

Modelling and Forecasting the Consumer Price Index in Bangladesh through Econometric Models

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Abstract

Persistent economic growth along with high Consumer Price Index (CPI) and low inflation is the major aim of the economic theory. This paper uses annual time series data on CPI from the period 1986 to 2018 and find the best econometric time series model for forecasting the CPI in Bangladesh. In this study different Autoregressive integrated moving average (ARIMA) model are used. To find the best ARIMA model we have used here Akaike information criteria (AIC), corrected Akaike information criteria (AICc) and Bayesian information criteria (BIC). This study presents ARIMA (2, 2, 0) model to forecast the CPI in Bangladesh based on the lowest values of AIC, AICc and BIC than other ARIMA models. Based on the selected ARIMA (2, 2, 0) model we forecast the CPI in Bangladesh from period 2019 to 2025. The results of the study show that the CPI in Bangladesh is to continue an upward trend with respect to time.

Keywords: Forecasting; CPI; Inflation rate; Box-Jenkins method; ARIMA models.

1. Introduction

Consumer Price Index (CPI) is the most widely used measure of inflation in financial analysis. The consumer price index (CPI) is a measure of the average change over time in the price of consumer items, goods and services that households buy for day to day living.

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The Consumer Price Index, CPI, a proxy for inflation, has been widely used as a leading indicator of economic change. Financial markets continuously assess expectations on the CPI and react to the innovations contained in new published data [5]. Persistent economic growth along with high CPI and low inflation is the major aim of the economic theory. Price stability is a healthy monetary policy that can enhance economic growth and prosperity. Inflation is widely discussed because it changes the purchasing power of money and real values of variables such as interest rates, wages and many others. Unexpected inflation also decreases the value of a country's currency in the global market and impacts the exchange rate. Therefore, an effective monetary policy depends largely on the ability of economists and policy makers to develop a reliable model that could help understand the ongoing economic processes and predict future developments. Over the last few years, the inflation rate of Bangladesh has been increased. The high rate of inflation in Bangladesh can be explained in terms of factors such as low rate of output growth, monetary expansion, higher dollar price of imports, exchange rate depreciation, increase in excise and sales taxes, and changes in administrative prices. Unexpected inflation also decreases the value of a country's currency in the global market and impacts the exchange rate. The inflationary impact of the depreciation of the exchange rate can similarly be regarded as an indirect effect of an escalation of money supply. Thus money supply would appear to be a key determinant of inflation in an economy. So CPI is one of the most challenging application of modern time series forecasting.

2. Literature Review

Quite a few studies have forecast the consumer price index by econometric models. Different econometric models are used to predict time series data. These methods includes moving are (MA), autoregressive (AR), Exponential smoothing, autoregressive integrated moving average (ARIMA), vector autoregressive (VAR), autoregressive conditional heteroscedasticity (ARCH), generalized autoregressive conditional heteroscedasticity (GARCH) models. One of the popular methods that commonly used for forecasting time series data is Autoregressive Integrated Moving Average (ARIMA) model. Adams and his colleagues (2014) fitted a time series model to the quarterly data of consumer price index (CPI) in Nigeria's Inflation rate between 1980 and 2010 and provided five years forecast for the expected CPI in Nigeria. They applied the Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) model and found that the best fitted model is ARIMA (1, 2, 1). Wayne (1998) asserts that using vector autoregressive model in forecasting exhibits significant degree of forecast accuracy when compared with other forecasting models [14]. Mordi (2012) developed a short-term inflation forecasting by using structure time series models for each CPI component constructed at a certain level of disaggregation. Short-term forecasts of the all items CPI was made as a weighted sum of the twelve CPI components forecast [11]. Meyler and his colleagues (1998) study to forecast Irish inflation applying ARIMA time series models [10]. Zhang, Che, Xu, and Xu (2013) have presented a forecast model for CPI in China for the period 1995–2008 and showed that ARMA model has a forecast accuracy relatively high [16]. Faisal (2011) used ARIMA model forecasting Bangladesh's inflation using monthly consumer price index (CPI) from March 2001 to August 2011. In this study the ARIMA model will be used to analyze time series data and forecasting for the CPI in Bangladesh [6]. Akhter (2013) in her paper, used the SARIMA models to predict the short-term inflation rate of Bangladesh using the monthly CPI from January 2000 to December 2012 [2] and the many other studies used Autoregressive Integrated Moving Average (ARIMA) model to forecast the time series data [2, 3, 4, 7, 12, 13]. So in this study we have made an effort to use ARIMA time series models for forecasting

consumer price index in Bangladesh.

