Forecasting Gross Domestic Product in the Philippines Using Autoregressive Integrated Moving Average (ARIMA) Model

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ABSTRACT: *Gross domestic product (GDP) plays a vital role in providing valuable insights into the size and performance of an economy. The GDP in the Philippines has shown steady growth over the years, reflecting the country's economic development and progress. This paper presents a GDP forecast for the next eight years in the Philippines using Autoregressive Integrated Moving Average (ARIMA) model. This study aims to develop an optimal ARIMA model using the Box-Jenkins Methodology, incorporating a range of tests and selection criteria. The ARIMA (1,2,1) model is a valid choice for forecasting GDP in the Philippines, supported by its accuracy, as evidenced by the acceptable MAPE and high R-squared value. The model successfully captures patterns and trends in the GDP data, despite the significant variability represented by the sigma-squared value. The forecasted GDP for 2022-2029 suggests a positive outlook with a steady growth trajectory. These findings have important implications for economic planning, policy-making, and decision-making in the Philippines, as the forecasted GDP provides insights into the country's future growth and development, influencing investment decisions, government strategies, and overall economic stability.*

KEYWORDS: autoregressive integrated moving average (ARIMA), box-jenkins methodology, forecast, gross domestic product (GDP), mean absolute percentage error, time-series analysis.

INTRODUCTION

Gross domestic product is essential as it provides insights into the size of an economy and its economic performance. The growth rate of an economy is a measure of the change in the GDP of a country in comparison to past periods. It serves as an indicator of the country's economic health and potential growth in the future. Measuring the growth rate of an economy is needed to comprehend the nature of the economy and the possible course it may follow in the next few years (Adithyan, 2023). A growing GDP means an economy is doing well. As illustrated by the

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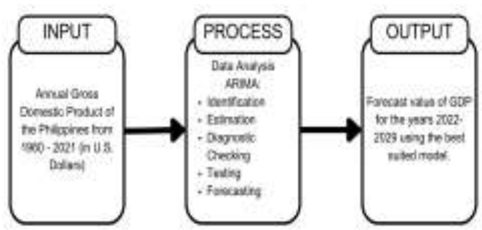
International Monetary Fund, when GDP is growing strongly, more employment opportunities are available since industries hire more employees. Also, people have more money in their pockets. However, employment decreases when a country's GDP is shrinking, especially during the global economic crisis. In certain circumstances, the GDP may grow, but not quickly enough to employ everyone who wants to work. Nonetheless, real GDP growth follows a cycle over time. A country's economy may have continuous growth, slow growth, or recession.

When talking about the Philippines, the latest recorded gross domestic product was also in 2021. The Philippines was ranked 37th with 394,086 (millions of US dollars), as stated by worldbank.org. In 2021, the Philippine Gross Domestic Product experienced a growth of 5.6 percent, as the Philippine Statistics Authority reported. The Philippines' economic strength is built on solid consumer demand backed by a thriving labor market and substantial remittances. The Philippines has numerous benefits because of its expanding urbanization, developing middle class, and large and young demographic.

The researchers aim to forecast the Philippines' gross domestic product from 2022 to 2029 by employing the Box-Jenkins Methodology. This approach involves formulating an optimal Autoregressive Integrated Moving Average (ARIMA) model. Economic forecasts, like gross domestic product, are vital to aid policymakers in making more informed decisions.

A. Conceptual Framework

Figure 1.1: Conceptual Framework for Gross Domestic Product Using ARIMA Model



In Figure 1.1, the annual gross domestic product of the Philippines from 1960 to 2021 was gathered from the World Bank (data.worldbank.org), an online data collection. The data was arranged using Microsoft Excel. Furthermore, the statistical software, RStudio, was utilized for the data analysis. This study used an autoregressive integrated moving average (ARIMA) model for forecasting. Identification, estimation, diagnostic checking, testing, and forecasting are the processes done to determine the best ARIMA model for forecasting the GDP in the country. The forecast value of GDP was presented for 2022–2029 using the best-suited model.

B. Statement of the Problem

The researcher's objective is to forecast the gross domestic product in the Philippines using the Autoregressive Integrated Moving Average (ARIMA) model. Mainly, it aims to answer the following questions:

1. What ARIMA model is best suited for forecasting the gross domestic product in the Philippines?
2. What is the level of accuracy exhibited by the ARIMA model when employed to forecast the gross domestic product in the Philippines?
3. What is the forecasted gross domestic product in the Philippines for 2022-2029?
4. What are the possible implications of the forecasted gross domestic product in the Philippines?

