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APPLICATION OF ARIMA MODEL FOR FORECASTING NATIONAL ECONOMIC GROWTH: A FOCUS ON GROSS DOMESTIC PRODUCT DATA

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ABSTRACT

This study aims to apply the Autoregressive Integrated Moving Average (ARIMA) model to predict national economic growth, specifically focusing on Gross Domestic Product (GDP) data. GDP data were collected from 2012 to 2023, categorized into training data for the period 2012-2022 and testing data for the year 2023. Utilizing the training data, the research findings indicate that the ARIMA (0,1,0) (0,0,1) model emerges as the most effective in forecasting Indonesia's GDP on a quarterly basis, considering current prices. Subsequently, the model was tested on the 2023 dataset, and it demonstrated accurate predictions aligned with patterns and trends identified during the training phase. The outcomes of this research contribute significantly to the field of economic forecasting in Indonesia, particularly in understanding and predicting the quarterly developments of GDP. The proposed ARIMA model can serve as an effective tool for decision-makers and economic analysts to strategically plan for future economic dynamics on a quarterly basis.

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1. INTRODUCTION

Currently, Indonesia is one of the countries included in the G20, representing nations with the largest Gross Domestic Product (GDP) globally [1]. GDP is a measure of the total market value of all goods and services produced by a country within a specific period[2]. Since GDP serves as the primary indicator of economic growth, the theory of GDP involves macroeconomic concepts and provides an overview of a country's economic health [2][3]. Indonesia's GDP, based on current prices for the year 2022, reached IDR 19,588.45 trillion [4]. The Indonesian government releases GDP figures quarterly. In 2023, the quarterly GDP of Indonesia consecutively amounted to IDR 5,072.31 trillion, IDR 5,226.57 trillion, and IDR 5,295.95 trillion, while the data for the fourth quarter of 2023 at the time of writing this article has not been released by the government [4]. Generally, the national GDP consistently shows an increase in each period, but a significant blow to the national GDP occurred during the COVID-19 pandemic. Throughout 2020, the national GDP was only IDR 15,443.35 trillion compared to IDR 15,832.26 trillion in 2019 [4]. This resulted in a contraction in the national economic growth of -2.07% when compared to the previous year [4].

Forecasting in the future economic conditions is one important objective of many analyses [5]. There is a strong association between fiscal policy and the rate of economic growth [3]. Therefore, the prediction of national GDP is one of the essential factors in determining the country's economic policies [3]. Time series analysis models are well-suited for this task as they are designed and have been proven to be an effective tool for understanding the behavioral patterns of datasets with sequential patterns over time [5]. Researchers worldwide have predicted quarterly economic growth using univariate and multivariate models [6]. The study by Hyndman and Athanasopoulos (2018) discussed ARIMA modeling techniques and its application in forecasting economic time series, including GDP. They highlight practical steps to implement this model and provide insights into its strengths and limitations [7]. ARIMA models are univariate series models, meaning they are designed to analyze and forecast a single time series variable [8]. Moreover, many economic time series exhibit non-stationary, so using ARIMA with their differencing components can transform non-stationary data into stationary data, making it easier to analyze and model [8]. Abdullah Ghazo (2021), utilizing data from 1976-2019, applied ARIMA to forecast GDP and CPI in Jordan, obtaining ARIMA (3,1,1) as the best model for GDP, while ARIMA (1,1,0) was the best for CPI. The results of this study demonstrate that the ARIMA model can be a useful tool in predicting GDP and other economic time series [8]. In addition, the effectiveness of this model depends on various factors, including data quality, parameter selection, and the inherent nature of the time series [9]. Moreover, Michael W. McCracken (2017) explored the application of ARIMA models for forecasting quarterly GDP growth in the United States. The study evaluates the performance of ARIMA models with different specifications and compares them with other forecasting methods. Meanwhile, Rosyidi Imam Santosa et al. (2018) examined the use of ARIMA models to forecast inflation rates in ASEAN (Association of Southeast Asian Nations) countries. The study evaluated the accuracy of ARIMA models in predicting inflation and compares them with alternative forecasting techniques.

