Forecasting GDP Growth Rates of Bangladesh: An Empirical Study

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Abstract

The Gross Domestic Product (GDP) is the market value of all goods and services produced within the boundary of a nation in a year. This paper aims to apply time series tools and forecast GDP growth in the Bangladesh economy. Forecasting of time series is an important topic in macroeconomics. We collected the data from World Development Indicators (WDI) and it has been collected over a period of 37 years by WDI, World Bank. Augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests were applied to investigate the stationary character of the data. Stata and R statistical software was used to build a class of Autoregressive Integrated Moving Average (ARIMA) and exponential smoothing methods to model the GDP growth. We applied several ARIMA (P, I, Q) models and employed the ARIMA (1,1,1) model as best for forecasting. This ARIMA (1,1,1) model was chosen based on the minimum values of the Akaike information criterion (AIC) and the Bayesian information criterion (BIC). Also, we applied the Exponential Smoothing to forecast the GDP growth rate. In addition, among the Exponential Smoothing models, the triple exponential model better analyzed the data based on lowest Sum of Square Error (SSE) and Root Mean Square Error (RMSE). Using these models, the values of future GDP growth rates are forecasted. Statistical results show that Bangladesh’s GDP growth rate is an increasing trend that will continue rising in the future. This finding will help policymakers and academicians to formulate economic and business strategies more precisely.

Keywords: Stationary time series, ARIMA, Time Series Forecasting, Exponential Smoothing, GDP growth rate, GDP growth in Bangladesh

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Introduction

GDP is the aggregate statistic of all economic activity; it captures the broadest coverage of the economy better than any other macroeconomic variables. It is the market value of all final goods and services produced within the borders of a nation in a year. GDP is often considered the best measure of how well the economy is performing. The issues of GDP growth have become the most concerning amongst modern macroeconomic variables. The growth is regarded as the most important index for assessing national economic development, economic health, and for judging the operating status of the macro economy (Ning et al. 2010). Since Adam Smith, economic growth has been an important topic in economic indicators and an important component of mainstream economics. The assessment of the current state of the economy is an important element in macroeconomic forecasting for a long-term analysis. Economic researchers are particularly interested in GDP forecasts for assessing and predicting the functional status of the economy of developing countries. Forecasting future economic outcomes is a vital component of the decision-making process for central banks, financial authorities, and economists for all countries. For the forecasting of time series, we used models that are based on a methodology that was first developed by Box and Jenkins (1976), known as ARIMA (Auto-Regressive-Integrated-Moving-Average) methodology. Box and Jenkins’ methodology has been used extensively by many researchers to highlight the future GDP growth. The market-based economy of Bangladesh is the 44th largest in the world in nominal terms. The steady increase of its economic growth means that Bangladesh, a less developed country, could be predicted to come out of its economic status quo. Given the new developments in Bangladesh’s GDP, economists are often inconclusive about how long the trend will continue.

Literature Review

A large variety of linear and nonlinear models are now available for modeling and forecasting macroeconomic time series data—see, for example, Terasvirta (2005), West (2005), Artis and Marcellino (2001), and White (2005) for recent overviews. Wei et al. (2010) applied data from China’s Shaanxi GDP from 1952 to 2007 to forecast the country’s GDP for the succeeding 6 years. Maity and Chatterjee (2012) scrutinized the forecasting of GDP growth for India applying an ARIMA (1,2,2) model. The results of their study displayed that predicted values follow a growing trend for the succeeding years. Zhao Ying used an ARIMA model with time series data of actual GDP from 1954 to 2004 in China to analyze and predict the national GDP growth pattern. Lu (2009) attempted to construct a time series model that was utilized to forecast the gross domestic product of China up to the first quarter of 2009. This paper was based on figures collected from secondary sources from the years 1962 to 2008, Lu got
ARIMA(4,1,0), which he applied for forecasting purposes. Zhang Haonan (2013) used three models: ARIMA, AR(1) and VAR, all of which examine the forecasting of per capita GDP of five regions in Sweden for the years 1993 to 2009. He showed that the performance of the AR(1) model is better than that of the ARIMA model. In Bangladesh, Bhuiyan, Ahmed, and Jahan (2008) developed a time series modeling and forecasting the GDP of manufacturing industries applying ARIMA model. Zakai (2014) discovers forecasting of GDP for Pakistan using quarterly data from 1953 to 2012. Choosing an ARIMA (1,1,0) model, Zakai can determine the size of the rise of Pakistan’s GDP for the years 2013 to 2025. Shahinia and Haderi (2013) test GDP forecasting for Albania using quarterly data from the first quarter of 2003 to the second quarter of 2013. For forecasting, they used two model groups: ARIMA and VAR. They found that the group of VAR models gives better results on GDP forecasting than the ARIMA model.

