Forecasting Bangladesh Industrial Production: A Simple Univariate ARMA Approach*

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1. INTRODUCTION

Bangladesh, a predominantly agrarian society, is striving hard to industrialize the economy by mobilizing resource from within and outside its geographic boundary. The recent years have seen significant improvement in the relative share of industry in the national economy. Relative shares of industry in Gross Domestic Product were 16.3 20.9 and 25.5 percents in the years of 1980, 1990 and 2002 respectively (ADB, 2003). Industrial growth has also been more or less steady despite the ongoing recession in the world economy. The average growth rate of industrial output was 6.56 percent during 1997 to 2001 (ADB,2003). Hence, forecasting industrial output is an important issue in analyzing the economic performance of Bangladesh which is showing a steady improvement in the relative share of industrial output in GDP. In fact, this is equally important for developed industrialized economies as well as for the LDCs. Actually, industrial sector is important in explaining aggregate fluctuation of the economy. In addition, forecasts of industrial output can be useful in more general forecasting models.

As far as Bangladesh economy is concerned, to the knowledge of the authors, no satisfactory forecasting model for industrial output in Bangladesh has yet been developed. At least one attempt however, is made to explain the behavior of the industrial output on sector basis (Dutta, 1993), which does not attempt to forecast the future behavior explicitly and also not substantiated by sophisticated econometric analysis. A number of attempts are made for other countries viz. for Italy (Bruno & Lupi, 2003), for the UK (Simpson et el, 2000) etc that use mainly univariate models and provide satisfactory forecast results. In this light, this paper is an attempt to develop a univariate forecasting model for Industrial output in Bangladesh. Such a univariate model provides a more sophisticated method of extrapolating time series in that they are based on the notion that the series that is to be forecasted has been generated by a stochastic process, with a structure that can be characterized and described. As we know, a time-series model provides a description of the random nature of the process that generates the sample of observations under study, which is given not in terms of a cause and effect relationship (as would be the case in a regression model) but in terms of how that randomness is embodied in the process. Hence, our objective is to develop a model that explains the movement of time series data of industrial output in Bangladesh by relating it to its past values and to a weighted sum of current and lagged random disturbances.

The structure of the rest of the paper is as follows: the Methodology Section explains general ARMA modeling as well as the procedures used to derive the particular specifications adopted. The following section tests the stationarity of the data series employed. The Model Specification Section intends to select an appropriate specification from various rival models. Substantive results are presented in the following section that shows both forecast results and their forecasting performance. Finally some conclusions are presented.

2. OBJECTIVES AND METHODOLOGY

The main objective of this study is to specify a short run forecasting model of industrial output within the ARMA framework. Our study is based on the monthly data of industrial output index of Bangladesh covering the period January 1992 to November 2002. These data are taken from the IFS CD Rom Version (September 2003). We have chosen 1992 as the starting year to avoid any possible structural break due to major political regime change in early 1990s. On the other hand we couldn't use the most recent industrial output data, as data were not available beyond November, 2002. We have used the data from January 1992 to December 2001 for the estimation purpose and the data for remaining eleven months for out of sample forecasting purpose.

An ARMA (Autoregressive-Moving average) model has the general form:

$$y_t = c + \sum_{i=1}^{p} \alpha_i y_{t-i} + \sum_{i=0}^{q} \beta_i \varepsilon_{t-i} \qquad [1]$$

