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FORECASTING INFLATION RATE WITH ALGORITHMIC ARIMA MODELING

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Abstract: While several studies exist on time series ARIMA modeling of inflation in Bangladesh, the adequacy of these models in terms of forecasting capability remains questionable. In these studies, the difficulty arises in finding the right model, as there are many candidates for forecasting, and choosing the optimal model is done seemingly on an ad hoc basis. To address this issue, we employ an automated search algorithm to programmatically find the optimal model. Acknowledging the potential risks of any automated process, we also compare this model with other manually chosen ARIMA models. It was found that the automated model outperformed other models in terms of forecasting accuracy.

Keywords: Inflation; forecasting; ARIMA modelling; Bangladesh

Subject classification codes: E31. E37, E42

1. INTRODUCTION

Inflation has been a prominent topic of discussion in Bangladesh for some time now, especially following the Ukraine-Russia war, which led to a global surge in prices (Observatory, 2023). Consequently, prices have also risen in Bangladesh. For the first time in several years, inflation has reached double digits (Tribune, 2013), causing significant concern among consumers, particularly the low-income group. Given the importance of inflation for policymaking, it is imperative for policymakers to be able to make informed monetary policy decisions in a timely manner. Therefore, reliable inflation forecasting is crucial for the monetary policy of any country.

Around the world, a number of studies are available which explored inflation modeling and forecasting. Studies on a few African countries such as Zambia, Ghana, South Africa, and Nigeria (Jere & Siyanga, 2016; Kelikume & Salami, 2014; Yusif et al., 2015; Kotsokoane & Rena, 2021) performed inflation forecasting with significant differences in methodologies. For Zambia, the study mainly used Holt's exponential smoothing methodology while Ghana and Nigeria's study focused on ARIMA modeling. Among Asian countries, Habibah et al. (2017) forecasted inflation using conventional ARIMA methods for Pakistan while Sun (2004) used an error-correction model for Thailand. Savitri et al. (2021) used Long Short Term Memory (LSTM) models for Indonesia. There are also other studies on a similar scope for Chile (Pincheira & Gatty, 2016) and for Ireland (Meyler et al., 1998).

Extensive research has been conducted also on the time series analysis of the inflation rate in Bangladesh. Several studies have investigated the determinants of inflation (Arif & Ali, 2012; T. Hossain & Islam, 2013; Uddin et al., 2014). The interaction between inflation and economic growth has also been thoroughly investigated (Ahmed, 2010; A. A. Hossain, 2015; M. E. Hossain et al., 2012; Majumder, 2016; Sumon & Miyan, 2017). Additionally, other studies have explored the link of inflation with various macroeconomic variables in Bangladesh. For instance, there are studies on the association of remittances with inflation (Khan & Islam, 2013), the impact of inflation on exchange rates (Mostafa, 2020), and the influence of inflation on income inequality (Muhibbullah & Das, 2019), among others.

While there are quite a few studies on the association between inflation and other core macroeconomic variables in Bangladesh, research on inflation modeling and forecasting is relatively limited. In one such study, Rahman et al. (2020) undertook the task of modeling the inflation rate using the ARIMA framework and manually searched through various models to find the best one for forecasting inflation. Studies by Akhter (2013), Islam (2017), and Faisal (2012) share a similar scope, with the former incorporating seasonality into the model.

These research works provide important contributions to inflation modeling but are inadequate in forecasting capability. All these studies, find the optimal forecasting model through some manual search. It leaves scope for ending up with a model which is sup-optimal. There might be another model not considered with better properties and improved forecasting capability. An automated process helps to reduce that uncertainty significantly. This automated process (Hyndman & Khandakar, 2008) is actually a step-wise algorithm[1] for forecasting with ARIMA models. We aim to compare this automated process with other conventional methods and thus try to find whether the automation improves forecasting accuracy.

