M. N. A. Bhuiyan[1*], Kazi Saleh Ahmed[2] and Roushan Jahan[1]

Study on Modeling and Forecasting of the GDP of Manufacturing Industries in Bangladesh

[1]Department of Mechanical Engineering, Tokyo Metropolitan University, 1-1, Minami-Osawa, Hachioji-shi, Tokyo 192-0397, Japan.
[2]Department of Statistics, Jahangirnagar University, Savar, Dhaka-1342, Bangladesh.
**Corresponding author. E-mail: alam78bh@ed.tmu.ac.jp*

CMU. Journal of Soc. Sci. and Human. (2008) Vol. 2(2)

ABSTRACT

Forecasting of the GDP of manufacturing industries plays a major role in optimal decision formulae for government and industrial sector in Bangladesh. This study aimed to divulge the contribution of this sector to the overall GDP for the next thirteen years, beginning from 2002-03, by using an appropriate model. To develop the appropriate model, time series data have been used. Since forecasting is one main objective of building the time series model, therefore at present, time series data are widely and frequently applied in the area of empirical research. Autoregressive Integrated Moving Average (ARIMA) or Box-Jenkins methodology is most popular for forecasting stationary time series data. To make forecast, firstly, we test the stationarity of the data, secondly, develop an appro-priate ARIMA model and finally, make forecast based on the selected model. Based on Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF) and resulting correlogram, the data are seen to be nonstationary. To make the data stationary, we have to take second difference. Primarily, nine ARIMA models are considered for GDP of Manufacturing Industries. After that we select three ARIMA models, i.e., ARIMA (220), ARIMA (221) and ARIMA (222) on the basis of smallest Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). Finally, ARIMA (221) is selected from these pre-selected models for GDP of Manufacturing Industries, based on the smallest values of Standard Error (SE (σ)), Absolute Mean Error (AME), Root Mean Square Error (RMSE) and Mean Absolute Percent Error (MAPE) and forecasting is made by using this model. In this paper, we divide the total period into two parts: i) Estimation period and ii) Forecast period. In the estimation period, we see that our estimated value fits the data very well and then we make forecast for the mentioned years. The forecast value of the manufacturing industries GDP shows a sustainable upward trend.

Key words: Forecasting, ARIMA, Stationary, ACF, PACF, AIC, BIC, SE (σ), AME, RMSE, MAPE.

INTRODUCTION

Manufacturing sector is one of the important activity sectors of a country. In case of Bangladesh, the contribution of this sector to national production and growth is not at a considerable level. The share of manufacturing industry in overall GDP in Bangladesh ranged from 9.4% in FY 1997-1998 to 15.62% in FY 2001-2002. The sectoral growth of GDP of manufacturing is 5% in 2001-2002. No strong courses of action have yet been taken to improve this sector. It is necessary to make forecast of the GDP of this sector for the future period so that the government and policy makers can set up their plans to get better output. Some of the cited literatures related to forecasting are discussed below:

Paul (1998) worked with "Modeling and Forecasting of Energy Consumption in Bangladesh". He applied Box-Jenkins (BJ) methodology or ARIMA methodology in his study and found that the data were nonstationary. After making the data stationary, he selected three ARIMA models on the basis of smallest AIC and BIC and finally selected the best ARIMA model based on minimum values of AME, RMSE, SE(σ) and MAPE and made forecast by this model. He made forecast by dividing the total period into three parts, namely, estimation period, validation period and forecast period. Helal Uddin (1998) showed the economic and environmental trend from 1996 to 2003 by using the time series from 1975 to 1995. He examined the stationarity of time series data and found that they were nonstationary. The data were made stationary by transforming them and constructed ARIMA model and forecasting was performed based on the model. Pindyck and Rubinfeld (1976) discussed about the properties of stationary and nonstationary time series, the calculation and the use of autocorrelation function and developed the methods by which time series models were specified, estimated and used for forecasting. They also showed how some non-stationary time series models could be differenced once or many times to produce a stationary series that enabled to develop a general integrated auto regressive moving average (ARIMA) model. By using the data from 1960 to 1967, they forecast the U.S hog production over a two-year horizon, using ARIMA model. Darmodar N. Gujrati (1995) examined the US GDP time series for the quarterly periods of 1970 to 1991. He found that US GDP was nonstationary on the basis of ACF and PACF. After making the first difference, it was stationary. He also applied four-step Box-Jenkins (BJ) or ARIMA methodology: identification, estimation, diagnostic checking and forecasting to the US GDP data. Using the above-mentioned data, forecasting was made for the first quarter of 1992. Hurvich and Tsai (1989) realized the problem of autoregressive model selection procedure and proposed one of the leading selection methods, AIC (Akaike, 1973). The minimum AIC criterion produces a selected model which is, hopefully, close to the best possible choice. George et al. (1988) discussed about the three stages: i) identification ii) estimation and iii) diagnostic checking of Box-Jenkins approach to find an ARIMA model for a given set of time series data which adequately represented the data-generating process. For each stage, they illustrated the single steps by analyzing the yearly price of corn in the United States from 1867 to 1948 and then made point forecast on the basis of the selected model. Granger et al. (1995) suggested that model selection procedures were better to use rather than formal hypothesis testing at the time of deciding on model specification. They also examined how well the model could be selected depending upon the minimum values of Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC). Box and Jenkins (1970) described extensively about an iterative model-building methodology. They explained the process of model identification, model estimation and model diagnostic checking for ARIMA model. They also discussed the properties of ARIMA models and showed how the models were used to forecast the future values of an observed time series. In the present study, twenty-three years GDP data of manufacturing industries have been used. The data are collected from Bangladesh Bureau of Statistics (BBS).

MODEL DISCUSSION

In time series analysis, ARIMA models are flexible and widely used. The time series model can provide short-run forecast for sufficiently large amount of data on the concerned variables very precisely. The abbreviation ARIMA (p, d, q) stands for Autoregressive-Integrated-Moving-Average with three parameters, p, the order of autoregression, d, the degree of differencing and q, the order of moving average. The ARIMA model, commonly known as Box-Jenkins model, is due to Box and Jenkins' work for forecasting of a large variety of time series data. The underlying assumption is that the time series to be forecast has been generated by a stochastic process.

ARIMA model is the combination of three processes such as (1) Auto-regressive (AR) process, (2) Differencing process, and (3) Moving Average (MA) process. These three processes are based on random disturbances that arise in the observation of empirical time series.

Auto-regressive Process

The auto-regressive process is defined as a linear combination of current value with its preceding value(s). The first order auto-regressive process AR (1) defines the current value as linear function of single preceding value. Similarly, the pth order auto-regressive process defines the current value as a linear combination of p preceding values. The autoregressive process is commonly denoted by AR (p), where the number in the parenthesis stands for order. Thus, the pth order auto-regressive process of a random variable yt can be represented as follows:

$$y_t= \mu +\alpha_1 y_{t-1}+\alpha_2 y_{t-2}+\alpha_3 y_{t-3}+\ldots\ldots\ldots\ldots\ldots+\alpha_p y_{t-p}+e_t$$

Where μ is the intercept parameter that is related to the mean of the variable, α's known auto-regressive parameters, and the errors et are assumed to be un-correlated random variables with zero mean, and common variance σ^2.

Differencing Process

Differencing process is an aid to identify the stationarity level of a time series. Level of stationarity is required for forecasting future value, because forecasting is valid only when underlying time series is stationary. If a time series differenced once to make it stationary, then the original series is said to be Integrated of order 1 and is represented by I (1). Similarly, if the original series differenced twice to make it stationary, the original series is said to be Integrated of order 2, and is represented by I (2). In general, if the time series differenced d times, it is Integrated of order d and represented by I (d). By convention, if d=0, the resulting process represents a stationary time series of order zero and is represented by I (0).

Moving Average Process

The third of the three processes of ARIMA modeling techniques is the moving average process. The error-generating process that includes the average of two adjacent random variables is known as moving average (MA) process of order one. Similarly, the error generating process that includes average of three adjacent random variables is known as the moving average process of second order. In general, if the error generating process includes the average of q+1 adjacent random variables, the process is known as moving average (MA) process of q^{th} order. Thus, the general q^{th} order moving average process, denoted by MA (q) of a random variable, can be represented as;

$$y_t = \mu + e_t - \beta_1 e_{t-1} - \beta_2 e_{t-2} - \beta_3 e_{t-3} - \ldots\ldots\ldots\ldots\ldots\ldots - \beta_q e_{t-q}$$

Where μ is the intercept parameter that is related to the mean of the variable, β's are unknown parameters, and the errors et are assumed to be un-correlated random disturbances with zero mean, and common variance σ^2.