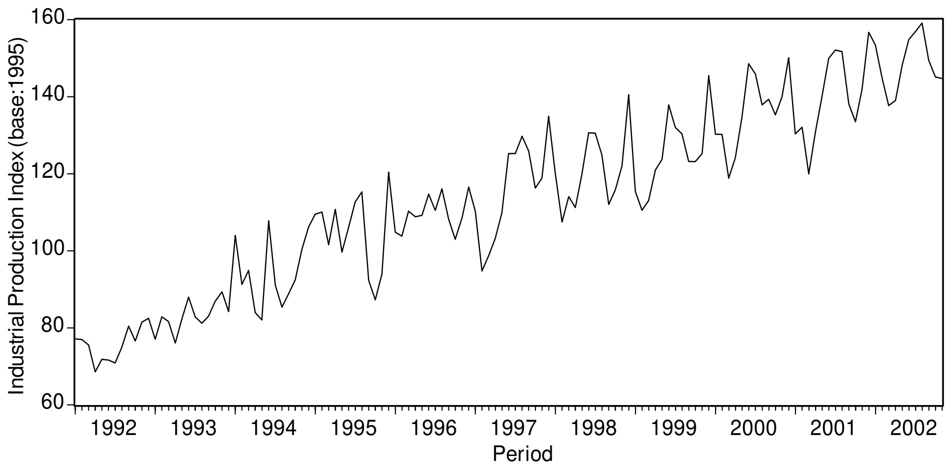
where y_t is a stationary variable, C is constant and ε_t is the error term. It can be seen from equation [1] that ARMA models consist of two main parts; the first is the Autoregressive part (AR) that includes lag values of the dependent variable and the second is the Moving Average part that contains the lag values of error terms. In fact, AR(p) and MA(q) can be treated as the restricted ARMA model. For an AR(p) model $\beta_i = 0 \; for \; i = 1,2,3... \; ...$ and for an MA(q) model $\alpha = 0 \; for \; all \; i.$ The main task of these types of model is to set the appropriate lag orders for AR and MA terms. In this paper we will follow standard Box-Jenkins procedure to specify the appropriate model. This procedure involves the following steps:

> *Step-1*: Check the stationarity of the industrial output series, and, if necessary, transform the series to induce stationarity.
>
> *Step-2*: From the examination of the data series as well as the autocorrelation and partial autocorrelation functions of the series (transformed series for nonstationary case) choose a few ARMA specifications for estimation and testing in order to arrive at a preferred specification with white noise residuals.
>
> *Step-3*: Calculate forecasts over a relevant time horizon from the preferred specification.

3. STATIONARITY CHECK

Figure 1 shows the graph of Industrial output indices for the period between 1992:01 and 2002:11.

Figure 1: Industrial Output Index



In the above figure what we notice at the first glance is the presence of a linear time trend. Industrial production is increasing over time. However, it is very difficult to get any idea about the stationarity of the series from this graph. Like many other macroeconomic monthly series, the industrial output series exhibits some seasonality. This is evident from the peaks roughly observed in every year ending.

To check the stationarity of the series we will use Augmented Dickey Fuller (ADF) test of the unit root. The unit root tests are mainly based on the following AR(1) process:

$$Y_t = \rho Y_{t-1} + \mathbf{X}_t' \boldsymbol{\delta} + \varepsilon_t \qquad [2]$$

where $\mathbf{X}_t$ is the vector of optional exogenous regressors which may consist of a constant, or a constant and a trend; ρ and $\boldsymbol{\delta}$ are parameters to be estimated, and $\boldsymbol{\varepsilon}_t$ is assumed to be white noise. If $|\rho| \geq 1$, Y is a nonstationary series and the variance of Y increases with time and approaches infinity. If $|\rho| < 1$, Y is a stationary series. Thus, the hypothesis of stationarity can be evaluated by testing whether the absolute value of ρ is strictly less than one.

The ADF test uses the modified version of [2], which suggests estimating the following equation:

$$\Delta Y_t = \alpha Y_{t-1} + \mathbf{X_t}'\boldsymbol{\delta} + \beta_1 \Delta Y_{t-1} + \beta_2 \Delta Y_{t-2} + \ldots + \beta_q \Delta Y_{t-q} + \upsilon_t \qquad [3]$$

where Y_t denotes the industrial output and $\Delta Y_t = Y_t - Y_{t-1}$, $\alpha = \rho - 1$ and the null hypothesis H_0: $\alpha = 0$ is tested against the alternative, H_1: $\alpha < 0$ based on the ADF-t statistic. We will use the critical values provided by Mackinnon (1996) to evaluate the null hypothesis. Observing figure 1, we include a constant and linear time trend as regressors in the test equation. Lag order (0 in this case) of the difference terms is determined by the Modified Akaike Information Criterion (MAIC). The result of the ADF unit root test is shown below (t-statistics are shown in the parentheses):

$$\Delta Y_t = 46.6 - 0.617 Y_{t-1} + 0.37 \text{trend} + \upsilon_t$$

(7.01) (-7.13) (6.69)

