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Modeling Inflation in Bangladesh

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Abstract

Inflation has a substantial impact on an economy because it affects the financial value of money and stability in the economy. Government and non-government policies might be hindered due to the excessive rate of inflation. This paper aims to model and forecast inflation by the Box-Jenkins autoregressive integrated moving average (ARIMA) technique using annual time series data on inflation from 1987 to 2017 in Bangladesh. It is found that ARIMA (2, 1, 0) model is the best optimal to forecast inflation for a period of up to eight years. Graphical tools, as well as theoretical tests such as Ljung-Box, Shapiro-Wilk, and runs tests have been used in the model diagnostics.

Keywords

ARIMA, Inflation, Forecasting, Model Validity, Model Diagnostics, Bangladesh

1. Introduction

Inflation which refers to the purchasing power of money is one of the most perpetual economic challenges in the world, particularly for the developing economies [1] [2]. Inflation has a substantial impact on the economy of a country because high inflation distorts level of price, discourages investment and hinders economic development. Controlling inflation or maintaining low inflation is critical to protecting the purchasing power of the poor, in particular food-price, in developing countries [3]. Inflation badly affects many economic indicators such as money supply, tax revenues, government expenditures, exports imports, gross domestic products (GDP), exchange rate, stock and bond returns, and others [4]. Inflation causes the devaluation of savings [5]. It is perceived that lower the inflation better the financial management. Because long term plans become hard to achieve when there is greater uncertainty in future inflation [6]. Inflation may be a non-ignorable problem if it goes out of control in a developing country similar to Bangladesh. Therefore, it is essential to keep an eye on inflation rate in any country for better financial management, to preserve wealth and greater stability in the economy. Proper investigation and steps may be helpful to control inflation at a tolerable level. Existing research on this economic variable is inadequate in Bangladesh. This paper is an endeavor to forecast inflation using univariate long term data of inflation from 1987 to 2017 in Bangladesh. The R programming language (version 4.0.0) has been used for data analysis purposes.

The rest of the study has been organized as follows: Section 2 demonstrates the literature review, Section 3 describes data and methodology, Section 4 presents the results and discussions, and the last Section 5 has drawn conclusions of the study.

2. Literature Review

In history, many studies were carried out on the comparative precision of different models of inflation forecasting. Yusif *et al.* [7] used artificial neural network modeling approach for forecasting inflation. Hafer and Hein [8] compared interest rate based forecasting model and univariate time series model based on monthly data from the United States, Belgium, Canada, England, France and Germany and found time series forecast of inflation model producing equal or lower forecast errors and has unbiased predictions than the interest rate based forecasts. Sun [9] combined short-term model with an equilibrium correction model for projecting core inflation using monthly data during 1995 to 2003 in Thailand. For Indonesia, Ramakrishnan and Vamvakidis [10] estimated a multivariate model to identify the leading indicators that have predictive information on future inflation using quarterly data from 1980 to 2000.

Vector autoregressive (VAR) models have been employed for forecasting inflation by Lack *et al.* [11] in Switzerland; Callen and Chang [12] in India; Kelikume and Salami [13], Inam [14] in Nigeria; and Younus and Roy [15] in Bangladesh. The generalized autoregressive conditional heteroscedasticity (GARCH) models were investigated for inflation forecasting by Nyoni and Nathaniel [6] in Zambia; Fwaga *et al.* [16] in Kenya; Ngailo *et al.* [17] in Tanzania; and Banerjee [18] for 41 developed and developing countries for the time period 1958-2016. Akhtaruzzaman [19] used cointegration and vector error correction modeling (VECM) technique in Bangladesh; and Bokil and Schimmelpfennig [20] employed three empirical approaches based on monthly data to forecast inflation in Pakistan.

