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Inflation forecasting using autoregressive distributed lag (ARDL) models

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Abstract: This study attempts to evaluate and compare the inflation-predicting performance of several ARDL models. Since there was no cointegration, the ARDL model does not employ an error correction term. Subsequently, model development showed that ARDL(2,2) should be used. Besides the formally developed model, some other more arbitrarily chosen ARDL models were also included, i.e., ARDL(1,1), ARDL(2,0), ARDL(1,0), ARDL(0,1), and ARDL(0,2). This research measures forecasting performance with inflation as the forecasting object. The duration of the monthly inflation statistics ranged from January 2011 to July 2022. The data were separated into two categories. The training data ranged between January 2011 and December 2021. After getting the appropriate parameters from the training data, the models generated projections from January 2022 to July 2022. The research determined that ARDL (1,0) was the most accurate inflation forecasting model, followed by ARDL (0,2) and formally constructed ARDL(2,2) finished in fourth place. This study suggests that the formal development of ARDL for forecasting purposes is unnecessary. Formal ARDL development is more appropriate for root cause analysis. In addition, the single autoregressive component indicates that most of the inflation value's information originated from the prior period. This suggests that the previous period's value is Indonesia's most significant predictor of inflation. The impact of greater period lags on inflation forecasting diminishes immediately.

Keywords: Forecasting; ARDL; Cointegration
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Introduction

Inflation signifies a general rise in the prices of goods and services. It carries a price that will harm social welfare (Serletis & Xu, 2021). A significant increase in the price of products and services will reduce the purchasing power of money, resulting in the population acquiring fewer goods and services. Overall, this indicates a decline in well-being. If inflation is unchecked, it frequently presents an impending economic crisis or turmoil (Kusumatrisna et al, 2022). Due to the drastic reduction in demand, soaring prices would eventually lead to a loss in economic output. Due to the reduction in purchasing power and demand, producers will even hesitate to maintain constant production levels. The impending economic catastrophe will threaten the financial sector, stock market, and even the nation's trading activity (Ahmed et al., 2020).

While low inflation supports economic growth, high inflation undermines economic growth (Atigala et al., 2022). Raging inflation has increased unemployment and poverty (Sijabat, 2022). With mild to intermediate inflation, producers will increase their production to earn more profit by increasing prices. Thus, productivity and general income will increase (Kurniasih, 2019). Generally, inflation causes a depletion in customers' resources used to acquire goods and services. Therefore, many parties keep an eye on the inflation rate. One of the party's concerns with inflation is the central bank. In fact, it has become the main focus of the central bank to control and curb inflation through monetary policy (Astuti & Udjianto, 2022). The central bank will construct its inflation targeting framework (ITF) to take steps to bring the inflation level within the acceptable range (Setiartiti & Hapsari, 2019). The more independent a central bank is in enforcing its duties, the more able it becomes to limit the negative impact of inflation (Kunaedi & Darwanto, 2020). Therefore, in devising the right monetary policy, the central bank must be able to forecast the inflation occurring in the economy. A wildly uncontrolled inflation has more probability of causing economic decline and crisis. The central bank must formulate the right monetary policy to prevent increasing inflation (Duong, 2022). Several variables have been known to have an influence or relationship with inflation. These variables include interest rate, stock index, and exchange rate. These variables will be used as the predictors in this research for forecasting the inflation rate. The literature review below will provide the reasoning for selecting interest and exchange rates as the inflation predictor.

The interest rate is one variable affecting inflation (Kurniawan et al., 2022). The interest rate is one of the main instruments for monetary policy conducted by central banks (Arintoko & Kadarwati, 2022; Johari et al., 2022). Sulistiana et al. (2017) found that the interest rate, proxied by the BI rate (interest rate targeted by the Indonesian central bank), is the most dominant factor that affects inflation. The relationship between these two variables is long-term, as the cointegrating relationship indicates. Moreover, Granger Causality proves that inflation will move the interest rate, evidence of monetary policy conducted by the central bank.

Similarly, Prieto and Lee (2019) found a long-term relationship between interest rates and inflations. Yadav et al. (2021) found that the stock market and inflation are inherently cointegrated. It means the movement of both variables would continue in the long term. Nghiem and Narayan (2021) found that interest rate positively influences inflation. This is reversely expected. This unusual result raises the question of monetary policy effectiveness in Vietnam. However, this result is likely in the case of Vietnam due to its high public debt and deeply ingrained inflation expectations. The stock index is also influential on the inflation rate. Pradhan et al. (2014) and Prieto and Lee (2019) found a long-term relationship between the stock index and inflation. Apparently, when the stock market index rises, economic activity increases productivity.