The remainder of this article is organized as the following: in Section 2, we discuss ARIMA modeling in general and look deeper into the underlying algorithm of automatic search for optimal models. Section 3 describes the data used in this study. In Section 4, core time series features of the data are discussed where the stationarity property of the series is analyzed. In Section 5, based on the results from the previous section, the necessary transformation in the data is applied followed by corresponding diagnostic tests. After ensuring the stationarity of the inflation data series, various models with different lag lengths are proposed to be compared against the one selected by the algorithm. Based on these models, in Section 6, forecasts are calculated which helps to make comparisons on forecast accuracy generated from these different models. Section 7 concludes.

2. ARIMA MODELING: MANUAL VS AUTOMATED SEARCH

ARIMA implies Autoregressive Integrated Moving Average modeling which combines Autoregressive (AR) first difference terms with Moving average (MA) terms. The full form of the model is as the following:

$$y'_t = c + \phi_1 y'_{t-1} + \ldots + \phi_p y'_{t-p} + \theta_1 \varepsilon_{t-1} + \ldots + \theta_q \varepsilon_{t-q} + \varepsilon_t$$

Here y'_t represent the first differenced series. The explanatory variables in this equation include both the lagged values of and , the random error component in the specified model. The above model can be expressed as ARIMA(p,d,q) where represents the order of the autoregressive component, is the order of error components and is the order of differencing. Many of the time series models are specific forms of this general ARIMA(p,d,q) model. For example, ARIMA(p,0,0) is identical to AR(p) models and ARIMA(0,0,q) is similar to MA(q) models. There are other cases such as ARIMA(0,0,0) is regarded as a White-noise series whereas ARIMA(0,1,0) is considered a Random-walk method.

In the same vein, manual search in the ARIMA framework involves exploring different models with various orders of p, d, or q to identify the optimal model based on model selection criteria. However, this approach may result in trial and error, and there is uncertainty about whether the optimal model will be identified. An alternative might be, instead of a manual search, to find the optimal model using a search algorithm. This automated search is known as the Hyndman-Khandakar algorithm (Hyndman & Khandakar, 2008). It consists of multiple procedures such as conducting unit root tests and minimizing AICc and MLE to derive the ARIMA model to search for the optimal model. In the following, we briefly summarize the internal mechanism of the algorithm as described by Hyndman & Khandakar (2008).

The first step in this algorithm is to find the optimal value of differencing by the repetition of KPSS tests. Next, we find the value of p and q through the minimization of the AICc. In this step, the main difficulty lies in the existence of many possible combinations of p and q. It is computationally not feasible to go after every such combination for a given value of d. As an alternative, this automatic algorithm employs a stepwise search in the whole space of the model.

First the following four models are considered: ARIMA(0,d,0), ARIMA(2,d,2), ARIMA(1,d,0) and ARIMA(0,d,1). Then a constant term is included unless the value of d equals 2. If d is less than 1, ARIMA(0,d,0) is estimated omitting the constant. The model with the smallest AICc is considered as the best of these models and that will be set as the current model. Then we usually consider different variations of the model by changing the values of p and q from the existing model by and also by including or excluding constant(c) terms from this model. The model judged in terms of minimum AICc becomes the new current model. This process continues until there is no further reduction in AICc. In this way, we end up with the optimal model which may or may not coincide with the manually searched models.

To compare these multitudes of models in terms of statistical properties, we need to estimate ARIMA models with data on the variable of our interest. This data used in the estimation process of different models is described in the following section.

3. DATA DESCRIPTION

Data has been gathered from various editions of economic trends (Bangladesh Bank, 2000-2023). Monthly economic trend data has been available for many decades, with Bangladesh Bank (2000-2023) being the main source. However, the primary data collection is conducted by the Bangladesh Bureau of Statistics (BBS). Each month, the BBS publishes Consumer Price Index (CPI) data along with corresponding inflation figures (BBS, 2024).