A vast majority studies across the world used Box-Jenkins ARIMA technique for modeling inflation. For instance, Salam *et al.* [21] in Pakistan, Habibah *et al.* [4] for SAARC countries; Faisal [22] in Bangladesh, Meyler *et al.* [23] in Ireland; Iftikhar [24] in Pakistan; Okafor and Shaibu [25], John and Patrick [26], Mustapha and Kubalu [27], Popoola *et al.* [28] in Nigeria; Jere and Siyanga [2] in Zambia; Islam [29] and Habibah *et al.* [4] in Bangladesh found ARIMA model as the better model for forecasting inflation. By augmenting seasonal component some studies found seasonal autoregressive integrated moving average (SARIMA) model as the best optimal. For example, Akhter [30] in Bangladesh, Out *et al.* [31] in Nigeria, and Lidiema [32] in Kenya used SARIMA for modeling and forecasting inflation.

Also, some authors implemented several methods simultaneously for comparison purposes. Nyoni and Nathaniel [6] used ARMA, ARIMA, and GARCH mdoels for forecasting inflation in Nigeria based on time series data on inflation rates from 1960 to 2016; of which they found ARMA (1, 0, 2) as the best optimal. Pincheira and Gatty [33] used FASARIMA, ARIMA, SARIMA and FASARIMAX methods for forecasting inflation of 18 Latin American and 30 OECD countries. Lidiema [32] found that SARIMA model was better model than the Holt-winter's triple exponential smoothing for forecasting inflation in Kenya. Ingabire and Mung'atu [34] found ARIMA (3, 1, 4) model better than VAR model for forecasting Rwanda's inflation rate.

Akhter [30] employed seasonal auto-regressive integrated moving average (SARIMA) model to forecast short-term inflation rate of Bangladesh using the monthly consumer price index (CPI) from January 2000 to December 2012. Though Islam [29] and Habibah *et al.* [4] attempted recently to forecast inflation by ARIMA (1, 0, 0) and ARIMA (3, 0, 0) models respectively, but their prediction slides the reality as we found the actual inflation rate obtained from Bangladesh Bureau of Statistics (BBS) differ substantially in the subsequent years. In this study, we thrive for a precise ARIMA model for forecasting inflation in Bangladesh.

3. Data and Methodology

To model inflation rate in Bangladesh, long term univariate time series data on inflation obtained from the World Bank (2019) from 1987 to 2017 were used. There are several approaches for modelling time series data with seasonal patterns. The autoregressive integrated moving average (ARIMA) model developed by Box and Jenkins [35] and Box and Tiao [36] is one of the frequently appeared approaches for handling time series data.

The ARIMA model that is usually denoted as ARIMA (*p, d, q*) addresses time dependence in several ways. Firstly, the time series are *d*-differenced to make the series stationary. When $d = 0$, the series is considered as stationary and modelled directly, and if $d = 1$, the differences between consecutive observations are modelled. Secondly, the time dependence of the stationary process X_t is modelled by incorporating p autoregressive models. The equation for order p is:

$$X_t = C + \sum \phi_i X_{t-i} + Z_t \quad (1)$$

where C is a constant, ϕ_i is the parameter of the model, X_t is the observed value at time t, Z_t represents random error. Thirdly, q stands for moving-average term. It includes the observations of the previous random errors. The equation for moving average of order q is:

$$X_t = \sum \theta_i Z_{t-i} + Z_t \quad (2)$$

θ_i is the model parameter, Z_t is the white noise or error term. Finally, we obtain the ARIMA model by combining Equations (1) and (2). Thus, the usual form of the ARIMA models can be presented as follows:

$$X_t = C + \sum \phi_i X_{t-i} + \sum \theta_i Z_{t-i} + Z_t \quad (3)$$

In the current study, the stationarity of the data was tested by augmented Dickey-Fuller (ADF) test. The candid ARIMA model was selected by judging the values of the criteria Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The Shapiro-Wilk test and runs test were used for checking the normality and randomness of the residuals.

