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Indonesian Consumer Price Index Forecasting Using Autoregressive Integrated Moving Average

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Abstract

The Consumer Price Index is one of the indicators used to confirm financial success in inflation management. This study aims to help determine the CPI prediction value in Indonesia for the next twelve periods in a month using the ARIMA (Autoregressive Integrated Moving Average) method using the data from January 2015 to March 2022. The results obtained show that the best model that can be used for forecasting is the ARIMA model (2,1,2) with drift with Akaike's Information Criterion (AIC) values of 2190.84. The results of Indonesia's accurate CPI forecasting can be used to assess inflation management for policymaking in the context of controlling inflation. It can be concluded that Based on the analysis, the optimal ARIMA model for forecasting Indonesia's CPI is ARIMA (2,1,2) with drift, aiding in evaluating inflation management for policymaking.

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INTRODUCTION

The Consumer Price Index (CPI) dynamically tracks the average price fluctuations of goods and services over time, serving as a pivotal gauge for inflation or deflation, crucial in guiding monetary policymaking [1], [2]. Gross Regional Domestic Product in spending, budget planning, and other fiscal policies by the government use CPI as the basis for determining [3]–[5]. Based on data from the Central Statistics Agency (BPS) Indonesia's CPI rate for the last 2 years tends to increase every month and it was recorded in March 2022 that the CPI number was 108.95. This increase in the value of inflation was caused by an increase in the CPI. Therefore, information is needed that can describe how the CPI is. One of the things that can be done is to estimate CPI numbers for the next several periods or forecasting [6], [7].

The use of past data to determine something that will be data by doing calculations is called forecasting [8], [9]. Forecasting is an accurate calculation in determining something that will come by using past data [10]–[12]. Technology plays a crucial role in making this easier [13], [14]. One of the forecasting methods that can be used is the ARIMA (Autoregressive Integrated Moving Average), a method that utilizes past and present information from a variable to produce accurate forecasts [15]. This is because the ARIMA method is quite effective in forecasting time series data for short-term forecasting, and

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CPI movements are not good if forecasted far into the future because monetary influences can occur at any time which also affects CPI data [16].

In addition, many previous researchers used the ARIMA method to perform forecasting, including Yuli Wigati, Rais, and Iut Tri Utami in 2015 which applied the ARIMA method in predicting the Consumer Price Index (CPI) in Palu–Central Sulawesi [17], and Ari Pani Desvina & Evi Desmita (2015) apply the ARIMA method in predicting the consumer price index in Pekanbaru City [18], [19]. Both stated that the ARIMA method is an effective and accurate method for forecasting time series data.

The results of forecasting will not get a 100% truth value, but an error value will be generated. Although the results of forecasting are not always precise, it is proven that forecasting has been widely used and helps well in various fields as the basis for planning, monitoring, and decision-making (policy). One of them is the CPI forecasting itself [20].

However, there are relatively few studies published in credible publications that explore the meta-analysis of CPI in a long period of time to see whether this method is still accurately applied over a long period of time. Due to the large influence of the Consumer Price Index (CPI) on the rate of economic inflation on whether or not the Indonesian economy is progressing, the ARIMA method can be used for all data patterns. The CPI data at the Central Statistics Agency (BPS), which tends to increase, including trend data patterns that are more suitable for using the ARIMA method. Therefore, this study aims to forecast Indonesia's CPI from January 2015 to March 2022 with ARIMA modeling to get the model with the best accuracy.

METHOD

The data used in this research is Indonesian CPI data. The data source used is secondary data from MACROVAR. MacroVar uses a systematic top-down approach to analyze financial markets, financial risk, macroeconomic fundamentals, global liquidity, and financial news. MacroVar models are open-source and transparent. Indonesia's CPI data used in this research is Indonesia's CPI data for January 2015 to March 2022. Indonesia's CPI value in this study is based on consumption patterns in the cost of living survey in 90 cities in 2018 (2018=100). The analysis technique used is time series analysis using the ARIMA model. Data processing used to analyze research data using R software.

