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Comparison of Several Univariate Time Series Methods for Inflation Rate Forecasting

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ABSTRACT

Forecasting inflation is very crucial for a country because inflation is one of indicator to measure development of the country. This study aims to evaluate the effectiveness of three univariate time series methods i.e., ARIMA (Autoregressive Integrated Moving Average), Double Exponential Smoothing (DES), and Trend Projection (TP), in forecasting Indonesia's monthly inflation rates using data from 2018 to 2022. The analysis identifies DES as the most accurate method, evidenced by its lowest Root Mean Square Error (RMSE) value of 2.9296, outperforming ARIMA and TP, which have RMSE values of 13.1479 and 3.47053, respectively. Consequently, DES was selected as the preferred model for forecasting inflation over the next 36 month, with the forecasts indicating a consistent downward trend in inflation throughout the year. While these findings highlight DES's effectiveness, the study also acknowledges limitations, including its reliance on univariate models that do not incorporate other economic variables, and the potential limitations of the dataset's specific time frame. To address these limitations, future research should consider multivariate models, integrate machine learning techniques, and conduct scenario analyses to improve forecast accuracy and robustness. Despite these constraints, the study provides valuable insights into inflation forecasting in Indonesia, offering a practical tool for policymakers and contributing to more informed economic decision-making.

Keywords: ARIMA, Double Exponential Smoothing, RMSE, Trend Projection

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1. Introduction

The economic well-being of a nation is contingent upon the presence of positive and consistent economic growth. One of the indicators to measure the development of a country is inflation (Lembang, 2017). Elevated inflation can exert a detrimental influence on the overall economy due to its significant and far-reaching consequences. Therefore, it is crucial to regulate the inflation rate (Silfiani, 2014). Consequently, the government, in formulating and preparing appropriate measures and policies to control inflation in the future, requires accurate forecasting of the inflation rate as a reference. Forecasting is a technique that uses historical data to predict future trends and is vital for making informed economic decisions. Inflation data, as a component of time series data, allows for predictions about future trends through the analysis of historical patterns (Wardani and Winarno, 2023).

In recent years, Indonesia has experienced varying levels of inflation, reflecting different economic conditions. The Statistics Indonesia (BPS) reported that inflation throughout 2020 was at 1.68%, the lowest rate ever recorded in Indonesia's history. In contrast, inflation in 2014 was notably high at 8.36%. Following this, inflation rates fluctuated, with 3.35% in 2015, 3.02% in 2016, 3.61% in 2017, and 3.13% in 2018. The period of 2019-2020 saw particularly low inflation due to decreased purchasing power amid the COVID-19 pandemic. As of August 2023, inflation was maintained within the target corridor of 3.0±1%, with a 3.27% (yoy) inflation rate reported by BPS. This controlled inflation is a direct result of consistent monetary policy and robust collaboration between Bank Indonesia and the Government (Central and Regional).

Several univariate time series methods have been applied to inflation forecasting in Indonesia. For example, Autoregressive Integrated Moving Average (ARIMA), Double Exponential Smoothing (DES), and Trend Projection

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(TP). Each of these methods offers distinct advantages in handling time series data. ARIMA, for instance, is particularly useful as it can be applied to various data patterns, including those with trends, provided that the data is stationary (Mizan et al., 2019). DES and Trend Projection, on the other hand, are advantageous because they can model trend patterns without requiring a stationary data process first (Silfiani and Lembang, 2023). Despite the demonstrated effectiveness of these methods, there is a noticeable gap in the literature regarding their comparative performance in forecasting inflation specifically for Indonesia.

Therefore, this study aims to fill this gap by comparing the effectiveness of ARIMA, Double Exponential Smoothing, and Trend Projection methods in forecasting inflation in Indonesia. By determining the best method based on the Root Mean Square Error (RMSE) for each approach, this research not only contributes to the academic understanding of time series forecasting but also offers practical insights for policymakers. Accurate inflation forecasts can inform government policy, helping to implement proactive measures to stabilize the economy. Additionally, the findings can guide individuals in making informed decisions about savings and investments for the future.