The BBS gathers price data from 154 main markets across the country, comprising 90 urban markets, including 12 from the capital city (Dhaka), four from Chattogram City, 18 from the remaining six Divisional Cities, and 56 from the remaining Districts. There are also 64 rural markets in 64 Districts (Bangladesh Bureau of Statistics, 2021). In each market, three price quotations per item, along with their varieties, are collected. Both rural and urban areas are surveyed monthly, while Dhaka and Chattogram City Corporation areas are surveyed per week in each month. Price data are sourced from selected stores or service providers for services. When constructing price indices, the average price of each item is used.

The Consumer Price Index (CPI) is calculated using two distinct consumer baskets: one for urban areas and another for rural areas. These baskets are based on the Household Income and Expenditure Survey (HIES) of 2016-17 and reflect goods and services consumed by households (Bangladesh Bureau of Statistics, 2019). Both urban and rural baskets encompass 383 food and non-food products which cover goods and services of 749 varieties. The weights assigned to items in the base year are determined by the average expenditure per household on each item, expressed as a percentage of total household expenditure (Bangladesh Bureau of Statistics, 2020).

4. TIME SERIES CHARACTERISTICS OF INFLATION DATA

4.1. Overall pattern

In Figure 1, we examine Bangladesh's inflation trends for the last two decades. We observe that in the early 2000s, inflation remained notably below the historical average of 6.3%. However, after 2008, we began to witness significant fluctuations in inflation data, a pattern that persisted until 2014. Subsequently, there was a period of relative stability in inflation rates up to 2021. Eventually, following the Ukraine-Russia conflict, prices have once again begun to rise, indicating potential volatility in inflation patterns in the foreseeable future.

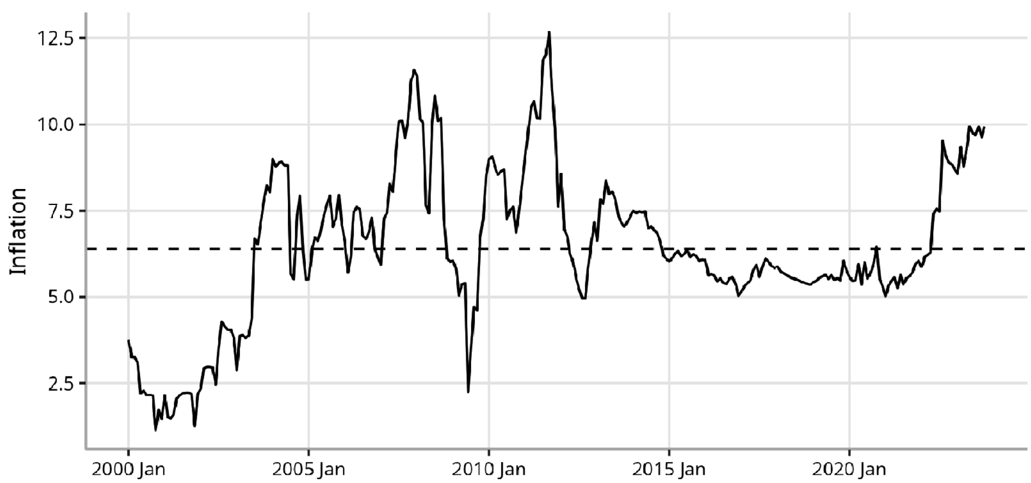

Figure 1: Overall inflation pattern

4.2. Stationarity property of inflation data

We will look into the time series properties of monthly inflation data series through autocorrelation functions (ACF) and partial autocorrelations (PACF). ACF and PACF are both fundamental tools in time series analysis, but they serve distinct purposes. The ACF measures the correlation between a series of interests and the series' lagged values, providing insight into the overall autocorrelation structure of the data. In contrast, the PACF measures the correlation between a series and the series lagged values while accounting for the correlations at shorter lags, thereby isolating the direct relationship between the series and specific lags. Essentially, the ACF captures both direct and indirect relationships between a series and its past values, while the PACF focuses solely on the direct relationships, rendering it particularly valuable for determining the order of autoregressive terms in a time series model (Box et al., 2015).