Arima Model

The ARIMA model is a time series analysis model approach that uses autocorrelation and time series residual variation. ARIMA often called the Box-Jenkins time series [21] s suitable to be applied to find the most appropriate pattern from a group of data (curve fitting), thus ARIMA fully uses past and present data from the dependent variable to make accurate forecasting [17], [22]. The ARIMA model is one of the time series forecasting model techniques that is only based on the observed variable data behavior [23], [24]. The arrangement of the ARIMA model consists of Autoregressive (AR), Moving Average (MA), and Integrated (I) models [25]. Integrated shows the value of the differencing order of non-stationary data to be stationary. ARIMA models are generally denoted by ARIMA (p, d, q) where p is the order (number of time lags) of the autoregressive model, d is the order of differencing (how many times the data has past values reduced), and q is the order of the moving-average model [26]. The general form of the ARIMA model can be expressed by equation 1.

$$Y_t = c + \phi_1 Y'_{t-1} + \phi_{p-1} Y'_{t-p} + \theta_1 e_{t-1} + \cdots + \theta_q e_{t-q} + e_t \quad (1)$$

ARIMA Modeling Stages

ARIMA modeling has four main stages, namely the identification stage, the model estimation stage, model checking or model diagnostics, and the forecasting stage. Model The ARIMA is a model that completely ignores independent variables in forecasting. ARIMA uses past and present values of the dependent variable to produce accurate short-term forecasts. but for long-term forecasting, the accuracy of the forecast is not good. The purpose of ARIMA is to determine a good statistical relationship between the predicted variables and the historical values of these variables so that forecasting can be done with this model.

At the identification stage, the ARIMA model requires time-series data to be stationary [27]. Stationary data can be tested with the Augmented Dickey-Fuller Test (ADF

Test). The transformation and differencing processes are carried out on non-stationary data so that the data becomes stationary. The p and q values in the ARIMA(p,d,q) model are carried out by looking at the Autocorrelation function (ACF) and Partial Autocorrelation (PACF) patterns [16]. The ARIMA (p,d,q) temporary predictive model identified as the best model can be carried out by considering the smallest AIC value [28].

In the next model estimation stage, parameter estimation and significance testing of parameter estimation in the selected model are carried out. If in selecting the selected model there is an inaccuracy in determining the estimation model, it will affect the prediction results which make the prediction results obtained less precise [29]. The model is considered feasible and appropriate if it fulfills the assumption that the residuals are white noise and are normally distributed [30]. The Ljung-Box test is used to examine the white noise residuals and the Lilliefors test and Shapiro test are used to determine the normality of the residual model.

After estimating the parameters, the next step is to test the model whether the model is good for use. To see a good model can be seen from the residuals. If the residual is white noise, then the model can be said to be good and vice versa. One way to see white noise can be tested through the ACF and PACF correlograms of the residuals. If ACF and PACF are not significant, this indicates residual white noise, meaning that the model is suitable. Besides that, it can be done with the Ljung-Box test to find out the white noise. If the initial hypothesis is accepted, the residual meets the white noise requirements.

Furthermore, the ARIMA model (p,d,q) can be used for forecasting if the model obtained meets all the assumptions. The flowchart of the ARIMA modeling stages can improve the reader's understanding as shown in Figure 1.

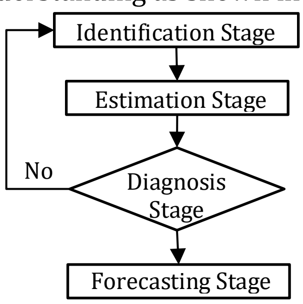

Figure 1. The flowchart of the ARIMA modeling stages

RESULTS AND DISCUSSION

The data used in this study is CPI data from January 2015 to March 2022 using a base year of 2018=100. The lowest Indonesian CPI value is the CPI in February 2015 which is 88.39 and the highest is March 2022 which is 108.95. The development of Indonesia's CPI can be seen in Figure 1. At the identification stage, the data must be stationary. Based on Figure 2, it can be concluded that the data has an increasing trend from time to time so the Indonesian CPI data is not stationary. The data also does not indicate seasonality. The stationarity of the data can be proven by the stationary test results through the Augmented Dicky Fuller test (ADF Test). Based on the test results obtained a p-value of 0.7238 which is still greater than the significance value limit $\alpha = 0.05$. Likewise, the variance performed by the Box-Cox test produces a lambda value of 3.777778. The lambda result is not equal to 1, meaning that the data is not stationary in variance which is shown in Figure 2 transforming and differencing the Box-Cox Plot.

