Sciencestatistics
Journal of Statistics, Probability, and Its Application
Available at https://scholar.ummetro.ac.id/index.php/sciencestatistics/index
DOI: https://doi.org/10.24127/sciencestatistics.v4i1.11252
Vol. 4, No. 1, 2026, 28-34
ISSN 2963-9875 (Online)
ISSN 2964-2884 (Print)

Modeling and Predicting Indonesia's Inflation Using the ARIMA Model

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Article Info

Article History:
Received: January 02, 2026
Revised: January 25, 2026
Accepted: January 29, 2026
Available online: January 31, 2026

Keywords:
ARIMA; AIC; forecasting; inflation; time series analysis

ABSTRACT

Inflation is one of the most important macroeconomic indicators used to evaluate the stability and performance of a country's economy. This study aims to model and predict Indonesia's monthly inflation rate using the Autoregressive Integrated Moving Average (ARIMA) approach. The dataset consists of monthly inflation observations from January 2010 to December 2025 obtained from Bank Indonesia. The analysis begins with testing the stationarity of the series using the Augmented Dickey–Fuller (ADF) test, followed by model identification through the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots. Several candidate models are estimated, including ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (1,1,1). Model comparison based on the Akaike Information Criterion (AIC) indicates that the ARIMA (0,1,1) model provides the lowest AIC value and is therefore selected as the most appropriate model. The forecasting results suggest that Indonesia's inflation rate is expected to remain relatively stable at around 3.63% over the next six periods. However, the prediction intervals become wider as the forecasting horizon increases, reflecting growing uncertainty in longer-term predictions.

INTRODUCTION

Inflation refers to a continuous increase in the general price level of goods and services over time. When inflation rises persistently, the purchasing power of consumers declines and economic stability may be affected. For this reason, inflation is widely used as an important indicator to assess macroeconomic performance. In Indonesia, maintaining price stability is one of the primary objectives of economic policy. Excessive inflation may disrupt economic activities, decrease real income, and create uncertainty in financial markets. Therefore, accurate inflation forecasting is necessary to support economic planning and assist policymakers in making appropriate decisions.

Time series analysis has frequently been employed to analyze and forecast economic indicators such as inflation. Among the various time series approaches, the Autoregressive

Integrated Moving Average (ARIMA) model is widely applied because of its flexibility in representing different patterns in temporal data. Previous studies have shown that ARIMA models are effective for predicting inflation dynamics. (Nyoni, T., & Bonga, 2021) found that the ARIMA model provides good inflation forecasting results in Zimbabwe. Another study by (Etuk, E. H., Moffat, I. U., & Chukwu, 2021) also demonstrated that ARIMA is effective for modeling inflation in Nigeria. In addition, (Saini, S., & Sinha, 2022) stated that ARIMA remains one of the most widely used methods in inflation forecasting due to its ability to capture patterns in time series data. More recent studies also emphasize that time series models such as ARIMA remain relevant in the analysis and prediction of inflation (Bhandari, A., & Frankel, 2023; Bhowmik, R., & Wang, 2020). Based on these considerations, this research focuses on modeling Indonesia's inflation rate using the ARIMA framework. By analysing historical inflation data, this study attempts to produce short-term forecasts that may provide insights regarding possible future inflation movements.

METHODS

This study applies the ARIMA model to analyze and forecast Indonesia's inflations. The ARIMA model combines three main elements, there are the autoregressive component (AR), the differencing process (I), and the moving average component (MA). Through these components, ARIMA is able to capture temporal dependence and random variations that commonly occur in time-series data (Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, 2021; Hyndman, R. J., & Athanasopoulos, 2021). The general mathematical form of the ARIMA model is expressed as:

$$\phi_p(B)(1-B)^d Y_t = \theta_q(B)\varepsilon_t \quad (1)$$

where
Y_t= observation value at time t
B= backshift operator
p= order of autoregressive
d= order of differencing
q= order of moving average
ε_t= error term assumed to be white noise.

The ARIMA model is widely used because of its capability to capture autocorrelation structures in time series data and produce accurate forecasts when the data exhibit linear patterns (Makridakis, S., Spiliotis, E., & Assimakopoulos, 2022; Shumway, R. H., & Stoffer, 2021a). The analysis in this study follows the Box–Jenkins procedure, which consists of several stages (Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, 2021; Hyndman, R. J., & Athanasopoulos, 2021):

1. **Model Identification**
   The first step involves visualizing the time series data using a time series plot to observe general patterns and fluctuations. Stationarity of the series is then examined using statistical tests. In addition, the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots are analyzed to identify possible orders of the AR and MA components.
2. **Parameter Estimation**
   After determining several tentative models, the next step is to estimate the parameters of each candidate ARIMA model. Parameter estimation is performed using statistical estimation techniques available in time series modeling procedures (Shumway, R. H., & Stoffer, 2021a).
3. **Diagnostic Checking**

After parameter estimation, diagnostic tests are performed to ensure that the residuals of the model behave randomly. A good ARIMA model should produce residuals that resemble white noise, meaning that they are independent and have constant variance. The Ljung–Box test is used to evaluate whether residual autocorrelation is present.

