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Exploring The Forecasting Inflation in Kota Palu: An Application of the ARIMA Model

Muhammad Syahrul Mubarak*
Departments of Economic Development, Faculty of Economics and Business, University of Diponegoro, Indonesia
* Corresponding author: syahrulmuhammad13@outlook.com

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Abstract

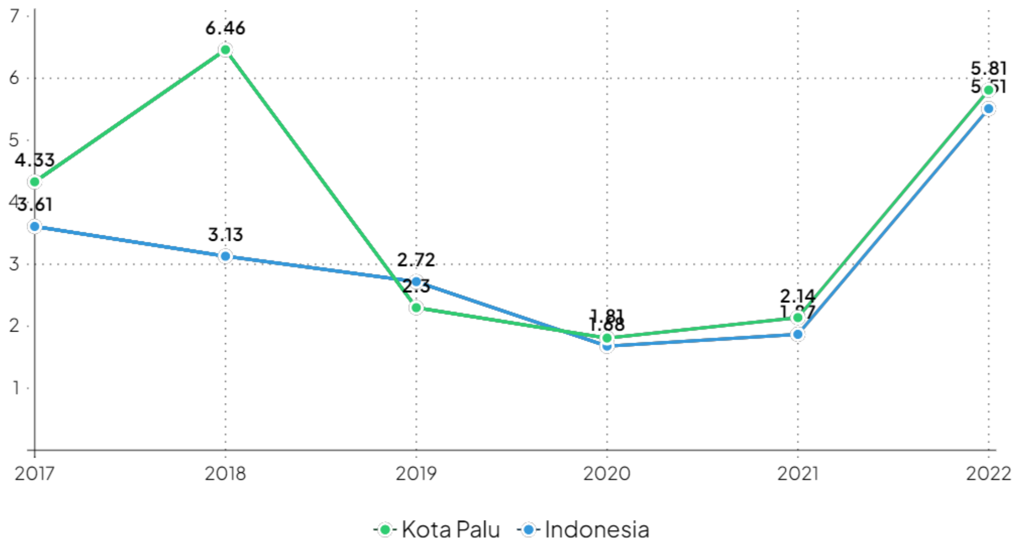
Inflation is an economic phenomenon that significantly impacts financial stability and the welfare of society. The movement of inflation in Kota Palu is challenging to explain using economic theories, as there are factors that are difficult to incorporate into models, such as the COVID-19 pandemic throughout 2020 to 2022, which impacted transportation, housing, and other services components. However, accurately predicting inflation rates remains a complex challenge. The objective of this study is to forecast the inflation movement for the year 2023. The data used in this analysis is the Consumer Price Index (CPI) of Kota Palu from January 2017 to March 2023, with 74 observations. ARIMA model with an Autoregressive (AR) model with lags six and nine was employed. The results of this study show that for the forecasted CPI or inflation from April 2023 to December 2023, the predicted CPI and inflation values closely approximate the actual CPI and inflation values. Therefore, the analysis can be considered accurate in predicting inflation movements.

INTRODUCTION

The movement of the inflation rate is frequently regarded as an economic indicator that attracts significant attention from the government due to its impact on economic stability and public welfare. For instance, elevated inflation can decrease individuals' purchasing power for consumer goods; This aligns with Hasyim (2017) perspective that inflation constitutes a crucial economic symptom and frequently garners the focus of economists and governments, with a sustained rise in prices being a prerequisite for inflation. Within this context, unregulated fluctuations in inflation will generate economic uncertainty within a given region.

According to Djirimu & Tombolotutu (2021), inflation has not been able to be controlled by the government. The reason is that the form of intervention carried out by the government is adaptive. It means that the government only positions itself as a regulator and supervisor, while the provision of public goods is left to the market. Government intervention as a provider and manager is highly dependent on market mechanisms. If the government feels that the market is effective, then its intervention tends to be low. This point is the weakness of the Indonesian government's economic liberalization that affects the regions.

Figure 1. Consumer Price Index of Indonesia and Kota Palu by Calendar Year (January-December) 2017-2022 (Percent)



Source : Badan Pusat Statistik

Based on Figure 1, the overall inflation data between Indonesia and Kota Palu during the 2017-2022 period shows a difference in inflation rates between the two entities. In 2018, national inflation decreased by 3.13 percent compared to 3.61 percent in 2017, while Kota Palu experienced a significant increase in inflation of 6.46 percent in 2018, whereas, in 2017, it was 4.33 percent. The difference indicates that Kota Palu faced higher inflationary pressure than the national inflation rate. The main factor was the natural disaster that hit Kota Palu and its surroundings at the end of September, which increased the inflation rate until the end of 2018 (BPS, 2020).