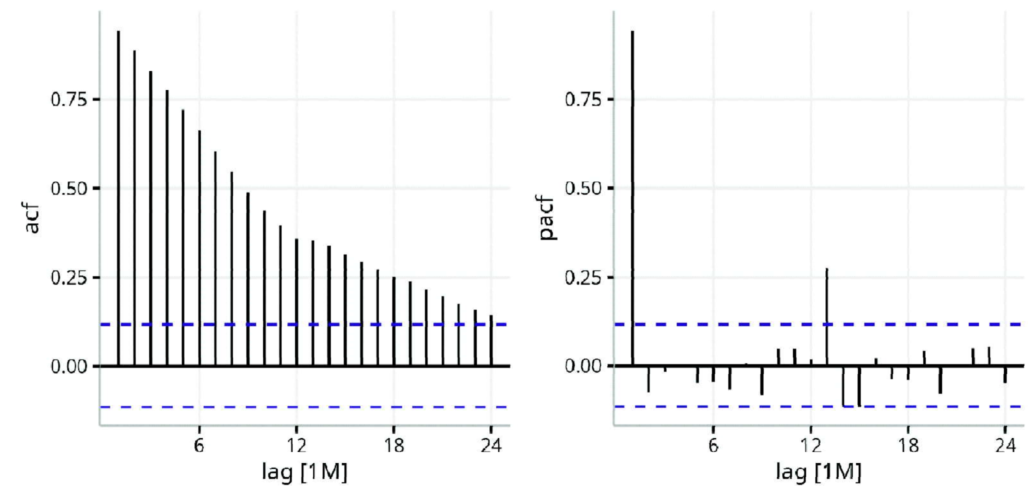

Figure 2: ACF and PACF of inflation data series

In Figure 2 (the left side panel), we observe exponentially declining autocorrelations, all of which are statistically significant. This suggests a pronounced presence of non-stationarity in the data. This observation is reinforced in the right panel, where we observe high statistical significance at lag 1 and relatively moderate significance at lag 13. This pattern may indicate a first-order autoregressive dependence with a significant seasonal effect.

Although Figure 2 indicates a strong indication of non-stationarity in the data, we require further formal confirmation of this observation. Hence, it is necessary to perform unit root tests to substantiate this evidence. In time-series econometrics, the stationarity of time-series data is assessed using the Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski-Phillips-Schmidt-Shin (KPSS). The ADF test, derived from the augmented Dickey-Fuller regression model (Dickey & Fuller, 1979), examines whether a unit root is present, which signals non-stationarity. PP test (Phillips & Perron, 1988) offers a non-parametric alternative to ADF, accounting for serial correlation with different methodologies. Both ADF and PP tests can accommodate various trends in the data. On the other hand, the KPSS test (Kwiatkowski et al., 1992), assuming stationarity in the null hypothesis and non-stationarity in the alternative, is particularly useful for discerning trend-stationarity or difference-stationarity. The choice among these tests varies depending on the specific features of the data and the assumptions being made about the underlying process.

In Table 1, the aforementioned unit root tests are presented. While there may be slight variations in the testing results, the overarching conclusion remains consistent. Under the Augmented Dickey-Fuller (ADF) tests, the null hypothesis of non-stationarity, cannot be rejected, whereas, under the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, we can reject the null hypothesis of stationarity at the 5% level of significance. Similarly, under the Phillips-Perron test, which also assumes non-stationarity, we cannot reject the null hypothesis at the 5% level of significance. Therefore, all these tests reach a consensus that the inflation data used in this study is non-stationary.

Table 1: Findings from the tests of unit root

Tests	*Test Statistics*	*P-value*
Augmented Dickey Fuller[a]	-2.859	0.214
KPSS[b]	0.709	0.013**
Phillips-Perron (PP)[a]	-2.664	0.085*

[a]H0:the series has a unit root ; [b]H0: the series is stationary; **Denotes 5% level of significance; *Denotes 10% level of significance

5. OPTIMAL MODEL SELECTION

While Table 1 provides clear evidence of non-stationarity, these tests also have eliminated the possibility of trend-related non-stationarity implicit in the procedure. Therefore, the remaining possibility is a random trend in the given time series, for which the conventional approach is to take the first difference (Hamilton, 1994).