This article proceeds with a literature review of the univariate time series methods employed in this study in Section 2, followed by the research methodology, including datasets and research steps, in Section 3. The results and discussion are presented in Section 4, and finally, the conclusion is provided in Section 5.

2. Literature Review

2.1. ARIMA

The ARIMA (Autoregressive Integrated Moving Average) approach is a technique used for analyzing periodic series that has trend pattern (Silfiani and Lembang, 2023). This approach originates from the fusion of the Autoregressive (AR) and Moving Average (MA) models, which were formulated by George Box and Gwilym Jenkins. Box-Jenkins proposed that the ARIMA approach can be divided into four stages: identification of time series methods, estimation of parameters for different methods, testing of the chosen method, and forecasting. (Wei, 2006).

According to Wei (2006) is a general model of ARIMA (p, d, q)

$$\phi_p(B)(1-B)^d Z_t = \theta_q(B)e_t \qquad (1)$$

ϕ = Parameter of autoregressive (AR)

θ = Parameter of moving average (MA)

p = Parameter of autoregressive (AR)

d = Differencing

e_t = residual (white noise)

2.2. Double Exponential Smoothing

Double Exponential Smoothing is a method used to predict trend-patterned time series data (Hyndman and Athanasopoulus, 2018). The forecasting model of Double Exponential Smoothing from Holt was obtained using two smoothing parameters, namely α and β (Irawan, Saptomo, Setiawati, 2019; Hayuningtyas, 2019). Double Exponential Smoothing from Holt is as follows (Hyndman, Koehler, Ord, and Snyder; 2008) :

$$S_t = \alpha X_t + (1-\alpha)(S_{t-1} + b_{t-1}) \qquad (2)$$

$$b_t = \beta(S_t - S_{t-1}) + (1-\beta)b_{t-1} \qquad (3)$$

$$F_{t+m} = S_t + b_t m \qquad (4)$$

where:

S_t = Smoothing value in the t-th period

b_t = T-period smoothing trend

F_{t+m} = T-period forecasting

α, β = Loading parameters $(0 < \alpha, \beta < 1)$

2.3. Trend Projection

Trend is a movement in a period that can sometimes be described with a straight line or smooth curve (Madu, 2016). Trend projection is a method of forecasting a series of times that correspond to a trend line against a series of past data points, then projected into future forecasting for medium and long-term forecasting. The Trend projection result will then become a forecast for the coming period.

The linear regression equation model of the Trend projection method is as follows (Wei, 2006; Hyndman and Athanasopoulus, 2018):

$$Y_t = a + bt \qquad (5)$$

where Y_t is the inflation of the t-th period, t is the sequence of periods.

3. Methodology

3.1. Data

The secondary data used in this study is the amount of inflation taken from Bank Indonesia, which is monthly data from January 2018 to December 2022. Data is divided into training data and testing data. The training data is 48 data, namely inflation data in January 2018-December 2021, while testing data is 12 data, namely inflation data in January-December 2022.

3.2. Research Procedure

In this study, a comparison test of time series data forecasting was carried out using 3 univariate time series methods, namely Autoregressive Integrated Moving Average, Trend Projection and Double Exponential Smoothing. The analysis steps carried out in the study are as follows:

1. Collecting data from Bank Indonesia
2. Provide a description of the Inflation Rate by displaying descriptive statistics.
3. Identify the pattern of Inflation Rate by displaying time series plot, Box plot, and Box-Cox transformation, ACF-PACF plot

4. Analyze the results of applying ARIMA, DES, and TP models
5. Perform a comparison test of 3 methods with RMSE
6. Forecasting using the best method
7. Interpret analysis result
8. Drawing conclusions

4. Result and Discussion

Descriptive statistical analysis provides a brief overview of the characteristics of inflation data in Indonesia. The results of descriptive statistical analysis of inflation data in Indonesia starting from 2018 to 2022 are presented in Table 2.