The 2018 earthquake, tsunami, and liquefaction affected infrastructure and economic activities in Palu. Damaged roads and bridges disrupted the movement of goods and services. In addition, the disaster destroyed many businesses and industries, such as the fishing, plantation, and mining industries. This situation caused an increase in the price of goods and services, especially food and daily necessities, where the inflation condition in 2018 for the transportation, communication, and financial services group was 7.69 percent, the processed food, beverages, cigarettes, and tobacco group was 8.12 percent, and the food ingredients group was 6.37 percent. In addition, the natural disaster also affected the price of supplies or equipment in the education, recreation, and sports group, where the inflation rate was 8.01 percent (BPS, 2019).

National inflation rose again in 2021 and 2022. In Indonesia, inflation reached 1.87 percent and 5.51 percent, respectively, making 2022 the year with the highest inflation rate from 2017 to 2022. This increase can be attributed to the economic activity following the COVID-19 pandemic and the performance of Indonesia's regional economies (Kementerian Keuangan, 2022).

The COVID-19 and post-COVID-19 pandemic contributed to the increase in the inflation rate of Kota Palu in 2021 and 2022. The reason is the restrictions on mobility and economic activity to minimize the spread of COVID-19 by the government. As a result, the production and supply of goods and services fell, and production costs increased. This condition causes an increase in the price of goods and services, impacting inflation. In the recreation, sports, and culture group during COVID-19, the inflation rate 2021 was 4.30 percent, the personal care and other services group was 3.74 percent, and transportation was 2.76 percent (BPS, 2022). In addition, after COVID-19 in 2022, the most considerable contribution to the inflation rate was in the transportation group at 12.75 percent, then the housing, water, electricity, and household fuel group at 10.20 percent, and the personal care and other services group at 7.39 percent (BPS, 2023).

This condition will make people expect the future inflation rate to be higher than last year. It has been discussed in the theory of rational expectations proposed by Robert Lucas, Thomas Sargent, Neil Wallace, and Robert Barro, stating that people form their estimates based on available information, and the government cannot fool the public. The public is fully informed and has the same information as the government (Pratiwi et al., 2014).

Baciu (2015) describes inflation expectations for implementing monetary policy with the title Stochastic Models for forecasting inflation rates—empirical evidence from Romania. The data used is monthly inflation data between January 1997 and August 2013. The results obtained predictions for September 2013, but there is a significant difference between the predictions made in the selected model with the actual inflation rate. Thus, a limitation of the Box-Jenkins methodology approach is that it cannot correctly predict inflation data in the medium and long term. In line with the opinion of Juhro and Bernard (2019) in their research entitled Forecasting Indonesian Inflation Within An Inflation-Targeting Framework: Do Large-Scale Models Pay Off? The Double Moving Average (DMA) approach documents that large-scale models have significant results in forecasting inflation in Indonesia, compared to simple models for inflation persistence over longer time horizons.

Meanwhile, different results were found by McKnight et al. (2019) by forecasting inflation based on a theory-based approach, namely the new Keynesian Phillips Curve (NKPC) with the title Inflation Forecasting using the New Keynesian Phillips Curve with a time-varying trend. The results of his research using quarterly data from 1970 to 2015 for the European Region and the United States show that the role of theory in estimation with the NKPC approach is significantly more accurate in predicting US inflation in the medium-term eight and twelve quarters ahead.

Monica et al. (2022), with research on Malang City Inflation Forecasting Using Autoregressive Integrated Moving Average Exogenous with Calender Variation Effect, explains the results of observations from January 2012 to May 2019 that the magnitude of inflation a month ago and four months ago affected inflation this month. The causes are seasonal effects and calendar variations a month before the Idul Fitri holiday also affect the inflation of Malang City. Forecasting results for June 2019 and October 2019 show Malang City experiencing deflation.

In contrast, Marpaung et al. (2022), in Forecasting the Inflation Rate in Central Java Using ARIMA Model, explains that using monthly data for the period January 2016-April 2021, the best model is ARMA (3,0,3) and finds that inflation will tend to increase in the next few months. Nevertheless, in April 2021, there was a difference between the actual value and the forecasting value. In the prediction, April 2021 experienced an increase in inflation due to entering the month of Ramadan, the holy month of Muslims, where that month, the prices of daily necessities increased. However, the actual value of April 2021 shows a different condition, where in that month, it decreased due to the requirements of the COVID-19 pandemic, which made people's purchasing power low.

A similar opinion is expressed by Mihalache and Dumitru (2023) in their research, Forecasting the Romanian Inflation Rate: An Autoregressive Integrated Moving-Average (ARIMA) Approach, which has a different view, according to him to predict a more actual inflation rate; we can use the ARIMA approach. In the short term, the ARIMA approach is more accurate because it compares actual and predicted values that are similar. So that policymakers can formulate inflation problems appropriately.