This will drive the increase in the general price of goods and services. Eldomiaty et al. (2020) found that stock prices negatively correlated with inflation in a long-run equilibrium. Yadav et al. (2021) found that the stock market and inflation are inherently cointegrated. It means the movement of both variables would continue in the long term.

The second variable that acts as the predictor for inflation in this research is the exchange rate. Sulistiana et al. (2017) proved the existence of cointegration in the models involving exchange rate and inflation. This indicates a long-term equilibrium between the exchange rate and inflation. Sunal (2018) investigated how exchange rates and money supply affect inflation. He found a cointegration relationship in the model in which inflation is the endogenous variable. This denotes a long-term effect of the exchange rate against inflation.

Besides, the short-term effect of the exchange rate occurs as well. Nghiem and Narayan (2021) found that depreciation in the exchange rate dampened inflation, and the strengthening of which caused a hike in inflation. The wealth effect or interest parity could cause this. Therefore, it is inconsistent with conventional thinking (Nghiem & Narayan, 2021). Yadav et al. (2021) found that exchange rate and inflation form some cointegrated relationship. The long-run equilibrium exists within these variables. Based on the explanation above, this research will employ interest rates, stock indexes, and exchange rates as predictors for forecasting inflation.

Prior research mostly used Autoregressive Integrated Moving Average (ARIMA), Vector Autoregressive (VAR) and machine learning models to forecast inflation (Akbulut, 2022; Baybuza, 2018; Kelikume & Salami, 2014; Ozgur & Akkoc, 2021). Kelikume and Salami (2014) employed Autoregressive Integrated Moving Average (ARIMA) and multivariate Vector Autoregressive (VAR) for predicting inflation in Nigeria. They found that multivariate VAR has a lower forecast error than ARIMA. Therefore, the forecasts from VAR more resemble the actual data. Baybuza (2018) demonstrated that machine learning models can be as good as econometrics models in predicting the inflation rate in Russia. The machine learning models tested include Lasso, Ridge, Elastic Net, Random Forest, and Boosting. He found that Random Forest and Boosting models can match the performance of econometrics models such as random walk and autoregression. Ozgur and Akkoc (2021) compared the performance of machine learning techniques, Autoregressive Integrated Moving Average (ARIMA), and multivariate Vector Autoregressive (VAR) in forecasting inflation.

The machine learning technique, represented by ridge, lasso, *ada lasso*, and elastic net methods, outperforms ARIMA and multivariate VAR. Ozgur and Akkoc (2021) addressed this result as the development in computer science that begins to outperform econometrics. Akbulut (2022) compared the VAR model with machine learning models. The VAR model can better forecast inflation compared with the machine learning models. Furthermore, Akbulut (2022) divided machine learning models into linear and nonlinear. In this regard, nonlinear machine learning models predict better than their linear counterparts. Inflation forecasting using the ARDL model is very scant in literature, let alone inflation forecasting in Indonesia. The utilization of the ARDL model for forecasting was mainly for predicting COVID-19 data (Negara et al., 2021), rainfall (Azmi et al., 2020), budget revenues (Fayziev et al., 2019), export quantities (Ningrum, 2018), money demand function (Siburian, 2014), and share price (Ali, 2023). Therefore, this research will fill in the gaps by providing forecast results on inflation using the ARDL method since there is not yet any research that employs ARDL to forecast inflation. ARDL will reveal the significance and importance of short-term and long-term effects in predicting inflation and whether previous period residuals will play an essential role in the forecast.

Research Method

This research employs monthly data from January 2011 until July 2022. The data will be divided into training and test data. Training data span from January 2011 up to December 2021. Training data will be used to generate ARDL models. ARDL models will show whether short-term and long-term components exist in the forecasting model. ARDL can also investigate the importance of last-period shocks or residuals in forecasting inflation. Including more explanatory variables such as stock index, interest, and exchange rate will reveal the statistical power of these variables in forecasting inflation. These models, in turn, will generate forecasts for January 2022 until July 2022. The forecast will be compared with the actual data, i.e. test data. From this comparison, we can find out which model has the best forecast accuracy.