3. Data and Methodology

3.1 Data Source

Data used in this study were records of Consumer Price Index (CPI) of Bangladesh for the period from 1986 to 2018 from the World Bank. Here 2010 is the base year whose index is 100.

3.2 Autoregressive Integrated Moving Average Model

The model used in this study is the Autoregressive integrated moving average (ARIMA).

The AR (p) model can be written as

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \dots + \varphi_p Y_{t-p} + \varepsilon_t \quad (1)$$

The MA (q) model can be written as

$$Y_t = \varepsilon_t - \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} - \dots + \theta_q \varepsilon_{t-q} \quad (2)$$

The combination of AR (p) and MA (q) model i.e. ARMA (p, q) model is expressed in the following form:

$$Y_t = \theta_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \dots + \varphi_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \dots - \theta_q \varepsilon_{t-q} \quad (3)$$

Where, Y_t and ε_t are the actual value and random error at time period t respectively; φ_i ($i=1,2,3,\dots,p$) and θ_j ($j=1,2,3,\dots,q$) are model parameters. The integer's p and q are referred to as order of autoregressive and moving average respectively. Random error term ε_t are assumed to be independently and identically distributed (i.i.d) with mean zero and constant variance σ^2 .

Using backward shift operator the ARMA (p, q) model can be written in the following form

$$\varphi(B)Y_t = \theta(B)\varepsilon_t \quad (4)$$

Where $\varphi(B) = 1 - \varphi_1 B - \varphi_2 B^2 - \dots - \varphi_p B^p$ and $\theta(B) = 1 + \theta_1 B + \theta_2 B^2 + \dots + \theta_q B^q$.

If the time series is not stationary, then we convert it to stationary by taking it differencing. If d is the order of difference series then the ARIMA (p, d, q) model can be written as

$$\varphi(B)\Delta^d Y_t = \theta(B)\varepsilon_t \quad (5)$$

3.3 Box-Jenkins ARIMA Approach

For estimating the ARIMA model the three stages of modeling as suggested by Box and Jenkins namely identification, estimation and diagnostic checking were undertaken. For model identification at first we test the stationary of the original data by using time series plot, autocorrelation function (ACF), and unit root test. If the series is not stationary then we need to difference of the series until to get stationary. After the stationarity of the time series was attained, ACF and PACF (partial autocorrelation function) of the stationary series are employed to select the order of the Autoregressive (AR) process and the order of the Moving Average (MA) process of the ARIMA model. Integrated (I) process, which account for stabilizing or making the data stationary. Estimation of the model was done by the least square method. In the diagnostic checking phase the model residual analysis was performed.

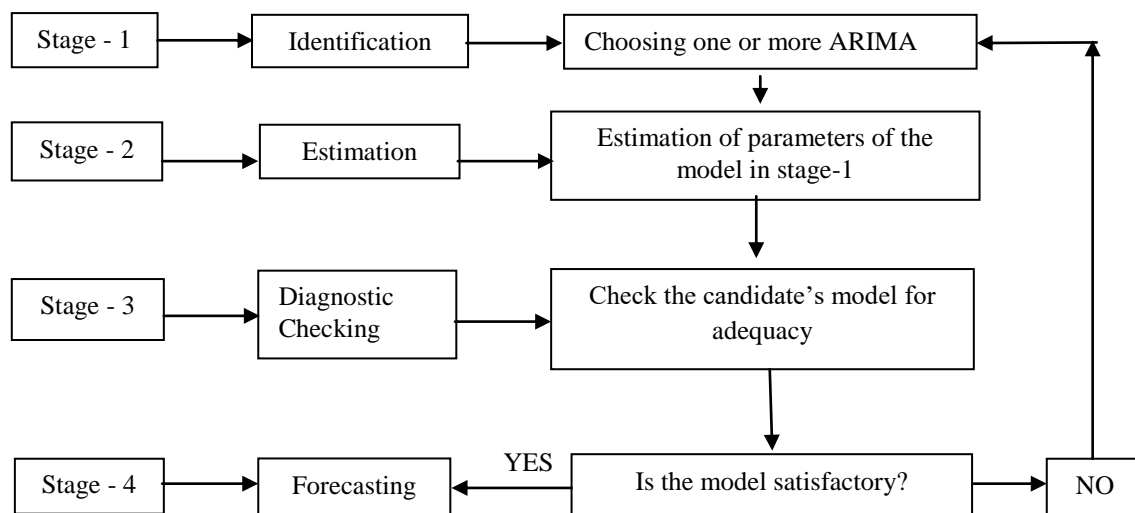


Figure 1: Stages of Box-Jenkins approach.

