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Modeling and Forecasting Inflation Rates in Bangladesh: An Application of ARIMA Models

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Abstract

As a key factor in an economy, inflation affects the buying power of currency and the stability of the financial condition of a country. This study aims to use the Autoregressive Integrated Moving Average (ARIMA) technique to model and forecast inflation, utilizing annual inflation data from 1987 to 2022 in Bangladesh. Data on Bangladesh's annual inflation rate, spanning several years, were collected from the World Bank website. The analysis utilized graphical techniques and theoretical tests, including the Augmented Dickey-Fuller test, Ljung-Box test, and Shapiro-Wilk test. Our findings indicate that the ARIMA (2,1,0) model is the most suitable for the inflation data in Bangladesh because it has the lowest Akaike Information Criterion (AIC). The suggested model in this research will help policymakers foresee the future inflation rate of Bangladesh, supporting them in making economic decisions and crafting relevant policies.

Keywords: Inflation, Bangladesh, ARIMA model, Model diagnostic, Forecasting

I. Introduction

Inflation refers to the "diminished buying capacity of money," which is reflected in the overall rise in the cost of commodities and services. Inflation has become a prominent global challenge in the last few decades. In developing economies like Bangladesh, inflation has a key role. It significantly impacts the economy by distorting the price levels of goods and services. A higher inflation rate discourages investment and creates obstacles in the way of the economy and subsequently the overall development of the economic zone. The government of a country must try its best to control or maintain low inflation to protect the purchasing power of the poor. In underdeveloped or developing countries, the price levels of basic human needs like food, clothes, housing, and medical services must be maintained by controlling the inflation rate so that the poor class of the people doesn't need to struggle to lead a bare minimum comfortable life. However, in countries like Bangladesh, it cannot always be sustained. Inflation rates profoundly influence various economic indicators, including consumer spending, business investments, employment rates, tax policies, interest rates, money supply, government expenditures, export-import balance, GDP, stock and bond returns, and exchange rates. It is discerned that as inflation decreases, the quality of financial supervision improves. Uncontrolled inflation may present a significant challenge in a developing nation like Bangladesh. Hence, it is vital to keep track of the rate of inflation within a country to ensure better fiscal governance and maintain economic stability and wealth. This research focuses on predicting the inflation rate using univariate data on Bangladesh's annual inflation from 1987 to 2022. In the existing literature, no study has yet considered this time frame to forecast Bangladesh's inflation.

A steady inflation rate is one of the factors when we can say the economy is strong. Many factors affect inflation, but it can be a big issue when the supply and demand chain is out of balance. Consumers get in big trouble when inflation rises. It decreases the purchasing power of fixed-income consumers. The Autoregressive Integrated Moving Average (ARIMA) methodology, developed by Box-Jenkin[1], is widely adopted globally to analyze inflation data. Rahman et al.[2] applied the ARIMA technique to model inflation in Bangladesh from 1987 to 2017. Islam[3] used a similar ARIMA approach to forecast inflation using yearly data from 1971 to 2015 and found the ARIMA (1,0,0) model to be the best for making five-year forecasts. In his 2001 study, Faisal[4] applied the ARIMA method for inflation modeling, using monthly Consumer Price Index (CPI) data from 2001 to 2011. Akhter[5] used a seasonal ARIMA model to predict short-term inflation in Bangladesh, analyzing seasonal CPI data from 2000 to 2012. The study by Salam et al.[6] employed ARIMA time series models to estimate future inflation in Pakistan. By employing the ARIMA model, Habibaet al.[7] forecasted inflation for four SAARC region countries- Bangladesh, Pakistan, India, and Sri Lanka- utilizing data spanning from 1981 to 2016.

