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# Forecasting Monthly Inflation in Bangladesh: A Seasonal Autoregressive Moving Average (SARIMA) Approach

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## Abstract

*The objective of this study is to forecast the trend of inflation in Bangladesh by utilizing past inflation data. To achieve this objective, we employed the Seasonal Autoregressive Integrated Moving Average (SARIMA) model which is an extension of the Autoregressive Integrated Moving Average (ARIMA) model. Monthly inflation data used for forecasting were derived from the Consumer Price Index (CPI) data obtained from the International Monetary Fund (IMF) database, covering the period from January 2010 to January 2023. Our analysis reveals that the SARIMA $(2,0,0)\times(1,0,1)_{12}$ model is the most appropriate fit. Based on this finding, we predicted the inflation trend in Bangladesh from February 2023 to December 2024. A comparison of our predicted values with the actual values indicates a high degree of correlation between the two. Although a few discrepancies were observed, they did not undermine our prediction since the parameters of the model lay within the 95% confidence interval.*

**Keywords:** *Inflation, Seasonality, SARIMA, Bangladesh.*

**JEL Classification:** *C51, C53, E31, E37.*

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## 1. Introduction

Inflation is a vital macroeconomic indicator used to assess economic stability. High inflation levels result in increased prices of goods and services, limiting people's ability to buy necessities. Conversely, stable inflation levels contribute to a healthy economy and welfare promotion. Inflation affects interest rates on savings, mortgages for businesses, and pension and welfare benefits. Maintaining stable inflation levels is essential to prevent negative impacts on socio-economic conditions.

The level of inflation is a well-known indicator used by policymakers to measure and regulate economic well-being (Enke & Mehdiyev, 2014). If inflation goes unchecked or exceeds the desired level, it can negatively affect people's purchasing power, leading to decreased investment, cost over-runs for projects, income inequality, and financial difficulties (Hurtado & Cortes-Fregoso, 2013). To make informed policy decisions, accurately predicting future inflation trends is crucial (McNelis & McAdam, 2004). In this study, we used the consumer price index (CPI) as a useful tool for measuring inflation. CPI reflects changes in the general price level of a group or basket of commodities and can be used to construct a frequency distribution of relative prices in an economy (Kharimah et al., 2015; Subhani & Panjwani, 2009). The rationale behind using CPI to forecast inflation levels is that it allows policymakers to make accurate investment and savings decisions, resulting in effective resource utilization and economic stability (Enke & Mehdiyev, 2014).

As a developing country, Bangladesh must prioritize controlling inflation to efficiently allocate its limited resources and stabilize currency volatility. Policy makers recognize that controlling inflation is crucial in light of increasing income inequality; however, inaccurate measurement of future inflation trends could result in ineffective policies and wasted resources. In this study, we utilized CPI data obtained from the IMF to forecast future inflation trends in Bangladesh. By using a general formula to compute inflation based on CPI data collected between January 2010 and January 2023, we applied the SARIMA model to predict inflation trends in Bangladesh from February 2023 to December 2024. These predictions can be used by policy makers to better control inflation and promote economic stability.

While most of the earlier studies accentuate exploring annual inflation with little attention to the seasonality effects, the usage of monthly inflation data incorporating seasonality effects makes our study a unique one. The experience of repeated price hikes several times within a year still awaits a rational account, which makes it a crying need to anticipate future aspects of the phenomenon for preventing further impairment. The rest of the study is organized in four sections. Section 2 reviews the earlier relevant literature while section 3 presents the methods and materials. Section 4 sheds light on the findings and section 5 concludes the study.

## 2. Literature Review

Throughout the years, numerous studies have attempted to estimate and forecast the expected inflation either on a monthly basis or annually for respective countries. The central focus of the studies, albeit identical, incorporated diverse approaches over different time ranges considering the nation-specific contexts.

Several studies have investigated inflation forecasting models across different countries and time periods. Suleman & Sarpong (2012) conducted research in Ghana covering the period from January 1990 to January 2012, utilizing the Box-Jenkins approach. They identified the ARIMA (3, 1, 3) (2, 1, 1) model as the most appropriate for their analysis.

Okyere & Mensah (2014) focused on Ghana for the period from January 2009 to December 2013, employing the Box-Jenkins approach. Their study concluded that the ARIMA (1, 2, 1) model was suitable for modeling inflation rates during that timeframe.

In Tanzania, Ngailo, Luvanda, & Massawe (2014) examined data from January 1997 to December 2010, using the GARCH methodology. Their findings indicated that the GARCH (1, 1) model provided the best results for forecasting.

Otu Archibong Otu et al. (2014) conducted a study in Nigeria, covering the period from November 2003 to October 2013 on a monthly basis. They applied SARIMA, determining that the SARIMA (1, 1, 1) $(0, 0, 1)_{12}$ model was appropriate for forecasting inflation.

Liko, Ramosaco, & Kashuri (2016) explored inflation forecasting in Albania from January 2000 to December 2016, using ARCH and GARCH methodologies. Their research identified GARCH (1, 0, 1) as the most effective model for predicting the rate of inflation.

Thabani Nyoni (2019) conducted two studies, one in Tanzania spanning from 1966 to 2017 and another in the Philippines from 1960 to 2017. Both studies applied ARIMA models, with the former using ARIMA (1, 1, 2) and the latter utilizing ARIMA (1, 1, 3).