The research variable of interest is inflation, since it is the object of the forecasting. It is posited that inflation is affected by interest rates, stock index, and exchange rate. Therefore, the independent variables will be the interest rate, stock index, and exchange rate. The following table lists the variables and the source.

Table 1 Research variables

No	Variable	Explanation	Source
1	INF	Inflation	Bank Indonesia
2	INT	Interest Rate	Bank Indonesia
3	IHSG	Stock Index	OJK/Otoritas Jasa Keuangan
4	EXR	IDR /USD Exchange Rate	Bank Indonesia

Before jumping into constructing the ARDL model, we first have to test for the stationarity of the variable. ARDL model requires stationary variables. The test for stationarity will be using the Dickey-Fuller test. This research will employ three kinds of Dickey-Fuller tests: test without constant nor trend, test with a constant and no trend, and test with a constant and a trend. The Dickey-Fuller models are as follows:

$$\Delta y = \gamma y_{t-1} + v_t$$
$$\Delta y = \alpha + \gamma y_{t-1} + v_t$$
$$\Delta y = \alpha + \lambda t + \gamma y_{t-1} + v_t$$

The variable t denotes the trend. The variable y will be all the variables used in this research: INF, INT, IHSG, and EXR. The variable will be declared stationary if the γ coefficient is statistically significant. If a variable is not stationary, it will be first differenced and be retested again for stationarity. After all the variables are stationary, we construct the ARDL model. We propose some models of ARDL. The models are ARDL(1,0), ARDL(2,0), ARDL(3,0), ARDL(0,1), ARDL(0,2), ARDL(0,3). Besides these models, we will also search for the most optimal ARDL by choosing a certain lag length through the Akaike Information Criterion (AIK). Also, we will include the ARDL model with a selected lag length and a cointegrating relationship. Therefore, a cointegration test is necessary. The general model for ARDL(n,m) is as follows:

$y_t = \delta + \sum_{i=i}^{n} \theta(i)\, y(t-i) + \sum_{i=i}^{m} \beta(i)\, x(t-i) + e_t$

The expression *t-i* denotes the prior *i* period. The *y* variable will be the INF variable, our forecasting object, while the *x* variables will be INT, IHSG, and EXR. Hence, inflation in a period will be affected by inflation in the prior periods together with the previous periods' interest rate, stock index, and exchange rate. However, if the variables are not stationary, then *y* will be replaced by *Δy,* and *Δx will replace x*. The cointegrating relationship exists whenever the difference in residual in a certain period is affected by the residual of the prior period. The formal test of cointegration is as follows:

$\Delta e_t = \beta e_{t-1} + v_t$

The term e_t will be derived from the equation:

$y_t = \alpha + \sum_{i=i}^{m} \beta(i)\, x(t) + e_t$

As stated previously, y_t will be replaced by INF, our object of forecasting. While INT, IHSG, and EXR will be the x_t variables

If the coefficient β is statistically significant, then the ARDL model will also include a cointegrating relationship. The ARDL model with the cointegrating relationship is as follows:

$y_t = -\rho(y_{t-1} - \alpha - \sum_{i=i}^{m} \beta(i)\, x(t)) + \sum_{i=i}^{n} \theta(i)\, y(t-i) + \sum_{i=i}^{m} \beta(i)\, x(t-i) + e_t$

Forecasting accuracy will be measured using Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error. The formula for MAPE and RMSE are as follows:

MAPE = 1/N x $(\sum_{n=1}^{t} \xi_n^2 / y_n)$

RMSE = $(1/N \times (\sum_{n=1}^{t} \xi_n^2))^{0.5}$.

The symbol ξ is forecast error derived from the difference between the model's and test data's forecasts. N refers to the total number of observations, while y_n is the test data value.

Result and Discussion

Figure 1 displays the plot of each variable based on the time reference to understand the behaviour of the time series.