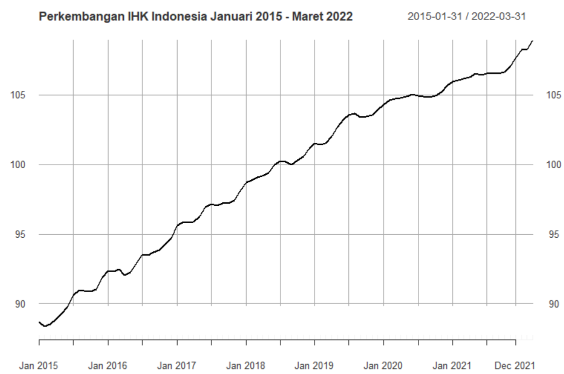

Figure 2. Indonesia's CPI development for January 2015 – March 2022

The data transformation uses lambda 3.777778. After transforming the data using the Box-Cox transformation, a lambda value equal to 1 is produced, which means that Indonesia's CPI data for the period January 2015 to March 2022 is stationary in variance, this can be seen in Figure 3.

The time series plot in Figure 3 indicates that the data is not yet stationary, because the fluctuations are still very high so that two differencing is required and causes the value of *d=2.* After that, differencing is done on the transformed CPI data. The results of the differencing process can be seen in Figure 4.

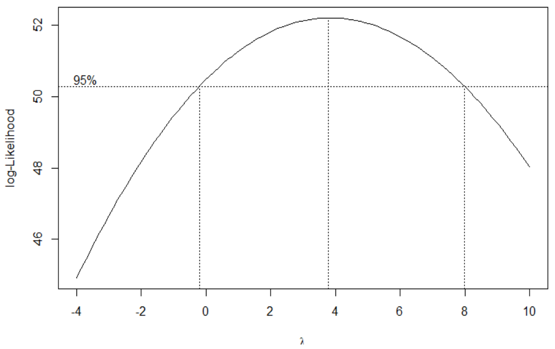

Figure 3. Box-Cox plot of Indonesian CPI data

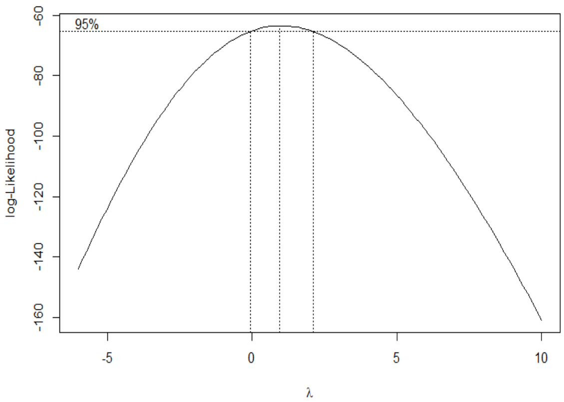

Figure 4. Box-Cox plot of Indonesian CPI data after transformation

Figure 4 shows that the data is stationary. This is evidenced by the results of the ADF Test producing a p-value = 0.02739 which is below the significance value α = 0.05. After the data is declared stationary, the next process is to determine the parameters of the temporary prediction model. After knowing the stationary assumption in the variance thenfollowed by checking the stationary assumption in the mean through ACF (Autocorrelation Function) plots.