The comparison of these studies reveals several differences. Firstly, researchers employed various forecasting methods, such as the stochastic approach, Double Moving Average (DMA), New Keynesian Phillips Curve (NKPC), Autoregressive Integrated Moving Average (ARIMA), and others. Secondly, there are variations in the study areas and periods. For instance, the monthly inflation data from Romania, Indonesia, Kota Malang, and Provinsi Jawa Tengah were examined. Lastly, the studies differ in terms of the accuracy of their predictions and the variance between the projected and actual inflation values.

Due to these variations, there is a research gap between other studies and the study that uses the ARIMA approach to attempt to predict inflation in Kota Palu. While other studies employ different techniques and data, this study uses the ARIMA approach and concentrates on the Kota Palu environment. As a result, the disparities in methodology, setting, and outcomes present a potential for further research and knowledge expansion on inflation forecasting in Kota Palu using strategies appropriate to the region.

RESEARCH METHODS

The research method used in this analysis is quantitative research. It uses secondary data in the form of monthly inflation data for Kota Palu from January 2017 to March 2023, with 74 observations. The data used in this study was collected from the Badan Pusat Statistik Kota Palu. The Consumer Price Index (CPI) or *Indeks Harga Konsumen* (IHK) data explains inflation in this study. To analyze this research, the author uses the Autoregressive Integrated Moving Average (ARIMA) model to obtain essential information in predictive analysis.

Several steps need to be taken to analyze data with the ARIMA method (Gujarati & Porter, 2012), namely, first, model identification. Using information from the correlogram of the data, the author looks for the values of p, d, and q. Second, estimate the parameters of the ARIMA model found in the first step. Third, test the diagnosis by using the results of the ARIMA model estimator; the author chooses a model that can explain the data well. Furthermore, finally, prediction, after obtaining a good model, then the author can use the selected model to predict.

The ARIMA model is also known as the Box-Jenkin approach, which consists of several models, namely autoregressive (AR), moving average (MA), autoregressive-moving average (ARMA), and autoregressive integrated moving average (ARIMA). The ARIMA model in this analysis follows the formula formulated by Shumway & Stoffer (2017), which includes elements x_{t-1}, x_{t-2}, ..., x_{t-p} for AR models, w_{t-1}, w_{t-2}, ..., w_{t-p} for MA models, dan x_{t-1}, ..., x_{t-p}, w_{t-1}, ..., w_{t-p} for ARMA models. In this study, the AR model assumes that the inflation variable is the dependent variable expressed by ihk_t is just a linear function of several previous actual ihk_t. So the author set up the equation (1).

$$CPI_t = \beta_0 + \beta_t CPI_{t-1} + \beta_2 CPI_{t-2} + \cdots + \beta_p CPI_{t-p} + e_t \quad (1)$$

Where CPI is the dependent variable (inflation/CPI), $CPI_{t-1}, CPI_{t-2}, CPI_{t-p}$ Is the lag of CPI, e_t As residual (confounding error), and p is the AR rate. In addition, the MA model assumes that the predicted value of the inflation variable ihk_t; is only influenced by the residual value of the previous period. So the form of the model is shown in equation (2).

$$CPI_t = \alpha_0 + \alpha_1 e_t + \alpha_2 e_{t-1} + \alpha_3 e_{t-2} + \cdots + \alpha_q e_{t-q} \quad (2)$$

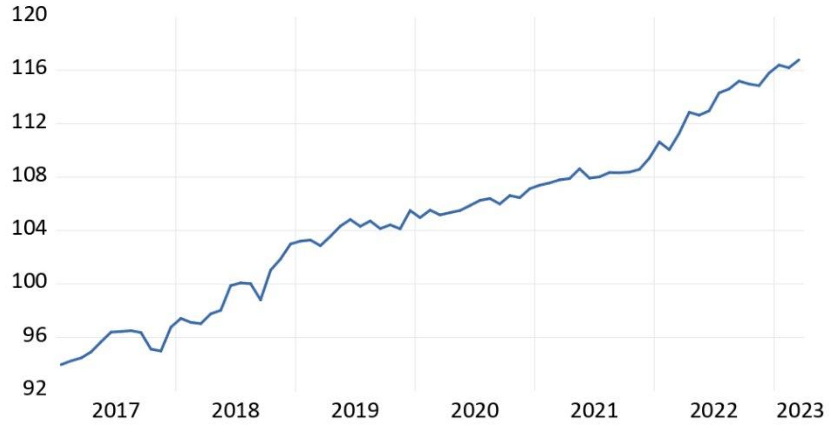
Where, e_t residual, $e_{t-1,} e_{t-2} e_{t-q}$ = lag of the residual, and q is the MA level. Moreover, of course, the variable CPI can also have the characteristics in equations (1) and (2) so that it can be derived from equation (3) in a combination of AR models and MA models called ARMA models.