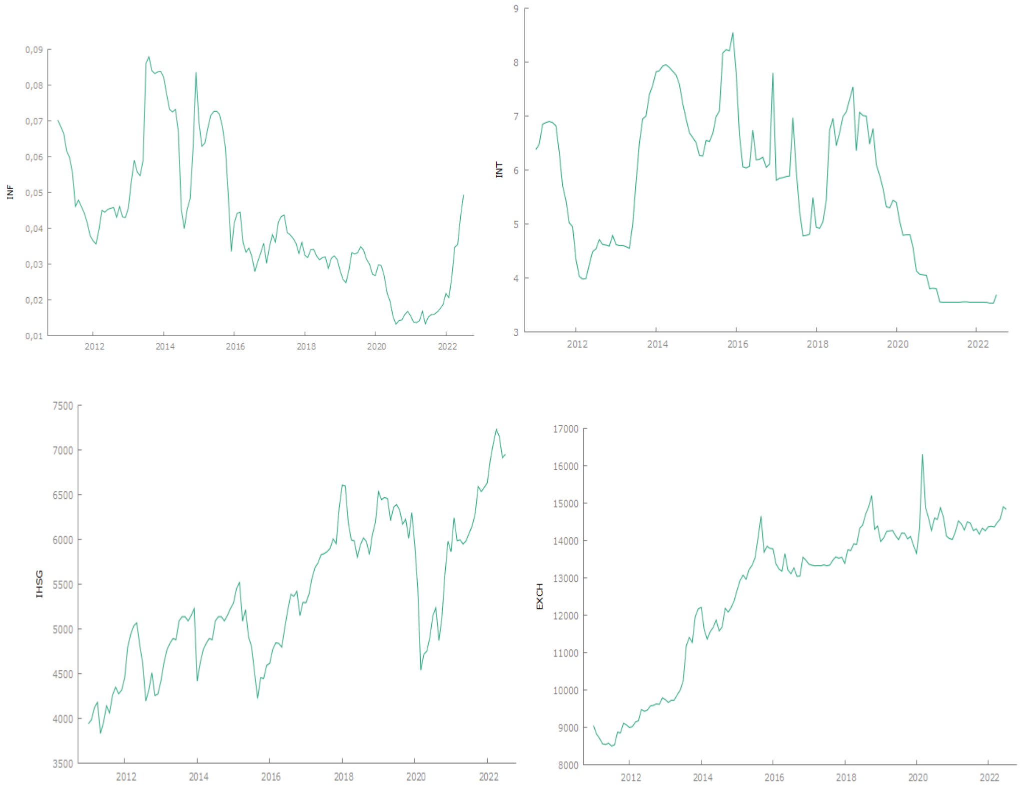

Figure 1 Time-Series Plot

Figure 1 displays the movement of each variable over time. The top left-hand corner figure plots the inflation series over time. We can see that the volatility was high from 2012 leading up to 2016. At the beginning of the research period, the inflation was heading downward for a sharp decrease. Over a year, there was more than a 3% decrease in inflation, from 7% to around 3.5%. However, the inflation rate was starting to pick up from 2013 onwards. A huge increase was occurring in 2013 and 2015. In 2013, the inflation rate reached 9% and gradually slowed down. In 2015, the inflation surged to almost 9% again and decreased when it approached 2016. This indicated turbulence in the economy because of a sharp increase in the general price of goods and services. From 2016 until the beginning of 2021, inflation decreased, followed by a mild volatility. The inflation rate ranged from 4% to slightly more than 1%. This was the time when Indonesia entered the pandemic. There was a slowdown in the economic activity as the government enforced social distancing. The slowdown was due to decreasing demand for goods and services generally. Although certain goods and services experienced increased demand, it was not enough to compensate for the loss of demand in the other goods and services.

Entering 2022, the inflation began its way upward significantly. At the end of the research period, the inflation rate was almost 5%. Overall, there is a decreasing trend in the movement of the inflation data in which marked volatilities are also present. The existing trend will ease inflation forecasting since the plot can reveal some patterns. The top right-hand corner of figure 1 shows the interest rate series plot. There is some similarity between the interest rate plot and the inflation plot. This is because the government usually tries to control inflation by increasing or decreasing interest rates. When inflation is high, the government will raise interest rates.

Similarly, when the inflation is low, the government will decrease the interest rate. Therefore, the interest rate movement will lag behind the inflation, because the government will act after the fact. When the inflation was high in 2013 and 2015, the rise in interest rate occurred in the middle of 2013 and approached the end of 2015. A rise in interest rate was hoped to tame the surging inflation. However, when the inflation started showing a downward trend from 2016 onwards, the interest rate was still high and only in 2018 did the interest rate start to decrease. Since then, the interest rate has been maintained at a deficient level. In 2022, the interest rate was around 3%.