ADF Test Statistic = -7.13, P value = 0.000

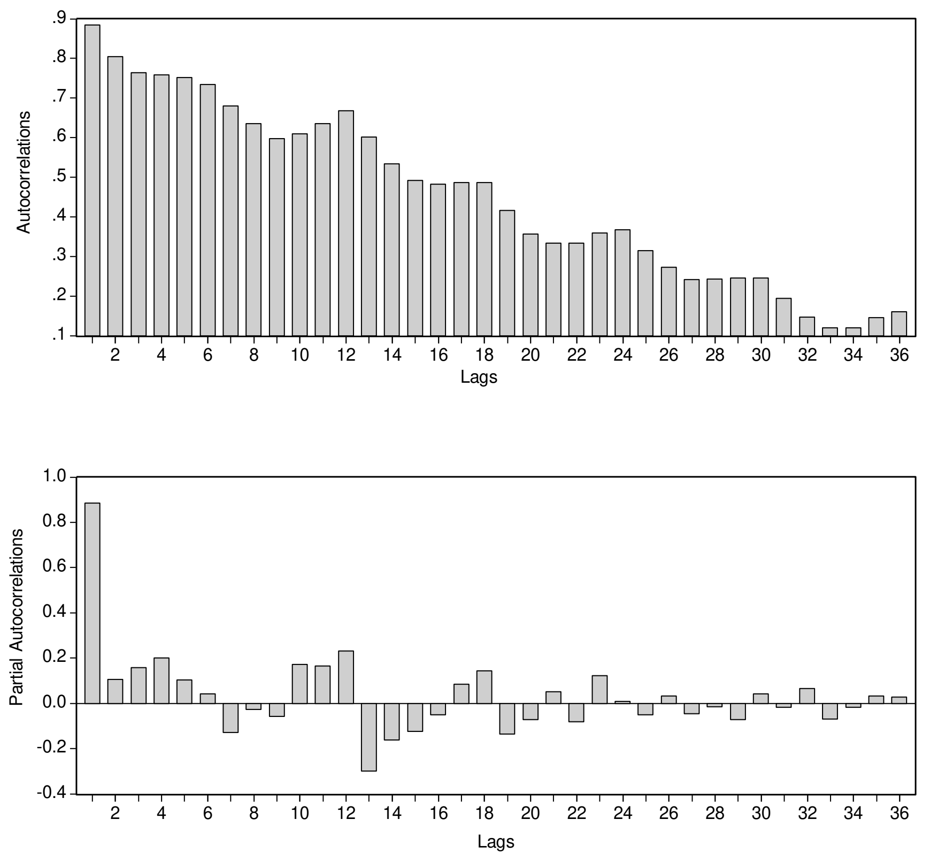
The significance of all the coefficients and the value of DW statistic close to 2 indicate the correct specification of the test equation. The ADF test statistic is highly significant. The above results clearly reject the unit root hypothesis. Thus we may consider the industrial output series as stationary.

4. MODEL SPECIFICATION

Following Box-Jenkins procedure, we first observe autocorrelation and partial autocorrelations of the industrial output series.

Figure 2 shows the autocorrelation function (ACF) and partial autocorrelation function (PACF) (up to lag 36) for the industrial output index that covers the period 1992:01 to 2001:12. Slowly decaying autocorrelations may give us an indication of the nonstationary series. However, the formal ADF test already rejected the nonstationarity hypothesis. The wavy pattern of the autocorrelation function is an indication of the presence of seasonality in the series.