Md. Shahajada Mia et al. (2019) focused on Bangladesh from 1986 to 2018, employing ARIMA. They found that the ARIMA (2, 2, 0) model provided the best forecast for the Consumer Price Index (CPI) in Bangladesh from 2019 to 2025.

Olalude Gbenga Adelekan et al. (2020) conducted research in Nigeria from January 2003 to October 2020 on a monthly basis, using both ARIMA and SARIMA. Their findings indicated that the SARIMA (3, 3) x $(1, 2)_{12}$ model performed best for monthly inflation forecasting.

Erkan Isigicok et al. (2020) studied Turkey from January 2002 to March 2019 on a monthly basis, applying ARIMA and Artificial Neural Network (ANN) models. The research highlighted the successful performance of the ARIMA model with its stationary structure.

Karadzic & Pejovic (2021) conducted a comparative study on countries in the European Union and the Western Balkans (Montenegro, Serbia, and Northern Macedonia) from January 2010 to March 2019. They employed ARIMA, Holt-Winters, and Neural Network Auto-Regressive (NNAR) models, concluding that NNAR provided the most accurate forecast for Western Balkan countries, while the ARIMA model was most accurate for EU countries.

Wati, Eltivia, & Djajanto (2021) focused on Indonesia from January 2010 to December 2019, using ARIMA. Their findings suggested that the ARIMA (12, 0, 12) model was the most effective for predicting monthly inflation.

Banerjee (2021) conducted research in India from January 1960 to December 2018, utilizing ARIMA. The study determined that the ARIMA (1, 1, 5) model was appropriate for predicting the Consumer Price Index (CPI).

Abdullah Ghazo (2021) studied Jordan from 1976 to 2019, employing ARIMA for GDP forecasting and ARIMA (1, 1, 0) for CPI forecasting.

Eni Farida and Mohamad As’ad (2021) focused on Indonesia from January 2015 to June 2019 on a monthly basis, utilizing ARIMA. Their research identified the ARIMA model (2, 0, 3) as the appropriate model for inflation forecasting.

Tahira Bano Qasim et al. (2021) examined Pakistan from January 1962 to December 2019 on a monthly basis, employing ARIMA and GARCH. The study concluded that the GARCH (2, 2) model was the best variance model for the series.

Rahul Singh Gautam & Jagjeevan Kanoujiya (2022) studied India from February 2011 to January 2022 on a monthly basis, focusing on ARIMA. Their research emphasized the importance of forecasting inflation using the 'target inflation' method.

Marpaung, Soesilowati, Rahman, Tegar, & Yuliani (2022) conducted research in Indonesia (Central Java) from January 2016 to April 2021, applying the Box-Jenkins or ARIMA method. The study found that ARMA (3, 0, 3) or AR (3) and MA (3) were the appropriate methods for their analysis.

Rahman & Islam (2020) explored inflation forecasting in Bangladesh from 1987 to 2017, using ARIMA. The study concluded that the ARIMA (2, 1, 0) model was the optimal choice for forecasting inflation over an eight-year period.

Lidiema (2017) focused on Kenya from November 2011 to October 2016, comparing SARIMA and the Holt-Winters triple exponential smoothing. The research indicated that the SARIMA model outperformed the Holt-Winters triple exponential smoothing in terms of forecasting accuracy.

## 3. Methodology

In this study, the Seasonal Autoregressive Integrated Moving Average (SARIMA) model advocated by Box and Jenkins (1976) is applied which is an extension of the Autoregressive Integrated Moving Average (ARIMA) model. ARIMA models belong to the subset of linear regression models that attempt to utilize historical data of the target variable to predict its future values by decomposing it into two parts namely, AR and MA processes. The term AR refers to regressing the variable on its own past values while MA takes the lagged prediction errors as inputs and the “I” stands for “integrated” implying the order of differencing to make the time series data stationary.

### 3.1. Autoregressive Integrated Moving Average Model

The general ARIMA model with its order is represented as ARIMA(p,d,q) where p, d and q are integers greater than or equal to zero and refer to the number of autoregressive lags, order of integration and number of moving average lags respectively (Hurvich & Tsai, 1989; Wolters & Kirchgässner, 2007; Kleiber & Zeileis, 2008). The model diminishes to an ARMA(p,q) model if and only if d=0. The model can be expressed mathematically as follows.

$$Y_t = \mu + \alpha_1 Y_{t-1} + \alpha_2 Y_{t-2} + \cdots + \alpha_p Y_{t-p} + \varepsilon_t - \theta_1 \varepsilon_{t-1} - \theta_2 \varepsilon_{t-2} - \cdots - \theta_1 \varepsilon_{t-q} \quad (1)$$

$$or, \quad Y_t = \sum_{k=1}^{p} \alpha_k Y_{t-k} - \sum_{k=1}^{q} \theta_k \varepsilon_{t-k} + \mu + \varepsilon_t \quad (2)$$

The backshift (lag) operator, L, and difference operator, $\nabla$ have been skipped while representing an ARIMA specification since the target variable is already stationary with integrated order zero i.e., d=0.