Notation of Autoregressive Integrated Moving Average Model

The general compact form of ARIMA (p, d, q) process can be represented as follows: If the original series y_t after appropriate times (say d) of differencing yields a series x_t, then $z_t = (1-L)^d y_t$

Where L is the back shift operator, $Ly_t = y_{t-1.}$ For d=1, $z_t = (1-L) y_t = y_t - y_{t-1} = \Delta y_t$

For d=2, $z_t = \Delta y_t - \Delta y_{t-1}$. The differencing operations used to produce a co-variance stationary time series z_t. If yt contains a polynomial trend of order d, then the trend can be removed by the differencing operation $(1-L)^d$. If z_t satisfies an ARMA (p, q) process, then $a(L)\ z_t = b(L)\ e_t$

where a(L) and b(L) are polynomials in the back shift operator L. The original series yt satisfying an ARIMA (p,d,q) process can be expressed as $a(L)\ (1-L)^d\ y_t = b(L)\ e_t$

In this study, the above format of the equation is used to estimate the underlying parameters. If any constant term occurs in the estimated equation, it is to be placed in the right-hand side as an additional term.

Box- Jenkins Approach

The BJ methodology consists of four steps, such as (1) identification (2) estimation (3) diagnostic checking and (4) forecasting. These stages of BJ procedure are summarized schematically in the following chart.

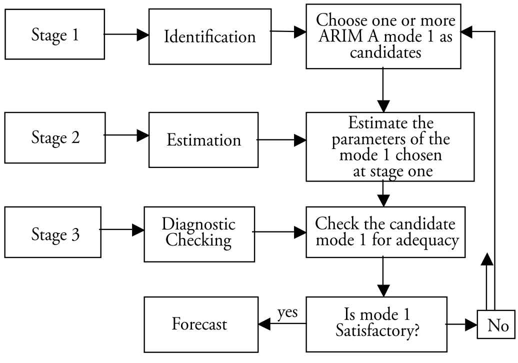

Figure 1. Stages in the Box-Jenkins approach.

RESULTS AND DISCUSSION

In this section, we first test the stationarity of the data on the basis of ACF, PACF and correlogram and found that the series is nonstationary. To make the data stationary, we have to take second difference of the data. Temporarily, nine ARIMA models are taken into consideration, namely, ARIMA (020), ARIMA (021), ARIMA (022), ARIMA (120), ARIMA (121), ARIMA (122), ARIMA (220), ARIMA (221) and ARIMA (222). From these, three models are then considered on the basis of smallest AIC and BIC. Estimation of the three models is performed and one model is finally selected according to the smallest AIC, BIC, SE (σ), AME, RMSE and MAPE and forecasting is made based on it. The analysis is performed by using the computer software packages EXCEL and SPSS.

Results of the Box-Jenkins methodology

Identification

The chief tools in identification are the Autocorrelation function (ACF), the partial autocorrelation function (PACF), and the resulting correlograms, which are simple plots of ACFs and PACFs against the lag length and also the graphs of ACFs and PACFs are shown below: [GDP of Manufacturing Industries = MGDP]

```
      Auto-  Stand.
 Lag  Corr.   Err.  -1 -.75  -.5 -.25   0   .25  .5   .75   1  Box-Ljung  Prob.
                    +----+----+----+----+----+----+----+----+
   1   .874   .196              .       I*******.*********        19.946   .000
   2   .738   .191              .       I*******.*******          34.842   .000
   3   .613   .187               .      I******.*****             45.628   .000
   4   .484   .182               .      I******.***               52.712   .000
   5   .354   .177               .      I*******                  56.708   .000
   6   .235   .172               .      I***** .                  58.577   .000
   7   .120   .167               .      I**    .                  59.092   .000
   8   .014   .162                .     *     .                   59.100   .000
   9  -.081   .156                .   **I     .                   59.368   .000
  10  -.166   .150                .  ***I     .                   60.592   .000
  11  -.237   .144                .*****I     .                   63.280   .000
  12  -.296   .138                ******I     .                   67.863   .000
  13  -.343   .132               **.****I    .                    74.612   .000
  14  -.372   .125               **.****I    .                    83.431   .000
  15  -.392   .118              ***.****I    .                    94.447   .000
  16  -.400   .110              ****.***I   .                    107.612   .000

Plot Symbols:      Autocorrelations *      Two Standard Error Limits.
Total cases:  23     Computable first lags:  22
```