Generally, ARIMA models use the back-shift operator B which is defined as $B_K(X_t) = X_{t-k}; t > k, t, k \in N$, where k is the index representing how many times back-shift operator B is applied to time series X_t characterized by time interval t, and N is the total number of time intervals. Using the following notations

$$\Phi(z) = 1 + \sum \phi_i z^i; \phi_p \neq 0$$

$$\Theta(z) = 1 + \sum \theta_i z^i; \theta_q \neq 0$$

Equation (3) can be written as

$$\Phi(B)(1-B)^d X_t = C + \Theta(B) Z_t$$

To determine an appropriate model for a given time series data, it is essential to figure out the autocorrelation function (ACF) and partial autocorrelation function (PACF) analysis, which exhibit how the observations in a time series are interrelated. The plot of ACF helps to determine the order of moving average terms, and the plot of PACF helps to determine autoregressive terms.

In the current study, the stationarity of the data was tested by augmented Dickey-Fuller (ADF) test. The candid ARIMA model was selected by judging the values of the criteria: Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The Shapiro-Wilk test and runs test were used for checking the normality and randomness of the residuals.

4. Results and Discussions

Data Inspection

The first step of time series analysis is to inspect the graph of the data [37]. The aim of inspecting the plot of the data is to observe if there is any visible pattern in the data i.e. to observe whether there is any seasonality in the data.

The first plot in **Figure 1** shows the inflation rate of Bangladesh since 1987 until 2017. It is observed from the graph that there is no apparent pattern and seasonality in the data. Also, no sign of stationary of the data is observed by this plot. The second plot which is the second difference of inflation rate of Bangladesh also shows no apparent seasonality in the data. Thus the graphs in **Figure 1** reveal that there is no seasonality and trend in the data.

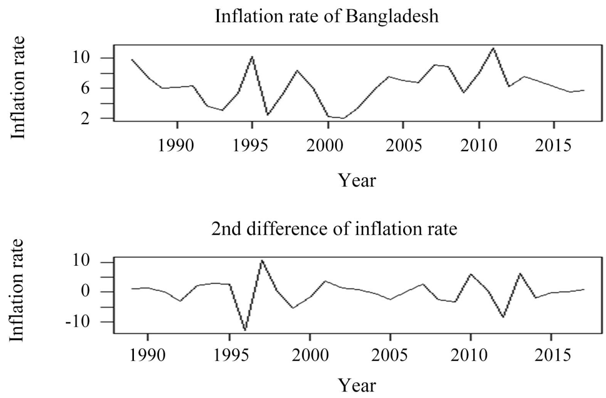

Figure 1. Plot of inflation rate of Bangladesh.

Checking Stationarity

The second step of time series model building is to check stationarity of the data which can be done by the augmented Dicky Fuller (ADF) test [37]. The non-stationarity of the time series data corresponds null hypothesis H_0 in the ADF test. **Table 1** indicates that original data as well as first order difference series are not stationary (p-value > 0.05). However, after taking second order difference, the series becomes stationary (p-value < 0.05).

Autocorrelation and Partial Autocorrelation Functions

The third step in time series analysis is to find the order of autoregressive (AR) and moving average (MA) models by ACF and PACF [37]. The ACF and PACF are two important functions for checking autocorrelations of different lags in the data. Significant autocorrelation of any time lag of the series indicates the order of the moving average model and significant partial autocorrelation indicates the order of the autoregressive model. However, orders of the moving average and autoregressive models are approximate, further analysis is required to confirm the orders.

In **Figure 2** we notice that only first order lag is significant in ACF plot and first three order lag is significant in PACF plot. Thus, our tentative model is ARIMA (3, 2, 1).

Model Determination

Selection of the best model is a crucial part of predicting inflation. There are some criteria such as AIC, BIC, and log likelihood for selecting the best model. The lower AIC, BIC and higher log likelihood values might indicate the probable best model. In **Table 1**, the augmented Dicky Fuller test found that data became stationary after taking second difference and later ACF and PACF helps finding the temporary orders of MA and AR models and thereby the tentative model was ARIMA (3, 2, 1). To find the competitive models, we can hover around the tentative ARIMA (3, 2, 1) model and compute criteria AIC and BIC values. We compare AIC and BIC values for different ARIMA models in **Table 2** to choose the best model.