In summary, these studies were reported in the world, which in turn motivated me to carry out this research which analyzes the potential for GDP growth in Bangladesh.

Research Objectives

- To test the stationarity in the data of GDP growth over the period.
- To study autocorrelation in the observed time series of GDP growth.
- To forecast GDP growth using an appropriate ARIMA(P,I,Q) Model.
- To forecast GDP growth using Exponential Smoothing Methods.
- To test model fitness using Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and the goodness of fit models.

Model

To forecast GDP growth, a simple ARIMA model has been taken into consideration in this work. The ARIMA model was popularized by George Box and Gwilym Jenkins in the early 1970s. It is an iterative process that includes four stages: identification, estimation, diagnostic checking, and forecasting of time series. An ARIMA model can be expressed as

\[ Y_t = \alpha + \sum \phi_p Y_{t-p} + \sum \theta_q \epsilon_{t-q} \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots (1) \]

where, \( Y_t \) = GDP growth rate at period t, \( Y_{t-p} \) = GDP growth rate at period (t-p), \( \theta_q \) = Random shock at period q, \( \epsilon_{t-q} \) = Random error term at period t, and (\( \alpha, \phi_p, \theta_q \)) are parameters to be estimated.

Since 1976, this model has gained enormous popularity due to its versatility in many areas in business and economics. A standard notation is used of ARIMA(P,I,Q) where the parameters are substituted with integer values to quickly indicate the specific ARIMA model being used. The parameters of the ARIMA(P,I,Q) model are defined as follows:

- \( P \) equals the number of lag observations included in the model, also called the lag order.
- \( I \) equals the number of times that the raw observations are differenced, also called the degree of differencing.
- \( Q \) equals the order of moving average. After establishing ARIMA, the next step is model forecasting. Model forecasting positions the difference between in-sample forecasting and out-of-sample forecasting. Sample forecasting explains how the chosen model fits the data in each sample, while out of sample forecasting is concerned with determining how a fitted model forecasts future values of the regress and given values of the repressors.

To develop a reliable forecasting model, the following factors will be considered:

(i) Accuracy level
(ii) Data and information availability
(iii) The time horizon for forecasting

Data and Methods of Analysis

To forecast GDP growth, data on this macroeconomic variable was collected from 1991 to 2015 from the World Development Indicators (WDI), World Bank. It is a single set of data for modeling that was comprised of annual levels of GDP growth for Bangladesh. The data file consists of 37 observations. A graphical representation of data reveals that GDP series follows an increasing pattern over this period (Fig 1).
In Figure 1 above, the GDP growth series usually follows an upward trend. This implies that both the mean and the variance are not constant. It does not follow a stationary pattern. Hence, data has been differenced to convert them from non-stationary to stationary. Furthermore, Augmented Dickey-Fuller (1979) and Phillips-Perron (1988) test have been conducted on this differenced GDP series of 37 observations.

Table 1 Results of the ADF Test on GDP Growth (Level)

| Variable | Hypothesis                          | t-statistic | P*   |
|----------|-------------------------------------|-------------|------|
| GDP growth | GDP growth has a unit root         | -2.69       | 0.0753 |

*MacKinnon (1996) one-sided p-values.