### 3.2. Seasonal Autoregressive Integrated Moving Average Model

The extension to SARIMA from ARIMA is preferred when there exists both seasonal and non-seasonal behavior in the data series. The SARIMA model is also known as the multiplicative seasonal autoregressive integrated moving average model denoted by ARIMA (p,d,q)×(P,D,Q). Here p, d and q are the non-seasonal AR, differencing, and MA components respectively while P, D and Q represent the seasonal AR, differencing, and MA components, respectively. The seasonal AR parameters represent the autoregressive relationships that exist between time series data separated by multiples of the number of periods per season. The general SARIMA model can be expressed as

$$Y_t = \sum_{i=1}^{p} \alpha_{is} Y_{t-is} + \sum_{i=1}^{q} \theta_{is} \varepsilon_{t-is} + \varepsilon_t \qquad (3)$$

### 3.3. Box-Jenkins Approach

Three stages of modeling including identification, estimation and diagnostic checking were followed as suggested by Box and Jenkins. The identification stage encompasses stationarity test of the series and lag length selection with the help of sample autocorrelation function (ACF) and partial autocorrelation function (PACF). The framework of Box-Jenkins approach has been depicted through a flow diagram in figure 1.

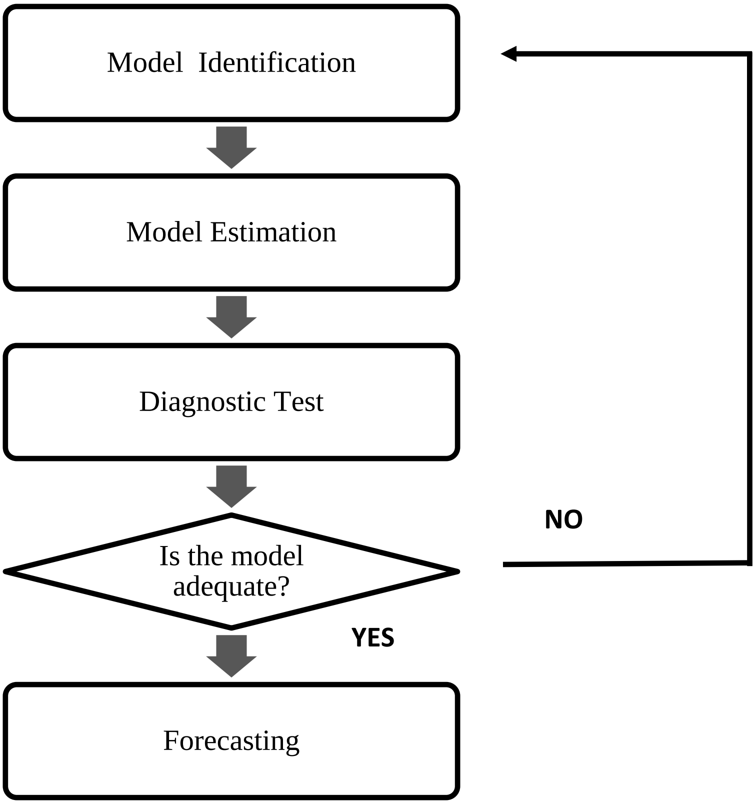


**Figure 1.** Stages of Box-Jenkins Method

### 3.4. Collection of Data

The secondary data of monthly consumer price index (CPI) is collected from the website of International Monetary Fund (IMF) from January 2010 to January 2023 which corresponds with the reports of Bangladesh Bureau of Statistics (BBS). The data period is chosen according to the availability of monthly CPI data which only exists from January 2010. The monthly inflation is thereby calculated using the following formula,

$$Inflation_t = \frac{CPI_t - CPI_{t-1}}{CPI_{t-1}} \times 100 \tag{4}$$

Here, t and t-1 refer to current and previous months, respectively. The monthly time series data of inflation is then utilized for the analysis of the study.

## 4. Results

### 4.1. Model Identification

#### 4.1.1. Data Inspection

Initially, it is convenient to observe the monthly inflation data of Bangladesh through eyeballing to detect any apparent pattern or behavior. Figure 2 shows the monthly inflation in Bangladesh since January 2010 until January 2023 where cyclical fluctuations are prevalent throughout the period with comparatively less volatility in the initial years than that of the latter years with several spikes between 2020 and 2022. Unlike the yearly inflation data, the monthly inflation plot indicates a potential existence of seasonality which needs to be further investigated.