Table 2 Descriptive Statistical Analysis

N	Mean	Minimum	Maximum	St.dev
60	2.81	1.32	5.95	1.16

Based on the results of descriptive statistical analysis in Table 2, the number of variables used consists of 60 periods with a total of 5 years. The analysis shows that inflation was at its lowest point in August 2020 at 1.32%, while the highest inflation was in September 2022 at 5.95%. The average inflation in Indonesia every month is 2.81% with a standard deviation of 1.16%. This shows that the standard deviation value is very small when compared to the average value, which means that the average value can be represented for the entire data.

4.1. Identify the Inflation Rate

Based on the results of descriptive statistical analysis; to strengthen trend analysis, visualization is necessary in the form of time *series plots.* The analysis is carried out to see whether the original data plot of inflation is a downtrend or uptrend pattern. The plot of inflation data for January 2018 – December 2022 can be seen in Figure 1.

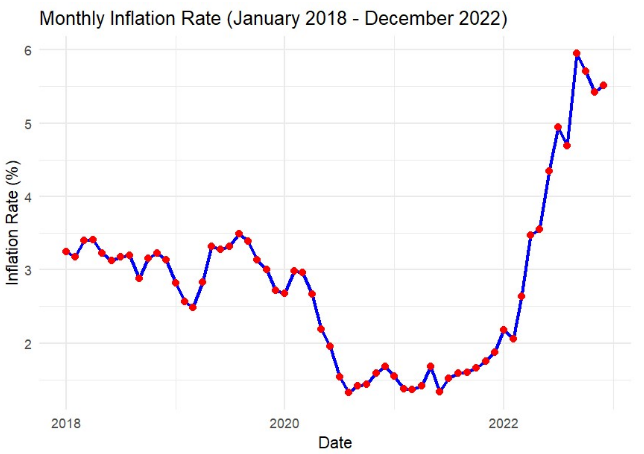


Figure 1 Time Series Plot of Inflation

The time series plot analysis in Figure 1 reveals a clear downward trend in inflation from 2018 to 2019. The peak of inflation experienced a significant decline from August 2019 to July 2020, followed by a gradual fall until 2021. The notable decrease in inflation during this period, particularly in 2020, was largely driven by the impact of the COVID-19 pandemic, which significantly reduced domestic economic activity. The pandemic led to lower consumer demand due to widespread lockdowns and economic restrictions, while global supply chains were also disrupted, reducing the pressure on prices. Additionally, the government's policies, including stimulus packages aimed at stabilizing the economy, and Bank Indonesia's monetary measures, helped to maintain price stability during this challenging period. In 2022, there has been a notable rise in inflation, particularly during the months of September to December. The significant decrease in inflation from 2019 to 2021 was mostly caused by a slow growth in domestic demand due to the COVID-19 epidemic, together with sufficient supply and effective coordination between Bank Indonesia and the Government at both the central and regional levels to ensure price stability. The inflation rate experienced a significant increase over the period of September to December 2022. This was mostly caused by the effects of revisions in subsidized fuel prices, the upward trend in water company tariffs, and the surge in demand for air transport during the holiday season (Sarbaini & Nazaruddin, 2023)

Boxplot analysis of time series data is a valuable tool for visually representing the distribution of data and identifying any exceptional values or outliers present in the time series data. Once the time series chart has been analyzed, the subsequent step is to represent it as a boxplot to detect any seasonal patterns. Figure 2 displays the inflation data plot from January 2018 to December 2022.