RELATED LITERATURE

A. Gross Domestic Product

Gross domestic product is a metric that determines the monetary worth of finished products and services produced within a nation's borders during a given period. It gives information about the country's national income, economic growth, and the economy's general health (Callen, 2008). Although GDP measures economic activity, it does not indicate the economy's general well-being (Diener et al., 2008).

To understand the country's economic condition, tracking the changes in the gross domestic product over time can be helpful. According to Robinson (2015), the GDP of the Philippines has exhibited an upward trend and has shown progress compared to previous decades. Based on a survey conducted by Bloomberg among economists, the Philippines is considered one of the rapidly expanding economies and is projected to be the second fastest-growing economy globally in 2015, with a growth rate of 6%, just behind China.

B. Inflation Rate and Gross Domestic Product

Inflation measures how prices of goods and services in the overall economy change over time. Hayek (1989) argued that understanding the correlation between the inflation rate and economic growth is essential because inflation causes issues and disturbances in the economy's operations, potentially affecting economic growth.

According to a study conducted by Bhat & Laskar (2016), a positive relationship exists between inflation and India's GDP during their study period. The same result was obtained by Agalega & Antwi (2013), whose paper employed multiple linear regression to establish a result between

Inflation and GDP in Ghana. However, analysis by Baene, Sihotang, & Khadafi (2021) showed that inflation negatively and significantly affects Indonesia's GDP.

In the Philippines, a study by Lubbock, Merin, & Gonzales (2022) revealed that the Ordinary Least Square (OLS) and Johansen's Cointegration test result suggested that inflation positively impacts economic growth and that there exists a long-run relationship. However, this differed from the work of Gonzalez et al. (2022). Using the same model, Ordinary Least Square (OLS), they have found that the inflation rate is insignificant towards economic growth, which indicates that it does not affect economic growth.

C. Unemployment and Gross Domestic Product

According to Okun's Law, an inverse relationship exists between unemployment and economic growth; an increase in a country's GDP would lead to a decreased unemployment rate (Cuaresma, 2003). Okun's Law can be applied to the Malaysian economy; their paper's results showed a negative relationship between unemployment and GDP (Noor, 2007). Makaringe and Khobai (2018) obtained the same findings by applying the Auto Regressive Distribution Lag (ARDL) bound test approach. Their analysis verified the presence of a long-term association between unemployment and economic growth, with an observed negative relationship.

Brooks (2002) notes that while employment opportunities have increased significantly in the Philippines over the past decade, the unemployment rate has remained almost twice that of neighboring countries. The study indicates that employment growth and GDP exhibit a positive correlation, suggesting that an expansion in the economy leads to more job opportunities. The research also highlights a negative correlation between unemployment and GDP, suggesting that a decline in economic growth worsens unemployment. As a result, the findings imply that policies to stimulate economic growth and increase the real minimum wage are necessary to reduce unemployment levels. The same finding is supported by Resurreccion (2014), employing Ordinary Least Squares (OLS) regression, confirming Okun's Law and Philips Curve in the Philippines.

D. Population and Gross Domestic Product

Dao (2012) observed a negative relationship between population growth and per capita GDP growth in developing countries. Similarly, the phenomenon of population aging, referred to as the decline in fertility rates and increased life expectancy, results in a decrease in the annual growth rate of GDP per capita. Specifically, research conducted by Maestes, Mullen, and Powell (2023) revealed a reduction of 0.3 percentage points per year in the GDP growth rate during the period spanning from 1980 to 2010. Analyzing economic aspects of inequality, Peterson (2019) noted that reduced population growth and restricted migration could contribute to increased national and economic inequality. Peterson (2019) also argued that a decline in population growth in high-income nations could give rise to social and economic challenges.

The research conducted by Martinico-Perez, Fishman, and Tanikawa (2017) highlights that the primary factor influencing resource consumption in the Philippines has shifted from population growth to the increasing affluence of the population. This finding emphasizes the need to prioritize sustainable economic development in the country. Likewise, the study conducted by Lubbock, Merin, and Gonzales (2022) employed advanced statistical methods, including Unit Root Test, Johansen's Cointegration Test, and Ordinary Least Squares, to examine the relationship between population growth and economic growth. The findings indicated a negative association between population growth and economic growth, suggesting that as the population continues to increase, there is a tendency for a decline in GDP. In the Davao Region, Philippines, Balubayan (2019) used a Vector Autoregressive Model (VAM) approach to examine the causal relationship between population growth and economic growth. The Granger test revealed a unidirectional causality from the gross regional domestic product (GRDP) to population growth, meaning that the economic progress in Davao has had a favorable effect on the region's population increase.