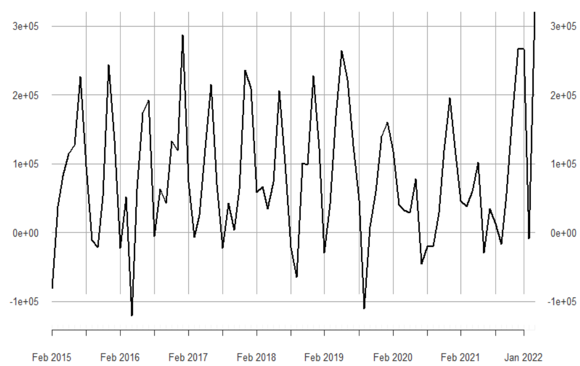

Figure 5. Indonesia's CPI development for January 2015 – March 2022 differencing results

Determination of the parameters of the provisional estimated model is carried out by determining the p and q values based on the ACF and PACF graphs in Figure 6. The determination of p and q values is carried out by trying all possible models to get the best results. By using R software we can select the best model through the resulting combinations. The combination of the ARIMA model from the results of the Indonesian CPI modeling with R software can be seen in Table 1.

To estimate the ARIMA model at the identification stage, it can be seen from the ACF (Autocorrelation Function) and PACF (Partial Autocorrelation Function) plots from data that is stationary in variance and mean. The ACF plot (Figure 5) on the CPI data shows that the ACF cut off at lags 1 and 3 while the PACF cut off at lags 1 and 2. So the estimated model is ARIMA (0,1,1), ARIMA (0,1,2), ARIMA (0,1,3), ARIMA (1,1,0), ARIMA (2,1,0), ARIMA (1,1,1),ARIMA (2,1,1),ARIMA (2 ,1,2), and ARIMA (2,1,3).

The parameters in the appropriate model are then estimated using the conditional least squares method. The estimated parameters must then be tested for their significance in the model. Hypothesis testing to test the significance of parameters. After estimating the model, the next steps are to test the significance of the parameters, namely to see whether the parameters from the predicted results are significant or not significant in the model.

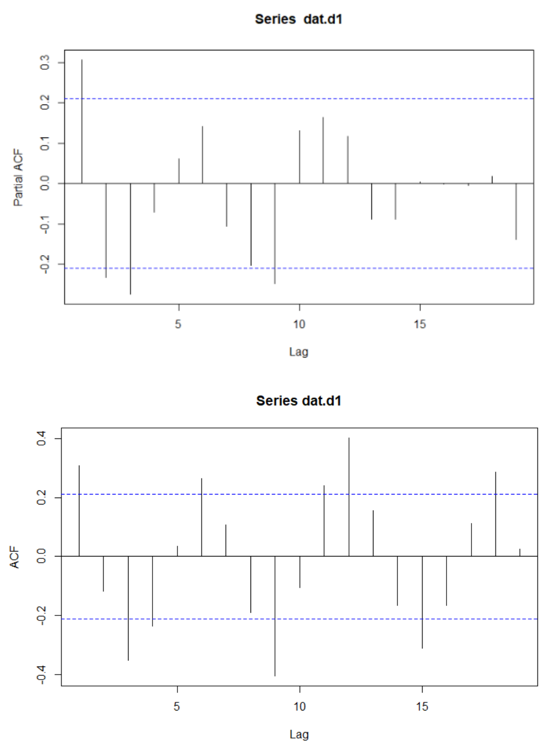

Figure 6. Graph of ACF and PACF of Indonesia's CPI data after differencing order 1

Based on Table 1, it shows that the ARIMA model (2,1,2) with drift is the best ARIMA modeling result with the smallest AIC value of 2190.84. The next step is to estimate the model by calculating the estimated parameters and testing the significance of the estimated parameters on the selected ARIMA model for forecasting CPI Indonesia. The results of parameter estimation and significance testing of parameter estimates can be seen in Table 2.

Based on Table 2, it shows that the significance level of the parameter is significant because it has a p-value of less than α = 0.05, so that all parameters can be used in the model. After obtaining parameter estimates and test results, the next step is to carry out the checking stage to see the suitability of the model, namely the residuals fulfill the white noise requirements and are normally distributed. The results of the Ljung-Box test and the Lilliefors test and the Shapiro test can be seen in Table 3.