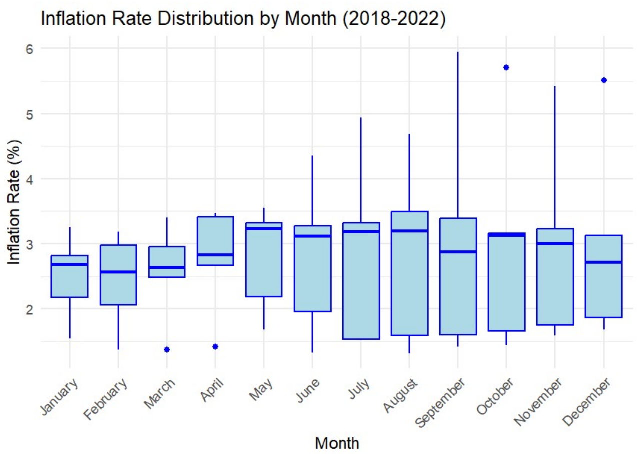


Figure 2 Inflation Boxplot

The boxplot analysis in Figure 2 illustrates the distribution of Indonesia's inflation data across different months. The overall pattern suggests that the inflation data exhibits a relatively consistent trend, with limited evidence of strong seasonality. The monthly inflation rates show some variability, but the fluctuations are generally contained within a narrow range, indicating that the data does not exhibit large random variations or abrupt short-term changes. This stability suggests that the inflation data follows a more predictable trend pattern over time.

However, while the boxplot indicates a relatively stable distribution of inflation rates across months, it is important to note that this does not necessarily imply that the data is stationary in its mean or variance over time. As observed in Figure 1, there have been periods of both increasing and decreasing inflation, suggesting potential non-stationarity. Therefore, it is crucial to conduct stationarity tests to assess the consistency of the mean and variance over time.

In this study, a stationarity test was performed using the Box-Cox transformation to determine the appropriate lambda (λ) for stabilizing the variance. The results of this analysis, as seen in the Box-Cox Plot in Figure 3, provide insights into the necessary adjustments for achieving stationarity in the inflation data.

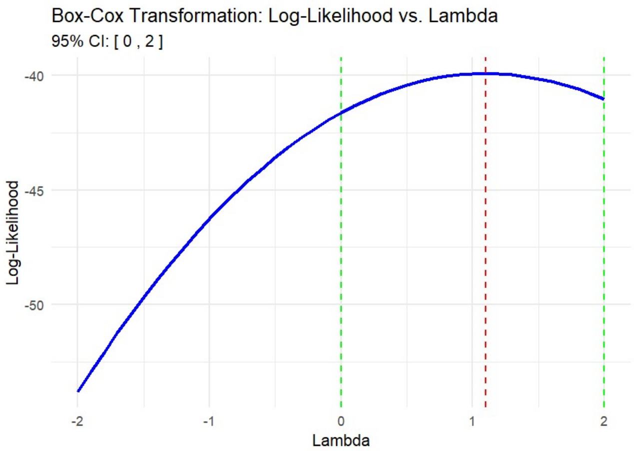
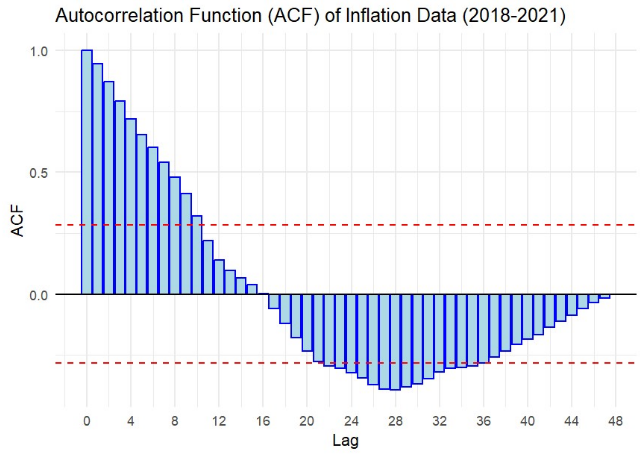