There is an abundance of research investigating the relationship between inflation and its determinants. Yet, few empirical studies have focused on this relationship in the context of Bangladesh. Analyzing data from 1978 to 2010, Arif and Ali[8] identified the major determinants of inflation in Bangladesh. Their findings revealed that, while both demand and supply side factors contribute to inflation, government expenditure and money supply are crucial. The research by Ahmed and Das[9] revealed that inflationary pressures in Bangladesh were triggered by world food and fuel prices. They also identified inflation inertia as a reason for the persistence of higher inflation. Paul and Zaman[10] investigated the timing and reasons behind the discrepancy in inflation rates between India and Bangladesh. Their research aimed at identifying the key factors driving inflation in both

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countries and evaluating if these factors could account for the inflation disparity. The study, which covered the years 1979 to 2010, revealed that the inflation disparity between India and Bangladesh can be mainly attributed to the differential in money growth across the two nations.

II.Data and Methodology

We used one-dimensional time series data on the yearly inflation rate from 1987 to 2022 sourced from the World Bank (2024)[11] website to develop a model for Bangladesh's inflation rate. There are many approaches to modeling time series data. The ARIMA model is among the most frequently used approaches. Box and Jenkins[1] developed the ARIMA model. The ARIMA (*p,d,q*) model represents the order of the autoregressive (AR) model, the degree of differencing (integrated form), and the order of the moving average (MA) model. Firstly, the *'d'* refers to the time series data being *d* times differenced to make the series stationary. The *'p'* means that the AR (*p*) model was used in that ARIMA model. Similarly, the *'q'* implies the use of the MA (*q*) model in the ARIMA (*p,d,q*) model. When $d=0$, the series is regarded as already stationary, and further procedures are implied directly on the series.When $d = 1$, the model is based on the difference between two successive observations. Similarly, when $d=2$, the second difference in the observations is considered stationary and used to model the data. The equation for order *p,* i.e. AR (*p*) is:

$$Y_t = \mu + \sum \emptyset_i Y_{t-i} + W_t.$$

Here, μ is a constant, $\emptyset_i$ denotes the model's parameter, Y_t represents the value observed at time t, W_t is the random error term. Observations of earlier random errors are included in the moving average term. The MA*(q)* model, representing a moving average of order *q*, is defined by the following equation:

$$Y_t = \sum \theta_j W_{t-j} + W_t.$$

Here, θ_i denotes the model parameter and W_t is the white noise term. Eventually, by combining the two preceding equations, we arrive at the specific ARIMA model, which is represented as

$$Y_t = \mu + \sum \emptyset_i Y_{t-i} + \sum \theta_j W_{t-j} + W_t$$

In this research, we utilized the Augmented Dicky-Fuller[12](ADF) test to evaluate the stationarity of the time series data.To identify the optimal ARIMA model, we compare the Akaike Information Criterion (AIC)[13] values.

III. Data Analysis

To analyze time series data, we should start by inspecting the plot. The graph will reveal if there is any specific pattern in the data. The first plot in Fig. 1 portrays Bangladesh's inflation rate from 1987 to 2022. The second and third plots of Fig. 1 show the first and second differences of the data, respectively.

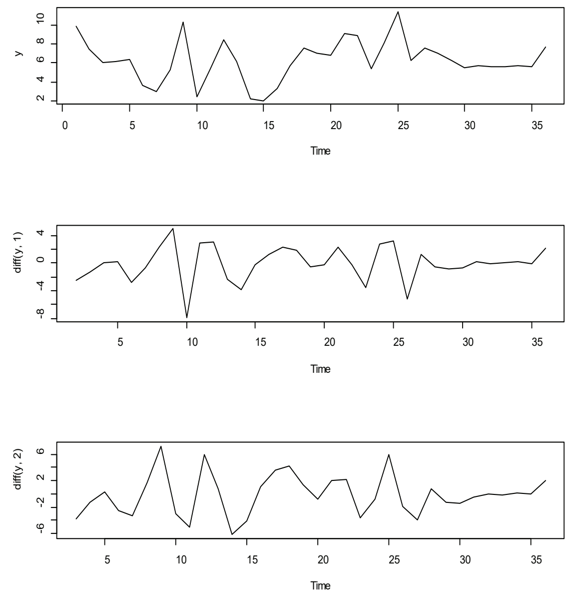

Fig. 1. Graph of Bangladesh's inflation rate

Fig. 1does not indicate whether the original and transformed data are stationary.