Figure 2: Autocorrelation and Partial Autocorrelation Functions of Industrial Output Index



The single spike at lag 1 in the partial autocorrelation function suggests an AR(1) model. Along with this, positive spike at lag 12 and negative spike at lag 13 hints at a multiplicative Seasonal Autoregressive (SAR(12)) model with the following specification:

Model 1:

$$(1-\alpha_1 L)(1-\delta L^{12})Y_t = c + \varepsilon_t \qquad [4.1]$$

where Y_t is the industrial output and ε_t is the error term. L is the lag operator defined as $L^i Y_t = Y_{t-i} \qquad (i = 1, 2, 3, \ldots \quad \ldots)$. We may rewrite equation [4.1] as

$$(1-\alpha_1 L - \delta L^{12} + \alpha_1 \delta L^{13}) Y_t = \varepsilon_t \qquad [4.2]$$

Now we can see that Model 1 is able to capture the facts of spikes at lag 1, 12 and 13 of the PACF. Thus we start our experimentation of the model building with equation [4.1], the result of which is reported here:

Estimated Model 1:

$$(1-\alpha_1 L)(1-\delta L^{12}) Y_t = c + \varepsilon_t$$

	Estimates	Std. Error	t-Statistic	Prob.
C	149.7392	13.67209	10.95218	0.0000
α_1	0.349226	0.093125	3.750068	0.0003
δ	0.827484	0.050212	16.47982	0.0000

Adj $R^2 = 0.86$,

Q Stat for Residuals (p Values are shown in parentheses*):*

Lag 6: 5.50	Lag 12: 20.699	Lag 18: 35.738	Lag 24: 49.64
(0.239)	(0.023)	(0.003)	(0.001)

All the estimated coefficients are highly significant. High value of R^2 also suggests very good fit of the model. However, these are not enough to find an appropriate model unless the estimated residuals turn out to be white noise. We were particularly interested in checking the serial correlation left in the residuals. To perform this, we calculate the Ljung-Box Q statistics from the autocorrelations and partial autocorrelations of the residual series up to 24 lags. If the estimated residuals are serially uncorrelated, the Q statistic for any specific lags should be insignificant. Here we report Q statistics for lags 6, 12, 18 and 24. We find that Q statistic is decisively significant at lags 12, 18 and 24, which is an indication of the presence of serial correlation in the residuals. It implies that model represented in equation [4.1] is not adequate and we need to look for a little more complicated model.

If we look at the ACF of the industrial production series, we may observe the slowly decaying autocorrelations with the relative peak at lag 12. Thus we may want to include an MA term with single lag 12 along with the AR(1) and SAR(12) in our model. This model can be represented as:

Model 2:

$$(1-\alpha_1 L)(1-\delta L^{12})Y_t = c + (1+\beta_1 L^{12})\varepsilon_t \qquad [5]$$

The result of which is shown below:

Estimated Model 2:

$$(1-\alpha_1 L)(1-\delta L^{12})Y_t = c + (1+\beta_1 L^{12})\varepsilon_t$$

	Estimates	Std. Error	t-Statistic	Prob.
C	943.2226	2845.279	0.331504	0.7409
α_1	0.364892	0.091959	3.967986	0.0001
δ	0.991984	0.027448	36.14060	0.0000
β_1	-0.896867	0.023559	-38.06874	0.0000

Adj R^2 = 0.8919

Q Stat for Residuals (p Values are shown in parentheses*):*

Lag 6: 8.443	Lag 12: 14.23	Lag 18: 18.808	Lag 24: 33.56
(0.038)	(0.114)	(0.223)	(0.04)

Q Stat for Squared Residuals (p Values are shown in parentheses*):*

Lag 6: 9.526	Lag 12: 13.00	Lag 18: 18.881	Lag 24: 22.086
(0.023)	(0.163)	(0.219)	(0.395)

Compared with the previous model, we can see that estimation of equation [5] gives relatively larger coefficients for AR and SAR terms. Nevertheless, all the coefficients are highly significant. The significant Q-stats for the residual at lag 6 and 24, however, still indicate the serial correlation in the residuals. Again, this suggests need for re-specification of the model.