Table 2 Results of the Phillips-Perron Test on GDP Growth (Level)

| Variable | Hypothesis               | t-statistic | P*    |
|----------|--------------------------|-------------|-------|
| GDP growth | GDP growth has a unit root | Z(rho)=-10.59 | 0.0723 |
| GDP growth | GDP growth has a unit root | Z(t)=-2.71   |       |

*MacKinnon (1996) one-sided p-values.

The results in Table 1 and Table 2 confirm that GDP series (of 37 observations) follow a nonstationary pattern, which in turn help to specify the Integrated (I) term in the ARIMA model.

Table 3 Results of the ADF test on GDP growth (First Difference)

| Variable | Hypothesis               | t-statistic | P*    |
|----------|--------------------------|-------------|-------|
| GDP growth | GDP growth has no unit root | -6.085***  | 0.000 |

*MacKinnon (1996) one-sided p-values.
| Variable      | Hypothesis                      | t-statistic      | P*   |
|---------------|---------------------------------|------------------|------|
| GDP growth    | GDP growth has no unit root     | Z(rho)=25.308*** | 0.000|
|               |                                 | Z(t)=-6.257***   |      |

*MacKinnon (1996) one-sided p-values.

The results in Table 3 and Table 4 show that real GDP is stationary in the first difference. Which is also highly significant at 1% significance levels.

Now the next steps are the specification of two more terms in the tentative ARIMA model: autoregressive (AR) and moving average (MA). In addition, a correlogram of the GDP series (37 observations), which deals with autocorrelation of GDP and its different lags with respective t-statistics, is shown in Figure 2.

![Correlogram of Growth, lags (12)](image)

Figure 2. Correlogram of Growth (Level data).

![Figure 3a and 3b. ACF and PACF of GDP growth (Level data)](image)

Figure 3 illustrates that there is a significant spike at ACF at lag 1, and after the first lag, the ACFs slowly decline. We can conclude, therefore, that time series is non-stationary. Again, from Figure 3, Partial Autocorrelation (PACF) of the difference series is estimated; we see that it has a significant spike at lag 1. So, we cannot reject the null hypothesis that the real GDP rate series is non-stationary. Since the ACF and PACF have spikes at lag 1, the differences can be used for this model.
Figure 4. First order differencing.

Figure 4 shows that after taking a difference of order 1 (period to period change), the time series seems to have been made stationary; there is no clear upward or downward trend. As a result, we can use this data for determining an ARIMA(P,I,Q) model.

Figure 5a and 5b. ACF and PACF after taking differences.

From Figure 5, it clearly shows that the ACF and PACF first difference series has no significant spikes at any lags. We can conclude that the time series is now stationary. ARIMA models with first differences, therefore, are recommended for the time series.

Figure 6a and 6b. The residuals of ACF and PACF after taking differences.

In Figure 6, the residuals of ACF and PACF show that the GDP growth series has no problem with residuals. There are no spikes which indicate a positive sign for using this model for forecasting.
In the Table 5 and 6, various ARMA and ARIMA models with several orders of autoregressive, moving average, and difference terms were compared based on their performance, checked, and verified by using statistics such as AIC and BIC. ARIMA (1, 1, 1) are good choices based on AIC, BIC, and significant level. The result

### Table 5. Several ARMA Models

|     | (1) (1,0,1) | (2) (0,0,1) | (3) (1,0,0) | (4) (2,0,0) | (5) (0,0,2) |
|-----|-------------|-------------|-------------|-------------|-------------|
| growth _cons | 5.252*** (2.57) | 5.130*** (17.22) | 5.128*** (7.17) | 5.160*** (4.92) | 5.122*** (14.26) |

|     | L.ar        | L2.ar       | L.ma        | L2.ma       |
|-----|-------------|-------------|-------------|-------------|
|     | 0.970*** (13.09) | 0.771*** (6.03) | 0.591*** (3.42) | 0.264 (1.56) |
|     | (-2.51) (4.59) |               | 0.645*** (4.08) |          |

| sigma _cons | 0.930*** (7.60) | 1.135*** (7.23) | 0.994*** (6.93) | 0.961*** (7.20) | 1.106*** (6.71) |

|     | N | AIC | BIC |
|-----|---|-----|-----|
|     | 37 | 109.3 | 115.7 |
|     | 37 | 120.8 | 125.6 |
|     | 37 | 111.4 | 116.3 |
|     | 37 | 111.3 | 117.7 |
|     | 37 | 120.8 | 127.3 |