However, instead of opting for the first difference, we choose to take the logarithmic difference of the inflation rate. This decision is grounded in the rationale that the logarithmic difference of any macroeconomic variable provides a clear economic

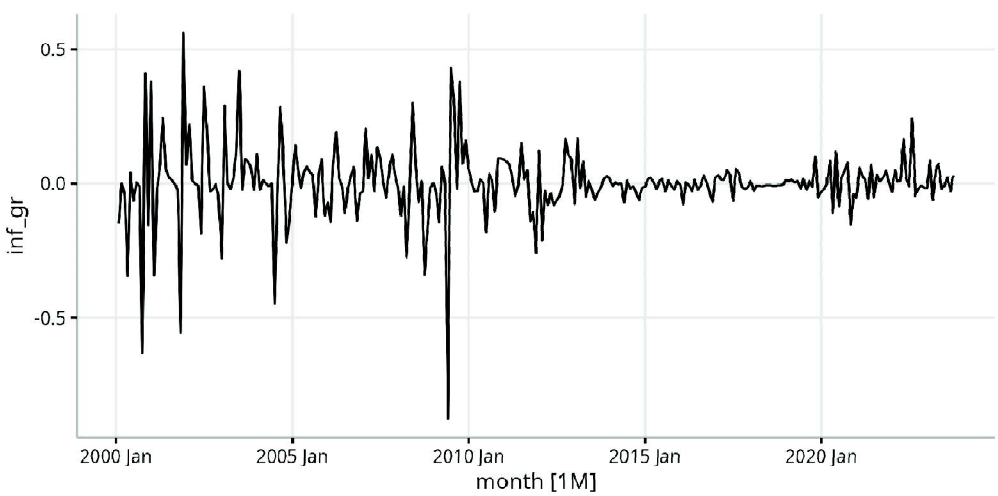

Figure 3: Inflation growth

interpretation by representing the growth rate of that particular variable (Jones, 1994). Subsequently, we proceed to analyze the time series characteristics of this transformed series to determine whether stationarity has been achieved.

This differenced series is plotted in Figure 3. Upon visual examination, we observe that although there is some degree of instability in the variance, the series seems to remain fairly stable around the mean. To further verify this observation, we can conduct formal testing procedures of unit root once again.

Table 2: Unit root tests on 1st difference of inflation rate

Tests	*Test Statistics*	*P-value*
Augmented Dickey Fuller[a]	-12.990	0.010***
KPSS[b]	0.045	0.100*
Phillips-Perron (PP)[a]	-19.895	0.010***

[a]H0:the series has a unit root; ***Denotes 1% level of significance; [b]H0: the series is stationary; *Denotes 10% significance level

The formal tests confirm that the inflation growth rate is stationary. Since we have found the necessary transformation to make the data stationary, we will now try to find a suitable model based on ACF and PACF as shown in Figure 4 below:

In Figure 4, a notable peak at lag 1 in the ACF indicates the presence of a non-seasonal MA(1) component. On the other hand, a notable peak at lag 12 in the ACF indicates the presence of a seasonal MA(1) component. This may imply that we start