3.4 Model selection Criteria

We have used this paper three criterion to select the appropriate ARIMA model namely Akaike Information Criterion (AIC), corrected Akaike Information Criterion (AICc) and Bayesian Information Criterion (BIC). The lowest value of AIC, AICc and BIC predict the best ARIMA model among the tentative models.

4. Results and Discussion

4.1 Stationary Test and Model identification

To identify the appropriate order of AR and MA at first we check the series stationary or not. The time series plot and Augmented Dickey Fuller test are used for examining the series stationary or not. Figure 2(a) shows that the original series of CPI in Bangladesh is non-stationary since the series is increasing with respect to time i.e. the mean of the series is not constant over time period. We also see that there is no seasonality in the series.

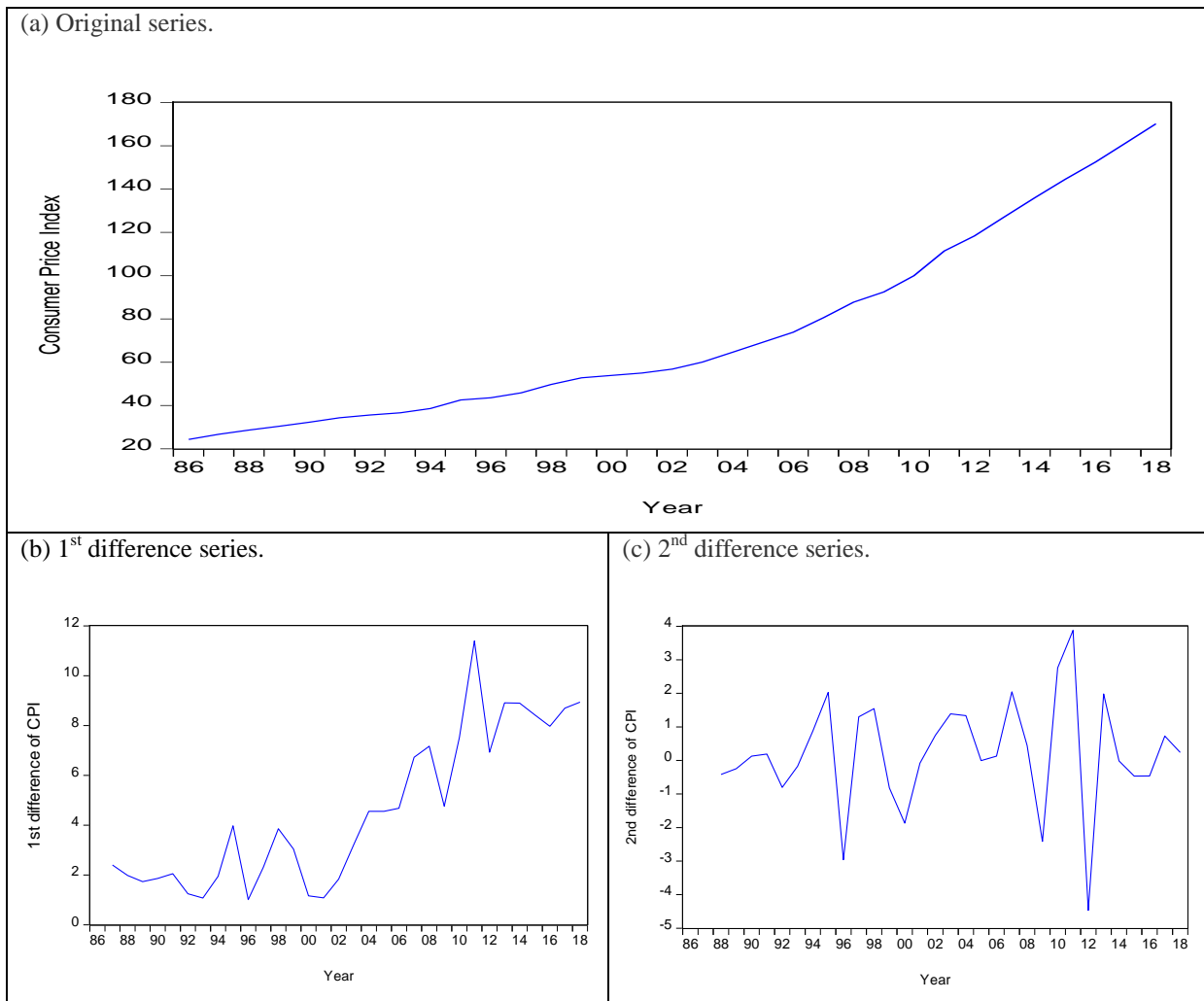


Figure 2: Time series plot of CPI in Bangladesh.