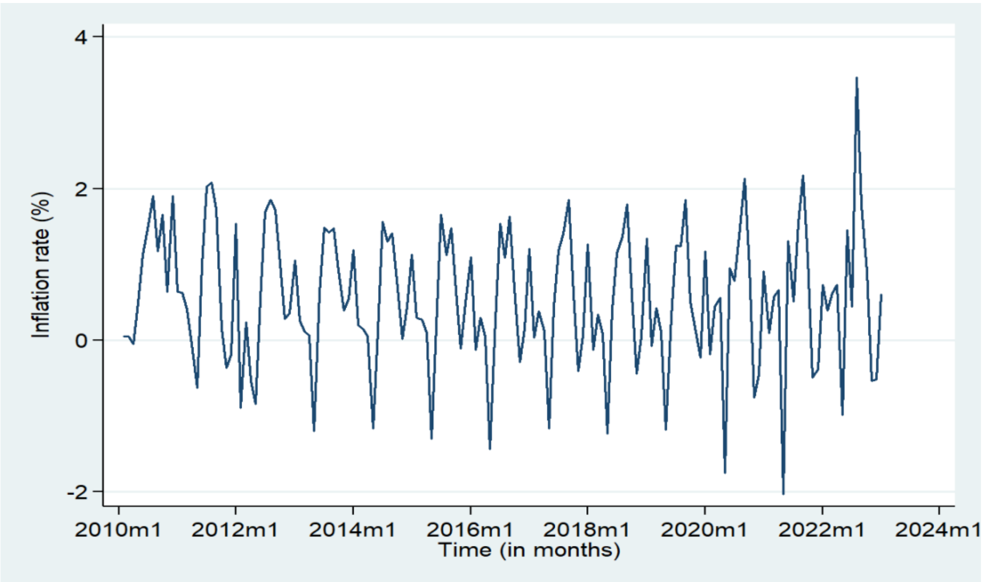


**Figure 1.** Monthly Inflation Rate between January 2010 to January 2023

#### 4.1.2. Checking Stationarity

The stationarity of the time series variable must be checked before identifying the optimum lag order of AR and MA models. Augmented Dicky Fuller (ADF) test and Phillip-Perron's (PP) test confirm that the data series is stationary at level form implying an integrated order of zero for the model. The series is found to be stationary including intercept and trend or excluding both the components. Results of the ADF and PP test are represented in Table 1. The critical values are presented at 5% level of significance.

**Table 1.** Test for Stationary

| Level | ADF Statistic | Critical Value | P-value | PP Statistic | Critical Value | P-value | Decision |
|---|---|---|---|---|---|---|---|
| Intercept | -9.249 | -2.886 | 0.0000 | -8.953 | -2.886 | 0.0000 | Stationary |
| Intercept and Trend | -9.253 | -3.443 | 0.0000 | -9.253 | -3.443 | 0.0000 | Stationary |
| Without intercept and trend | -7.309 | -1.950 | 0.0000 | -7.309 | -1.950 | 0.0000 | Stationary |

#### 4.1.3. Autocorrelation and Partial Autocorrelation Function

The integrated order for both seasonal and non-seasonal components will be zero i.e., d=1 and D=1 since the variable is stationary at level form. The next step is to identify the optimum lag length for the AR and MA models with the aid of Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) for both seasonal and non-seasonal components. The sample ACF shown in figure 2 suggests that q=1 since it has one significant spike at lag 1 and then diminishes. Similarly, the PACF in figure 3 has one significant spike at lag 1 implying p=1 for the non-seasonal ARIMA component. Again, ACF and PACF both have another significant spike at lag 12 suggesting P=1 and Q=1 for the seasonal component of the model. Thus, the most appropriate model will hover around SARIMA (1,0,1)×(1,0,1)12 model which can be selected based on the Akaike Information Criterion (AIC) and Schwartz Bayesian Information Criterion (BIC).