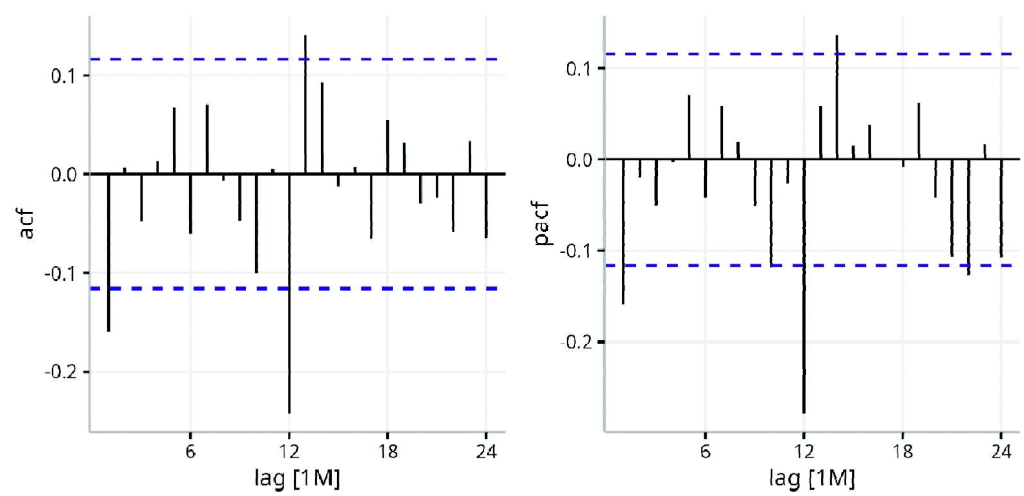

Figure 4: ACF and PACF of Inflation growth

with an ARIMA (0,1,1) $(0,1,1)_{12}$ model, which incorporates a first difference, a seasonal difference and both non-seasonal MA(1) and seasonal MA(1) components. However, starting with PACF might lead us to select an ARIMA (1,1,0) $(0,1,1)_{12}$ model as we have found significant spikes in lag 1 and lag 12.

These initial models act as our starting points to find the optimal model. Additionally, we aim to investigate different versions of these models. Alongside these conventional models, our plan involves using a search strategy to pinpoint the most suitable model as outlined in Section 2. By utilizing both manually chosen models and algorithmic search methods our goal is to thoroughly explore the modeling landscape. This approach helps us to consider a spectrum of options and choose the model that aligns best with our data and goals. In doing so, this approach aims to improve the robustness and precision of the modeling process.

To choose the optimal one among these multitude of models, we will use three model selection measures: Akaike Information Criterion (AIC), Corrected AICc, and Schwarz's Bayesian Information Criterion (BIC). Before utilizing these metrics to select the optimal model, we offer a brief discussion of their characteristics in the following.

The Akaike Information Criterion (AIC) assesses model performance by balancing goodness of fit with complexity to avoid overfitting (Akaike, 1974). However, AIC may be less reliable with small sample sizes due to its reliance on asymptotic assumptions (Hurvich & Tsai, 1989). To account for small sample sizes, the corrected AIC (AICc) includes an adjustment, making it more suitable for datasets with fewer observations. Conversely, the Bayesian Information Criterion (BIC) imposes a stricter penalty on model complexity compared to AIC, leading to a preference for more straightforward models. This makes BIC particularly useful when evaluating a large number of candidate models. Researchers often argue that if a true underlying model exists, BIC is more

Table 3: Values for different model selection criteria

	Model selection criterion		
ARIMA models	*AIC*	*AICc*	*BIC*
Manually constructed			
ARIMA(0,1,1)(0,1,1)	-253.2	-253.1	-242.4
ARIMA(0,1,1)(1,1,1)	-266.3	-266.1	-251.8
ARIMA(1,1,0)(0,1,1)	-142.5	-142.4	-131.7
ARIMA(1,1,0)(1,1,1)	-157.6	-157.5	-143.2
Algorithmically optimized			
ARIMA(2,0,2)(1,0,1)	-366.5	-366.1	-341.0

Source: Authors' calculation

likely to identify it given a sufficiently large dataset (Hyndman & Athanasopoulos, 2021). In practice, all three criteria—AIC, AICc, and BIC—are commonly computed, with decisions often guided by their consensus. However, in cases where consensus cannot be reached, BIC is frequently relied upon for the final model selection due to its preference for simplicity and robustness in large sample contexts.