Checking Stationarity

To determine if the data is stationary, the Augmented Dicky-Fuller[12](ADF) test can be used. The null hypothesis H_0 of the ADF test represents non-stationarity in the given time series data. Once the test statistic is calculated, it should be compared to the Dickey-Fuller Test critical value. The ADF test results for the original data, along with its first and second differences, are shown in Table 1.

Table 1. Results of the Augmented Dickey-Fuller Test

Components	***Original data***	***First order difference***	***Second order difference***
Dickey-Fuller	-2.2453	-3.174	-3.2882
Order of the lag	0	1	2
p-value	0.4777	0.1173	0.09029
Outcome	Non-sta-tionary	Non-station-ary	Stationary

The table-1 suggests that the original data is non-stationary (p-value > 0.1). Similarly, the first-order differenced series is also non-stationary, while the second-order difference achieves stationarity (p-value < 0.1).

Autocorrelation Function and Partial Autocorrelation Function

Now, determining the order of both the AR and MA models are required. For this purpose, we use the autocorrelation function (ACF) and partial autocorrelation function (PACF). Autocorrelation indicates the order of the moving average component, whereas partial autocorrelation reveals the order of the AR component. Further analysis is still required to confirm the exact orders of both the AR and MA parts. As observed in Fig. 2, the ACF plot indicates that significance is only present at the second-order lag. Again, it is shown that the second and third-order lags in the PACF plot are significant. Hence, our preliminary model is ARIMA (3,2,2).

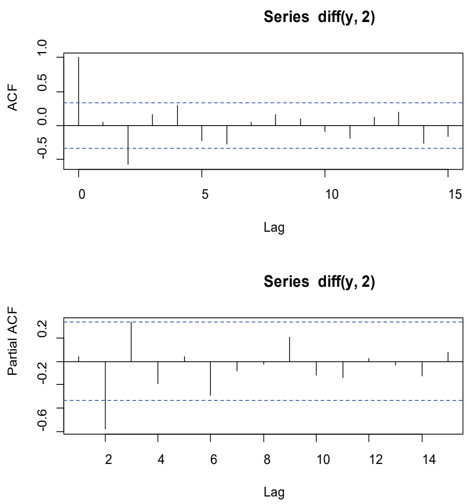

Fig. 2. ACF and PACF graph of the observations

Model Specification

Selecting an accurate model is crucial for predicting future inflation. In this study, we will calculate the AIC values of the potential models to identify the most accurate one. The lower the AIC value, the better the model fits and predicts. The AIC values have been calculated and presented in Table 2 to compare the models.

Table 2. AIC table

Order of ARIMA Model	*AIC*
(0, 2, 0)	193.58
(0, 2, 1)	168.85
(0, 2, 2)	165.04
(1, 2, 0)	188.63
(1, 2, 1)	169.18
(1, 2, 2)	166.2
(2, 2, 0)	175.77
(2, 2, 1)	162.52
(2, 2, 2)	164.26
(3, 2, 0)	168.07
(3, 2, 1)	164.11
(3, 2, 2)	165.49

The lowest AIC value of 162.52, as seen in the table-2 below, corresponds to the ARIMA (2,2,1) model. We therefore tentatively select this model to predict inflation. Table 3 displays the coefficients obtained from fitting the ARIMA (2,2,1) model.