To confirm this Augmented Dickey Fuller (ADF) test was also observed. From Table 1 see that the p-value is greater than 5 percent level of significance hence the series is non-stationary. To achieve stationary the trend component should be extracted from the original series.

It could be achieved by using the method of differencing. The first difference of the original series are also non-stationary since the trend have a systematic pattern and the mean is not constant over time (shown in figure 2(b)). From table-2 we can say that the 1st difference of the series remained non-stationary.

Although the intercept and trend level are stationary. After 2nd differencing, from figure 2(c) we can see that there is no systematic pattern (i.e. increase or decrease movement) of the trend and mean is constant over time hence the 2nd difference of the original series are stationary.

To confirm this we performed ADF test. Table-3 shows that all the p-value of different levels are lower than 5% level of significance therefore there 2nd difference of the CPI series is stationary.

Table 1: ADF test of original series

Level	ADF statistic	Critical values (5% sig.)	Probability	Decision
Intercept	3.040199	-2.960411	1.0000	Non-Stationary
Intercept and trend	-0.779418	-3.574244	0.9562	Non-Stationary
Without intercept and trend	3.508643	-1.952066	0.9997	Non-Stationary

Table 2: ADF test of 1st difference series

Level	ADF statistic	Critical values (5% sig.)	Probability	Decision
Intercept	-0.145438	-2.967767	0.9349	Non-Stationary
Intercept and trend	-3.703578	-3.562882	0.0371	Stationary
Without intercept and trend	-1.952910	1.305150	0.9478	Non-Stationary

Table 3: ADF test of 2nd difference series

Level	ADF statistic	Critical values (5% sig.)	Probability	Decision
Intercept	-7.402565	-2.967767	0.0000	Stationary
Intercept and trend	-7.359325	-3.574244	0.0000	Stationary
Without intercept and trend	-6.978436	-1.952910	0.0000	Stationary

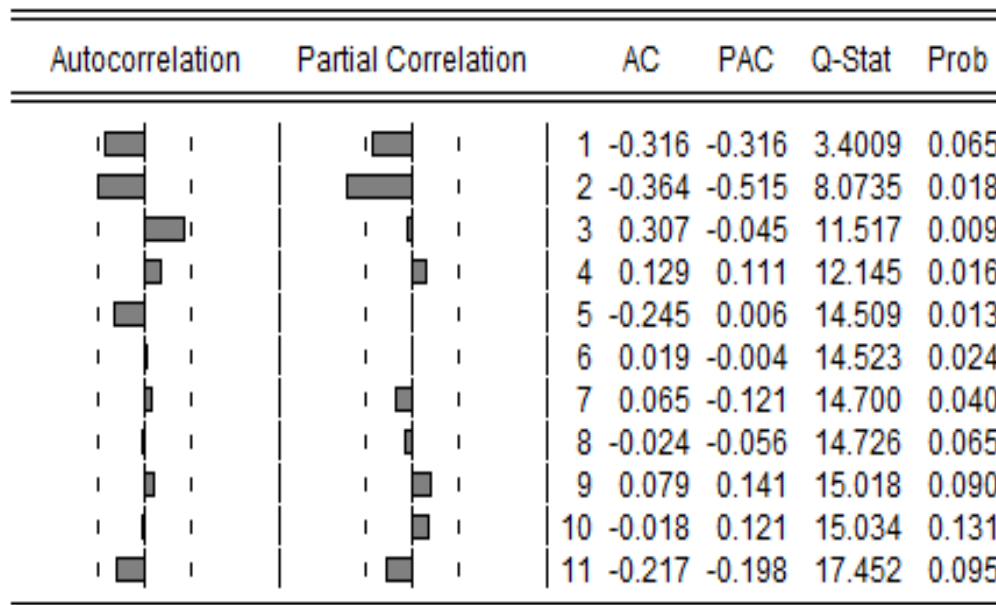


Figure 3: ACF and PACF plot of 2nd difference of CPI series.