4. Model Selection

The Akaike Information Criterion (AIC) is used to compare candidate models. The model with the smallest AIC value is selected because it indicates a better balance between model accuracy and complexity (Hyndman, R. J., & Athanasopoulos, 2021).

5. Forecasting

Once the best model has been determined, it is used to generate forecasts of future inflation values. Forecast intervals are also calculated to reflect the uncertainty associated with the predictions.

RESULT AND DISCUSSIONS

Model Identification

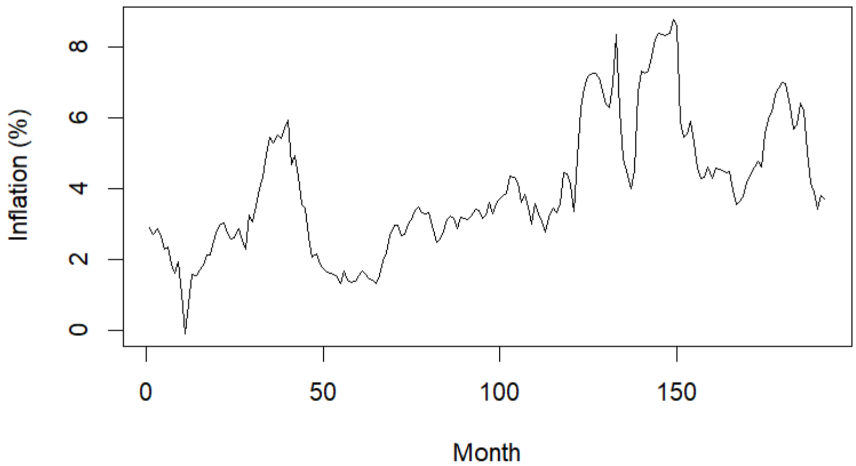


Figure 1. Time series plot of Indonesia's inflation from January 2010 to December 2025.

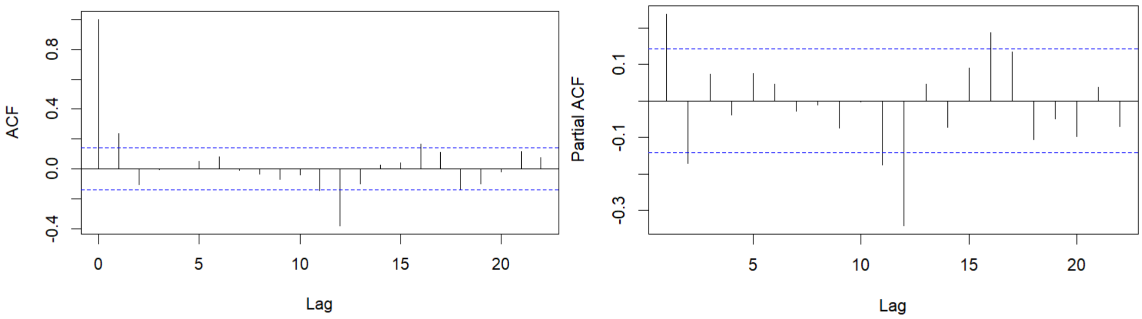
Figure 1 is the time series plot of Indonesia's monthly inflation rate from January 2010 to December 2025 shows noticeable fluctuations across time. Several periods display relatively high inflation, while other periods indicate more moderate price increases. These variations reflect the dynamic nature of inflation movements influenced by various economic factors. From the time series plot, the inflation data appear to fluctuate around different levels, suggesting that the data may not be stationary. In time series analysis, stationarity is an important assumption for building a reliable model because non-stationary data may lead to biased or inefficient forecasts (Hyndman, R. J., & Athanasopoulos, 2021; Tsay, 2020).

To confirm the stationarity condition, the Augmented Dickey–Fuller (ADF) test is applied to the original data. The test result produces a Dickey–Fuller statistic of −3.1297 with a p-value of 0.1034. Because the p-value exceeds the 5% significance level, the null hypothesis of a unit root cannot be rejected. That means the mean and variance of the series may change over time, which violates the basic assumptions required for many time series models (Enders, 2022).

To address this issue, a first differencing transformation was applied to the inflation data. Differencing is commonly used to remove trends and stabilize the mean of a time series (Montgomery, D. C., Jennings, C. L., & Kulahci, 2021). After applying first differencing, the

ADF test is conducted again. The result shows a Dickey–Fuller statistic of −4.8236 with a p-value of 0.01, which is smaller than the 5% significance level. This result indicates that the differenced series is stationary and suitable for further modeling.

After achieving stationarity, the identification of model orders is performed using ACF and PACF plots. These plots are essential tools for identifying the appropriate order of autoregressive and moving average components in the model (Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, 2016; Hyndman, R. J., & Athanasopoulos, 2021).



(a) (b)

Figure 2. (a) ACF Plot; (b) PACF Plot.