In **Table 2** we observe that the lowest values of AIC and BIC are 144.0352 and

149.5044 respectively corresponding to ARIMA (2, 2, 1) and thus ARIMA (2, 2, 1) would be selected tentatively for inflation prediction.

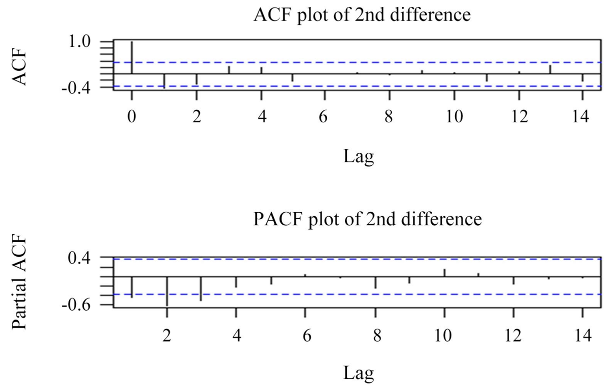

Figure 2. Graph of ACF and PACF.

Table 1. Augmented Dicky-Fuller test.

Terms	Original data	First order diff	Second order diff
Dicky-Fuller	−2.201	−2.839	−4.797
Lag order	3	3	3
p-value	0.495	0.250	<0.01
H_0	Non-stationary	Non-stationary	Stationary

Table 2. Model selection based on AIC and BIC.

Model	AIC	BIC
ARIMA (2, 2, 1)	144.0352	149.5044
ARIMA (3, 2, 1)	145.6860	152.5225
ARIMA (2, 2, 2)	145.8133	152.6498
ARIMA (0, 2, 2)	146.1254	150.2273
ARIMA (2, 2, 3)	146.1870	154.3908
ARIMA (0, 2, 3)	146.3224	151.7916
ARIMA (3, 2, 2)	146.4867	154.6905
ARIMA (1, 2, 2)	147.5073	152.9765
ARIMA (1, 2, 3)	147.9245	154.7610
ARIMA (3, 2, 0)	148.4830	158.0540
ARIMA (3, 2, 0)	148.6002	154.0694
ARIMA (0, 2, 1)	148.9322	151.6668
ARIMA (1, 2, 1)	149.5374	153.6393
ARIMA (2, 2, 0)	155.0452	159.1471
ARIMA (1, 2, 0)	165.8131	168.5476
ARIMA (0, 2, 0)	169.7274	171.0947

Table 3 presents the coefficients, standard errors, and 95% confidence intervals of the ARIMA (2, 2, 1) model. Thus, the fitted model ARIMA (2, 2, 1) can be written as follows:

$$\left(1-\phi_1 B-\phi_2 B^2\right)(1-B)^2 X_t=\left(1+\theta_1 B\right) Z_t$$

$$\left(1+0.3614B+0.4750B^2\right)(1-B)^2 X_t=(1-B) Z_t$$

$$\left(1+0.3614B+0.4750B^2\right)(1-B) X_t=Z_t$$

where B denotes back shift operator, X_t is the time series data, Z_t represents white noise. Due to having an estimate as −1.000 corresponding to the coefficient of MA1, the ARIMA (2, 2, 1) reduces to ARIMA (2, 1, 0). Therefore, ARIMA (2, 1, 0) which has lower AIC (141.1012) and BIC (145.3048) values than that of ARIMA (2, 2, 1) has been taken into consideration as the final model for forecasting inflation in Bangladesh. Table 4 presents the coefficients, standard errors, and 95% confidence intervals of the ARIMA (2, 1, 0) model.

Finally, the selected ARIMA (2, 1, 0) model can be written algebraically as follows:

$$\left(1-\phi_1 B-\phi_2 B^2\right)(1-B) X_t=Z_t$$

$$\left(1+0.3776B+0.4915B^2\right)(1-B) X_t=Z_t$$

where the interpretations of notations remain as before.