$$CPI_t = \beta_0 + \beta_t CPI_{t-1} + \beta_2 CPI_{t-2} + \cdots + \beta_p CPI_{t-p} + \alpha_0 e_t + \alpha_1 e_{t-1} + \alpha_2 e_{t-2} + \cdots + \alpha_q e_{t-q} \quad (3)$$

RESULT AND DISCUSSION

For equations (1), (2), and (3) not to produce superior/false modeling or models that have significant errors, modeling CPI data must be stationary both in average and in variance/variance. Figure 2 shows that the CPI data has an upward trend. This condition is the first indication that the CPI data during the study period is not stationary. It is necessary to test again through a correlogram by looking at autocorrelation (AC) and partial autocorrelation (PAC) to determine that the CPI is not stationary.

Figure 2. ***Consumer Price Index*** **of Kota Palu January 2017-March 2023**



Source : Badan Pusat Statistik

Table 1 shows the correlogram that gives us the Q-statistic. Hereafter, we refer to the Q-statistic as the LB statistic. Up to a lag of 32, the LB statistic value is 573.02, while the x^2 statistic values with df of 32 at α = 10% and α = 5% are 42.5847 and 46.1943. The value of the LB statistic is greater than the value of the chi-squares (x^2) statistic, so the data is not stationary.

After testing the correlogram, it is necessary to compare the absolute value of the ADF statistic with the Mackinnon critical value through the ADF unit root test. This test also sees whether the CPI data is stationary or not. Although the two tests in Figure 2 and the table are sufficient, the unit root test must be included in the data stationarity testing procedure. The reason is that the constant and time trend variables are included in the unit root test. The unit root test has two assumptions if the time series data contains a unit root, it means that the data is not stationary or the hypothesis is ϕ = 0. The second assumption is that the data is stationary with the alternative hypothesis ϕ < 0.

Table 1. Correlogram Test

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
. |*******	. |*******	1	0.949	0.949	70.348	0.000
. |****** |	. | . |	2	0.901	-0.004	134.58	0.000
. |****** |	. | . |	3	0.851	-0.038	192.73	0.000
. |****** |	. | . |	4	0.806	0.012	245.53	0.000
. |****** |	. | . |	5	0.763	0.006	293.54	0.000
. |***** |	. | . |	6	0.721	-0.016	337.02	0.000
. |***** |	.*| . |	7	0.673	-0.085	375.44	0.000
. |***** |	. | . |	8	0.625	-0.019	409.16	0.000
. |**** |	. | . |	9	0.577	-0.035	438.33	0.000
. |**** |	. | . |	10	0.531	-0.016	463.40	0.000
. |*** |	. | . |	11	0.482	-0.059	484.39	0.000
. |*** |	. | . |	12	0.437	0.000	501.89	0.000

. |*** |	. | . |	13	0.397	0.030	516.57	0.000
. |*** |	. | . |	14	0.360	0.005	528.85	0.000
. |** |	.*| . |	15	0.319	-0.077	538.63	0.000
. |** |	. | . |	16	0.286	0.058	546.62	0.000
. |** |	. | . |	17	0.255	0.011	553.09	0.000
. |** |	. | . |	18	0.230	0.028	558.44	0.000
. |*. |	. | . |	19	0.204	-0.039	562.72	0.000
. |*. |	. | . |	20	0.177	-0.033	565.99	0.000
. |*. |	.*| . |	21	0.144	-0.067	568.21	0.000
. |*. |	. | . |	22	0.119	0.044	569.76	0.000
. |*. |	. | . |	23	0.095	-0.028	570.76	0.000
. |*. |	. | . |	24	0.076	0.019	571.41	0.000
. | . |	. | . |	25	0.055	-0.024	571.77	0.000
. | . |	. | . |	26	0.035	-0.024	571.91	0.000
. | . |	. | . |	27	0.013	-0.032	571.93	0.000
. | . |	. | . |	28	-0.006	0.005	571.93	0.000
. | . |	. | . |	29	-0.021	0.043	571.99	0.000
. | . |	. | . |	30	-0.035	-0.025	572.14	0.000
. | . |	. | . |	31	-0.049	-0.015	572.45	0.000
. | . |	. | . |	32	-0.065	-0.051	573.02	0.000

Table 2. Unit Root Test of Consumer Price Index Kota Palu, Constant Trendlessness

Lag Length: 0 (Automatic based on SIC, maxlag=11)		t-Statistic	Prob.
Augmented Dickey-Fuller test statistic		-0.115601	0.9432
Test critical values	1% level	-3.521579	
	5% level	-2.901217	
	10% level	-2.587981	

Table 2 shows the test results with a constant without a trend. Since the optimal length of inaction is crucial, this unit root test includes the length of inaction based on the SIC criterion. The absolute value of the ADF statistic is smaller than the Mackinnon critical value at each significance level, so the CPI data is not stationary. The ADF statistic value is -0.115601, and the Mackinnon critical value at α=1%; α=5%; α=10% are -3.521579; -2.901217; -2.587981 respectively.