Nevertheless, we can expect a rise in interest rates since inflation shows signs of a sharp increase. The interest rate movement shows no apparent trend. However, we can see that a high-interest rate is more likely to be followed by a high interest rate in the future. The same goes for low-interest rates. This is the hallmark of time series data. The bottom left-hand corner of figure 1 shows the movement of IHSG over time. Some regular volatility can be seen. This denotes the seasonality component in the stock index. At certain times in a year, the stock index has a peak and a through. In other words, the stock index will rise at certain times, and then decline.

From 2011 until 2016, the pattern of seasonality is very obvious. Entering 2018, however, the pattern started to change. The stock index kept on rising until the end of 2019, although some seasonality is still present. In 2020, the sharp decrease in the stock index marked the commencement of the pandemic. The stock index plunged drastically. This represents the pessimistic expectation of the investors regarding the economy during the pandemic. However, the stock index started to rise again, approaching 2021. Since then, the upward trend has continued up until the end of the research period. This upward trend leaves a trail of apparent trends. In general, the stock index has an increasing trend. The right-hand corner shows the movement of the USD/IDR exchange rate. The exchange rate of the US Dollar has been positive since the beginning of the research period. USD has a strong inclination to strengthen against IDR. The positive trend is markedly obvious.

Nevertheless, some volatilities remain existent. In 2014, 2016, 2019, and 2020, we saw a sharp increase in the exchange rate. A sudden decrease immediately follows the sharp increase. Overall, we can extrapolate the trend and expect USD's exchange rate to remain bullish. Having plotted the time series for each variable, we turn to the stationarity check. Firstly, we plot the correlograms of each variable. This correlogram will give us a visual representation of the stationarity of each variable. Figure 2 displays the correlogram.