The objectives of this research include implementing the ARIMA model on GDP time series data to understand national economic patterns and trends, and evaluating the accuracy and precision of the ARIMA model in predicting GDP based on current prices. Distinguishing itself from previous research endeavors, this study holds particular significance as it endeavors to enrich the existing literature concerning the utilization of ARIMA models within the national economic landscape. By incorporating the most current data available, including the post-COVID-19 era, this study aims to offer insights that accurately reflect the evolving economic dynamics in Indonesia. This updated perspective is paramount in providing stakeholders, including governmental bodies and businesses, with a more robust and informed foundation for strategic planning and policy formulation. Thus, this study's innovative approach, coupled with its utilization of up-to-date data encompassing the post-COVID-19 period, positions it as a pivotal contribution to the field of economic analysis and forecasting.

2. RESEARCH METHODS

2.1. Research Object and Variables

The data employed in this study consist of secondary data in the form of quarterly Indonesian Gross Domestic Product (GDP) data based on current prices according to expenditure for the years 2012-2023, obtained from the Central Bureau of Statistics (BPS) [10]. The acquired data are divided into training and testing data sets. This division is undertaken with the objective of enhancing the forecasting capabilities of the generated model [11]. The training data span from January 2012 to December 2022, while the testing data cover the period from January 2023 to December 2023 [6].

2.2. Time Series Model

2.2.1 ARIMA Model

The ARIMA model was initially introduced in 1976 by George Box and Gwilym Jenkins. This time series model, characterized by linearity, combines Autoregressive (AR) and Moving Average (MA) components, and is known for its highly accurate short-term forecasting precision [12]. However, this model can also be applied to non-stationary data through the process of differencing [6]. The general form of the ARIMA model (p, d, q) (P, D, Q)^L is defined as follows:

$$Y_t = \frac{\theta_q(B)\Theta_Q(B^L)}{\phi_p(B)\Theta_p(B^L)(1-B)^d(1-B^L)^D} a_t \quad (1)$$

with,

$\phi_p(B) = (1 - \phi_1 B - \phi_2 B^2 - \cdots - \phi_P B^p)$ is the coefficient of the non-seasonal AR component with a degree of p,

$\theta_q(B) = \left(1 - \theta_1 B - \theta_2 B^2 - \cdots - \theta_q B^q\right)$ is the coefficient of the non-seasonal MA component with a degree of q,

$\Phi_P(B^L) = (1 - \Phi_1 B^L - \Phi_2 B^{2L} - \cdots - \Phi_P B^{PL})$ is the coefficient of the seasonal AR component with a degree of P,

$\Theta_Q(B) = \left(1 - \Theta_1 B^L - \Theta_2 B^{2L} - \cdots - \Theta_Q B^{QL}\right)$ is the coefficient of the seasonal MA component with a degree of Q,

$(1 - B)^d$ is the differencing for the non-seasonal order d,

$(1 - B^L)^D$ is the differencing for the seasonal order L with a degree of D,

a_t is the residual value at time t that satisfies the white noise assumption,

$t = 1,2, \ldots, n$ with n being the number of observations [13].

2.2.2 The Stages of ARIMA Modeling

- **Splitting Training and Testing Data**
  The training data consists of monthly Indonesian economic growth data from January 2012 to December 2023, while the testing data encompasses monthly Indonesian economic growth data from January 2023 to December 2023.

- **Model Identification**
  At this stage, stationary tests for mean and variance are conducted. This is typically assessed using the Augmented Dickey-Fuller (ADF) test [14], where:

$$\boldsymbol{\Delta Z_t = \gamma Z_{t-1} + \sum_{i=2}^{p} \beta_i \Delta Z_{t-1+1} + a_t} \quad (2)$$

with $\boldsymbol{Z_t}$= observed variables, $\boldsymbol{\Delta Z_t = Z_{t-1+1}}$, $\boldsymbol{T} =$ time. The formulation of hypotheses for the ADF unit root test is the following [14].

$\boldsymbol{H_0: \gamma = 0}$ or time series data are not stationary
$\boldsymbol{H_1: \gamma \neq 0}$ or time series data are stationary

If the computed T-value exceeds the critical value for the chosen significance level, the conclusion is to accept H_0, implying that the data has a unit root or is non-stationary. Conversely, if the computed T-value is less than the critical value, H_0 is rejected, suggesting that the data does not have a unit root and is stationary [15]. Meanwhile, the Kwiatkowski Philips Schmidt and Shin (KPPS) test is broadly utilized in empirical work as an accompaniment to the standard unit root test [16]. In this research, the KPPS test used to assess whether the differenced data has achieved stationary variance with the statistics is as follows.