E. Related Studies

1) ARIMA Model

Previous scholarly literature utilized different approaches to forecast economic time series variables. One such approach, introduced by Box and Jenkins (1976), is known as the univariate forecasting or Autoregressive Integrated Moving Average (ARIMA) model. The ARIMA model provides a comprehensive approach to forecasting time series data by considering the autoregressive, moving average, and differencing components. To identify a given variable's overall trend, the method concentrates on historical values, including the model's lagged forecast errors from previous periods. Other researchers extensively employed the ARIMA model to forecast various variables, demonstrating its capability to accurately predict outcomes when all process conditions are satisfied, particularly in generating short-term forecasts (Wabomba, Mutwiri & Fredrick, 2016).

Among these studies is by Babu & Reddy (2015), which used the linear method, ARIMA, and complex nonlinear methods such as Neural Network and Fuzzy Neuron to forecast the exchange rate of the Indian Rupee (INR) from 2010 to 2015 against the United States Dollar (USD), British Pound (GBP), Euro (EUR) and Japanese Yen (JPY). The results found that the ARIMA model was the best approach in predicting the exchange rate than the complex nonlinear models since the fuzzy neuron model deviates much from the actual data. In contrast, the AIC and BIC of the neuron network are more significant than that of the ARIMA model.

2) ARIMA Model in the Philippines

In the Philippines, businesses and policymakers widely utilize the ARIMA model to forecast crucial economic indicators such as GDP growth, inflation rates, exchange rates, stock market indices, and other key macroeconomic variables. These forecasts are vital in informing decision-making processes and risk mitigation strategies. Nyoni (2019) conducted a research study utilizing annual time series data from 1960 to 2017 in the Philippines to model and predict the inflation rate. The results indicated a projected decrease in the inflation rate from 5.6% in 2018 to 0.3% by 2027. These findings hold important implications for the Bangko Sentral ng Pilipinas (BSP), emphasizing the need to maintain compliance with the mandated inflation-targeting framework.

Another research used the ARIMA model to predict unemployment, underemployment, and employment in the Philippines quarterly from 2020, progressively using the quarterly data from 2005 to 2019 with 60 observations for each economic participation. The projected quarterly figures for 2020 indicate a downward trajectory in unemployment rates and an upward trajectory in employment rates. However, it rises during the third quarter before decreasing again in the final quarter (Angco et al., 2021).

3) Forecasting GDP using ARIMA Model

Numerous studies have widely utilized the ARIMA model to forecast Gross Domestic Product (GDP) in various countries. One study that incorporated the ARIMA model to forecast GDP per Capita in Egypt and Saudi Arabia was by Eissa (2020), wherein the researcher used the annual historical data from 1960 to 2018 in Saudi Arabia and from 1968 to 2018 in Egypt to forecast the GDP per Capita for the next twelve years (2018 to 2030). Box-Jenkins' approach was used to find the best-fit model. The forecast shows continuous growth in the GDP per Capita in both Egypt and Saudi Arabia.

Another research employed the ARIMA model and multiple linear regression to predict GDP in Bangladesh. The researcher used the GDP data in US dollars from 2001 to 2018 to predict the GDP of Bangladesh from 2019 to 2025, and the best ARIMA model obtained was ARIMA (1,2,1), with the lowest RMSE among the other ARIMA models. The study's findings indicate that GDP will continue to increase over the next seven years. At the same time, employment positively correlates with GDP, implying that GDP tends to rise as net export and foreign direct investment decline. As employment increases, the GDP in Bangladesh also tends to increase (Uddin & Tanzim, 2021). Wabomba, Mutwiri, and Fredrick (2016) employed the Box-Jenkins methodology to forecast the annual GDP data of Kenya. The findings indicated a continuous growth in Kenya's GDP over the subsequent five years, from 2013 to 2017.

F. Synthesis

The compiled literature and studies discuss various economic indicators and possible effects on GDP. The relationship between inflation and economic growth varies across countries and specific periods. Some studies find a positive correlation, suggesting that inflation can stimulate economic growth, while others find no significant or negative relationship. For unemployment, according to Okun's Law, there is an inverse relationship between unemployment and economic growth. An increase in GDP leads to a decrease in the unemployment rate. For unemployment, according to

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Okun's Law, there is an inverse relationship between unemployment and economic growth. An increase in GDP leads to a decrease in the unemployment rate.