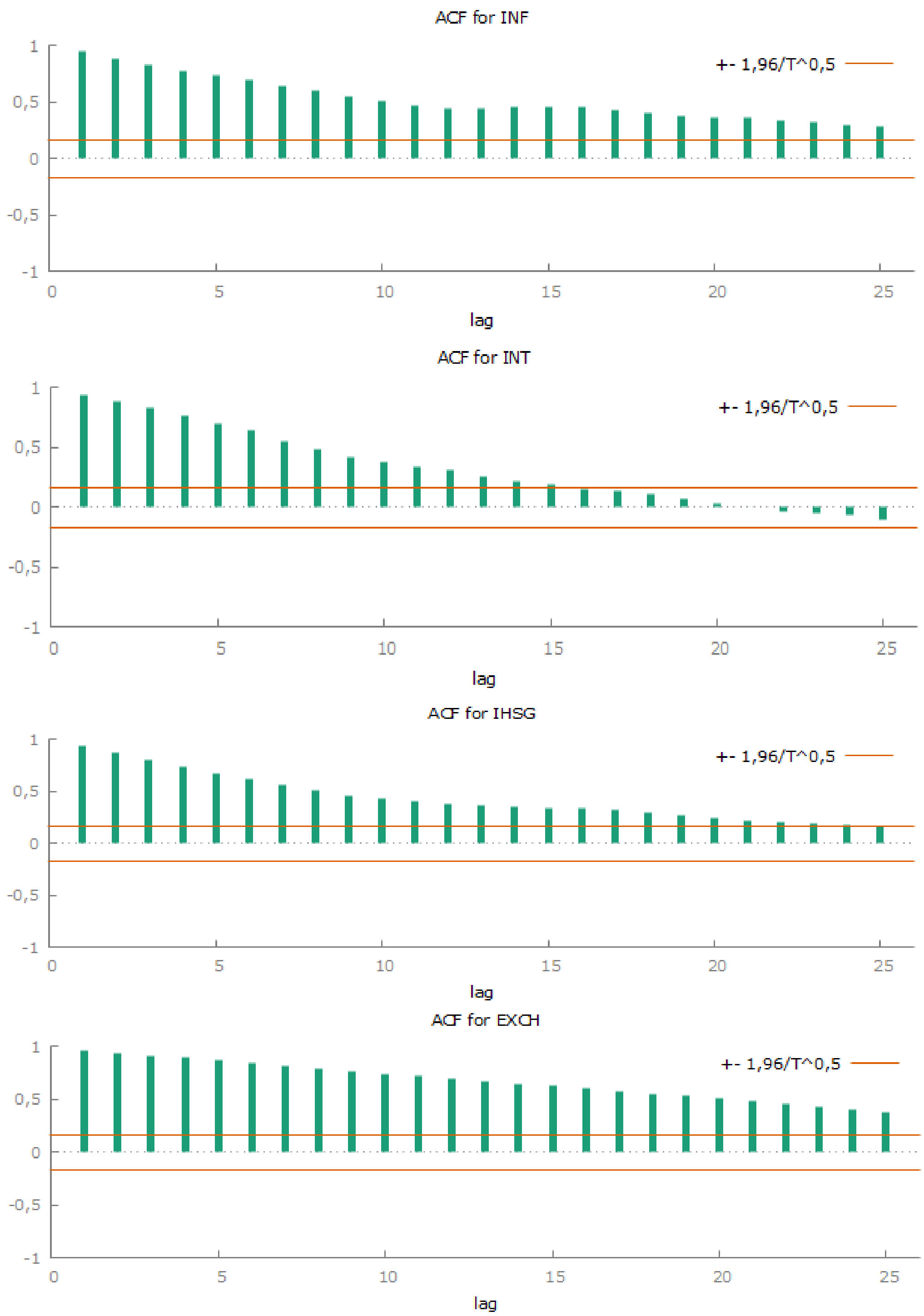

Figure 2 Correlograms of INF, INT, IHSG, and EXCH

Figure 2 shows the correlation of a variable with its series from previous periods. This will give us insights into the stationarity of the variables. All the variables correlate significantly with its prior periods series even after ten period lags. For INF, lag 25 still significantly correlates with the current period series. For INF, the number is 15 lags. While for IHSG, the lag 22 still correlates significantly with the current period. The correlation is even stronger for EXCH, in which lag 25 is still positively significant. Overall, there is a gradual decline in all the variables along with time. The strongest correlation exists in lag 1. The further the lag, the weaker the correlation. If a significant correlation still exists at a longer lag, we might suspect the data are not stationary. This can give rise to spurious regression if the data analysis continues with nonstationary data. Therefore, we must conduct the formal stationarity test to investigate this issue further.

Test of stationarity is conducted by employing the Dickey-Fuller testing procedure. The test involves testing without a constant and trend, with a constant, and with a constant and a trend. The procedure is conducted against all the variables.

Table 2 Dickey Fuller Test of Stationarity at Level

Variable	Dickey-Fuller Test	Coefficient of γ	p-value
INF	Without a constant and a trend	-0,00655215	0.4291
	With a constant	-0,02925340	0.7174
	With a constant and a trend	-0,08648670	0.6922
INT	Without a constant and a trend	-0,00397397	0.4241
	With a constant	-0,04562600	0.4876
	With a constant and a trend	-0,06342460	0.5725
IHSG	Without a constant and a trend	0,00329844	0.9170
	With a constant	-0,03609200	0.4850
	With a constant and a trend	-0,11459500	0.1368
EXCH	Without a constant and a trend	0,00435012	0.9871
	With a constant	-0,02636600	0.3568
	With a constant and a trend	-0,06701080	0.5404

Table 2 shows the results of the Dickey-Fuller stationarity test. The null hypothesis for this test is that the variable is nonstationary. Hence, we seek to reject the null hypothesis by achieving a p-value that is smaller than 0.05. The testing results show that none of the variables is stationary. All the p-values are above 0.05. Therefore, we must manually change the variables and redo the Dickey-Fuller test. The result is shown in the Table 3.

Table 3 Dickey Fuller Test of Stationarity at First Difference

Variable	Dickey-Fuller Test	Coefficient of γ	p-value
INF	Without a constant and a trend	-1,37861	0.0000
	With a constant	-5,02871	0.0000
	With a constant and a trend	-1,38834	0.0001
INT	Without a constant and a trend	-0,905263	0.0000
	With a constant	-0,915963	0.0002
	With a constant and a trend	-1,16958	0.0105
IHSG	Without a constant and a trend	-0,887224	0.0000
	With a constant	-0,896728	0.0000
	With a constant and a trend	-0,896812	0.0000
EXCH	Without a constant and a trend	-1,08688	0.0000
	With a constant	-1,43798	0.0000
	With a constant and a trend	-1,46823	0.0000

Table 3 shows the result of the stationarity test conducted at the first difference. It shows that all the variables are stationary when differenced once. This is typical of time-series data. Just like before, the null hypothesis is the variable is not stationary. The p-values for all the tests are below 0.05. Hence, the null hypothesis is rejected. The data are stationary. Therefore, the forecasting process will be conducted in the first difference. Having established the stationarity of the data, we continue to determine the lag length. The following table shows the result of the test.