If you continue to process Kota Palu's consumer price index data that is not stationary, then the problem of skewed regression will occur, and predictions cannot be made. Thus, it is necessary to transform the non-stationary Kota Palu CPI data into static data through the data differentiation process or the degree of integration test.

Table 3. Unit Root Test of Consumer Price Index Kota Palu, Constant Trendlessness in First Difference

		t-Statistic	Prob.
Lag Length: 0 (Automatic based on SIC, maxlag=11)		-9.406213	0.0000
Augmented Dickey-Fuller test statistic			
Test critical values	1% level	-3.522887	
	5% level	-2.901779	
	10% level	-2.588280	

Table 3 shows that all absolute values of ADF statistics are more significant than the Mackinnon critical value at each α, so the CPI data is static data at the first difference. The ADF statistical value is -9.406213 while the Mackinnon crucial value at α=1%; α=5%; α=10% are -3.522887; -2.901779; -2.588280, respectively.

After knowing that the data is stationary at the first difference, in the following procedure, we need to look at the correlogram pattern of AC and PAC at the first difference in Table 4 to see whether equation (1) or equation (2) or equation (3) can be used to predict the movement of inflation. According to Ghozali & Ratmono (2017), several processes must be considered to know which equation to use. The process is shown in Table 5.

Table 4. Correlogram Test in First Difference

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.111	-0.111	0.9422	0.332
.*| . |	.*| . |	2	-0.103	-0.117	1.7726	0.412
.*| . |	**| . |	3	-0.194	-0.225	4.7488	0.191
. |*. |	. |*. |	4	0.145	0.082	6.4297	0.169
. | . |	.*| . |	5	-0.063	-0.090	6.7507	0.240
. |** |	. |** |	6	0.299	0.293	14.133	0.028
. | . |	. | . |	7	-0.043	0.057	14.290	0.046
. | . |	. | . |	8	-0.049	-0.004	14.494	0.070
**| . |	**| . |	9	-0.316	-0.243	23.142	0.006
. |*. |	. | . |	10	0.128	-0.025	24.572	0.006
. | . |	. | . |	11	0.016	-0.042	24.596	0.010
. |*. |	. | . |	12	0.155	0.034	26.784	0.008
.*| . |	. | . |	13	-0.128	-0.030	28.287	0.008
. | . |	. | . |	14	0.040	0.054	28.436	0.012
**| . |	.*| . |	15	-0.254	-0.120	34.580	0.003
. | . |	. | . |	16	0.050	-0.063	34.821	0.004
. | . |	. | . |	17	0.036	-0.019	34.952	0.006
. |*. |	.*| . |	18	0.078	-0.108	35.557	0.008
.*| . |	. | . |	19	-0.084	0.032	36.287	0.010
. | . |	. | . |	20	0.058	0.051	36.636	0.013
.*| . |	. | . |	21	-0.077	0.073	37.263	0.016
.*| . |	.*| . |	22	-0.092	-0.156	38.174	0.018

<table>
<tr><td>. | . |</td><td>. | . |</td><td>23</td><td>0.023</td><td>0.001</td><td>38.231</td><td>0.024</td></tr>
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<tr><td>. | . |</td><td>. | . |</td><td>26</td><td>-0.058</td><td>-0.042</td><td>40.645</td><td>0.034</td></tr>
<tr><td>. | . |</td><td>. | . |</td><td>27</td><td>-0.057</td><td>-0.018</td><td>41.041</td><td>0.041</td></tr>
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<tr><td>. | . |</td><td>. | . |</td><td>29</td><td>-0.024</td><td>-0.053</td><td>41.296</td><td>0.065</td></tr>
<tr><td>. | . |</td><td>.*| . |</td><td>30</td><td>-0.026</td><td>-0.166</td><td>41.381</td><td>0.081</td></tr>
<tr><td>. |*. |</td><td>. | . |</td><td>31</td><td>0.092</td><td>-0.025</td><td>42.477</td><td>0.082</td></tr>
<tr><td>.*| . |</td><td>.*| . |</td><td>32</td><td>-0.115</td><td>-0.123</td><td>44.261</td><td>0.073</td></tr>
</table>