We may now look again at the wavy seasonal pattern of the ACF of the industrial output series. It can be seen that every wave has the duration of about six months. Thus we introduce multiplicative Seasonal MA term (SMA (12)) along with

MA(6) term and multiplicative Seasonal AR (SAR(12)) with AR(1) term in our new specification, which can be shown as:

<u>Model 3</u>:

$$(1-\alpha_1 L)(1-\delta L^{12})Y_t = c + (1+\beta_1 L^6)(1+\gamma L^{12})\varepsilon_t$$

[6]

the estimation results of which are shown below:

Estimated Model 3:

$$(1-\alpha_1 L)(1-\delta L^{12})Y_t = c + (1+\beta_1 L^6)(1+\gamma L^{12})\varepsilon_t$$

	Estimates	Std. Error	t-Statistic	Prob.
C	1708.259	8959.224	0.190670	0.8492
α_1	0.365602	0.092180	3.966170	0.0001
δ	0.995816	0.023481	42.40898	0.0000
β_1	-0.178433	0.095791	-1.862734	0.0654
γ	-0.890753	0.024360	-36.56691	0.0000

Adj R^2 = 0.8957 ***Q Stat for Residuals*** (p Values are shown in parentheses*):*

Lag 6: 1.125	Lag 12: 7.06	Lag 18: 11.489	Lag 24: 27.041
(0.57)	(0.53)	(0.647)	(0.134)

Q Stat for Squared Residuals (p Values are shown in parentheses*):*

Lag 6: 7.039	Lag 12: 11.45	Lag 18: 19.72	Lag 24: 25.81
(0.03)	(0.177)	(0.139)	(0.172)

This model apparently produces better results. All the ARMA coefficients are reasonably significant. Q statistics for the residuals (up to 24 lags) are all insignificant, which indicates no serial correlation in the estimated residuals. However we may have to deal with different kind of problem indicated by the Q statistics of the squared residuals. We see that the Q statistic for the estimated squared residual is significant at lag 6. Although not reported here, lag 5 and 7 also show the significant (at 5% level) Q statistics. This implies the variances of the residuals are serially correlated. Stated differently, this may be an indication of the ARCH (Autoregressive Conditional Heteroscedasticity) effect. A series is said to have an ARCH effect if its unconditional (long run) variance is constant but there are periods in which the variance is relatively high / low. In the graph of the industrial output indices in figure 1, we may observe the smaller fluctuations of the series prior to the year 1994. There is, however, much more certain statistical test for ARCH effect, which is known as ARCH-LM test. In terms of the previous model we perform this LM test, and with lag 1, the result is shown below:

ARCH LM (1) Test for Model 3:

$$\hat{\varepsilon}_t^2 = \underset{(0.00)}{31.54} + \underset{(0.0651)}{0.179}\hat{\varepsilon}_{t-1}^2$$

F Statistic = 3.4749 (0.0651)

nR^2 = 3.4272 (0.0641)

We can reject the null hypothesis of no ARCH at 6% level of significance.

Thus we may need to incorporate this ARCH effect in our ARMA model (equation 5). After some experimentation with the order of ARCH process, we finally specify the following generalized ARCH (GARCH, in short) model:

Model 4:

$$\begin{aligned} &(1-\alpha_1 L)(1-\delta L^{12})Y_t = c + (1+\beta_1 L^6)(1+\gamma L^{12})\varepsilon_t \\ &\sigma_t^2 = b_0 + b_1\varepsilon_{t-1}^2 + b_2\sigma_{t-1}^2 + b_3 Y_t \end{aligned} \qquad [7]$$

where σ_t^2 denotes the conditional variance of the residual. According to our specification, the main difference between model 3 and 4 is that model 3 assumes constant variance for the residual but model 4 assumes that the variance of the estimated residuals is a function of the news about the volatility of the series in the previous period (ε_{t-1}^2), last period's forecast variance (σ_{t-1}^2) and current level of Y. The result of the estimation of this model is shown below. As before all the ARMA coefficients are found significant. Now the constant term also turns out to be significant which was insignificant in the model with no accommodation for ARCH. The coefficients in the variance equation are all also significant. Most importantly, Q statistics for residuals as well as for the squared residuals at any lag are insignificant at conventional 5% level.