Existing literature highlights the superior predictive performance of the ARIMA model compared to other complex nonlinear models, including Neural Network, Fuzzy Neuron, and ANFIS. These studies demonstrate that the ARIMA model consistently delivers more accurate forecasts, making it a preferred choice for predicting specific variables in various domains.

The ARIMA model is widely used in the Philippines to forecast critical economic indicators. Studies have applied the ARIMA model to predict inflation rates, unemployment, underemployment, employment, and electricity consumption in the country. This methodology has proven its efficacy and superiority over other models in several studies conducted in the Philippines. The forecasts generated by the ARIMA model are valuable for businesses and policymakers in making informed decisions and formulating appropriate economic policies.

METHODOLOGY

A. Box-Jenkins Methodology

This study aims to forecast the gross domestic product in the Philippines using the ARIMA model that is the best fit. The researchers utilized a predictive research design and employed the Box-Jenkins Methodology to identify the suitable ARIMA model. This methodology is a systematic approach for analyzing and forecasting time series data, which is suitable for the research. In addition, the ARIMA model will be utilized to forecast the gross domestic product in the Philippines for 2022-2029.

Figure 3.1
Box-Jenkins Methodology

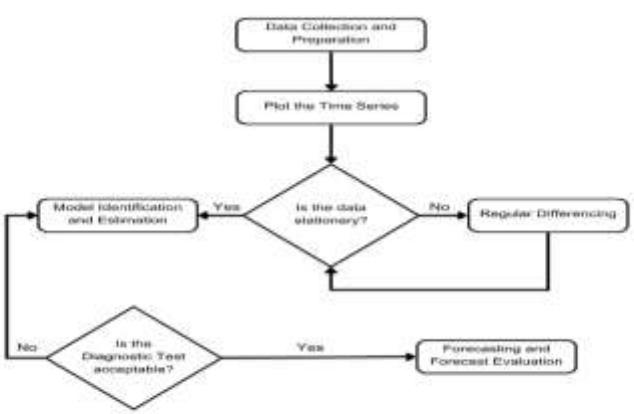

Figure 3.1 illustrates the formulation of an Autoregressive Integrated Moving Average (ARIMA) model using the Box-Jenkins Methodology.

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The collected historical data was plotted and underwent data partition: training and testing set. The stationarity test begins with plotting the Partial Autocorrelation Function (PACF) and Autocorrelation Function (ACF). The training set was subjected to Augmented Dickey-Fuller (ADF) test, Phillips-Perron (PP) test, and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test for further validation of the data stationarity. If the data is non-stationary, differencing is necessary to make it stationary; otherwise, the model identification and estimation begin with selecting the lower Akaike Information Criterion (AIC), Akaike Information Criteria with correction (AICc), and Bayesian Information Criterion (BIC). The invertibility and Ljung Box test were then used for diagnostic tests. Finally, the optimal ARIMA model was used for forecasting and evaluation to measure the prediction error.

B. Data Collection and Procedure

The data was retrieved from World Bank Open Data-a site designed to make World Bank data accessible. The World Data Bank has a development Data Group that manages statistical and data work and maintains several macro, financial, and sector databases. For this study, the researchers used the annual gross domestic product (current US$) in the Philippines from the years 1960 up until 2021.

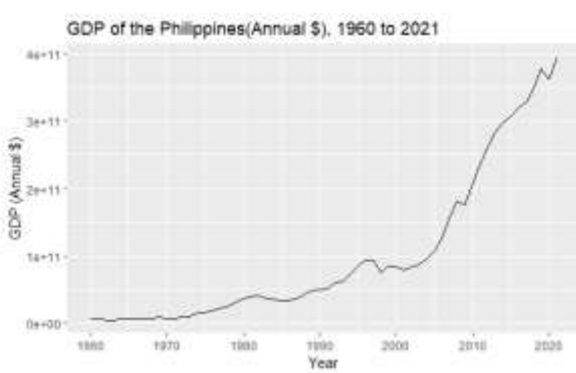
The data gathering procedure was done as follows; first, the data was collected from World Bank Open Data. It was downloaded and organized using Microsoft Excel. Second, the data was exported into RStudio, the R programming language. The Box-Jenkins Methodology was utilized to find the ARIMA model best fit for the forecasting, and conclusions were drawn.