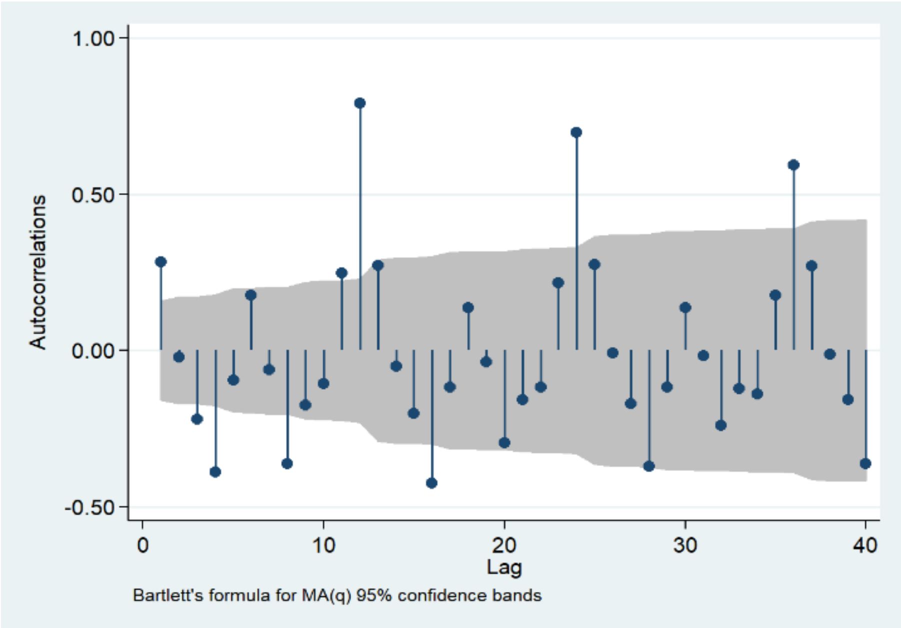


**Figure 3.** Autocorrelation Function (ACF)

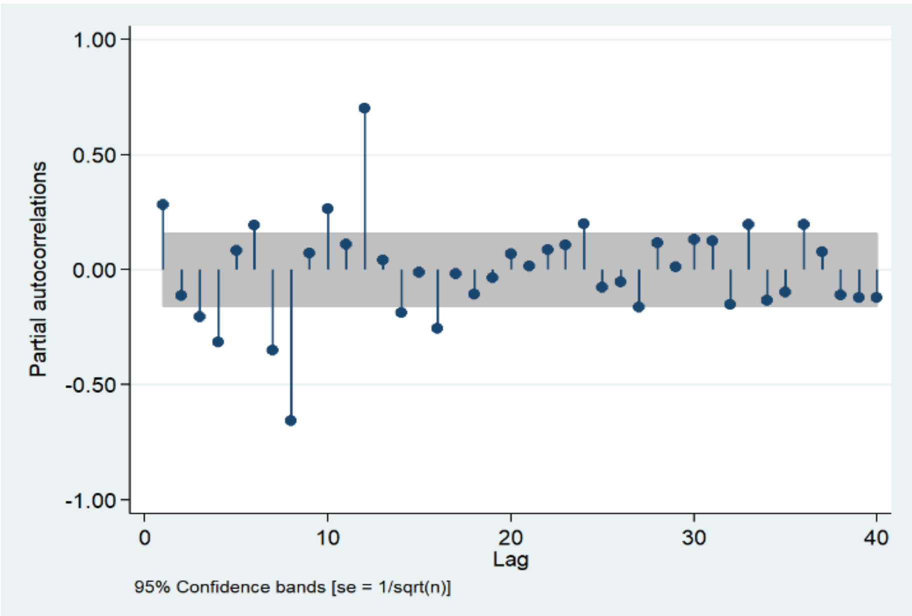


**Figure 4.** Partial Autocorrelation Function (PACF)

## 4.2. Estimation

### 4.2.1. Model Selection

After identifying the lag lengths of the potential model, ordinary least squares (OLS) method is utilized to estimate the parameters of the appropriate model. The procedure for choosing the best model relies on choosing the model with the minimum AIC and BIC. The values of log likelihood are also mentioned in order to confirm the accuracy of estimation. A higher log likelihood value and a lower standard error would correspond with the most suitable SARIMA structure. Table 2 depicts the values of AIC, BIC, log likelihood and number of significant coefficients for each of the proposed models.

**Table 2.** Selection of Appropriate Model using AIC and BIC Criteria

| Model | AIC | BIC | Log likelihood | Significant coefficients |
|---|---|---|---|---|
| $(1,0,1)\ (0,0,0)_{12}$ | 409.9972 | 422.1966 | -200.9986 | 3 |
| $(1,0,1)\ (1,0,0)_{12}$ | 203.5367 | 218.786 | -96.76837 | 3 |
| $(1,0,1)\ (0,0,1)_{12}$ | 311.1141 | 326.3634 | -150.5571 | 3 |
| $(1,0,1)\ (1,0,1)_{12}$ | 194.7166 | 213.0157 | -91.35828 | 4 |
| $(1,0,2)\ (0,0,0)_{12}$ | 392.5512 | 407.8005 | -191.2756 | 4 |
| $(1,0,2)\ (1,0,0)_{12}$ | 196.9409 | 215.2401 | -92.47047 | 5 |
| $(1,0,2)\ (0,0,1)_{12}$ | 304.882 | 320.1313 | -147.441 | 4 |
| $(1,0,2)\ (1,0,1)_{12}$ | 188.9726 | 210.3216 | -87.48628 | 4 |
| **$(2,0,0)\ (1,0,1)_{12}$** | **187.5203** | **205.8194** | -87.76015 | **4** |
| $(2,0,1)\ (0,0,0)_{12}$ | 385.4811 | 400.7303 | -187.7405 | 4 |
| $(2,0,1)\ (1,0,0)_{12}$ | 198.267 | 216.5661 | -93.13349 | 3 |
| $(2,0,1)\ (0,0,1)_{12}$ | 304.1501 | 322.4492 | -146.075 | 5 |
| $(2,0,1)\ (1,0,1)_{12}$ | 188.8698 | 210.2188 | **-87.43492** | 4 |
| $(2,0,1)\ (2,0,0)_{12}$ | 189.1965 | 210.5455 | -87.59824 | 4 |

### 4.2.2. SARIMA Estimation

From table 2, the model with minimum AIC and BIC criterion are chosen which leaves us with a SARIMA $(2,0,0)\times(1,0,1)_{12}$ model. The model also retains the highest log likelihood among all others. Although the model does not have the lowest variance among all the tentative models, it is only second to the least variance. Table 3 represents the regression coefficients of SARIMA $(2,0,0)\times(1,0,1)_{12}$.

**Table 3.** Estimation of the parameters of SARIMA Model

| Inflation | Coef. | St.Err. | t-value | p-value |
|---|---|---|---|---|
| AR (1) | -0.016 | 0.049 | -0.33 | 0.745 |
| AR (2) | 0.230*** | 0.050 | 4.63 | 0.000 |
| SAR (1) | 0.961*** | 0.030 | 31.74 | 0.000 |
| SMA (1) | -0.388*** | 0.123 | -3.16 | 0.002 |
| Constant | 0.396*** | 0.015 | 26.40 | 0.000 |
| *Mean dependent var* | 0.550 | *SD dependent var* | 0.888 | |
| *Number of obs* | 156 | *Chi-square* | 2363.700 | |
| *Prob > chi2* | 0.000 | *Akaike crit. (AIC)* | 187.520 | |

**Note:** The ***, **, and * are statistically significance levels at 1%, 5%, and 10% respectively.

At 95% confidence interval, all the coefficients except AR(1) component are statistically significant according to the analysis in table 3. Both the seasonal AR and MA components are highly significant for the model. It is evident that the seasonal components have relatively higher effect on the dependent variable than the non-seasonal ones. One explanation for the first lag of the AR component being insignificant may lie in the type of data. Monthly inflation may be affected more by the second lag than the first one since prices are generally sticky and might take an interval to be adjusted. The inflation rate of the current month is largely affected by the month before previous month while remaining barely affected by the 'immediate' previous month. For instance, a price shock in fuel price will translate into further inflation on other sectors as well as on the nation as a whole but it will happen gradually rather than instantly.