Figure 2. Autocorrelations: MGDP from 1979-80 to 2001-02.

```
   Pr-Aut-  Stand.
Lag  Corr.    Err.  -1   -.75   -.5  -.25    0    .25  .5    .75   1
                      +----+----+----+----+----+----+----+----+
  1   . 874   .209              .         I*** ****.** ****** *
  2   -.108   .209              .      * *I         .
  3   -.030   .209              .        *I         .
  4   -.096   .209              .      * *I         .
  5   -.090   .209              .      * *I         .
  6   -.047   .209              .        *I         .
  7   -.086   .209              .      * *I         .
  8   -.060   .209              .        *I         .
  9   -.059   .209              .        *I         .
 10   -.070   .209              .        *I         .
 11   -.042   .209              .        *I         .
 12   -.062   .209              .        *I         .
 13   -.049   .209              .        *I         .
 14   -.028   .209              .        *I         .
 15   -.059   .209              .        *I         .
 16   -.040   .209              .        *I         .

Plot Symbols:        Autocorrelations *        Two Standard Error Limits.
Total cases:   23      Computable first lags:   22
```

Figure 3. Partial Autocorrelations: MGDP from 1979-80 to 2001-02.

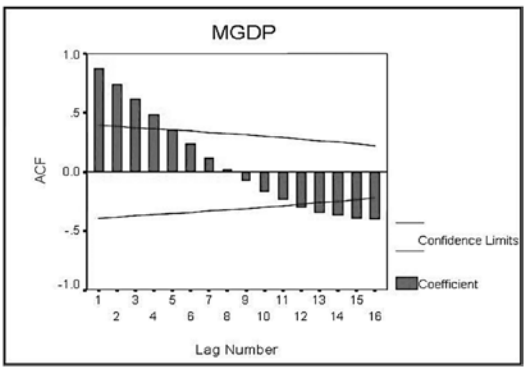

Figure 4. ACF of MGDP.

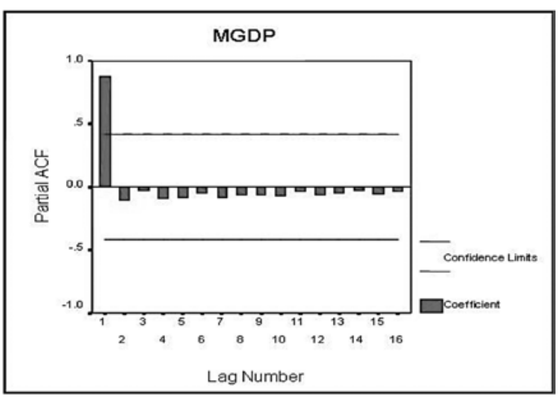

Figure 5. PACF of MGDP.

Transformations: difference (1)

```
       Auto- Stand.
  Lag  Corr.  Err.   -1   -.75 -.5  -.25 0    .25  .5   .75  1      Box-Ljung  Prob.
                     +----+----+----+----+----+----+----+----+
    1   .379   .199              .       I********                      3.621   .057
    2   .261   .195              .       I*****  .                      5.421   .067
    3   .488   .190              .       I*******.**                   12.030   .007
    4   .107   .185               .      I**    .                      12.366   .015
    5   .164   .179               .      I***   .                      13.201   .022
    6   .225   .174               .      I***** .                      14.877   .021
    7   .037   .169               .      I*     .                      14.925   .037
    8   .036   .163               .      I*     .                      14.974   .060
    9  -.144   .157                .  ***I     .                       15.821   .071
   10  -.229   .151                .*****I     .                       18.119   .053
   11  -.131   .144                .  ***I     .                       18.945   .062
   12  -.349   .138               *.*****I     .                       25.363   .013
   13  -.381   .131              ***.****I    .                        33.865   .001
   14  -.130   .123                 . ***I    .                        34.975   .001
   15  -.171   .115                 . ***I    .                        37.190   .001
   16  -.184   .107                  ****I   .                         40.159   .001

  Plot Symbols:      Autocorrelations *     Two Standard Error Limits.
  Total cases:   23    Computable first lags after differencing:   21
```