Estimated Model 4:

$$(1-\alpha_1 L)(1-\delta L^{12})Y_t = c + (1+\beta_1 L^6)(1+\gamma L^{12})\varepsilon_t$$

$$\sigma_t^2 = b_0 + b_1\varepsilon_{t-1}^2 + b_2\sigma_{t-1}^2 + b_3 Y_t$$

	Estimates	Std. Error	z-Statistic	Prob.
C	229.4776	41.19560	5.570439	0.0000
α_1	0.472526	0.112462	4.201641	0.0000
δ	0.927319	0.026550	34.92758	0.0000
β_1	-0.198338	0.105113	-1.886895	0.0592
γ	-0.535471	0.089619	-5.974940	0.0000
Variance Equation				
b_0	318.0190	96.85419	3.283483	0.0010
b_1	0.259426	0.132282	1.961165	0.0499
b_2	-0.694004	0.162457	-4.271923	0.0000
b_3	-1.990113	0.672988	-2.957128	0.0031

Adj R^2 = 0.8695 DW : 2.04

Q Stat for Residuals (p Values are shown in parentheses*):*

Lag 6: 3.78	Lag 12: 7.47	Lag 18: 18.62	Lag 24: 28.352
(0.15)	(0.48)	(0.18)	(0.101)

Q Stat for Squared Residuals (p Values are shown in parentheses*):*

Lag 6: 4.88	Lag 12: 10.032	Lag 18: 19.996	Lag 24: 24.00
(0.09)	(0.263)	(0.130)	(0.242)

The formal ARCH LM test could not reject the no ARCH hypothesis for any lag specification (not reported here). Although this model is a quite good one, we can still try to find some better model, as some of the Q stats for residuals and squared residuals in this model are only marginally insignificant.

In search of a better model we may return to the model 3 (equation 6) and try to incorporate ARCH specification in this model. Note that the calculated Q statistics for squared residuals in model 3 are found significant for the lags 4 to 10. These might be the indication of the presence of ARCH effect. The formal ARCH LM (1) test on this model shows the presence of ARCH effect at 10% level of significance.

ARCH LM (1) Test for Model 2:

$$\hat{\varepsilon}_t^2 = 33.65 + 0.163\hat{\varepsilon}_{t-1}^2$$
$$(0.00) \quad (0.0949)$$

F Statistic = 2.8409 (0.0949)   **nR^2 = 2.8186 (0.0931)**

p-values are in parentheses

The suggested GARCH model is:

$$(1-\alpha_1 L)(1-\delta L^{12})Y_t = c + (1+\beta_1 L^{12})\varepsilon_t$$
$$\sigma_t^2 = b_0 + b_1\varepsilon_{t-1}^2 + b_2\sigma_{t-1}^2 + b_3 Y_t \qquad [8]$$

The result of the estimation is shown below:

Estimated Model 5:	$(1-\alpha_1 L)(1-\delta L^{12})Y_t = c + (1+\beta_1 L^{12})\varepsilon_t$ $\sigma_t^2 = b_0 + b_1\varepsilon_{t-1}^2 + b_2\sigma_{t-1}^2 + b_3 Y_t$			
	Estimate	Std. Error	z-Statistic	Prob.
C	238.6053	51.59849	4.624270	0.0000
α_1	0.516633	0.115334	4.479460	0.0000
δ	0.928115	0.031024	29.91637	0.0000
β_1	-0.565369	0.095167	-5.940813	0.0000
	Variance Equation			
B_0	334.2981	102.2236	3.270262	0.0011
B_1	0.240220	0.102809	2.336577	0.0195
b_2	-0.721578	0.154760	-4.662564	0.0000
b_3	-2.059769	0.708525	-2.907125	0.0036