$$LM = \sum_{t=1}^{T} \left(\frac{s_t^2}{\hat{\sigma}_\varepsilon^2}\right) \tag{3}$$

where $S_t = \sum_{t=1}^{T} \hat{\varepsilon}_t$ and $\hat{\sigma}_\varepsilon^2$ is the estimate of variance σ_ε^2 of process ε_t from the equation [16].
In the next stage, subsequently, data patterns are identified to determine the appropriate values for p and q. This involves creating data plots, selecting suitable transformations, and calculating the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) of the original data. ACF and PACF calculations serve the purpose of confirming the differencing order required to achieve stationarity. Following the transformation, ACF and PACF calculations are performed, along with differencing processes, to identify the values of p and q and determine the trend value ($d > 0$).

- **Model Parameter Estimation**

  The model is estimated using the least squares method that performed by seeking parameter values that minimize the sum of squared errors (the difference between actual and forecasted values). In the initial stage, a good estimated model is selected by conducting hypothesis tests for parameters as follows [17].

  H_0: insignificant parameters
  H_1: significant parameters
  with the following test statistics:

  $$t_{statistics} = \frac{\hat{\emptyset}_i}{SE(\hat{\emptyset}_i)} \tag{4}$$

  Decision to reject H_0 if $|t_{statistics}| > t_{\alpha/2,(n-n_p)}$ or p-value less than α then parameters are significant. Subsequently, diagnostic tests are conducted if the model is deemed significant [17].

- **Diagnostic Check**

  A white noise assumption test is conducted, taking into consideration residual model lags, and employing the Ljung-Box test and one sample t-test, where a p-value > 0.05 is considered indicative of satisfactory results. White noise testing can be conducted using the Ljung-Box test with the following hypothesis [17].
  $H_0: \rho_1 = \rho_2 = \cdots = \rho_k = 0$ (residuals are white noise)
  H_1: at least there is 1 $\rho_k \neq 0$ for k=1, 2, …, k (residuals are not white noise)
  with the following test statistics.

  $$Q^* = n(n+2)\sum_{k=1}^{K}(n-k)^{-1}\hat{\rho}_k^2 \tag{5}$$

  with n is number of observations, ρ_k is residual of lag ACF to k, Q^* is parameter with Chi-Square distribution with K-p-q degree of freedom with p is AR and q is MA. If $Q^* > \chi^2_{(\alpha;df=K-p-q))}$ or p-value $< \alpha$ then reject H_0 [17].

- **Forecasting**

  The model, having passed the diagnostic check, is utilized to forecast short-term economic growth in Indonesia. The general forecasting equation is constructed as follows.

  $$\hat{y}_t = \mu + \phi_1 y_{t-1} + \cdots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \cdots - \theta_q e_{t-q} \tag{6}$$