After the series has been stationarized by second differencing, the next step in fitting an ARIMA model is to determine how many AR or MA terms are needed to correct any autocorrelation that remains in the second differenced series. Therefore, the order of AR and/or MA terms that are needed to fit a model are tentatively

identified by looking the ACF and PACF plots of the 2nd differenced series. Since after 2nd difference we get a stationary series so the order of d will be 2. It is obvious from the sample ACF of the 2nd difference series (shown in figure 3) the most dominating spike at lag 2 are statistically significant for PACF. Now we consider the different types of tentative models as much as possible from which we select the best model using the model selection criterion. Since the characteristics of a good ARIMA model is parsimonious ignoring the higher order of p and q, the tentative models on the basis of model selection criterion are as follows:

Table 4: Different ARIMA models for CPI in Bangladesh.

Model	AIC	AICc	BIC
ARIMA (1,2,0)	120.5	120.93	123.37
ARIMA (1,2,1)	119.56	120.45	123.86
ARIMA(1,2,2)	120.29	121.83	126.03
ARIMA(0,2,1)	115.57	118	120.44
ARIMA(0,2,2)	119.48	120.37	123.78
ARIMA(2,2,0)	115.15	116.04	119.45
ARIMA(2,2,1)	117.12	118.66	122.85
ARIMA(2,2,2)	116.7	119.1	123.87

From the above table-4 we see that the values of AIC, AICc and BIC of ARIMA (2, 2, 0) model is lower than other tentative models. So we can say that the model ARIMA (2, 2, 0) is the best tentative model and we use this model for our forecasting purposes. The OLS results of ARIMA (2, 2, 0) model are shown in the following table 5.

Table 5: OLS results of ARIMA (2, 2, 0) model.

Type	Coefficient	Standard Error	t Statistic	P value
Constant	0.4422	0.2506	1.76	0.089
AR (1)	-0.4843	0.1608	-3.01	0.005 (Significant)
AR (2)	-0.5229	0.1610	-3.25	0.003 (Significant)

4.2 Diagnostic Checking

Correlograms of residuals of ARIMA (2, 2, 0) (shown in figure 4) model are observed and it is found that no significant spikes are observed in any diagram. Plot of residuals also suggest the adequacy of the models and suggest that there is no serial correlation. The normal probability plot (shown in figure 5) suggest that the residuals of ARIMA (2, 2, 0) are normally distributed. Therefore, the ARIMA (2,2,0) was successfully selected as an accurate model for forecasting the CPI in Bangladesh.

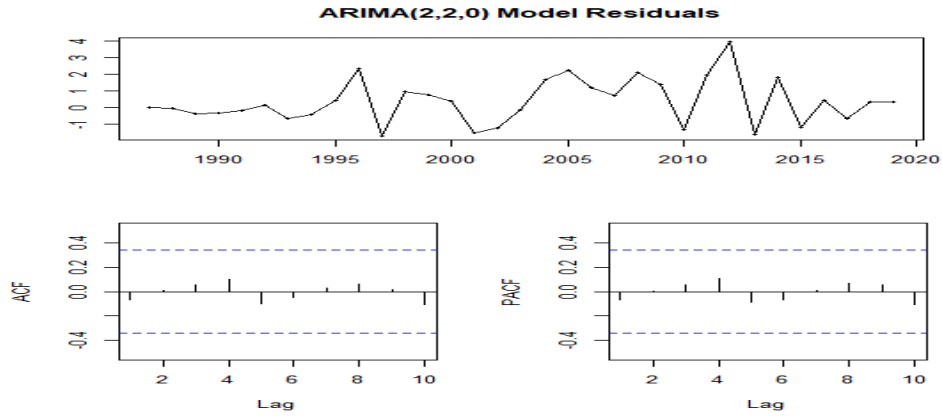


Figure 4: Correlogram plots of residuals of ARIMA (2, 2, 0) model.

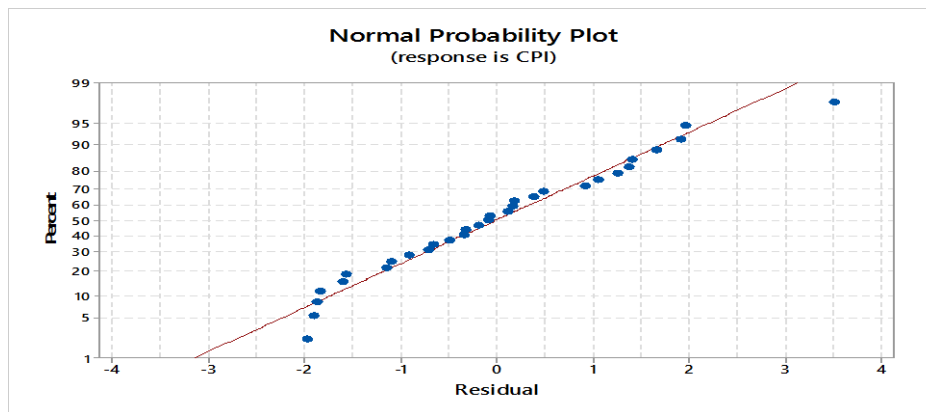


Figure 5: Normal probability plot of residuals of ARIMA (2, 2, 0).