Model Diagnostics

Randomness and independence of residuals are two important assumptions in modeling. The ACF plot in Figure 3 shows that residuals are scattered both sides of zero line without making any pattern. Therefore, it is believed that residuals are randomly distributed. Randomness of the residuals can also be checked by Wald-Wolfowitz runs test. The large *p*-value (>0.05) in Table 5 implies that the null hypothesis of randomness is not rejected and thus residuals are random in nature. Further, we notice in Figure 3 under the PACF plot that none of the points are outside the significance line which proves the independence of residuals. The Ljung Box test in Table 6 supports the evidence of independence further by providing larger *p*-value (>0.05) and thereby not rejecting the null hypothesis of independence.

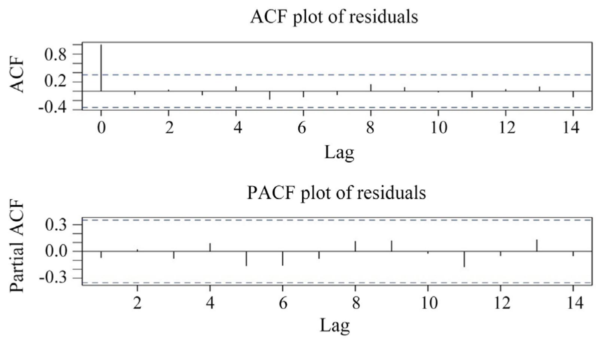

Figure 3. Diagnostic plot of residuals.

Table 3. Coefficients of ARIMA model.

Components	Coefficients	SE	95% CI
AR1	−0.3614	0.1622	(−0.6793, −0.0435)
AR2	−0.4750	0.1565	(−0.7817, −0.1683)
MA1	−1.0000	0.1420	(−1.2783, −0.7217)

Table 4. Coefficients of ARIMA (2, 1, 0) model.

Components	**Coefficients**	**SE**	**95% CI**
AR1	−0.3776	0.1586	(−0.6884, −0.0667)
AR2	−0.4915	0.1528	(−0.7910, −0.1921)

Table 5. Wald-Wolfowitz runs test for randomness.

Runs = 13,	n_1 = 15,	n_2 = 15	n = 30
Test Statistic = −1.4864,	p-value = 0.1372,	H_0: Randomness	

Table 6. Ljung Box test.

χ^2 = 0.16161,	df = 1,	p-value = 0.6877,	H_0: Independence

The normality assumption of residuals can be checked by a Q-Q plot. The Q-Q plot shows that the points are roughly lie on a straight line which ensures the normality assumption of residuals (**Figure 4**). Further, Shapiro-Wilk normality test (**Table 7**) has p-value greater than 0.05 which leads not to reject the null hypothesis at 5% level of significance. Thus, it is concluded from the results that residuals are normal.

Plot of Fitted Versus Actual Values

The actual and fitted values of inflation rate have been presented in **Figure 5** which indicates that selected model performs well in terms of prediction. Although there exists some discrepancy between fitted and actual values, it might be reasonable to carry on for prediction.

Forecasted and Real Values of Inflation

Using ARIMA (2, 1, 0) model we have forecasted eight steps ahead values (from year 2018 until year 2025) of inflation in Bangladesh (**Table 8**).

In **Table 9**, we presented actual inflation data from Bangladesh Bureau of Statistics (BBS) where point to point inflation (%) means inflation calculated based on previous month and 12 months average inflation (%) means inflation calculated based on last 12 months. However, we notice overwhelmingly that forecasted and actual inflations closely match for the available years, particularly for year 2018, year 2019 and year 2020 (**Table 8** and **Table 9**). As predicted and actual values are nearly close, the ARIMA (2, 1, 0) model and its predictability might be acceptable for predicting inflation for a developing economy, particularly for Bangladesh. However, it is noted that our model is differing from models found in studies by Islam [29] and Habibah *et al.* [4]. The main reasons could be use of different sets of data. Also, as noted by Stockton and Glassman [38], for purposes of forecasting, econometric models differ not only in their specification, but also in the quantity and quality of the information presumed to be available to the forecaster.