### 4.3. Diagnostic Tests

#### 4.3.1. White Noise Test

The accuracy of the best fit model to data relies on crucial assumptions about the residuals. One of the assumptions of a superior ARIMA model is that the residuals must follow a white noise process. This means the residuals have a mean zero, constant variance and are uncorrelated. The ACF plot of residuals suggests that the residuals are uncorrelated. It can also be affirmed through a more robust white noise test using Portmanteau Q statistic. Table 4 shows the results of the white noise test and a Chi-squared value greater than 0.05 ensures the acceptance of the null hypothesis. Thus, the residuals follow a white noise process.

**Table 4.** White Noise Test of Residuals

| Portmanteau (Q) statistic | Prob>Chi2(40) |
|---|---|
| 43.8190 | 0.3127 |
| $H_0$ = Residuals follow a white noise process | |

Moreover, the bell-shaped histogram of the error terms as well as an almost linear normal probability plot indicates that the residuals are normally distributed.

#### 4.3.2. Stability and Invertibility Conditions

Another critical issue is whether the AR and MA parameters satisfy the stability and invertibility conditions, respectively. This can be identified by looking into the corresponding eigen values of AR and MA roots. The AR and MA roots lie within a unit circle referring to a stationary and invertible estimated seasonal ARMA process as shown in figure 5.

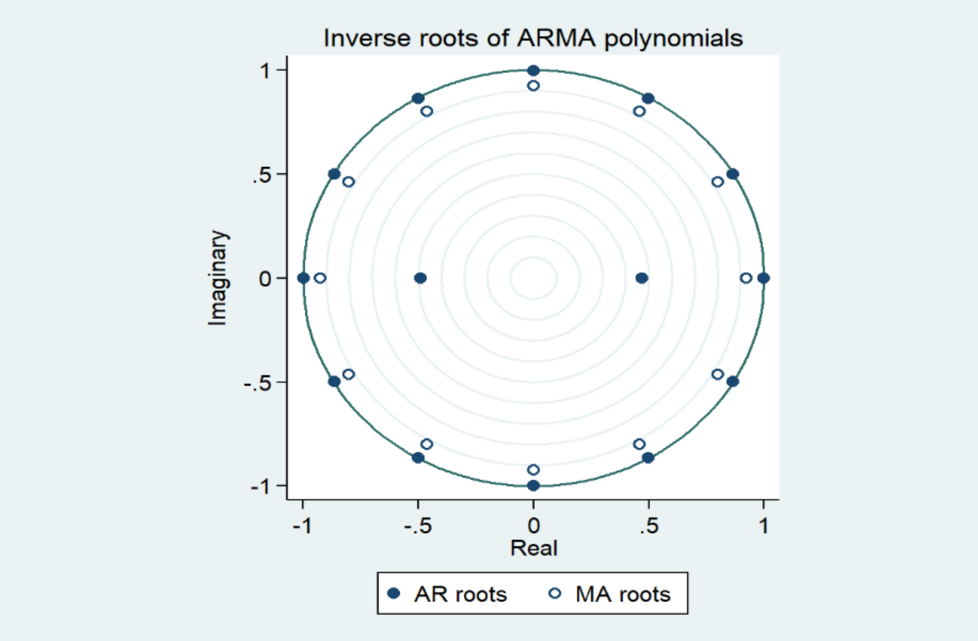


**Figure 5.** Stability and Invertibility Test

### 4.4. Forecasting

Forecasting is a statistical tool that assists policy makers as well as scholars to anticipate future uncertainty based on the behavior of current and past performances. Forecasting lays the foundation for economic and business provision, inventory and production management and optimization of industrial processes as suggested by Box and Jenkins (1976).

Once our model is identified and its parameters are estimated, we use it to predict future monthly inflation. Relying upon the best fit model SARIMA $(2,0,0)\times(1,0,1)_{12}$ model, results of the forecasted monthly inflation rate is summarized in table 5 from February 2023 to December 2024 in Bangladesh.