Figure 2 shows that the ACF graph has a relatively strong correlation at the first lag and then decreases slowly across the following lags, which may indicate the existence of a moving average element. The PACF graph, on the other hand, presents a clear spike at lag 1, suggesting that an autoregressive term may also be present in the series. When both ACF and PACF patterns decrease gradually instead of cutting off sharply, the data-generating process can be associated with a mixed ARMA model. Based on this identification step and after applying one differencing to obtain stationarity, several potential models are evaluated, namely ARIMA (0,1,1), ARIMA (1,1,0), and ARIMA (1,1,1).

Parameter Estimation

After identifying several candidate models, the next step is parameter estimation. The estimation results are summarized in Table 1.

Table 1. Estimation Result of Candidate ARIMA Models.

Model	Parameter	Estimate	P-value	Significance
ARIMA (1,1,0)	AR (1)	0.236952	0.0007228	Significant
ARIMA (0,1,1)	MA (1)	0.333265	1.846e-05	Significant
ARIMA (1,1,1)	AR (1)	-0.27612	0.1159	Not Significant
	MA (1)	0.57816	8.484e-05	Significant

The estimation results show that in the ARIMA (1,1,0) model, the AR (1) parameter is statistically significant with a p-value below 0.05. This indicates that the previous observation of the differenced inflation series significantly influences the current value. For the ARIMA (0,1,1) model, the MA (1) parameter is also statistically significant. This result implies that the current inflation value is influenced by the previous error term or random shock. In contrast, the ARIMA (1,1,1) model shows that although the MA (1) parameter is significant, the AR (1) parameter is not statistically significant because its p-value exceeds the 5% significance level. This suggests that the autoregressive component does not significantly contribute to explaining the variability of the series in this model.

Diagnostic Checking

After estimating the parameters of the candidate models, diagnostic checking is performed to evaluate the adequacy of each model. A suitable ARIMA model should produce residuals that behave randomly and do not exhibit autocorrelation. This means that the residuals have no systematic pattern and are not correlated with their past values (Shumway, R. H., & Stoffer, 2021).

To evaluate the adequacy of the models, residual diagnostics are conducted using the Ljung–Box test. For the ARIMA (1,1,0) model, the Ljung–Box statistic is 0.33299 with a p-value of 0.5639, indicating that residual autocorrelation is not significant. Similarly, the ARIMA (0,1,1) model produces a Ljung–Box statistic of 0.2637 with a p-value of 0.6076. Since the p-value is greater than 0.05, the residuals can be considered independent and consistent with the white noise assumption. These findings suggest that both models are statistically adequate for representing the data (Chatfield, C., & Xing, 2019; Shumway, R. H., & Stoffer, 2021a; Wei, 2019).

Model Selection

After confirming that both candidate models satisfy the residual diagnostic requirements, the next step is to determine the best model by comparing AIC values. The AIC value is calculated using the following formula:

$$AIC = -2\ln(L) + 2k \tag{2}$$

where Lrepresents the maximum likelihood value of the model and $k$denotes the number of estimated parameters. Therefore, the model with the smallest AIC value is considered the most appropriate model because it provides the best balance between model accuracy and simplicity (Burnham, K. P., & Anderson, 2020; Claeskens, G., & Hjort, 2019).

Table 2. AIC Values for Candidate Models.

Model	AIC Value
ARIMA (1,1,0)	286.6392
ARIMA (0,1,1)	281.9911

Based on Table 2, the AIC value of ARIMA (0,1,1) model is smaller than that of ARIMA (1,1,0) model, with an AIC value of 281.9911.

Forecasting

Table 3 presents the forecasting results using the ARIMA (0,1,1) model. the predicted inflation rate remains relatively stable at approximately 3.63% for the next six months. This suggests that inflation is expected to remain stable in the short term. The model also produces prediction intervals at 95% confidence levels. These intervals provide a range within which future inflation values are likely to fall with a certain probability. In time series analysis, uncertainty naturally grows as predictions move further away from the observed data because future values depend on accumulated forecast errors (Hyndman, R. J., & Athanasopoulos, 2021).

Table 3. Inflation Forecast Results

Period	Point Forecast	Lo 95	Hi 95
Jan 2026	3.630879	2.6493024	4.612455
Feb 2026	3.630879	1.9949715	5.266786

Mar 2026	3.630879	1.5359103	5.725847
April 2026	3.630879	1.1607384	6.101019
Mei 2026	3.630879	0.8354729	6.426285
Jun 2026	3.630879	0.5442958	6.717462

CONCLUSIONS AND SUGGESTIONS

Based on the analysis results, the best model obtained for forecasting inflation in Indonesia is ARIMA (0,1,1). The forecasting results indicate that the predicted inflation rate remains relatively stable at approximately 3.63% for the next six months. This suggests that inflation is expected to remain stable in the short term.

Several suggestions can be proposed from this study. First, future research may consider incorporating additional macroeconomic variables such as exchange rates, interest rates, or money supply to improve forecasting accuracy using multivariate time series models. Second, researchers may compare the performance of ARIMA with other forecasting methods, including machine learning approaches or hybrid models, in order to obtain more accurate predictions.

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