Table 3 clearly shows that the algorithmically optimized model exhibits the lowest value for all model selection criteria. Consequently, we designate this model as the optimal choice. Notably, among the manually constructed models, ARIMA(0,1,1)(1,1,1) yields the lowest value across all three measures. The algorithmically optimised model suggests that we use a seasonal ARIMA model of the order (2,0,2) $(1,0,1)_{12}$ of the following form:

$$Y_t = \underset{(0.053)}{1.407}Y_{t-1} - \underset{(0.043)}{0.834}Y_{t-2} - \underset{(0.034)}{1.549}e_{t-1} + \underset{(0.022)}{0.965}e_{t-2} + \underset{(0.149)}{0.422}Y_{t-12} - \underset{(0.117)}{0.741}e_{t-12} + \varepsilon_t$$

We can conduct tests on the residuals of this model to further confirm that our selection of the optimal model is correct. To that end, we first run some graphical diagnostic tests on the residuals of these models. In Figure 5, multiple test results are presented graphically.

The upper panel of Figure 5, illustrates the movement of residuals through the designated time period and appears to be centered around a stationary mean. The left-hand figure on the bottom panel traces the ACF which shows none of the spikes at different lags are statistically strongly significant. The right-hand figure shows the

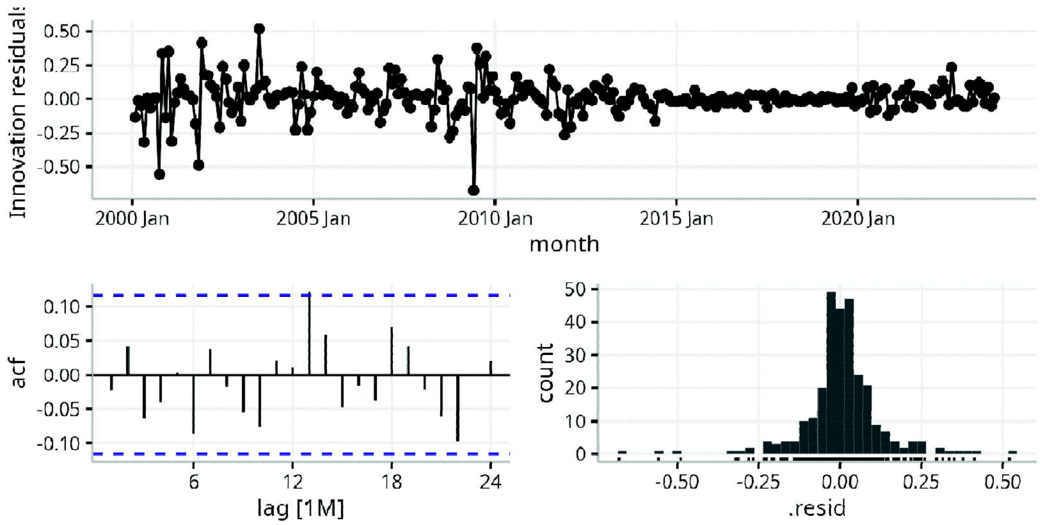

Figure 5: Diagnostic tests on residuals

probability distribution of residuals as roughly normal. Therefore, these residuals do not display much deviation from the White noise assumption.

Apart from visual evidence, we also employ a formal test, named the Ljung Box test to confirm stationarity of the residuals (Ljung & Box, 1978). The residuals test results in a p-value of 0.697. The p-value is sufficiently large to indicate that we fail to reject the null hypothesis (H€) of no autocorrelation in the residuals.

Having identified the optimal model, we will retain it as a candidate and evaluate it against the other models outlined below. The comparison will be mainly made in terms of forecast accuracy.

6. COMPARISON OF FORECAST ACCURACY

To assess the forecast accuracy of the ARIMA models, we will split the original dataset into training and testing subsets. Typically, the test data subset comprises 20% of the overall data. Accordingly, we have designated the training dataset to encompass observations up to the end of 2017, resulting in 215 observations. The remaining data constitutes the test dataset, comprising 60 observations. We will apply the previously discussed models to the training dataset, generate predictions for the test dataset, and then assess the accuracy of these predictions.

Before evaluating the accuracy of the forecasts, we will briefly describe the three accuracy metrics used in the following analysis: Mean Absolute Scaled Error (MASE), Root Mean Squared Error (RMSE), and Mean Absolute Error (MAE).