**Table 5.** Forecasting monthly inflation from February 2023 to December 2024

| 2023 | | 2024 | |
|---|---|---|---|
| ***Month*** | ***Forecasted Inflation*** | ***Month*** | ***Forecasted Inflation*** |
| | | January | 0.69 |
| February | 0.22 | February | 0.25 |
| March | 0.53 | March | 0.56 |
| April | 0.65 | April | 0.66 |
| May | -1.21 | May | -1.13 |
| **June** | **1.26** | **June** | **1.24** |
| July | 0.54 | July | 0.55 |
| **August** | **2.57** | **August** | **2.49** |
| **September** | **1.83** | **September** | **1.79** |
| October | 0.92 | October | 0.91 |
| November | -0.45 | November | -0.40 |
| December | -0.39 | December | -0.34 |

The prediction reveals that inflationary pressure is higher particularly in the third quarter of the month owing mostly to food and non-alcoholic beverages, housing, energy, and transport since they carry more than 75% weightage of the aggregate inflation. This phenomenon is coherent to the post-budget impact after the month of July, which traditionally includes prices of fuel, energy, and transport. If inflation after the annual budget can be restrained within a tolerable ceiling, economic instability can be precluded. The surprising fact is the change in prices the month before the budget announcement. The reason for such eccentric event may lie beneath the discretion of a handful dishonest businessmen who take advantage of the upcoming budget to raise the prices of various goods beforehand. According to the report of the Financial Express on 20 July 2022, Bangladesh witnessed the highest inflation in June 2022 in last nine years, where prices of food and petroleum are the major contributors.

Figure 6 shows the actual and forecasted data of monthly inflation on a line graph over time. Comparing with predicted values, it can be observed that they are close to the true values except for a few discrepancies which do not discourage our prediction since the parameters of the model lie within 95% confidence interval.

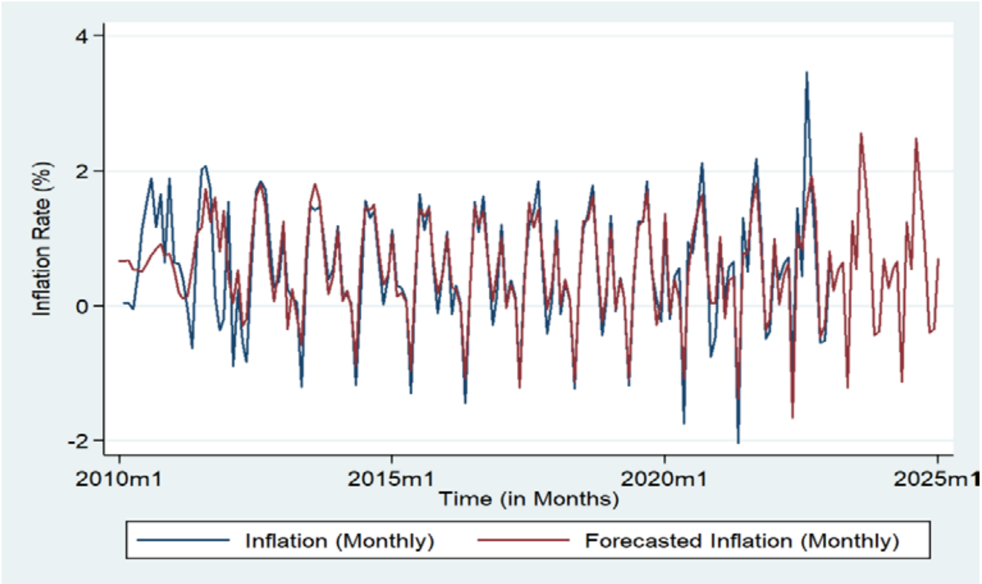


**Figure 6.** Actual Inflation vs Expected Inflation

## 5. Conclusion

The purpose of our study was to analyze monthly inflation rates and forecast future trends using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. After considering various model options, we determined that SARIMA $(2,0,0)\times(1,0,1)_{12}$ is the most suitable based on the AIC and BIC statistics. Our results were further validated through diagnostic tests, which confirmed the effectiveness of the chosen model. Our analysis revealed that monthly inflation rates in Bangladesh are typically highest in June, August, and September. These months experience a significant increase in prices for goods and services, which can have a detrimental impact on the welfare of the population. However, we also found that one month contributes significantly to mitigating the post-inflationary effects, although this is not enough to offset the overall negative impact on the economy. By forecasting future monthly inflation rates from February 2023 to December 2024, our study provides an initial glimpse into the potential impact of recent events on inflation in Bangladesh. While the predictions may not be completely accurate, they serve a crucial role in highlighting the need for continued vigilance and proactive measures to maintain stable inflation levels and promote economic stability. Overall, our findings emphasize the importance of ongoing analysis and monitoring of inflation trends to mitigate the potential negative impacts on socio-economic conditions.

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Hereby, we consciously assure that the manuscript reflects authors' own original work, which has not been previously published elsewhere or is not currently being considered for publication elsewhere. Additionally, the paper properly credits the meaningful contributions of co-authors. No funding was availed for our study. The monthly CPI data used in the study is explicitly available on the IMF website. We also confirm that we have NO affiliations with or involvement in any organization or entity with any financial interest, or non-financial interest in the subject matter or materials discussed in this manuscript. In addition, all sources used in the study are properly disclosed. We agree with the above statements and declare that this submission follows the policies outlined in the Guide for Authors and in the Ethical Statement.

**References**

Banerjee, A. (2021). Forecasting Price Levels in India: An ARIMA Framework. *Academy of Marketing Studies Journal*, 25(1), 1-5.

Box, G.E., & Jenkins, G.M. (1976). *Time series analysis: Forecasting and Control*. San Francisco. Calif: Holden-Day.

Enke, D., & Mehdiyev, N. (2014). A Hybrid Neuro-fuzzy Model to Forecast Inflation. *Procedia Computer Science*, 36, 254-260. doi:https://doi.org/10.1016/j.procs.2014.09.088

Farida, E., & As'ad, M. (2021). The Forecasting of Monthly Inflation in Malang City Using An Autoregressive Integrated Moving Average. *International Journal of Economics, Business and Accounting Research*, 5(2).