Table 5. Identification process Equation (1); Equation (2); Equation (3)

Equation	ACF Patterns	PACF Patterns
Equation (1)	Decreases exponentially	Significant spikes (out of interval/dashed line) up to lag p
Equation (2)	Significant spikes (out of interval/dashed line) up to lag p	Decreases exponentially
Equation (3)	Decreases exponentially	Decreases exponentially

Table 4 shows that only lag six and nine are significant spikes, the rest are not substantial (around the 95% confidence interval), and the PACF is only effective at lag 6. Based on this information, it is concluded that the model used is equation (1). Therefore, we can reduce equation (1) to equation (4).

$$CPI_t = \beta_0 + \beta_6 CPI_{t-6} + \beta_9 CPI_{t-9} + e_t \text{.......}(4)$$

CPI_t is the consumer price index of Kota Palu or inflation; CPI_{t-6} and CPI_{t-9} are a six-month and nine-month lag of CPI and the residual or confounding error. Thus, the output is found as shown in Table 6.

Table 6. Output Estimation Equation (4)

Variable	Coefficient	t-Stat	Prob
C	0.311759	4.396439	0.0000
AR(6)	0.235425	1.972311	0.0525
AR(9)	-0.288178	-2.562204	0.0126
R-squared		0.176936	
F-stat		5.016004	
Prob.		0.003303	

The equation (4) estimation result in Table 6 shows a goodness-fit value of 17.7%, F value of 5.016, and significance with an F<5% probability of 0.003. The lag 6 and 9 variables are significant at α=10% and α=5%, respectively. Therefore, model equation (4) can be derived back to equation (5).

$$CPI_t = 0.3117 + 0.2354 CPI_{t-6} - 0.2881 CPI_{t-9} + e_t \text{.......}(5)$$

Equation (1) assumes that the ARIMA model ignores independent variables in forecasting and determines an excellent statistical relationship between the forecasted variable and the historical value of the variable. So, we need diagnostic checking to see whether equation (5) is compatible with the empirical data. It is done by looking at the correlogram and partial correlogram for the residual values of equation (5). In addition, a heteroscedasticity test is also conducted to see whether the forecasting results are accurate or not. High volatility will result in the forecasting ability or precision changing occasionally.

Table 7. Correlogram Test in Equation (5)

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.*| . |	.*| . |	1	-0.111	-0.111	0.9486	
.*| . |	.*| . |	2	-0.153	-0.167	2.7690	
.*| . |	.*| . |	3	-0.067	-0.110	3.1246	0.077
. |*. |	. |*. |	4	0.128	0.083	4.4453	0.108
. | . |	. | . |	5	0.022	0.024	4.4846	0.214
. | . |	. | . |	6	-0.016	0.019	4.5057	0.342
. | . |	. | . |	7	-0.026	-0.001	4.5643	0.471
.*| . |	.*| . |	8	-0.079	-0.096	5.0988	0.531
. | . |	. | . |	9	0.006	-0.030	5.1019	0.648
. | . |	. | . |	10	0.073	0.043	5.5740	0.695
. | . |	. | . |	11	0.032	0.039	5.6645	0.773
. | . |	. |*. |	12	0.039	0.093	5.8035	0.831
.*| . |	.*| . |	13	-0.157	-0.123	8.0764	0.706
. | . |	. | . |	14	0.047	0.018	8.2821	0.763
.*| . |	.*| . |	15	-0.101	-0.156	9.2556	0.753
. | . |	. | . |	16	0.054	-0.011	9.5372	0.795
. | . |	. | . |	17	-0.020	-0.016	9.5782	0.845
.*| . |	.*| . |	18	-0.077	-0.084	10.174	0.857
. | . |	. | . |	19	-0.025	-0.012	10.237	0.893
. |*. |	. | . |	20	0.075	0.045	10.827	0.902
. | . |	. | . |	21	-0.004	-0.037	10.829	0.929
.*| . |	.*| . |	22	-0.110	-0.100	12.132	0.911
. | . |	. | . |	23	-0.002	-0.034	12.132	0.936
. | . |	. | . |	24	0.070	0.029	12.682	0.942
. | . |	. | . |	25	-0.005	0.020	12.685	0.958
. | . |	. | . |	26	-0.031	-0.022	12.797	0.969
. | . |	. | . |	27	-0.039	-0.013	12.977	0.977
. | . |	.*| . |	28	-0.032	-0.098	13.099	0.983
. | . |	. | . |	29	-0.023	-0.052	13.166	0.988
. | . |	.*| . |	30	-0.058	-0.139	13.596	0.990
. | . |	. | . |	31	0.059	0.011	14.049	0.991
.*| . |	.*| . |	32	-0.100	-0.116	15.375	0.987