Adj R^2 = 0.86 DW = 2.08

Q Stat for Residuals (p Values are shown in parentheses*):*

Lag 6: 5.23	Lag 12: 8.18	Lag 18: 17.14	Lag 24: 24.74
(0.16)	(0.52)	(0.311)	(0.258)

Q Stat for Squared Residuals (p Values are shown in parentheses*):*

Lag 6: 1.38	Lag 12: 10.429	Lag 18: 19.104	Lag 24: 26.32
(0.71)	(0.317)	(0.209)	(0.195)

Obviously this model produces the best results so far. All the coefficients in ARMA and variance equations are significant. Moreover, the Q statistics of the estimated residuals and squared residuals up to lag 24 are not significant at any reasonable level of significance. Another advantage of this model over model 4 is that this is more parsimonious. However, ultimate model selection will be done based on the forecasting ability of the model. In the next section we will examine the forecasting ability of these two models.

5. FORECASTING

We have so far introduced five ARMA models for the industrial output of Bangladesh. It is already shown that the first three models could not pass the diagnostic tests. Model 4 and 5 are the preferred ones where we assume a GARCH (1,1,Y) process for the error variance. In model 4 we include a constant, AR(1), multiplicative SAR for lag 12 and MA({12}) as regressors. In model 5 we retain AR(1) and SAR({12}) and also include MA({6}) with multiplicative SMA({12}). It is found that estimated coefficients and their standard errors are similar in these two models. It can be noted that these models can explain about 86% of the total variation in industrial output index.

As noted earlier, we have estimated these models using the data that cover the period between 1992:01 and 2001:12. We retain remaining samples between 2002:01 and 2002:11 for out of sample forecasting. In the following figures we have shown the dynamically forecasted values of industrial output index for these eleven months.

Figure 3: Forecast of Industrial Production based on Model 4

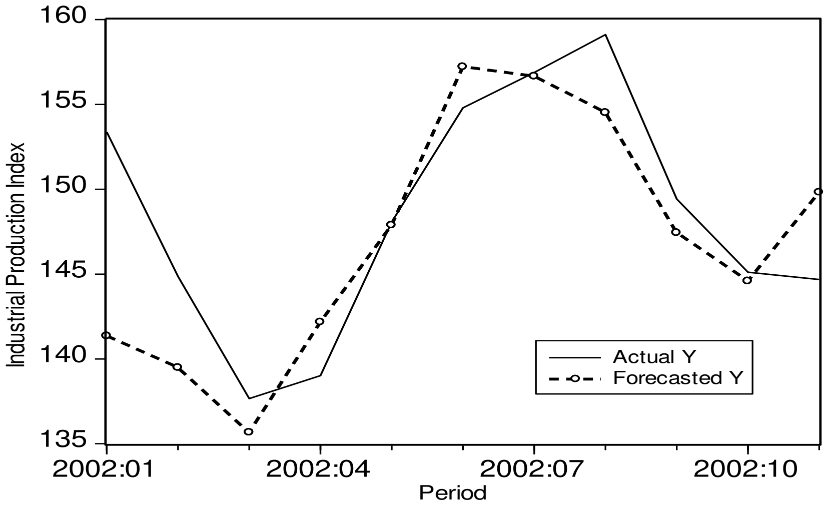
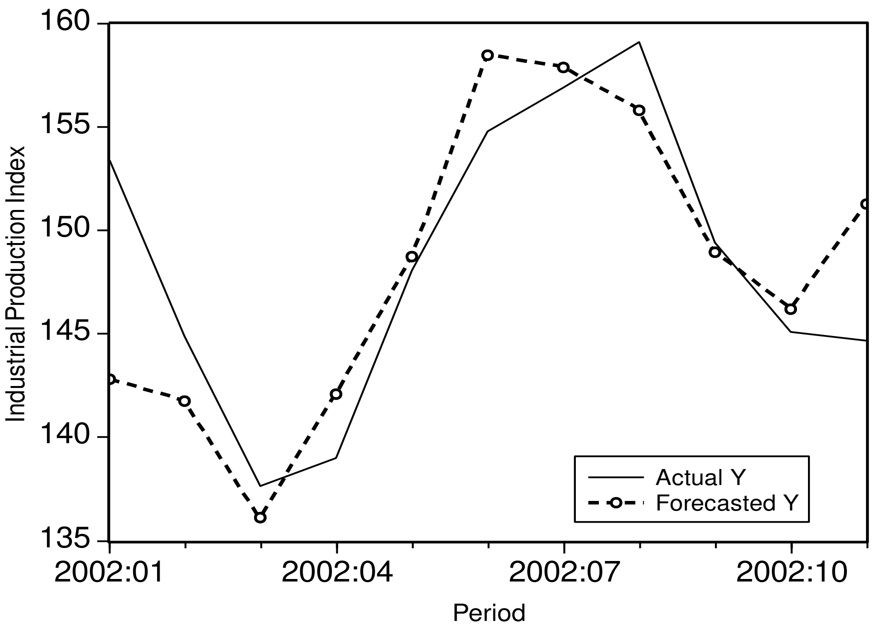