Figure 6. Autocorrelations: First difference of MGDP.

Transformations: difference (1)

```
  Pr-Aut- Stand.
  Lag  Corr.  Err.   -1   -.75 -.5  -.25 0    .25  .5   .75  1
                     +----+----+----+----+----+----+----+----+
    1   .379   .213             .       I********.
    2   .137   .213             .       I***       .
    3   .417   .213             .       I********.
    4  -.264   .213             .  *****I          .
    5   .148   .213             .       I***       .
    6  -.073   .213             .      *I          .
    7   .063   .213             .       I*         .
    8  -.152   .213             .    ***I          .
    9  -.270   .213             .  *****I          .
   10  -.134   .213             .    ***I          .
   11   .007   .213             .       *          .
   12  -.212   .213             .   ****I          .
   13  -.172   .213             .    ***I          .
   14   .164   .213             .       I***       .
   15   .244   .213             .       I*****    .
   16   .093   .213             .       I**        .

  Plot Symbols:      Autocorrelations *     Two Standard Error Limits.

  Total cases:   23    Computable first lags after differencing:   21
```

Figure 7. Partial Autocorrelations: First difference of MGDP.

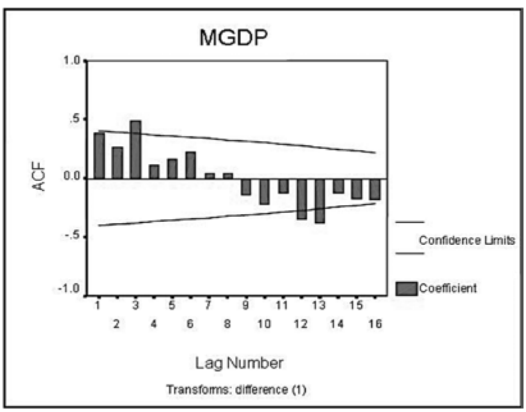

Figure 8. ACF for the first difference of MGDP.

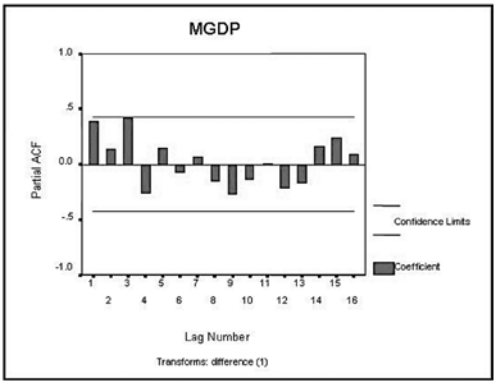

Figure 9. PACF for the first difference of MGDP.

Transformations: difference (2).

```
      Auto-  Stand.
 Lag  Corr.   Err. -1   -.75  -.5 -.25   0   .25  .5   .75   1  Box-Ljung  Prob.
                    +----+----+----+----+----+----+----+----+
   1  -.410   .203           ****** **I        .                    4.058   .044
   2  -.306   .198           . **** **I        .                    6.437   .040
   3   .537   .193           .        I*** ****.** *               14.186   .003
   4  -.365   .188           .***** **I        .                   17.964   .001
   5  -.008   .182            .       *      .                     17.966   .003
   6   .223   .176            .       I*** *  .                    19.562   .003
   7  -.204   .170            .  ** **I       .                    21.002   .004
   8   .154   .164            .       I***    .                    21.888   .005
   9  -.040   .158             .     *I      .                     21.954   .009
  10  -.167   .151             .   ***I      .                     23.173   .010
  11   .274   .144             .      I*** **.                     26.810   .005
  12  -.135   .137              . * **I     .                      27.791   .006
  13  -.248   .129              *** **I     .                      31.512   .003
  14   .281   .120              .     I*** *.*                     36.962   .001
  15  -.049   .111               .   *I    .                       37.154   .001
  16  -.102   .102               .  **I    .                       38.153   .001

 Plot Symbols:      Autocorrelations *      Two Standard Error Limits.

 Total cases:  23     Computable first lags after differencing:  20
```

Figure 10. Autocorrelations: Second difference of MGDP.