Based on Table 2, it shows that the significance level of the parameter is significant because it has a p-value of less than α = 0.05, so that all parameters can be used in the model. After obtaining parameter estimates and test results, the next step is to carry out the checking stage to see the suitability of the model, namely the residuals fulfill the white noise requirements and are normally distributed. The results of the Ljung-Box test and the Lilliefors test and the Shapiro test can be seen in Table 3.

Table 1. Arima Model Combination

Model	*AIC*
ARIMA(0,1,1) with drift	2208.27396441843
ARIMA(0,1,2) with drift	2209.77753115719
ARIMA(0,1,3) with drift	2207.63894623199
ARIMA(1,1,0) with drift	2210.9040998301
ARIMA(2,1,0) with drift	2206.12819375106
ARIMA(1,1,1) with drift	2210.12221701175
ARIMA(2,1,1) with drift	2204.21513467416
ARIMA(2,1,2) with drift	2190.84024038107
ARIMA(2,1,3) with drift	2192.05646136413

Source: Indonesia consumer price index (processed)

Table 2. ARIMA Parameter Estimation Significance Test Results (2,1,2)

term	*estimate*	*std.error*	*statistic*	*p.value*
ar1	0.94	0.03	28.21	0.00
ar2	-0.97	0.03	-30.89	0.00
ma1	-0.79	0.07	-10.62	0.00
ma2	0.94	0.06	14.83	0.00
drift	83324.81	9100.26	9.16	0.00

Source: Indonesia consumer price index (processed)

Table 3. Test Statistical Results

Statistik Uji	*Nilai Statistik*	*p-value*
Uji Ljung-Box	15.4776965533155	0.90600013721021
Uji Lilliefors	0.0716891398674613	0.330026838112096
Uji Shapiro	0.973685748967089	0.0730340908398245

Source: Indonesia consumer price index (processed)

The Ljung-Box test results show that the residual model includes white noise with a p-value = 0.906 greater than the significance of α. The normality test with the Lilliefors test and the Shapiro test shows that the residual model has a normal distribution with p-values respectively 0.33 and 0.073 and is greater than the significance value α. After obtaining the best model, namely the ARIMA model (2,1,2) with drift, forecasts can be made for the next twelve periods which can be seen in Table 4. Forecasting results are in Table 4 for the next twelve periods (April 2022 – March 2023) shows that during this period there will be an increase every month. This information can be used as material for price control strategies in the coming months.

Based on the analysis of the forecasting results carried out, it can be seen that the CPI for the next period continues to increase every month. This means that the inflation rate will also continue to increase in line with the increase in the value of the CPI [31], [32]. The continuously increasing inflation rate will have an impact on the economy of a region and even a country [33], [34]. This will have an impact on increasing prices for goods and services which are a long-term community need, depreciating currency values, and even increasing the poverty rate [35]–[37]. Therefore, it is important to take actions that can reduce inflation. There are many ways to do this. A simple example is fish farming or another example is producing organic fertilizers [38], [39]; this can help control the increase in prices of goods, which is one of the components of the Consumer Price Index. By knowing the value of the CPI forecast, hopefully, it can be used as a consideration for the government in making policies to overcome economic conditions in the future.

Table 4. Forecasting Results

Periode	*Forecast*
88	109.15
89	109.38
90	109.59
91	109.75
92	109.88
93	110.03
94	110.23
95	110.45
96	110.65
97	110.80
98	110.94
99	111.09

Source: Indonesia consumer price index (processed)

CONCLUSION

Based on the analysis that has been carried out, the best ARIMA model obtained for predicting Indonesia's Consumer Price Index (CPI) is ARIMA (2,1,2) with drift with an AIC value of 2190.84. The results of Indonesia's accurate CPI forecasting can be used to assess inflation management for policymaking in the context of controlling inflation.

For advancing our understanding in upcoming studies, a more granular examination of CPI forecasts across various Indonesian regions is paramount to curtail inflation surges. The current scope was constrained to a national-level ARIMA CPI model due to data accessibility challenges in regional contexts.

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