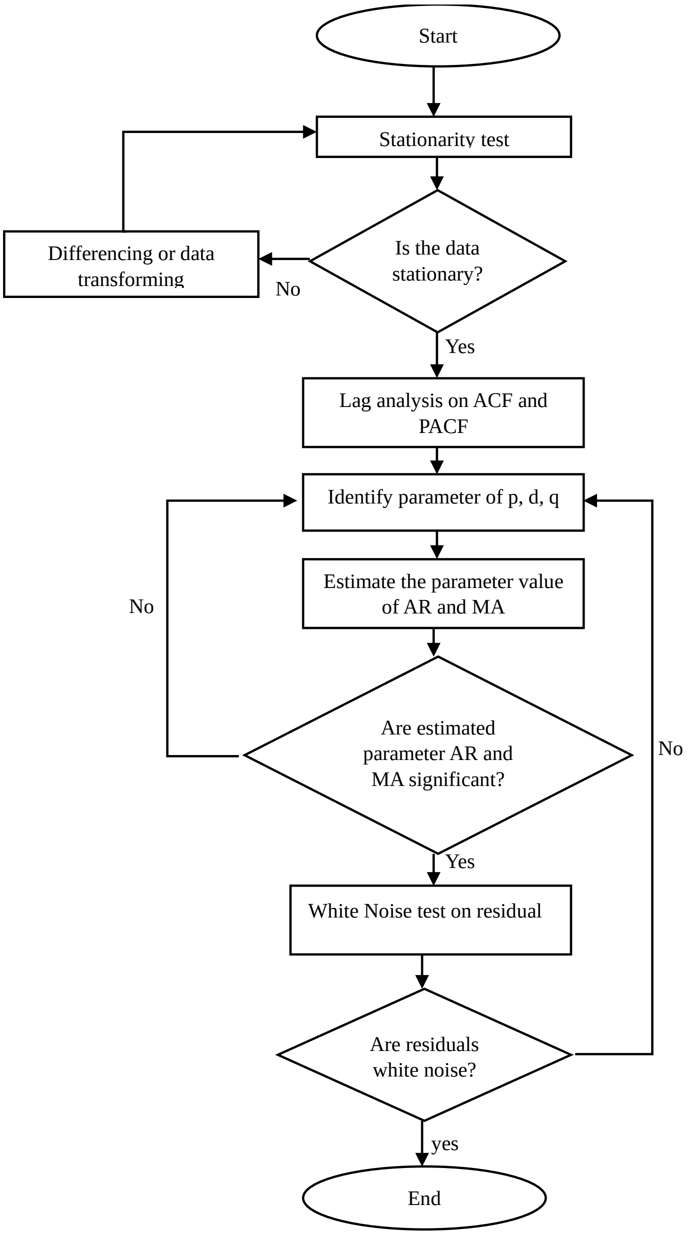

Figure 1. Flowchart of ARIMA

2.3. Gross Domestic Product (GDP)

The theoretical framework of GDP involves macroeconomic concepts, offering insights into the economic well-being of a country[2]. GDP can be assessed through three primary approaches: the production approach (output of goods and services), the expenditure approach (consumer spending, investment, government expenditure, and net exports), and the income approach (wages, profits, and indirect taxes)[6]. The calculation of GDP is beneficial for understanding a country's productivity level, evaluating the social welfare of its population, and gauging overall prosperity. The economic growth of a nation over time is measurable through GDP[2]. Positive GDP growth signifies economic expansion, while negative growth indicates economic contraction. Sustainable economic growth has the potential to generate new employment opportunities, elevate per capita income, and improve living standards. Components of GDP expenditure, such as consumer spending, investment, and government expenditure, reflect economic activities and aggregate demand. GDP also encompasses net exports (exports minus imports), indicating the extent of a country's involvement in international trade and whether it maintains a trade surplus or deficit.

3. RESULTS AND DISCUSSION

3.1 Characteristics of Indonesia's Gross Domestic Product (GDP)

Indonesia is among the 20 countries with the largest Gross Domestic Product (GDP), collectively known as the Group of Twenty (G20). Indonesia holds the 16th position in the global ranking of countries with the largest GDP[1]. In the year 2022, Indonesia's GDP is recorded at IDR19,588.445 trillion[4]. The statement highlights Indonesia's prominent economic standing on the global stage, as it is recognized as one of the top 20 nations with the highest GDP. The G20, consisting of major economies, plays a crucial role in international economic cooperation. Indonesia's position at 16th in the global GDP ranking underscores its substantial economic contribution and significance. The specific GDP figure for the year 2022, amounting to IDR19,588.445 trillion, provides a quantitative measure of Indonesia's economic output and further emphasizes its noteworthy presence in the international economic landscape.

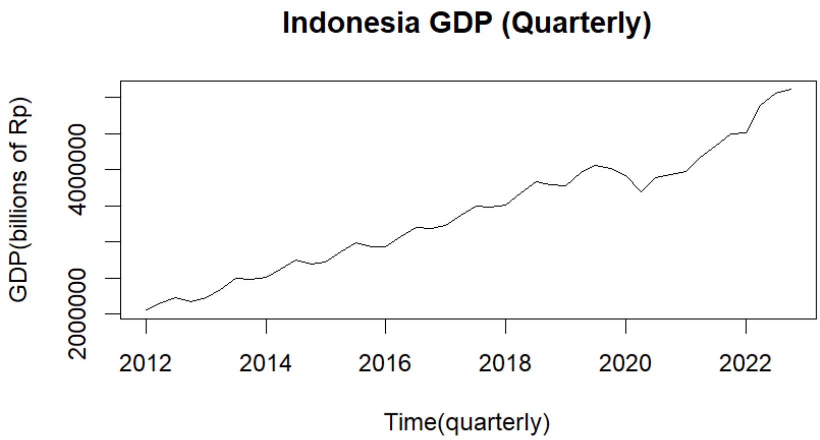

Figure 2. Time Series Plot of Indonesia's Gross Domestic Product (GDP) for the Quarters of 2012-2022