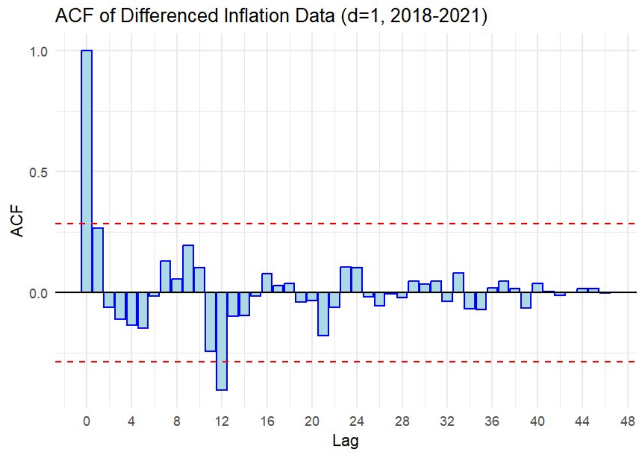
Figure 3 Box-Cox Inflation Plot

According to the Box-Cox Plot analysis in Figure 3, it can be shown that Indonesia's inflation data is steady across different variations. This is indicated by the rounded value (λ) of 1, which suggests that no adjustment is required. In addition, stationary testing is typically conducted using the ACF test. The ACF results displayed in Figure 4 are based on the Indonesian inflation data used for training.

Figure 4 (a) shows that there are four values that fall beyond the confidence interval. Data is considered stationary when the average does not deviate beyond three times the confidence interval. Based on the research results, it is evident that Indonesia's inflation data does not exhibit stationarity in terms of its average. Therefore, to achieve stationarity in the data, it is necessary to apply differencing initially and then replot the autocorrelation function (ACF). After doing the initial differencing and obtaining the ACF plot, it can be concluded that Indonesia's inflation data is stationary in terms of its average, as just 1 lag falls inside the confidence interval.



(a)

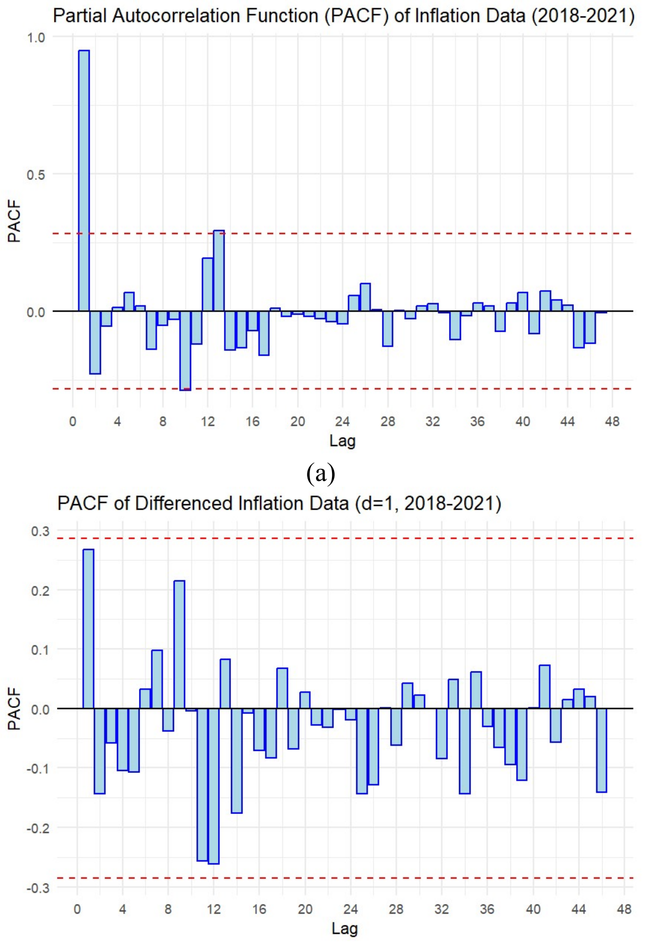


(b)

Figure 4 (a) ACF Inflation and (b) ACF Inflation with Differencing 1

4.2. ARIMA Method Analysis

ARIMA modelling involves analyzing the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF). Following the ACF plot, a PACF plot is conducted to ascertain the ARIMA model. The investigation revealed that the ACF plot showed one lag outside the confidence interval, while the PACF plot showed no lags outside the confidence interval. Based on these findings, the models created were ARIMA (0,1,1). The primary ARIMA model, namely ARIMA (0.1,1), achieved a substantial model identification compared to the other ARIMA model. This is due to the P-Value being less than 0.05, specifically 0.0271. Figure 5 displays the PACF plot and its the first difference.