Transformations: difference (2).

```
   Pr-Aut-  Stand.
 Lag  Corr.   Err. -1   -.75  -.5 -.25   0   .25  .5   .75   1
                    +----+----+----+----+----+----+----+----+
   1  -.410   .218             .****** **I         .
   2  -.570   .218           **. ****** **I         .
   3   .190   .218             .          I*** *    .
   4  -.251   .218             .     *** **I        .
   5   .057   .218             .          I*        .
   6  -.156   .218             .       * **I        .
   7   .059   .218             .          I*        .
   8   .111   .218             .          I**       .
   9  -.005   .218             .          *         .
  10  -.117   .218             .        **I         .
  11   .104   .218             .          I**       .
  12   .005   .218             .          *         .
  13  -.275   .218             .    **** **I        .
  14  -.206   .218             .      ** **I        .
  15  -.082   .218             .        **I         .
  16   .107   .218             .          I**       .

 Plot Symbols:      Autocorrelations *      Two Standard Error Limits.

 Total cases:  23     Computable first lags after differencing:  20
```

Figure 11. Partial Autocorrelations: Second difference of MGDP.

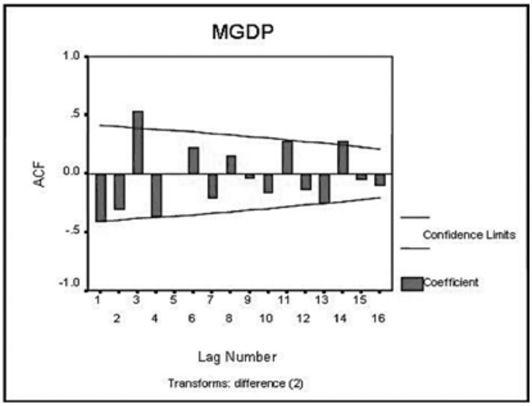

Figure 12. ACF for the second difference of MGDP.

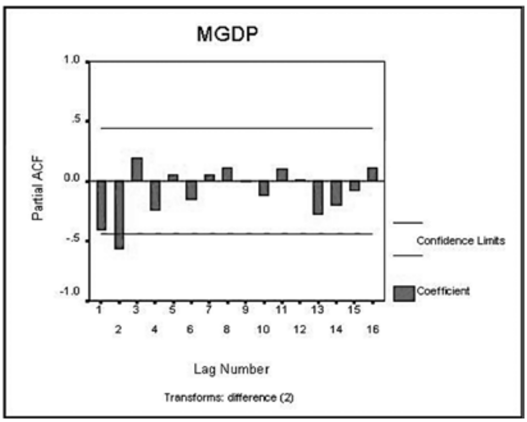

Figure 13. PACF for the second difference of MGDP.

Figures 2, 3, 4 and 5 show the correlogram and partial correlogram and the graph of ACF and PACF of the MGDP series. From these figures, two facts stand out: First, the ACF declines very slowly; as shown in figure 2, ACF up to 4 lags out of 16 lags are individually significantly different from zero, for they all are outside the 95% confidence bounds. Second, after the first lag, the PACF drops dramatically, and all PACFs after lag 1 are statistically insignificant. Also, the graph of ACF and PACF shows that the MGDP data do not satisfy the condition of stationarity that are represented in Figure 4 and Figure 5. So the data of Manufacturing GDP is non-stationary. To make the data stationary, we have done some transformation. We did first difference of the data to achieve stationarity. Figures 6, 7, 8 and 9 show the correlogram and partial correlogram and the graph of ACF and PACF of first difference of the data. From these figures, we conclude that the first difference of the data is not stationary.