Table 8. Heteroskedasticity Test: ARCH in Equation (5)

Heteroskedasticity Test: ARCH			
F-statistic	0.685522	Prob. F(1,71)	0.4105
Obs*R-squared	0.698092	Prob. Chi-Square(1)	0.4034

The results of Table 7 show that the AC and PAC of the residual values are insignificant or nothing outside the 95% confidence interval line. Similarly, the Box-Pierce Q-statistic is not significant. Table 8 also supports the output of Table 7, where the Chi-square probability value of 40.34% is more significant than α = 5%, which means it is not significant and does not have heteroscedasticity problems. Thus, it can be concluded that the residual value in equation (5) is random or white noise, so we no longer need to look at other ARIMA models because this model is the best.

Table 9. Forecasting Result

Month	CPI Actual Value	CPI Forecasting Value	Inflation Actual (%)	Inflation Forecasting (%)
October 2022	114.97	113.88	-0.20	-0.19
November 2022	114.86	114.19	-0.10	-0.09
December 2022	115.78	114.51	0.80	0.80
January 2023	116.39	114.82	0.53	0.52
February 2023	116.19	115.13	-0.17	-0.17
March 2023	116.78	115.44	0.51	0.50
April 2023		115.75		-0.88
May 2023		116.06		0.27
Juni 2023		116.38		0.28
July 2023		116.69		0.27
August 2023		117		0.27
September 2023		117.31		0.26
October 2023		117.62		0.26
November 2023		117.94		0.27
December2023		118.25		0.26

Based on the forecast results in Table 9, it can be seen that the forecast using equation 5 is more accurate in the short term, as the comparison of actual and forecast values is not very different, even if the forecast value is close to the actual value. This finding aligns with Marpaung et al. (2022) and Mihalache and Dumitru (2023). However, it contradicts the analyses of Baciu (2015) and McKnight et al. (2019), which state that the predicted value with the actual value obtained by the Box-Jenkins approach has a significant difference, so the prediction is inaccurate.

These results are not the fault of the method used. Instead, they are caused by the fact that these researchers use too many observations, which makes the residual variance of the time series data inconstant. According to Hossain et al. (2019), too much forecast data may include periods where the data are not stationary. In this case, further differencing will be needed to achieve stationarity. However, too much differencing can also remove important information from the data, resulting in an inaccurate forecast model. In his study, Baciu (2015) also explains that when analyzing inflationary movements over time, the variances often do not remain constant over time.

According to Widarjono (2018), if there are too many observations, the residual variance of the time series data may not be constant. It may change from one period to another or may contain heteroskedasticity. Although the problem of heteroskedasticity generally occurs in cross-sectional data, the possibility of autocorrelation and heteroskedasticity problems cannot be ruled out in time series data. Therefore, it is essential to use appropriate and relevant observations in inflation forecasting to improve forecast accuracy.

Table 9 shows a -0.88% decrease in inflation for Palu in April 2023. This decrease was during Ramadan and Eid al-Fitr when people's purchasing power should have increased. However, the decline in purchasing power was caused by several factors. One is the impact of widespread layoffs during the pandemic: One possibility is that widespread layoffs caused people to hold back on spending. Second, the phenomenon of short-term work: the economic uncertainty resulting from these layoffs may make people more cautious about spending their money: In addition, the phenomenon of people working for short periods, for example, only two or three months, can also have an impact on people's purchasing power. When people work temporarily, their income may be limited; This makes them more cautious about spending.

Thirdly, there is a change in the shopping culture from offline to online shopping: In addition to the above factors, the shift in people's shopping culture from offline to online shopping can also impact purchasing power. Online shopping has become more popular and accessible in recent years. This change may affect how people shop and reduce their offline spending.

From May 2023 to December 2023, the CPI forecast for Kota Palu increased with estimated inflation of between 0.26% to 0.28%. These conditions indicate a gradual increase in prices during this period. The price increase could have been caused by seasonal factors where demand increases, such as the Eid al-Adha holiday in June 2023 with an estimated inflation of Kota Palu of 0.28%, the Christmas holiday in December showed a relatively small increase with an estimated CPI of 118.25 and an estimated inflation of 0.26. In addition, unavoidable harmful weather factors also affect production costs and demand or purchasing power.

Looking to the future, these findings suggest that policymakers and market participants need to expect gradual price increases in Palu City. Demand and inflation may be affected by seasonal factors such as holidays. Therefore, adequate supply and demand management and appropriate pricing policies must be considered to maintain price stability and reduce inflationary pressures during such periods. In addition, production and cost management, as well as attention to people's purchasing power, must also consider the influence of adverse weather factors. In conclusion, this predicted price increase underscores the importance of careful planning and appropriate policies in dealing with inflationary dynamics in Palu.