**t statistics in parentheses**

* p<0.05, ** p<0.01, *** p<0.001

### Table 6. Several ARIMA Models

|     | (1) (1,1,1) | (2) (1,1,0) | (3) (2,1,0) | (4) (2,1,2) | (5) (2,1,1) |
|-----|-------------|-------------|-------------|-------------|-------------|
| Growth _cons | 0.109*** (6.60) | 0.150 (1.23) | 0.133 (1.44) | 0.108*** (6.73) | 0.108*** (5.37) |

| ARMA | L.ar | L2.ar | L.ma | L2.ma |
|------|------|-------|------|-------|
|      | 0.126*** (3.82) | -0.358* (-2.20) | -0.493** (-2.71) | -0.805*** (-3.84) | 0.134 (0.77) |
|      | (-2.00) (0.18) |               | 0.0361 (0.18) | -0.129 (-0.82) |          |
|      | -1.000 (0.08) | -0.0328 (0.05) | -1.000 (0.00) |          |
|      |               | -0.967* (-2.22) |          |

| sigma _cons | 0.774*** (7.30) | 0.954*** (8.87) | 0.905*** (7.34) | 0.756*** (4.59) | 0.765 (0.00) |

|     | N | AIC | BIC |
|-----|---|-----|-----|
|     | 36 | 93.09 | 97.84 |
|     | 36 | 104.9 | 109.7 |
|     | 36 | 103.4 | 109.7 |
|     | 36 | 95.99 | 103.9 |
|     | 36 | 96.55 | 104.5 |

**t statistics in parentheses**

* p<0.05, ** p<0.01, *** p<0.001
indicates that the proposed model, ARIMA (1, 1, 1), performed well in terms of in-sample and out-of-sample. Thus, the ARIMA (1,1,1) model is used in this paper for future forecasting. Therefore, other than within sample forecasts, this study also estimated 10 years out of sample forecasts of the model to measure the forecasts ability. Results indicate that Bangladeshi GDP growth will continue to rise. The 10-year forecast of Bangladeshi GDP growth rates are presented in Table 7.

Table 7 Comparative Trend of Growth Rate for the Next 10 Years Using ARIMA (1,1,1)

| Year | Projected Growth Rate | Lower limit | Upper Limit |
|------|-----------------------|-------------|-------------|
| 2019 | 8.14                  | 8.07        | 8.26        |
| 2020 | 8.26                  | 8.03        | 8.50        |
| 2021 | 8.38                  | 8.14        | 8.63        |
| 2022 | 8.54                  | 8.31        | 8.78        |
| 2023 | 8.69                  | 8.46        | 8.93        |
| 2024 | 8.84                  | 8.61        | 9.08        |
| 2025 | 8.99                  | 8.75        | 9.23        |
| 2026 | 9.14                  | 8.90        | 9.38        |
| 2027 | 9.29                  | 9.06        | 9.50        |
| 2028 | 9.44                  | 9.20        | 9.68        |

Table 7 consists of the forecasted growth for the next 10 years using the ARIMA(1,1,1) model. The third and fourth columns are lower and upper limits of the forecasted growth during the years 2019–2028. There is an expected smooth increase of GDP growth in Bangladesh.

Figure 7. GDP Growth forecasting.
Figures 7 and 8 attempt to forecast the real GDP growth rate in Bangladesh within the sample and next 10 years with an ARIMA model. In figure 8, we also included the upper and lower bound.