According to Figure 2, Indonesia's GDP, based on current prices on a quarterly basis, which serves as a measure of national economic growth, has consistently exhibited significant growth year after year. However, a sharp contraction is noticeable throughout the year 2020 due to the repercussions of the global economic downturn caused by the COVID-19 pandemic, subsequently impacting Indonesia's national economy. Consequently, in the year 2020, Indonesia's GDP during the 2nd, 3rd, and 4th quarters continued to experience contraction when compared to the corresponding periods in the previous year. Specifically, in the 2nd quarter of 2020, Indonesia's GDP amounted to IDR 3,690.742 trillion, while it was IDR 3,964.075 trillion in the 2nd quarter of 2019. In the 3rd quarter of 2020, Indonesia's GDP was IDR 3,897.852 trillion, compared to IDR 4,067.358 trillion in the 3rd quarter of 2019. For the 4th quarter of 2020, Indonesia's GDP stood at IDR 3,931.411 trillion, in contrast to IDR 4,018.606 trillion in the 4th quarter of 2019. In 2021, the Indonesian economy gradually rebounded in conjunction with the government's implementation of eased Large-Scale Social Restrictions (PSBB). This policy had a positive impact on the reopening of economic activities, contributing to the recovery of Indonesia's economy post-pandemic. This positive trend is evidenced by the continuous upward trajectory of Indonesia's GDP.

3.2 ARIMA Model for Forecasting Indonesia's GDP

The construction of the ARIMA model begins with the process of identifying patterns within the GDP data. In this phase, tests for stationarity in both mean and variance are conducted. From Figure 2, it is evident that the data is not stationary in variance due to varying variances over time that remain constant. Meanwhile, the ADF test, facilitated by R Studio, indicates that the data is not stationary in mean, as the obtained P-value is 0.99. Hence, differencing is deemed necessary. Upon differencing, a *P-value* of 0.01 is obtained, leading to the conclusion that the data is now stationary in mean. This observation is further supported by the differencing plot in Figure 3 and the ACF and PACF results in Figure 4.

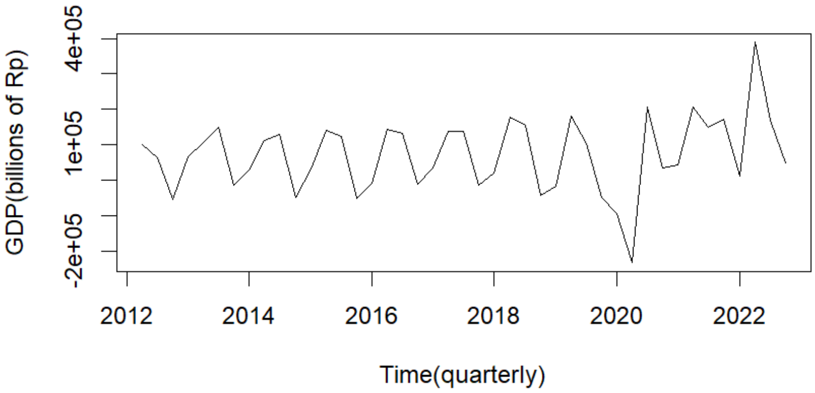

Figure 3. **Time Series Plot of Indonesia's Gross Domestic Product (GDP) after Differencing**

Furthermore, to assess whether the differenced data has achieved stationary variance, a Unit Root KPSS Test can be conducted. Based on the data analysis using R Studio, a *P-value* of 0.1 is obtained, signifying a failure to reject the null hypothesis. According to the hypothesis in this test, it can be asserted that the variance mean is constant, or in other words, the data satisfies the assumption of variance stationarity.