4.3 Forecasting

Forecasting is the process of making predictions of the future based on past and present data and analysis of trends. In our study we have selected ARIMA (2, 2, 0) model as the best model to forecast the consumer price index of Bangladesh. Using ARIMA (2, 2, 0) model to forecast CPI in Bangladesh from 2019 to 2025 are displayed in the following table 6:

Table 6: Forecast values using ARIMA (2, 2, 0) model

Year	CPI	95% confidence limit of CPI	
		Lower limit	Upper limit
2019	179.047	176.312	181.783
2020	188.273	183.306	193.241
2021	197.804	190.918	204.689
2022	207.450	198.005	216.895
2023	217.323	204.911	229.735
2024	227.468	212.058	242.878
2025	237.805	219.149	256.460

Figure 6 display the observed value vs predicted values and shown that the observed value and predicted approximately equal. Therefore we can say that ARIMA (2, 2, 0) model appropriately fit the data.

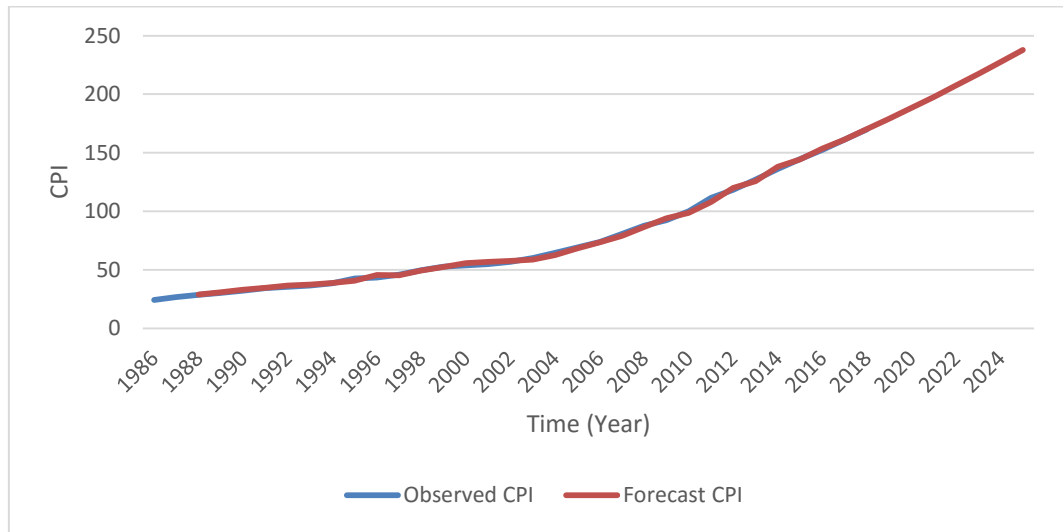


Figure 6: Forecast value of CPI from 2019 to 2025.

5. Conclusions

In this study, we attempt to search the optimal ARIMA model to predict the future values of CPI in Bangladesh using the data from 1986 to 2018. The time series plot, ACF and PACF plot and unit root test suggest that the original series and 1st difference series CPI in Bangladesh are non-stationary but 2nd difference series is stationary. Then applied the Box-Jenkins procedure on the 2nd difference of CPI series and we identify the corresponding ARMA (p,q) process. Thereafter we select different ARIMA (2, 2, 0) models among different tentative model since it gives the lowest AIC, AICc and BIC values. The diagnostic test suggest that the residual are normally distributed and there is no serial correlation i.e. the selected model is more appropriate than others. Based on the selected ARIMA (2, 2, 0) model we have to predict the CPI of Bangladesh from 2019 to 2025. The results of the study show that the CPI in Bangladesh is to continue an upward trend with respect to time (shown in figure 6).

Acknowledgements

The authors are grateful to the anonymous referee for a careful checking of the details and for helpful comments that improved this paper.

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