MASE checks how well a forecasting model performs compared to a simple benchmark, usually the naive seasonal method or the naive random walk method. It checks the model's ability to perform better than these basic benchmarks, giving ideas on its effectiveness across different forecasting periods and time series patterns (Hyndman

Table 4: Forecast accuracy

	Forecasting accuracy measures		
ARIMA models	*RMSE*	*MASE*	*MAE*
Manually constructed			
ARIMA(0,1,1)(0,1,1)	0.063	0.315	0.045
ARIMA(0,1,1)(1,1,1)	0.064	0.319	0.046
ARIMA(1,1,0)(0,1,1)	0.061	0.301	0.043
ARIMA(1,1,0)(1,1,1)	0.061	0.302	0.043
Algorithmically optimized			
ARIMA(2,0,2)(1,0,1)	0.058	0.275	0.039

Source: Authors' calculation

& Koehler, 2006). RMSE computes the square root of the average squared differences between observed and forecasted values, providing an indicator of error in the same units as the original data (Willmott & Matsuura, 2005). MAE calculates the average of the absolute differences between observed and predicted values, offering a straightforward assessment of forecasting accuracy without considering the direction of the errors (Dawson, 2018).

In Table 4, consistent with our observations in Table 3, the algorithmically optimized model demonstrates superior forecast accuracy measures. While ARIMA (0,1,1)(1,1,1) shows the best performance in terms of model evaluation metrics among the manually constructed models, it does not deliver the same level of forecast accuracy as the other models. Notably, both ARIMA(1,1,0)(0,1,1) and ARIMA(1,1,0)(1,1,1) produces superior results in this aspect. Nevertheless, as noted earlier, the algorithmic approach outperforms in all aspects of forecast accuracy.

In the preceding section, we determined the optimal model through algorithmic search. Now, our focus shifts to generating forecasts using this optimal model. We will produce two types of forecasts: one using the transformed variable to depict the forecast of inflation growth, and another showcasing the forecast when this transformed variable is converted back to the original level series of inflation rate.

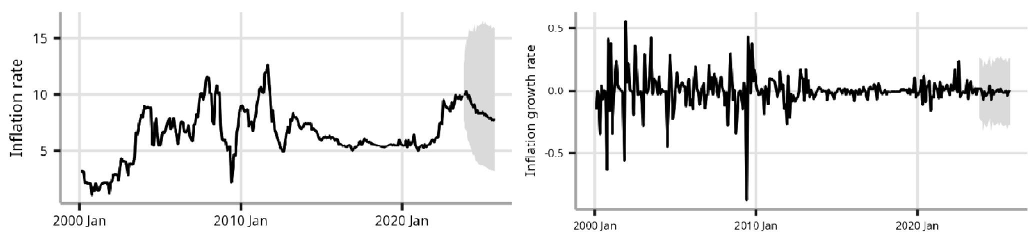

Figure 6: Out-of-sample (2 years) forecasts with Algorithmically optimised model

In Figure 6, the left panel displays the forecasting of the differenced series, while the right panel illustrates the forecasting in the original series derived from the differenced data. While the inflation growth exhibits a slight decline towards the end of the forecast period, the inflation rate in the level series demonstrates a steady decline throughout the forecast period.

7. CONCLUSION

In this research, we performed an analysis comparing manually formed ARIMA models and algorithmic automated search methods for forecasting inflation. Our findings revealed that the algorithmic approach outperformed the manually formed models both in terms of model selection criteria and forecasting accuracy. This shows the superiority of algorithmic search in providing better modeling options for macroeconomic forecasting. Consequently, this study filled a gap in forecasting endeavors in Bangladesh which often fell short of generating actual forecasted values. Looking toward the future, there is significant potential for further research to expand upon this work by comparing the automated model with other forecasting techniques such as exponential smoothing (ETS). Such comparative studies will offer deeper insights into finding better modeling approaches for macroeconomic forecasting.

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