**Exponential Smoothing**

Here we also applied exponential smoothing as an alternative to the previous forecasting methods. Forecasts produced using exponential smoothing methods are weighted averages of past observations, with the weights decaying exponentially as the observations get older. In this paper, the three exponential smoothing methods are applied to smooth data. All methods provide long-term forecasts and dynamic estimation. The double and triple exponential smoothing provides several advantages and additional options.

The simple or single exponential smoothing method is suitable for forecasting data with no trend or seasonal pattern:

\[ S_t = \alpha X_t + (1-\alpha) S_{t-1} \]

Here \( \alpha \), a smoothing factor, is used to control the speed which the updated forecast will adapt to local levels (or mean) of the time series and \( 0 < \alpha < 1 \). When \( \alpha = 1 \), the simple exponential smoothing method is equivalent to the naive no change extrapolation method. Conversely, when \( \alpha = 0 \), the forecast will be a constant taking its value from the starting value for Level.

The Holt or double exponential smoothing method is the most popular. It was proposed by Holt with extending simple exponential smoothing to allow forecasting of data with a trend:

\[ F_t = \alpha X_t + (1-\alpha) (F_{t-1} + b_{t-1}) \]
\[ b_t = \gamma (F_t - F_{t-1}) + (1-\gamma)b_{t-1} \]
\[ F_{t+m} = F_t + b_t \]

Here \( \alpha \) and \( \gamma \), the starting values for level and trend, are required for double exponential method, and \( 0 < \alpha, \gamma < 1 \). However, if the same value is used for both \( \alpha \) and \( \gamma \), double exponential smoothing method is correspondent to Brown’s double exponential smoothing method. Furthermore, if \( \gamma = 0 \) and the starting value for trend is also set to zero, double exponential smoothing produces the same forecasts as the simple exponential smoothing method.

The triple or Holt-Winters seasonal method comprises the forecast equation and three smoothing equations—one for the level, one for trend and one for the seasonal component:

\[ S_t = \alpha \frac{Y_t}{I_{t-s}} + (1-\alpha) (S_{t-1} + b_{t-1}) \]
\[ b_t = \gamma (S_t - S_{t-1}) + (1-\gamma)b_{t-1} \]
\[ I_t = \beta \frac{Y_t}{I_{t-L}} + (1-\beta) I_{t-s} \]
\[ F_{t+m} = (S_t + b_t) I_{t-s+m} \]

The triple exponential smoothing method requires starting values for Level, Trend, and Seasonality, where \( \alpha, \beta \) and \( \gamma \) are the smoothing factors, and \( 0 < \alpha, \beta, \gamma < 1 \). Here \( \alpha \) = smoothing coefficient for level, \( \gamma \) =smoothing coefficient for trend, \( \beta \) = smoothing coefficient for seasonality. \( F_{t+m} \) =Smoothed forecast value for \( Y \).
Table 8. Forecast the GDP Growth in Bangladesh by Three Smoothing Methods (2019-2028)

| Year | Single Exponential Smoothing | Double Exponential Smoothing | Triple Exponential Smoothing |
|------|------------------------------|------------------------------|-----------------------------|
| 2019 | 7.42                         | 7.44                         | 7.64                        |
| 2020 | 8.03                         | 8.44                         | 8.33                        |
| 2021 | 8.26                         | 8.66                         | 8.56                        |
| 2022 | 8.38                         | 8.67                         | 8.33                        |
| 2023 | 8.54                         | 8.76                         | 8.77                        |
| 2024 | 8.69                         | 8.87                         | 8.90                        |
| 2025 | 8.84                         | 9.008                        | 9.04                        |
| 2026 | 8.99                         | 9.14                         | 9.18                        |
| 2027 | 9.14                         | 9.29                         | 9.32                        |
| 2028 | 9.29                         | 9.44                         | 9.46                        |

Table 8 presents 10 years of forecasted GDP growth rate using the fitted single, double, and triple exponential smoothing model. Different values of $\alpha$, $\beta$, $\gamma$ have been tried to obtain the most accurate fitted model. The optimality and accuracy of smoothing coefficients ($\alpha$, $\beta$, and $\gamma$) have been measured through Sum of Square Error (SSE) and Root Mean Square Error (RMSE), which minimizes residuals, is the best optimal solution. Graphs of the smoothed series are shown in Figures 8 through 10, which are closely fitted to actual values.