Table 4 Lag Length Determination

Lags	AIC	SIC	HQC
1	-7.4918720	-7.3478610	-7.4334260
2	-7.5221650	**-7.3541530***	**-7.4539780***
3	-7.5049550	-7.3129410	-7.4270270
4	-7.4878070	-7.2717910	-7.4001380
5	-7.4702840	-7.2302670	-7.3728740
6	-7.4592310	-7.1952120	-7.3520810
7	-7.4417990	-7.1537780	-7.3249070
8	-7.4242870	-7.1122650	-7.2976550
9	-7.4077440	-7.0717200	-7.2713710
10	-7.3909840	-7.0309580	-7.2448700
11	-7.3944990	-7.0104710	-7.2386430
12	-7.5325330	-7.1245030	-7.3669360
13	-7.5169740	-7.0849430	-7.3416370
14	-7.5152060	-7.0591720	-7.3301270
15	-7.5182430	-7.0382080	-7.3234230

Table 4 shows the lag length determination based on several criteria. AIC stands for Akaike Information Criterion. SIC is the Schwarz Information Criterion, and HQC is the Hannah Quinn Criterion. SIC and HQC determine the optimal lag length to be 2. The criterion value is the lowest at two lags, according to SIC and HQC. Length at Lag 1 is the second lowest criterion value. Surprisingly, AIC recommends using 25 lag lengths (not shown in the table). Based on the results above, we will use 1 and 2 lag lengths in the forecasting process. A lag length of 2 will be used because SIC and HQC recommend using the lag length. SIC is known for penalizing a model with longer lags. Therefore, ARDL models in this research will not use lag length longer than 2. The next step will be determining whether cointegration exists in the model. If cointegration exists, then we will include an ARDL with cointegration. The following equation indicates the result of the cointegration test (without constant):

$$\Delta e_t = \beta e_{t-1} + v_t$$
$$\quad\; -0.1061427$$
$$\quad\; (0.042308)$$

The above equation shows that the β parameter is insignificant (p-value less than 0.05). This acts as a proof that the variables are not cointegrated. Therefore, we must include an ARDL model that excludes cointegration. The complete ARDL model will be:

$\Delta INF_{t+1} = \alpha + \beta_1 \Delta INF_t + \beta_2 \Delta INF_t + \gamma_1 \Delta INT_t + \gamma_2 \Delta INT_{t-1} + \delta_1 \Delta IHSG_t + \delta_2 \Delta IHSG_{t-1} + \lambda_1 \Delta EXCH_t + \lambda_2 \Delta EXCH_{t-1}$

The above model is ARDL (2,2). We posit that this model has the best forecasting performance. In order to have robust results, we will also include ARDL(1,0), ARDL(2,0), ARDL(0,1), ARDL(0,2) and ARDL(1,1). The following table shows the forecasting results and the forecast accuracy measures.

Table 5 Forecast Results

	REAL	ARDL(2,2)	ARDL(1,1)	ARDL(1,0)	ARDL(2.0)	ARDL(0,1)	ARDL(0,2)
January 2022	0.021800	0.01878	0.018708	0.020766	0.018700	0.018318	0.018806
February 2022	0.020600	0.01816	0.018526	0.021237	0.018503	0.017858	0.018361
March 2022	0.026400	0.01833	0.018599	0.021277	0.018162	0.017596	0.017986
April 2022	0.034700	0.01916	0.018589	0.021201	0.017760	0.017593	0.018217
May 2022	0.035500	0.01837	0.018596	0.021095	0.017371	0.017425	0.018709
June 2022	0.043500	0.01611	0.018185	0.020980	0.016999	0.017366	0.019036
July 2022	0.049400	0.01452	0.017534	0.020863	0.016629	0.016870	0.019094

Table 5 compares forecast results among the various ARDL models. We can see at the beginning of the forecast period. ARDL(1,0) results in the most precise result. It predicts that for January 2022, the inflation will be 2.0766%. This is most similar to the real inflation in January 2022 (the REAL column), which amounts to 2.18%.

In contrast, ARDL(0,1) produces the least precise result. It predicts inflation to be 1.8318%. The real data shows that the real inflation always surges over the year. It begins with 2.18%, which then increases to 2.06%. It finally winds up at 4.94%. The ARDL method is more likely than not to yield stable results. The forecasts are not volatile and fluctuate. ARDL will likely result in inaccurate results in turbulent economic conditions. ARDL is powerful for forecasting in times of good economic condition. When the economy is conducive, the forecast results will gradually increase. Therefore, the values generated will tend to be smoothed. The following table shows the forecast accuracy of each method.