(a)

(b)

Figure 5 (a) PACF and (b) PACF *Differencing* 1

The main model can be formed several estimation models with a combination of orders from the main model. This study used RMSE values to measure the forecasting accuracy of the ARIMA method obtained. The RMSE value indicates the result of the error presentation of the forecast. The RMSE value results of the significant model can be seen in Table 3.

Table 3 Parameter Significance Test

Model	*P-Value*	Conclusion
ARIMA (0,1,1)	0.0328	Significant

Based on the results of Table 3, the ARIMA model (0,1,1) is stated as the best model with a *P-Value* of 0.0328 less than α=0.05 indicating that the ARIMA model (0,1,1) has significant parameters. After testing the significance of the parameters, the next step is to perform a diagnostic test of the model. This test aims to find out and test the feasibility assumptions of the model to be forecasted. The test used is a residual *white noise* test by measuring the *P-Value of* the Ljung-Box test. A viable model is one that assumes that residues from *white noise* have no correlation. Ljung-Box Test Results are shown in Table 4.

Table 4 Ljung-Box Test and Normal Dist. Test

Model	Ljung-Box Test		Normal Dist. Test
	to Lag	*P-Value*	*P-Value*
ARIMA (0,1,1)	6	0.9168	>0.1500
	12	0.1493	
	18	0.4309	
	24	0.4928	

source: analysis results using SAS software.

Based on Table 4, the ARIMA model (0,1,1) is said to be a viable model for use in forecasting. This is because the *P-Value value* in each lag is more than α=0.05 so that a decision can be made to fail to reject H0. That is, in every residual of *white noise* there is no autocorrelation, so it is assumed to be mutually free. The *P-Value* value of the Kolmogorov-Smirnov test for the normal distribution test is >0.1500 greater than α=0.05. This shows that the ARIMA model (0,1,1) satisfies the assumption that its residuals have a normal distribution.

4.3. Analysis of Double Exponential Smoothing

DES (*Double Exponential Smoothing*) analysis begins by looking for optimal alpha and gamma modeling. The gamma parameter (γ) is used to eliminate a bit of flexibility in the data generated during the forecast. The results of the calculation of optimal parameters can be seen in Table 5.

Table 5 Exponential Smoothing Parameter

Parameter	Score
α (level)	0.9999
γ (trend)	1e-04

Based on the results of inflation data processing, the optimal parameters found are α=0.9999 and γ=1e-04. In this study, the measurement of forecasting accuracy used RMSE (Root Mean Squared Error), which is square root of MSE (Mean Squared Error), for testing data. An RMSE value of about 2.9296 indicates an error rate in forecasting. The lower the RMSE value, the smaller the error rate in forecasting. The smoothing graph of the Double Exponential Smoothing method can be seen in Figure 5.

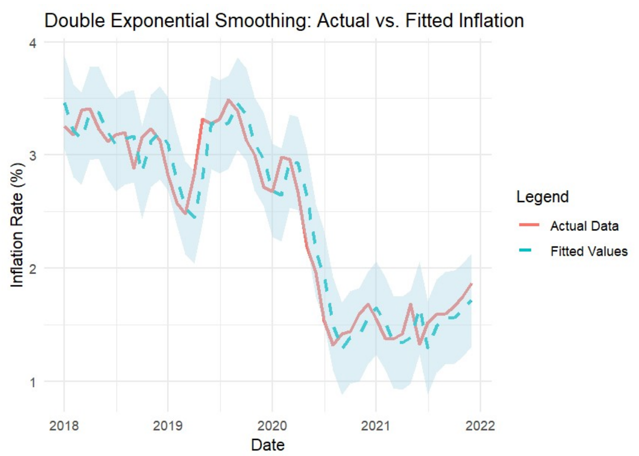


Figure 5 Double Exponential Smoothing Plot

4.4. Analysis of Trend Projection

The results of forecasting Indonesia's inflation data using the Trend projection method. Based on the Trend Projection method, the output is obtained in Table 6.