Table 3. Table of coefficients for the ARIMA(2,2,1) model

Component	*AR1*	*AR2*	*MA1*
Coefficient	-0.3655	-0.4782	-1.0000
Standard Error	0.1523	0.1474	0.1171

From Table 3, we may write the fitted ARIMA (2,2,1) model using backshift operator B as below-

$$(1-B)^2(1-\emptyset_1 B-\emptyset_2 B^2)Y_t = (1-\theta_1 B)W_t$$

$$(1-B)^2(1+0.3655\,B+0.4782\,B^2)\,Y_t = (1-B)W_t$$

$$(1-B)(1+0.3655\,B+0.4782\,B^2)\,Y_t = W_t$$

Since the coefficient of the MA1 component is -1.0000, it effectively simplifies the ARIMA (2,2,1) model to an ARIMA (2,1,0) model. When we examine the AIC for the ARIMA (2,1,0) model, we observe that it is 159.2, which is lower than the AIC of the initial ARIMA (2,2,1) model. Thus, the ARIMA (2,1,0) model is designated as the final model for forecasting Bangladesh's inflation rate. Next, we will determine the coefficients for the AR and MA parts of this model.

Table 4. Table of coefficients for the ARIMA (2,1,0) model

Component	*AR1*	*AR2*
Coefficient	-0.3803	-0.4929
Standard Error	0.1492	0.1443

So, the model ARIMA (2,1,0) can be mathematically written as-

$$(1+0.3803\,B+0.4929\,B^2)(1-B)Y_t = W_t$$

Model Diagnostics

As we have found our desired model, now we will need to check some important characteristics of the residuals of this model. For example, normality, independence, and randomness are the three most important characteristics of them. For this purpose, at first, we examine the ACF plot and PACF plot of the residuals. In Fig. 3 we have shown the plots. We can see that firstly in the ACF plot, the residuals are scattered on both sides of the zero (0.0) line. So, we may conclude that, since there is no visible pattern in the graph, the residuals may be randomly distributed.

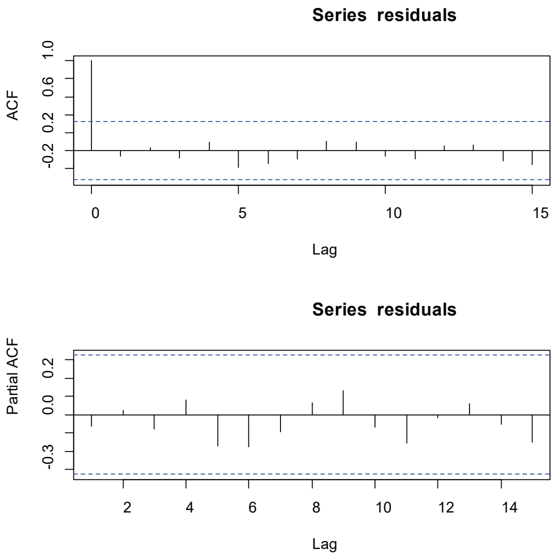

Fig. 3. ACF & PACF graph of the residuals

Later on, the second graph is of the PACF plot. Similarly, no point is beyond the significance line and also there is no visible pattern in it too. Hence, it means that the residuals are independently distributed.

We can check the independence by statistical tests also. To do so, we may use the Ljung Box test.[14] The p-value here determine if the null hypothesis (H_0= residuals are independent) is true or not. From Table 5, we see that the p-value is 0.699 (>0.05). This suggests that the null hypothesis of independence cannot be rejected at the 5% significance level.

Again, normality can be tested using the Shapiro – Wilk test.[15] Here the rule of evaluation by p-value remains the same. Table 5 presents the results of these tests.

Table 5. **Shapiro-Wilk assessment of normalityand Ljung Box test for independence**

Shapiro-Wilk test		***Ljung Box test***		
W	***p-value***	***X^2***	***df***	***p-value***
0.98551	0.9088	0.14855	1	0.6999

The p-value provided in the table-5 implies that the null hypothesis asserting normality remains valid at the 5% level, meaning that the residuals can be considered normally distributed. In addition to other methods, a Q-Q plot can be used to test the normality of the residuals, as illustrated in Fig. 4.