Table 6 Forecast Accuracy Measures

	ARDL(2,2)	ARDL(1,1)	ARDL(1,0)	ARDL(2.0)	ARDL(0,1)	ARDL(0,2)
Root Mean Squared Error (RMSE)	0.019202	0.018033	0.015761	0.018798	0.018737	0.017547
Mean Absolute Percentage Error (MAPE)	40.39%	38.65%	30.89%	40.39%	41.25%	38.41%

Table 6 shows the parameters for forecast accuracy. The first parameter is RMSE. This shows the average squared error for each model. The higher the number, the less accurate the method. The method that generates the lowest value is ARDL(1,0). This signifies that the results from ARDL are most closely related to the actual data. ARDL(0,2) is in the next place in terms of accuracy. ARDL(1,1) performs worse than ARDL(1,0) and ARDL(0,2). However, it still performs better than ARDL(2,0), ARDL(0,1), and ARDL(2,2). Hence, ARDL(2,2) makes the most forecast errors and performs worst among all the methods. Forecast accuracy is better understood when it is viewed from the error percentage. ARDL(1,0), ARDL(1,1), and ARDL(0,2) make an average error of around 30%. For the rest of the methods, the forecast error even exceeds 40%. Since the inflation rate is small, a little deviation will result in a seemingly worst forecast accuracy.

These results show how much the ARDL forecast results deviate from the real data. Fayziev et al. (2019) established an ARDL model for forecasting that also included one autoregressive component. This indicated that most of the information valuable in the forecasting is contained in the period before. A lag of longer than 1 will not really be instrumental in forecasting using ARDL, in the case of inflation. The use of 1 lag length shows the dynamic movement of inflation that has short-term proclivity. Ningrum & Surono (2018) tested the ARDL model whose lag is more than 1. They found that the efficacy of the forecast results was being outperformed by the Vector Autoregressive Model (VAR) with only one lag. The result of this study also agrees with Labibah, Jamal, & Dawood (2021), who established ARDL with 1 lag model as the best model. Forecasting future value depends on the last value of the variable in question since it contains the most information.

Conclusion

This research purports to compare the forecasting performance of various ARDL models. In this research, a specific ARDL model was constructed by following the usual formal procedure of ARDL testing. First, the variables were tested for stationarity. Once it was found out that the variables were not stationary, the variables were first differenced. This method proved successful in making the variables all stationary. Subsequently, we proceeded to lag length determination. After lag determination, we continued the cointegration test. There was no cointegration existed in the model. Hence, ARDL(1,1) resulted from the ARDL model's formal construction.

We posited that this model is the best among other ARDL models for forecasting. As comparisons, we include ARDL(1,0), ARDL(2,0), ARDL(0,1), AARDL(0,2), and ARDL(2,2). The forecast results showed that ARDL(1,0) has the best forecasting performance. The average mean error is 30.89%. ARDL(1,1) came third with the mean error of 38.65%. This proves that the ARDL from the formal construction is not the best for forecasting. The formal ARDL model is more frequently used for testing influence. Thus, it is not necessarily better for forecasting purposes. Secondly, the ARDL model tends to produce stable forecasts. We can see from the forecast results, there is not much volatility. This portends to the suitability of the ARDL model to be implemented in a stable economic condition. On the contrary, in a turbulent economic condition, the ARDL model cannot map the pattern of volatility and seasonality. This is exactly the limitation of this research.

The test data in this research were data right after the pandemic. In Indonesia, the inflation data is much more volatile post-pandemic. The surge in inflation after the pandemic is virtually drastic. In this case, ARDL models might not produce volatile results that mimic the turbulent economy. Future research could use the ARDL model that does not use first difference variables. This model has the potential to capture better the dynamic component existing in the data. Also, the comparisons of ARDL and machine learning models are necessary, since this will reveal how well ARDL can compete with advanced computer science for forecasting purposes.

Author Contributions

Conceptualisation, R.M.P; Methodology, R.M.P; Analysis, R.M.P; Original draft preparation, R.M.P; Review and editing, R.M.P; Visualization, R.M.P.

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Conflicts of Interest

The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

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