Table 6 Results of Linear Regression Analysis

Variable	Coef.	P-Value
Constant	3.624	0.000
t	-0.0477	0.000

Based on the results of the analysis in Table 5, the following model is obtained:

$$Y_t = 3.624 - 0.0477t \tag{9}$$

Equation 9 shows that the inflation rate will fall by about 0.0477 each month assuming the other variables are constant. After obtaining the Trend Projection model, we can calculate the forecasting accuracy in testing data using RMSE. RMSE for Trend Projection is 3.47053.

4.5. Selection of the Best Method

This study uses RMSE values to measure the accuracy of forecasting inflation data in Indonesia. RMSE (Root Mean Square Error) is a widely used metric for evaluating the precision of forecasting models, with lower values indicating better model performance. In this study, RMSE values are used not only to assess the accuracy of each forecasting method but also to determine the most suitable method for predicting inflation in Indonesia for the next 12 months of the 2023 period. The following are the results of RMSE values from the three methods analyzed:

Tabel 7 Comparison of RMSE

Method	RMSE
ARIMA	13.1479
DES	2.9296
TP	3.47053

Based on the results of the analysis in Table 7, it is evident that the Double Exponential Smoothing (DES) method is the most accurate model for forecasting inflation, as it has the lowest RMSE value of 2.9296. This result indicates that DES provides the best fit to the historical inflation data among the three methods considered. The superior performance of DES can be attributed to its ability to effectively capture and smooth out the trend components in the inflation data, thereby minimizing the forecast errors compared to ARIMA and Trend Projection (TP).

The analysis of RMSE values for the three forecasting methods—ARIMA, Double Exponential Smoothing (DES), and Trend Projection (TP)—provides valuable insights into their respective performances in predicting inflation in Indonesia. The significantly lower RMSE value for DES (2.9296) suggests that this method is particularly effective in capturing the underlying trend in inflation data. DES's strength lies in its ability to smooth out short-term fluctuations while accurately modeling the trend component, making it especially suitable for time series data with a pronounced trend but less variability in seasonal or irregular components.

In contrast, the higher RMSE values for ARIMA (13.1479) and TP (3.47053) indicate that these methods are less effective in this specific context. ARIMA, while versatile, may not be as effective when the time series exhibits strong trends without a stationary process. TP, although simpler, might not be sufficiently sophisticated to handle the nuances in inflation data compared to DES.

This study has several limitations that should be considered when interpreting the results. Firstly, the analysis is based on a specific dataset of Indonesian inflation rates, which may not encompass all external factors that influence inflation, such as international market dynamics, policy changes, or unexpected economic events. The dataset's time frame might also limit the generalizability of the findings. Additionally, each forecasting method operates under certain assumptions; for example, ARIMA assumes data stationarity, which may not hold without appropriate transformations. The accuracy of the models could be affected by these assumptions, introducing potential biases. Moreover, the study focuses solely on univariate time series models, which rely only on historical inflation values and exclude other explanatory variables, such as interest rates or exchange rates, that could improve the accuracy and robustness of the forecasts.

Given these limitations, further research could explore the incorporation of multivariate time series models, such as Vector Autoregression (VAR) or ARIMAX, which include additional explanatory variables to provide a more comprehensive forecasting framework. Additionally, comparing traditional time series methods with machine learning approaches, such as Random Forests, Support Vector Machines, or Neural Networks, could yield new insights, particularly in capturing complex patterns in time series data. Future studies might also benefit from scenario analysis to assess the impact of different economic conditions—such as economic recovery or global recession—on inflation forecasts, offering valuable guidance for policymakers. Finally, exploring the effectiveness of these forecasting methods over longer horizons, beyond 12 months, could provide further understanding of their robustness and reliability across different time frames.