To apply Box –Jenkins methodology, the data must be stationary. For this reason, second difference of the data is made to make it stationary. Figures 10, 11, 12 and 13 show the correlogram and partial correlogram and the graph of ACF and PACF of second difference. This figure shows that the second difference of the MGDP data is stationary. Here, we select primarily nine ARIMA models which have been previously mentioned.

Estimation of the Models

Here, the selected models are estimated and also computed for the values of AIC and BIC. According to the smallest values of AIC and BIC, three ARIMA models are secondarily selected and it is done with the help of computer package. The estimates of the selected models are:

ARIMA (220),

$$(1 +.83423L +.77187L^2)(1-L)^2\, y_t = 692.59169+e_t$$

ARIMA (221),

$$(1 + 1.07277L +.90998L^2)(1-L)^2\, y_t = 675.91176 + (1+.96916L)e_t$$

ARIMA (222),

$$(1+.\ 96992L +.82507L^2)(1-L)^2\, y_t = 678.11929 + (1+.53955L -.36395L2)e_t$$

Diagnostic Checking

From the above estimated models we select one of them on the basis of some important criteria that can be shown in table 1.

Table 1. Values of Diagnostic Criterion for Selecting ARIMA model for MGDP in Bangladesh.

Criterions	Models		
	ARIMA (220)	**ARIMA (221)**	**ARIMA (222)**
AIC	420.97055	413.9485*	417.85921
BIC	424.377	418.4905*	423.5367
SE(σ)	4858.6704	3673.3771*	4103.1153
AME	3450.875	2715.183*	2916.377
RMSE	4658.559	3720.971*	4046.411
MAPE	1.861719	1.499018*	1.613658

(The values of the criterion for a model with starlet show that the model is better than other two models).

The above table represents that ARIMA (221) shows the minimum values of all criteria comparing to the other two models. So we conclude that ARIMA (221) should be selected to be the best model for forecasting.

Forecasting

In the final stage of Box -Jenkins method, we make forecast of the GDP of manufacturing industries in Bangladesh by using the ARIMA (221) model that is shown in table 2.

Table 2. Forecast MGDP (in mill.Taka) in Bangladesh from 2002-03 to 2014-2015 by using ARIMA (221) model.

Year	MGDP (Observed)	ARIMA(221)
Estimation Period		
1979-1980	96311	NA
1980-1981	100523	NA
1981-1982	101783	105410.9118
1982-1983	105272	105501.8561
1983-1984	114664	111031.495
1984-1985	121030	119702.4995
1985-1986	129882	128200.4182
1986-1987	140210	142117.8315
1987-1988	141118	147168.8477
1988-1989	145029	147736.637
1989-1990	156163	153979.3135
1990-1991	166133	160744.8572
1991-1992	178391	177584.8048
1992-1993	193771	191994.7766
1993-1994	209554	207348.0849
1994-1995	231517	226097.4368
1995-1996	246351	253488.527
1996-1997	258795	258619.0902
1997-1998	280908	282469.8013
1998-1999	289882	295381.2524
1999-2000	303679	301016.5061
2000-2001	331308	328776.4116
2001-2002	340176	344111.2413

Forecast Period	
2002-2003	354882.3068
2003-2004	382413.67
2004-2005	392890.0676
2005-2006	412008.0066
2006-2007	439391.3274
2007-2008	452060.2655
2008-2009	475009.0553
2009-2010	502335.8189
2010-2011	517627.6547
2011-2012	543862.3727
2012-2013	571325.5379
2013-2014	589529.1397
2014-2015	618564.3088

*1 US$= TK. 67

The forecast value of the GDP of manufacturing industries (MGDP) can be shown in the Figure 14.

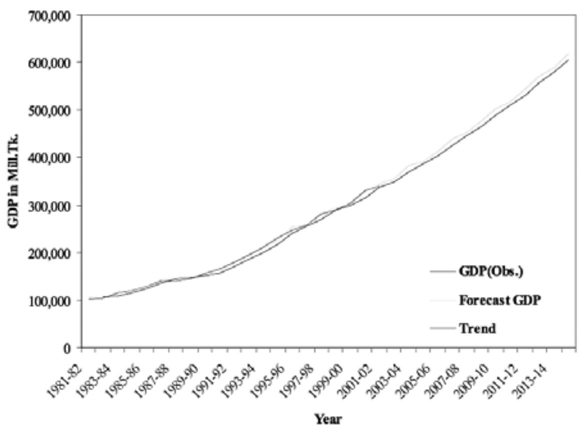

Figure 14: Forecast GDP in Mill. Tk. of Manaufacturing Industries in Bangladesh from 2002-03 to 2014-15 by using ARIMA (221) model.

