. Box-Jenkins ARIMA Models: Introduction to Regression Time Series and Forecasting. NanitaProkash; 2017.

VII. Jovanovic, B. &Petrovska M. (2010). Forecasting Macedonian GDP: Evaluation of different models for short-term forecasting. Working Paper, National Bank of the Republic of Macedonia.

VIII. Ljung, G. M., & Box G. E. P. (1978). On a measure of a lack of fit in time series models. Biometrika, 75(2), pp: 335-346.

IX. Maity, B., &ChatterjeeB. (2012). Forecasting GDP growth rates of India: An empirical study. Int J of Economics and Management Sciences, 1(9), pp: 52-58.
X. Ning, W., Kuan-jiang, B. and Zhi-fa, Y. (2010). Analysis and forecast of Shaanxi GDP based on the ARIMA model, Asian Agricultural Research, Vol.2 No. 1, pp. 34-41.

XI. Shahini, L. & Haderi S. (2013). Short term Albanian GDP forecast: One quarter to one year ahead. European Scientific Journal, 9(34), pp: 198-208.

XII. Wei Ning, BianKuan-Jiang. & Yuan Zhi-fa (2010). Analysis and forecast of Shaanxi GDP based on the ARIMA model. Asian Agricultural Research, 2(1), pp: 34-41.

XIII. Zakai, M. (2014). A time series modeling on GDP of Pakistan. J of Contemporary Issues in Business Research, 3(4), pp: 200-210.

XIV. Zhang, H. (2013). Modeling and forecasting regional GDP in Sweden using autoregressive models. Working Paper, Högskolan Dalarna University, Sweden.