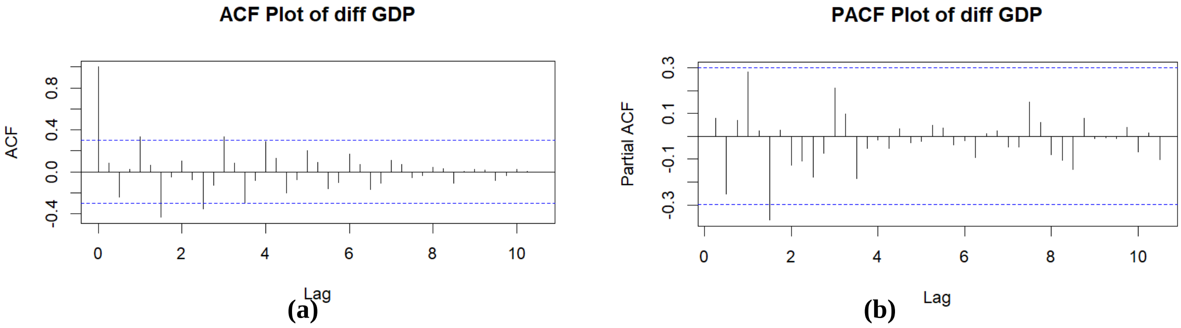

Figure 4. **ACF and PACF Plot of Differencing GDP Data**
(a) ACF Plot, (b) PACF Plot
Source: R Studio, 2023

Figure 4 illustrates that the ACF plot exhibits a cut-off after lag 3, while the PACF plot reveals a relatively high lag. These ACF and PACF plots are utilized to determine the MA and AR orders. According to the ACF and PACF plot, the best-fit ARIMA model is determined to be ARIMA (0,1,1) and ARIMA (0,1,3). A summary of the ARIMA output is presented in **Table 1** below.

Table 1. **The Estimation of ARIMA Model Selection Parameters on the Training Data with a Confidence Level of 95%**

Model	Parameter	Estimation	Std.Error	P value	AIC
ARIMA (0,1,1)	θ_1	0.35923	0.13592	0.008219	1130.791
ARIMA (0,1,3)	θ_1	0.148276	0.176288	0.40029	1133.172
	θ_2	-0.072332	0.118558	0.54179	
	θ_3	0.409333	0.180328	0.2321	

Source: *R Studio, 2023*

From the model parameter results obtained through R Studio, it is evident that ARIMA (0,1,1) is statistically significant within the 95% confidence interval, whereas ARIMA (0,1,3) is only significant in MA 3. By using the Akaike Information Criteria (AIC) values as the criterion for model goodness-of-fit on the training data, it is found that the ARIMA (0,1,1) model is the best model for forecasting or predicting Indonesia's GDP values, with an AIC value of 1130.791. Following the determination of the best-fit model, the subsequent step involves diagnostic checks. In this phase, assumptions regarding residual white noise are tested using the Ljung-Box, and normality is assessed through the examination of the probability distribution graph. The Ljung-Box test yields a *P-value* of 0.1152, indicating the fulfillment of the assumption of residual white noise. This observation is further supported by **Figure 5**, where all *p-values* are depicted above the threshold line. This signifies the absence of autocorrelation.

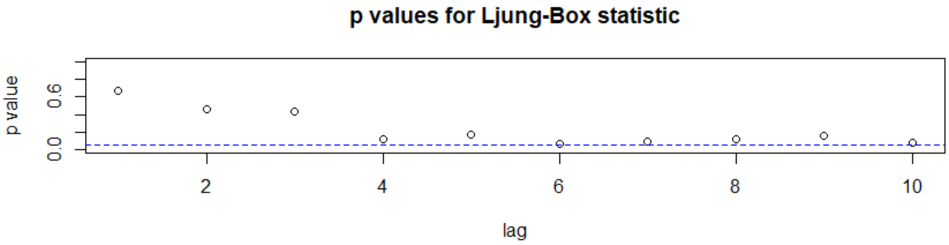

Figure 5. **Ljung-Box Statistic**
Source: R Studio, 2023

Meanwhile, employing a one-sample t-test yields a *p-value* of 0.9988, signifying the fulfillment of the normality assumption. This observation is further corroborated by **Figure 6**. In statistical analysis, assessing the normality of residuals is crucial to ensure the validity of the model assumptions. The utilization of a one-sample t-test provides a quantitative measure of the normality of the residuals. In this context, the obtained *p-value* of 0.9528 suggests that the assumption of normality is satisfied, as the *p-value* exceeds the conventional significance level of 0.05.