Table 7. Shapiro-Wilk normality test.

Test Statistic = 0.98415,	p-value = 0.9146,	H_0: Normal

Table 8. Eight steps ahead prediction of inflation.

Year	Forecasted Inflation	Predict. Error
2018	5.97	2.28
2019	5.77	2.68
2020	5.72	2.75
2021	5.83	3.06
2022	5.82	3.39
2023	5.77	3.56
2024	5.79	3.74
2025	5.81	3.97

Table 9. Real inflation data in Bangladesh.

Year	Month	Inflation	
		Point to point (%)	Mean (%) (12 month)
2018	January	5.88	5.76
2018	December	5.35	5.54
2019	January	5.42	5.51
2019	December	5.75	5.59
2020	January	5.57	5.6
2020	February	5.46	5.6

Source: Bangladesh Bureau of Statistics (BBS).

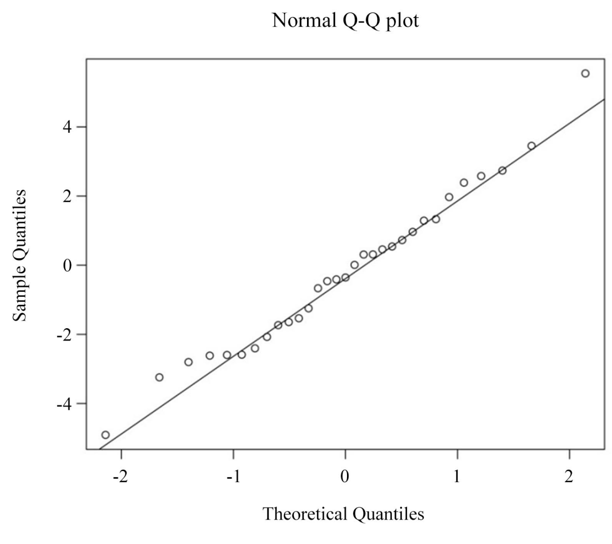

Figure 4. Q-Q plot of residuals.

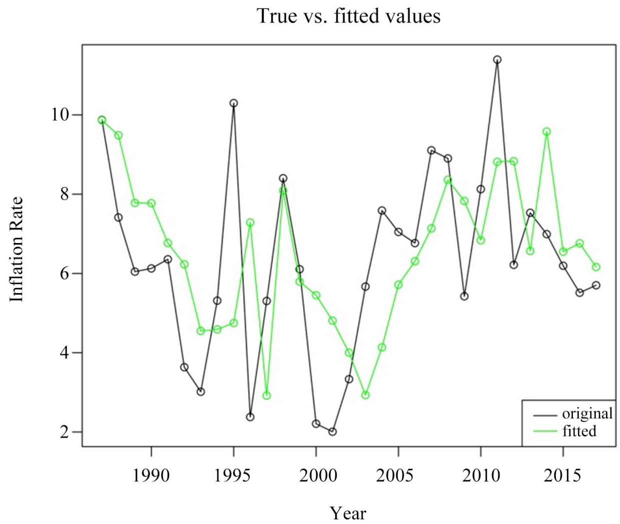

Figure 5. Fitted versus real values of inflation rate.

5. Conclusion

In this paper, we attempted to build up a suitable model for predicting inflation rate and found ARIMA (2, 1, 0) is the best optimal for forecasting inflation in Bangladesh up to eight years (**Table 8**). Comparison between actual and predicted values of inflation (**Table 9**) shows the efficiency and diagnostics analyses (**Figure 3**, **Figure 4**, **Table 5**, **Table 6**) show the validity of our model. By using this model interested stakeholders can forecast inflation rate in Bangladesh and thereby the policymakers can make use of the forecasted inflation rate at the time of making various economic policies. This study can be a good reference for inflation forecasting in other developing countries similar to Bangladesh.

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Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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