In the above figure, MGDP is plotted against their respective years. Here, we showed the previous trend and future trend together. The MGDP shows an upward trend. From the above graph, we see that the past value (data) fits very well, i.e., the estimated line represents the data approximately very closely. From the year 1990-1991, the MGDP shows a linear trend.

CONCLUSION

Manufacturing industries are one of the most important economic sectors of a country. In Bangladesh, manufacturing industries are passing through a tough time. The miserable condition started from during the time of liberation (1971) because most of the industries were out of order at that time. Besides this, political instability is one of the reasons for least development in this sector. Also, due to lower infrastructural development, the local and foreign investors are losing inspiration to invest in this sector. As a result, the development of manufacturing is running at a slow motion. Day by day, the political situation is improving and that's why the GDP of this sector also shows increasing trend. The result of this paper showed the future picture of manufacturing industries for thirteen years, beginning from 2002-2003. We here would like to quote from the following lines of the Poverty Reduction Strategy Paper (PRSP), the strategy paper for poverty reduction in Bangladesh, "for sustained growth and poverty reduction, the government would pursue a globally-competitive industrialization strategy, dictated by the dynamic comparative advantage of the country. This means an employment-intensive industrialization with emphasis on Small and Medium Enterprises (SMEs) and export-oriented industries". So it stressed the need of more-strengthened small and medium industrial sector to achieve sustainable economic growth and poverty reduction. Before that, we need concrete evidence of the performance of this sector at disaggregated level. This paper discloses the performance of manufacturing sector from 1979-1980 to 2001-2002 and also shows us the future movement. To formulate future development plan for this sector, it is essential to know the previous condition and also see the future trend. In this study, forecasting is done by using some sophisticated statistical tools so that the government and policy makers can easily realize about the future contribution of the GDP of manufacturing industries to the overall GDP and could take initiatives to how to improve this sector.

REFERENCES

BBS, Statistical Year Book of Bangladesh, 1980 to 2000, Bangladesh Bureau of Statistics (BBS)

BBS, National Accounts Statistics of Bangladesh, (Revised Estimates, 1989-90 to 1998-99).

BBS, National Accounts Statistics (Gross Domestic Product, 2000-2001).

BBS, National Accounts Statistics (Preliminary Estimates of GDP, 2001-2002).

Box, G.E.P, and Jenkins G.M.1970. TIME SERIES ANALYSIS forecasting and control. First printing, Holden-Day, Inc., San Francisco, California.

George, G. Judge, R.Carter Hill, William E.Griffiths, Helmut Lutkepohl, and Tsoung-Chaolee. 1988. Introduction to the theory and practice of econometrics. Second Edition, John Wiley & Sons.

Granger, C.W.J., M.L. King, and H. White.1995. Comments on testing economic theories and the use of model selection criteria. Journal of Econometrics, Vol. 67,173-187.

Gujarati, Damodar N.1995. Basic econometrics. Third edition, McGraw-Hill, Inc.

Helal Uddin Ahmed. 1998. Analysis of some selected economic and environmental time series of Bangladesh. PhD Thesis, Department of Statistics, Jahangirnagar University, Dhaka, Bangladesh

Hurvich, Clifford M., and Chih-Ling Tsai.1989. Regression and time series model selection in small samples. Biometrika, Vol. 76, No. 2, 297-307.

Paul, J.C.1998. Modeling and forecasting the energy consumption in Bangladesh. PhD. Thesis, Department of Mathematics, University of North Bengal, West Bengal, India.

Pindyck, R.S., and D.L.R. Rubinfeld. 1976. Econometric models and economic forecasts. McGraw-Hill, New York, Second Edition.

CMU. Journal of Soc. Sci. and Human. (2008) Vol. 2(2)

none