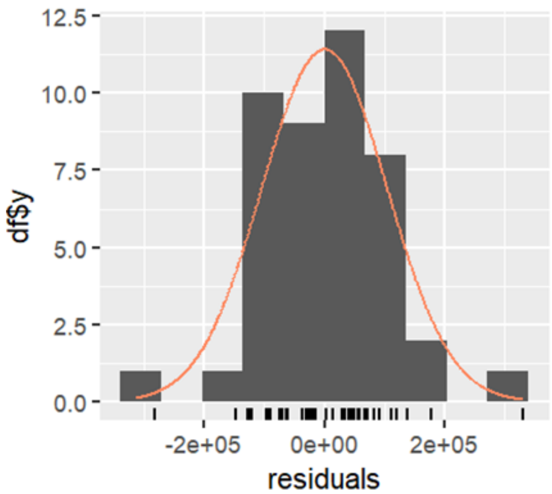

Figure 6. **Normal Distribution**
Source: R Studio, 2023

Additionally, **Figure 6**, presumably a graphical representation of the residuals, provides a visual confirmation of the normality assumption. A symmetric distribution around the center and minimal skewness or outliers in the plot would further validate the normality of the residuals. Therefore, these combined findings suggest that the residuals of the ARIMA (0,1,1) model conform to a normal distribution, reinforcing the reliability of the model's assumptions.

Subsequently, quarterly GDP data forecasting is conducted based on the ARIMA model (0,1,1). However, prior to this, in **Figure 7**, a comparison is made between the actual quarterly GDP data for Indonesia and the predicted data generated using the ARIMA (0,1,1) model. The predicted data is represented by the red line. It is evident that the lines closely overlap, indicating minimal discrepancies between the actual data and the forecasted data. This alignment between the actual and forecasted data suggests that the ARIMA model (0,1,1) is proficient in capturing the underlying patterns and trends inherent in the quarterly GDP data for Indonesia. The minimal discrepancies observed underscore the reliability and accuracy of the forecasting model in replicating the actual economic conditions. This graphical representation, serving as a validation of the model's performance, bolsters confidence in its utility for predicting future GDP trends, thereby providing valuable insights for economic planning and decision-making.

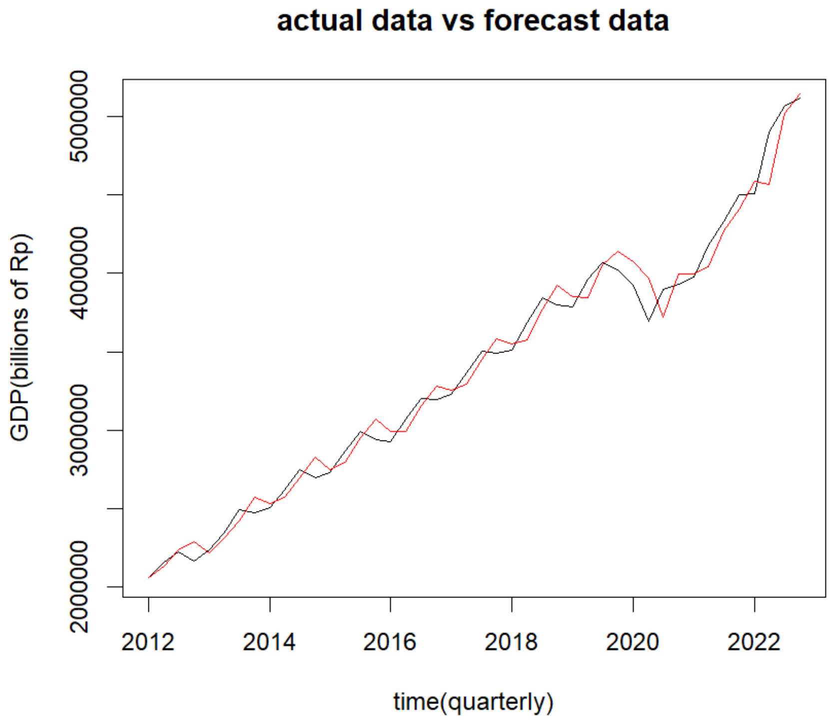

Figure 7. Comparison of Actual Data with Forecasted Data Based on the ARIMA Model (0,1,1)
Source: R Studio, 2023

The forecasting process involving the ARIMA model (0,1,1) is an essential step in assessing the model's performance in predicting quarterly GDP data for Indonesia. **Figure 7** provides a visual representation of the comparison between the actual quarterly GDP data and the predictions generated by the ARIMA model. The use of a distinctive red line to represent the predicted data facilitates a clear differentiation between the observed and forecasted values.