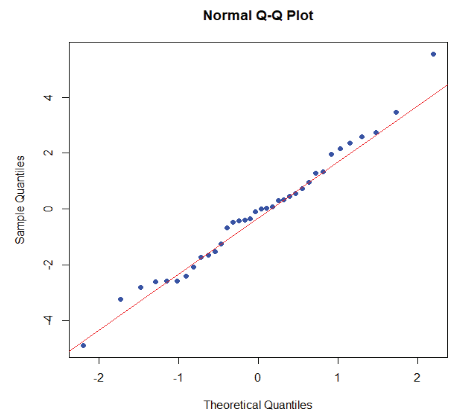

Fig. 4. Q-Q plot displaying the residuals

The plot in Fig. 4 shows that the data points approximately fall on the Q-Q line, which means that the residuals are normal. We may conclude that the residuals resemble white noise, implying that the overall fit of our model is satisfactory.

Actual Values versus Fitted Values

We can visualize the actual values and the fitted values on a single graph to test the model's predictive performance. In other terms, to measure the model's compatibility with the data. In Fig. 5 the actual values from the data set and the predicted values by the fitted model are plotted on the same graph. While the graph reveals some deviations between the fitted and actual values, the model still seems reasonable for predictions.

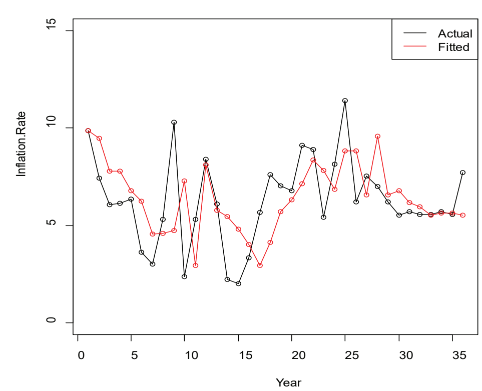

Fig. 5. Actual vs fitted values of Inflation Rate

Forecasting Inflation Rate

With the chosen model in place, we can forecast the annual inflation rate in Bangladesh for the next 10 steps. The forecasted values are detailed in Table 6.

Table 6. Ten steps ahead Inflation forecasting

Year	*Predicted Inflation Rate*	*Standard Error*
2023	6.95	2.14
2024	6.17	2.52
2025	6.84	2.58
2026	6.97	2.88
2027	6.59	3.19
2028	6.67	3.34
2029	6.83	3.51
2030	6.73	3.72
2031	6.69	3.89
2032	6.75	4.04

Although the final model chosen in this research mirrors the one found by Rahman et al.[2], the forecasted inflation figures differ, largely due to the different periods covered in each study.

IV. Conclusion

This study was undertaken to identify a plausible ARIMA model for predicting the annual inflation rate in Bangladesh. The data on the annual inflation rate was sourced from the World Bank's website. To begin with, we examined the stationarity of the data, finding that taking the second difference rendered the inflation rate data stationary. Based on the ACF and PACF plots, we initially chose order 2 for the moving average component and order 3 for the autoregressive component. The ARIMA (2,2,1) model was primarily chosen due to its lowest AIC, but it was ultimately reduced to ARIMA (2,1,0), which had a lower AIC value than the initial model. After performing statistical tests and reviewing graphs and plots for the residuals' randomness, independence, and normality, ARIMA (2,1,0) was confirmed as the best model. To further assess the model's validity, the actual and fitted values were plotted on the same graph. Subsequently, a 10-step-ahead forecast of the annual inflation rate was performed using the fitted model. The ARIMA model forecasts an inflation rate of 6.95% in 2023, followed by a decrease to 6.17% in 2024. The rate is expected to fluctuate in the subsequent years, with only modest changes overall.

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