Faulina, R., Lusia, D., Otok, B., & Kuswanto, H. (2012). Ensemble method based on anfis-arima for rainfall prediction. 2012 *International Conference on Statistics in Science, Business and Engineering*, (pp. 1-4). Langkawi: IEEE.

Gautam, R.S., & Kanoujiya, J. (2022). Inflation Targeting: An Application of ARIMA Modelling Using Forecasting of CPI and WPI. *Iconic Research and Engineering Journals*, 5(11), 195-198.

Ghazo, A. (2021). Applying the ARIMA Model to the Process of Forecasting GDP and CPI in the Jordanian Economy. *International Journal of Financial Research*, 12(3), 70.

Hurtado, J., & Cortes-Fregoso, J. (2013). Forecasting Mexican inflation using neural networks. *23rd International Conference on Electronics, Communications and Computing* (pp. 32-35). Mexico: IEEE.

Hurvich, C.M., & Tsai, C.L. (1989). Regression and time series model selection in small samples. *Biometrika*, 76(2), 297-307.

Işığıçok, E., Öz, R., & Tarkun, S. (2020). Forecasting and technical comparison of inflation in Turkey with box-jenkins (ARIMA) models and the artificial neural network. *International Journal of Energy Optimization and Engineering*, 9(4), 84--103.

Karadzic, V., & Pejovic, B. (2021). Inflation Forecasting in the Western Balkans and EU: A Comparison of Holt-Winters, ARIMA and NNAR Models. *Academy of Economic Studies*, 23(57), 517.

Kharimah, F., Usman, M., Widiarti, W., & Elfaki, F. (2015). Time series modeling and forecasting of the consumer price index Bandar Lampung. *Science International*, 27(5B), 4619-4624.

Kleiber, C., & Zeileis, A. (2008). *Applied econometrics with R.* New York: Springer Science & Business Media, LLC.

Lidiema, C. (2017). Modelling and forecasting inflation rate in Kenya using SARIMA and Holt-Winters triple exponential smoothing. *American Journal of Theoretical and Applied Statistics*, 6(3), 161-169.

Liko, R., Ramosaco, M., & Kashuri, A. (2016). Modeling the Behavior of Inflation Rate in Albania Using Time Series. *Journal of Advance in Mathematics*, 13(3), 7257-7263.

Marpaung, G.N., Soesilowati, E., Rahman, Y.A., Tegar, Y.D., & Yuliani, R. (2022). Forecasting the Inflation Rate in Central Java Using ARIMA Model. *Indonesian Journal of Development Economics*, 5(2), 163-173.

McNelis, P.D., & McAdam, P. (2004). *Forecasting Inflation with Thick Models and Neural Networks*. Frankfurt: European central Bank.

Mia, M.S., Nabeen, A.H., & Akter, M.M. (2019). Modelling and forecasting the consumer price index in Bangladesh through econometric models. *American Scientific Research Journal for Engineering, Technology, and Sciences*, 59(1), 118-127.

Ngailo, E., Luvanda, E., & Massawe, E.S. (2014). Time Series Modelling with Application to Tanzania Inflation Data. *Journal of Data Analysis and Information Processing*, 2(2), 49-59.

Nyoni, T. (2019). Munich Personal RePEc Archive (MPRA). Retrieved April 1, 2023, from https://mpra.ub.uni-muenchen.de/92429/

Okyere, F., & Mensah, C. (2014). Empirical Modelling and Model Selection for Forecasting Monthly Inflation of Ghana. *Mathematical Theory and Modeling*, 4(3), 99-106.

Olalude, G.A., Olayinka, H.A., & Constance, A.U. (2020). Modelling and forecasting inflation rate in Nigeria using ARIMA models. *KASU Journal of Mathematical Science*, 1(2), 127--143.

Otu, O.A., Osuji, G.A., Jude, O., Ifeyinwa, M.H., & Iheagwara, A.I. (2014). Application of Sarima models in modelling and forecasting Nigeria's inflation rates. *American Journal of Applied Mathematics and Statistics*, 2(1), 16-28.

Qasim, T.B., Ali, H., Malik, N., & Liaquat, M. (2021). Forecasting Inflation Applying ARIMA Model with GARCH Innovation: The Case of Pakistan. *Journal of Accounting and Finance in Emerging Economies*, 7(2), 313--324.

Rahman, M.L., & Islam, M.M. (2020). Modeling Inflation in Bangladesh. *Open Journal of Satistics*, 10(6), 998.

Suleman, N., & Sarpong, S. (2012). Empirical Approach to Modelling and Forecasting Inflation in Ghana. *Current Research Journal of Economic Theory*, 4(3), 83-87.

Wati, D.A., Eltivia, N., & Djajanto, L. (2021). Inflation Forecasting by Commodity Using the Autoreggressive Integrated Moving Average (ARIMA) Method. In *Proceedings of 2nd Annual Management, Business and Economic Conference* (AMBEC 2020) (pp. 226-231). Atlantis Press.

Wolters, J., & Kirchgässner, G. (2007). *Introduction to modern time series analysis* (2nd ed., Vol. 271). Verlag Berlin Heidelberg: Springer.