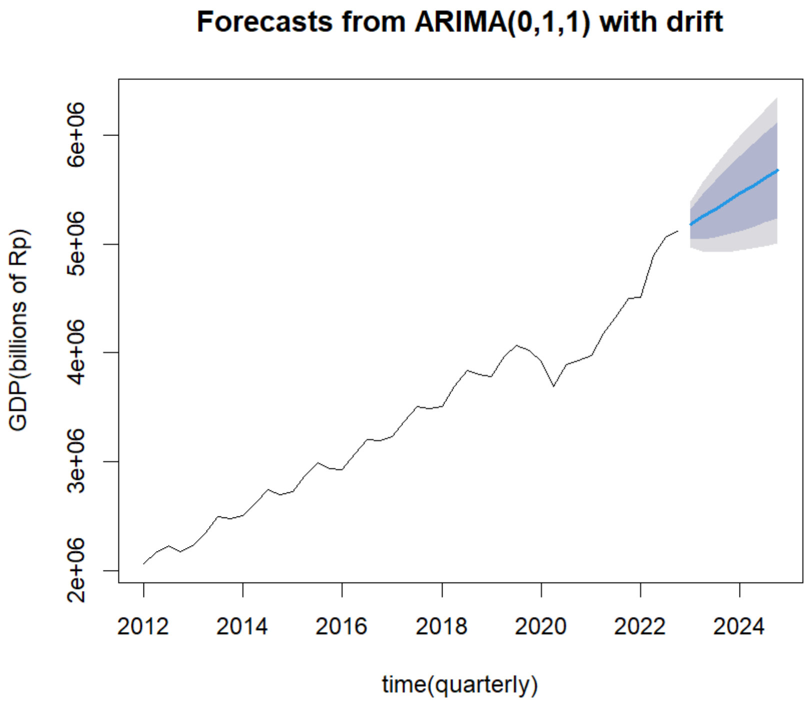

Figure 8. Forecasted Data Based on the ARIMA Model (0,1,1)
Source: R Studio, 2023

Figure 8 shows that the ARIMA (0,1,1) model, a time series forecasting method incorporating a moving average component with order 1 and a differencing parameter of 1, is applied to project future values of the GDP specifically for the year 2024. Below is the forecasting ARIMA (0,1,1) model:

$$Y_t = Y_{t-1} + 0.3592e_{t-1} + a_t \tag{7}$$

Consequently, insights into the prognostication of Indonesia's quarterly GDP, grounded in contemporary pricing structures, are elucidated in **Table 2** below.

Table 2. Gross Domestic Product (GDP) at Current Prices Forecasted Data

Year	Quartal	Actual GDP (IDR Billions)	Forecast GDP (IDR Billions)
2023	Q1	5072311	5044218
	Q2	5226579	5043406
	Q3	5295957	5061598
	Q4	-	5088779
2024	Q1	-	5121496
	Q2	-	5158064
	Q3	-	5197513
	Q4	-	5239221

Data Source: *Indonesia Central Statistics Agency 2023 & R Studio 2024*

The presented statement articulates the findings derived from a forecasting model, specifically the ARIMA (0,1,1) model, employed for predicting Indonesia's GDP. The model's selection is based on its superior performance in forecasting, particularly when considering the prevalent market prices. In the context of time series analysis, the notation (0,1,1) delineates the autoregressive, differencing, and moving average components of the ARIMA model. The reference to **Table 2** suggests the existence of a tabulated representation containing the prognostications for Indonesia's GDP derived from the aforementioned model.

4. CONCLUSIONS

The ARIMA (0, 1, 1) model embodies a highly pertinent methodology for forecasting Indonesia's GDP growth, accounting for prevailing price factors and presented at quarterly intervals in the short term. The model configuration indicates the absence of significant autoregressive (AR) and first-order moving average (MA) components within the realm of time series analysis while demonstrating the presence of one differencing (I) level and one influential second-order moving average component. Clearly, the model projects a sustained quarterly increasing trend in Indonesia's GDP, underscoring an anticipation of continued positive growth in each quarter in the near future, even amidst other factors potentially affecting economic growth. The model's strength lies in its adeptness at delineating periodic trend changes, thus offering critical insights for decision-makers and economic analysts. With a short-term focus, this model provides deeper insights into how price fluctuations can impact Indonesia's economic growth each quarter, facilitating more efficacious planning in response to market dynamics.

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