CONCLUSION

Based on the analysis results, the author found that the data of *Indeks Harga Konsumen* Kota Palu is stationary at first difference. So the Box-Jenkin approach is the Autoregressive (AR) model with lags at lag six and nine. AR (6,9,0) forecasting shows that the predicted value of the CPI and inflation with the actual value of the CPI and inflation is similar; in other words, in the short term, the expected value is accurate to use in forecasting. For this reason, in April 2023, it decreased, while in May 2023-December 2023, it increased gradually.

The limitation of the research is that the author only uses information on the monthly general CPI Kota Palu, so it is unknown which commodity component caused the increase and decrease in the CPI or inflation occurred. It means that we need to know information essential to understanding inflation dynamics. Therefore, the subsequent analysis needs to include forecasting analysis on several commodity components that have contributed to the CPI or inflation in Kota Palu.

REFERENCE

Baciu, I.-C. (2015). Stochastic models for forecasting inflation rate. Empirical Evidence from Romania. *Procedia Economics and Finance*, 44-52.

Badan Pusat Statistik (2019). *Perkembangan Indeks Harga Konsumen/Inflasi 2018.* Palu: Badan Pusat Statistik Provinsi Sulawesi Tengah.

__________________ (2020). *Perkembangan Indeks Harga Konsumen/Inflasi 2019.* Palu: Badan Pusat Statistik Provinsi Sulawesi Tengah.

__________________ (2022). *Perkembangan Indeks Harga Konsumen/Inflasi 2021.* Palu: Badan Pusat Statistik Provinsi Sulawesi Tengah.

__________________ (2023). *Perkembangan Indeks Harga Konsumen/Inflasi 2022.* Palu: Badan Pusat Statistik Provinsi Sulawesi Tengah.

Dian Pratiwi, M. I. (2014). Pengujian Efek Fisher: Pengaruh Ekspektasi Inflasi Dan Kegiatan Ekonomi Terhadap Tingkat Bunga Nominal Di Indonesia. *Ekomaks*, 21-27.

Djirimu, M. A., & Tombolotutu, A. D. (2021). *Catatan Kritis Atas Kinerja Pembangunan Ekonomi Provinsi Sulawesi Tengah Periode 2009-2019.* Yogyakarta: Penerbit DEEPUBLISH.

Ghozali, I., & Ratmono, D. (2017). *Analisis Multivariat dan Ekonometrika.* Semarang: Badan Penerbit - Undip.

Gujarati, D. N., & Porter, D. C. (2012). *Dasar-dasar Ekonometrika Edisi 5 Basic Econometrics.* Jakarta: Salemba Empat.

Hasyim, A. I. (2017). *Ekonomi Makro.* Indonesia: Prenada Media.

Hossain, Z., Rahman, A., Hossain, M., & Karami, J.H. (2019). Over-Differencing and Forecasting with Non-Stationary Time Series Data. *Dhaka University Journal of Science*, 21-26.

Juhro, S. M., & Lyke, B. N. (2019). Forecasting Indonesia Inflation Within An Inflation-Targeting Framework: Do Large-Scale Models Pay Off? *Bulletin of Monetary Economics dan Banking*, 423-436.

Kementerian Keuangan (2022). *Laporan Ekonomi & Keuangan: Gejolak Ekonomi Global Masih Terus Berlanjut*. Indonesia: Badan Kebijakan Fiskal, Kementerian Keuangan.

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*, 163-173.

McKnight, S., Mihailov, A., & Rumler, F. (2020). Inflation forecasting using the New Keynesian Phillips Curve with a time-varying trend. *Economic Modelling*, 383-393.

Mihalache, R.-P., & Bodislav, D. A. (2023). Forecasting the Romanian Inflation Rate: An Autoregressive Integrated Moving-Average (ARIMA) approach. *Theoretical and Applied Economics*, 67-76.

Monica, M., Suharsono, A., & Ampa, A. T. (2022). Malang City Inflation Forecasting Using Autoregressive Integrated Moving Average Exogenous with Calendar Variation Effect. *Al-Khwarizmi: Jurnal Pendidikan Matematika dan Ilmu Pengetahuan Alam*, 149-162.

Shumway, R. H., & Stoffer, D. S. (2017). Time Series Analysis and Its Applications: With R Examples. Jerman: Springer International Publishing.

Widarjono, A. (2018). *Ekonometrika: Pengantar dan Aplikasinya Edisi Kelima.* Yogyakarta: UPP STIM YKPN.