Figure 9. Forecasting by Single Exponential Smoothing method (2019-2028).

Figure 10. Forecasting by Double Exponential Smoothing method (2019-2028).
In Figures 9 through 11, there are three different forms of exponential smoothing, known as single, double (Holt), and triple (Holt-Winters’ seasonal exponential smoothing). The first one finds a smooth approximation; the second extracts a linear trend, and the third one considers seasonality (regularly recurring). All graphs show an increasing trend.

Table 9. Error Comparison in Three Different Exponential Smoothing Models

| % error | Single Exp Smoothing | Double Exp Smoothing | Triple Exp Smoothing |
|---------|----------------------|---------------------|---------------------|
| SSE     | 14.53                | 13.11               | 7.6374              |
| RMSE    | .762                 | .724                | .552                |

In Table 9, the triple exponential smoothing yields the lowest value of the Sum of Square Error (SSE) and Root Mean Square Error (RMSE) for the next 10 years. So, it can be concluded that the triple exponential model fits the data better than both double and single exponential model. To estimate optimal values of smoothing constants, forecasts are computed with several values of $\alpha$, $\beta$, and $\gamma$, with increments. Three forecasting accuracy techniques, such as SSE and RMSE, are used to select the most accurate forecast for the next 10 years. This is because GDP growth data contains both trend and seasonal components which are only fully considered in a triple exponential model. Among models with very different error statistics, we can choose whether we would prefer a little more responsiveness or a little more smoothness in the forecasts. Empirical evidence suggests that, if the data have already been adjusted for growth, then it may be imprudent to choose triple or Holt-Winters exponential smoothing for forecasting.

Conclusion

Forecasting macroeconomic variables provide a clear picture of what the state of the economy will be in the future. Having the relevant models to forecast these macroeconomic variables is significant for policymakers and the government in allocating resources efficiently in order to formulate better policies. This study compares the forecasting ability of the ARIMA model and the Exponential Smoothing methods. This paper forecasts increasing growth in Bangladesh’s GDP beginning in 2019. First, an ARIMA model has been estimated to forecast GDP growth rate for 10 years ahead by utilizing time series data during the period from 1982 to 2018. ARIMA (1,1,1) model is best fitted based on the Akaike information criterion (AIC) and Bayesian information criterion (BIC). Next, this process applied Exponential Smoothing methods. From Table 9, it can be concluded that the triple exponential model fits the data better than both the single and double exponential models because of the lowest Sum of Square Error (SSE) and Root Mean Square Error (RMSE). According to the forecasted values, Bangladeshi GDP growth shows a higher growth trend in the next 10 years. However, the forecasting result of this model is only a series of predicted values; the national economy of Bangladesh is a dynamic and complex system. As a developing country, Bangladesh has faced a lot of development interruptions, unexpected shocks, and other economic disturbances. Additionally, natural hazards can also cause a relative change of macroeconomic indicators. Therefore, the country should pay attention to the risk of adjustment and maintain the stability and continuity of economic growth by protecting the economy from severe shocks. Hopefully, the findings of this study have some important implications for policy makers, managers and researchers. Also, this study will encourage them to conduct further studies about forecasting GDP growth in Bangladesh. The findings will be better if future researchers will take consideration of the other models such as the State Space model, Markov...
Switching model, Vector Autoregressive(VAR) model, and Vector Error Correction Model (VECM). However, it would be interesting to expand this research by including factors that may have an influence on GDP growth such as the growth rates of the population, the human capital, the development of technology, the industrial growth rate, political stability, oil price, net exports, and the immigration rate.

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