4.6. Forecasting of Double Exponential Smoothing

Based on the results of RMSE values from three methods, namely ARIMA, TP, and DES, it is known that the DES method provides the smallest RMSE value. This indicates that the error rate in forecasting is quite good in the DES method. Therefore, in this study, the method chosen to be used is the DES method. This decision is based on performance evaluation through RMSE values. Choosing a forecasting method with a lower error rate is considered a good move, as it demonstrates the model's ability to produce forecasting close to its true value.

Figure 6 presents the forecasting results using the DES method, which indicate a downward trend in inflation of Indonesia over the next 36 months. This projected decline aligns with the historical downward trend observed in the original inflation data from 2018 to 2022. The consistent trend identified by the DES model reinforces its effectiveness in capturing the underlying patterns in the inflation data, making it a reliable tool for forecasting changes in inflation trends. The results suggest that the DES model is well-suited for describing and predicting the direction of inflation short-term forecast.

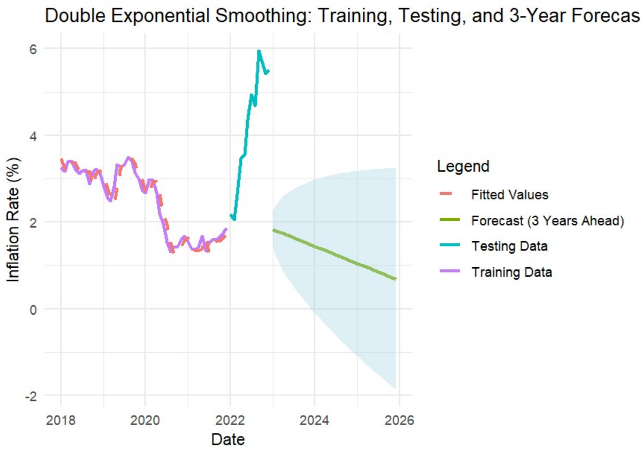


Figure 6. Results of DES Method Forecasting (%) Indonesian Inflation until 2026

The forecasted values suggest a gradual decline in inflation throughout the year, which is consistent with the downward trend observed in previous years. The DES method not only accurately reflects past inflation trends but also provides reliable predictions for the upcoming year, making it a valuable tool for policymakers and analysts in anticipating future inflation dynamics.

5. Conclusion

Indonesia's monthly inflation data for 2018-2022 exhibits a trend pattern, making it suitable for analysis using the ARIMA (Autoregressive Integrated Moving Average), DES (Double Exponential Smoothing), and TP (Trend Projection) methods, which are classic univariate time series techniques that accommodate trends. The analysis of RMSE values for each method—13.1479 for ARIMA, 2.9296 for DES, and 3.47053 for TP—demonstrates that the DES method is the most accurate for forecasting Indonesia's inflation over the next 12 periods in 2023. The DES method's lower RMSE indicates its superior ability to minimize forecast errors compared to the other two methods. Consequently, the DES method was selected as the best approach for forecasting inflation in this study. The forecast results using DES suggest a downward trend in Indonesia's inflation for each month of 2023.

Despite the robustness of these findings, the study has several limitations. Firstly, it relies on historical inflation data from 2018-2022 without considering other influential economic variables, such as interest rates or exchange rates, which could provide a more comprehensive understanding of inflation dynamics. Additionally, the study employs only univariate time series models, which, while effective for trend analysis, do not account for the potential impact of external factors. Furthermore, the dataset's specific time frame might limit the generalizability of the results to other periods or economic conditions.

For future research, it is recommended to explore multivariate time series models, such as Vector Autoregression (VAR) or ARIMAX, which incorporate additional explanatory variables to improve forecast accuracy. Comparing these traditional methods with machine learning techniques could also offer new insights into inflation forecasting. Additionally, extending the analysis to include longer forecast horizons or scenario analysis could provide valuable information for policymakers and economists, helping them to better prepare for different economic scenarios.

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