Figure 4: Forecast of Industrial Production based on Model 5



The two figures are almost identical. Both the forecasted series roughly mimic the actual series. On average, both models under-predict the industrial production in the first and third quarters and over-predict in the remaining two quarters. However, these two models exhibit slight differences in the magnitudes of the forecast errors. The forecasting evaluation based on various forecasting error criteria is summarized in the following table:

<u>Forecast Evaluation</u>:

		Model 4	Model 5
Root Mean Squared Error		4.717268	4.305568
Mean Absolute Error		3.419541	3.189317
Mean Absolute Percentage Error		2.293223	2.138738
Theil Inequality Coefficient		0.015951	0.014500
Proportions of Mean Squared Error	**Bias Proportion**	0.097331	0.003878
	Variance Proportion	0.000450	0.002392
	Covariance Proportion	0.902219	0.993730

In terms of all basic criteria it is evident that model 5 produces the smaller forecast errors. Mean squared error, Mean absolute error and Mean absolute percentage error are slightly bigger in model 4. Theil inequality coefficients are very close to zero in both model indicating almost perfect fit.

We also report the components of total mean squared for both models. The bias proportion tells us how far the mean of the forecast is from the mean of the actual series. The variance proportion tells us how far the variation of the forecast is from the variation of the actual series. The covariance proportion measures the remaining unsystematic forecasting errors. Note that the bias, variance, and covariance proportions add up to one. If the forecast is "good", the bias and variance proportions should be small so that most of the bias should be concentrated on the covariance proportions. Here we observe that in model 4 bias and variance proportions account for about 10 percent, whereas in model 5, these two proportions account for only 1 percent. Particularly the bias proportion is relatively large (about 9%) in model 4, which indicates that mean of the forecasts does a poor job of tracking the mean of the dependent variable. On the contrary, in model 5 most of the errors (about 99%) come from the unsystematic sources, indicating very good forecast performance. Thus we may treat model 5 as our desired forecasting model.

6. CONCLUSION

In this paper we tried to develop a short run forecasting model of industrial production for Bangladesh using the information about the history of industrial production. In attempting to do so we introduced several ARMA models and based on some diagnostic tests we finally chose two models for forecasting. We then showed that between these two models, one model is preferred over another for forecasting purpose. Our preferred model suggests an ARMA specification with multiplicative seasonal autoregressive term. This model implies that we can forecast the industrial output series; at least for few months ahead using the information about last month's industrial output, seasonal variation in the series and shocks occurred in the same period of last year. There may exist many other variables, which can be used for forecasting industrial output. However, our analysis shows that information regarding the history of industrial output alone can be very useful in predicting the future values of the series.

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