RESULTS AND DISCUSSIONS

A. Stationarity Test

1) Plot the Time Series

Figure 4.1Time Series Data of Gross Domestic Product in the Philippines (1960-2021)



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The growth of the Gross Domestic Product depicts an upward trend, evident with 62 observations. The plot indicates that the GDP from the early 2000s has rapidly increased, reaching its highest point in 2021 with minor fluctuations. Moreover, the time series of GDP is non-linear, exhibiting an increasing pattern that indicates the non-stationarity of the entire series.

2) Data Partition

Figure 4.1

Data Partition of GDP in Philippines (1960-2021)

Economic time series data sets were divided into two subsets: training and testing datasets. The training dataset comprised 80% of the original data, while the testing dataset comprised 20%. The purpose of splitting the data this way was to use the training data to build models and the testing data to evaluate their accuracy.

3) Partial Autocorrelation Function (PACF) And Autocorrelation Function (ACF) Plots

Figure 4.3

PACF Plot of GDP Training Set Time Series

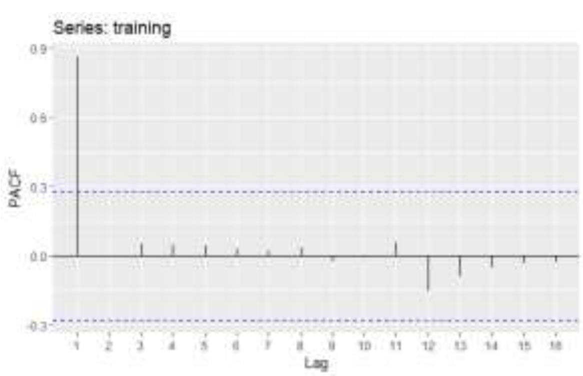

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Table 4.1

PACF Values of GDP Training Set Time Series

Partial autocorrelations of series 'training', by lag

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
0.863	0.000	-0.031	0.048	0.044	-0.031	0.022	0.033	-0.028	-0.012	0.054	-0.355	-0.002	-0.050	-0.015	-0.030

In Figure 4.3, there is a lag of order one that falls outside the 95% confidence level and has a value of 0.863, as shown in Table 4.1. It implies a strong correlation between the first and second observations in the time series. Hence, this can be an indication of non-stationarity in the time series.

Figure 4.4

ACF Plot of GDP Training Set Time Series

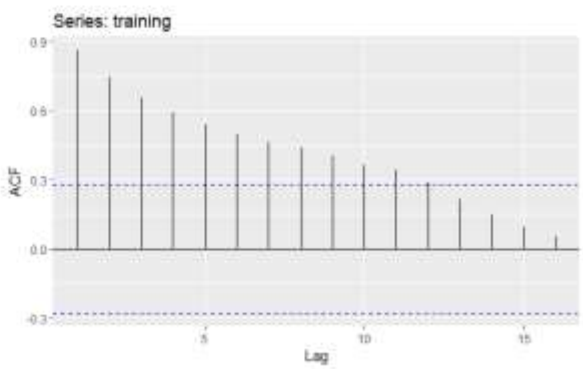

Table 4.2

ACF Values of GDP Training Set Time Series

Autocorrelations of series 'training', by lag

0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
1.000	0.863	0.745	0.657	0.590	0.540	0.499	0.464	0.437	0.406	0.361	0.343	0.285	0.214	0.144	0.095	0.051

Figure 4.4 depicts the Autocorrelation Function (ACF) of the training set for the GDP time series. The ACF plot reveals a gradual and slow decline in autocorrelation values as the lag increases, as indicated in Table 4.2. This observation strongly suggests that the time series is non-stationary.

4) Augmented Dickey-Fuller Test, Philipps-Perron, & Kwiatkowski-Phillips-Shmidt-Shin Tests

Table 4.3

ADF Test for GDP Training Set Time Series

```
        Augmented Dickey-Fuller Test

data:  training
Dickey-Fuller = -0.46414, Lag order = 3, p-value = 0.9798
alternative hypothesis: stationary
```

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Table 4.3 presents the results of the Augmented Dickey-Fuller (ADF) Test. The obtained p-value of 0.9798 exceeds the predetermined significance level of 0.05. This indicates insufficient evidence to reject the null hypothesis of non-stationarity. Therefore, based on the ADF test, the time series is non-stationary.

Table 4.4

PP Test for GDP Training Set Time Series

```
	Phillips-Perron Unit Root Test

data:  training
Dickey-Fuller Z(alpha) = 2.9841, Truncation lag parameter = 3, p-value = 0.99
alternative hypothesis: stationary
```

The PP test examines data stationarity and follows a similar approach to the ADF test. It involves analyzing the p-value corresponding to the test statistic to determine whether the data is stationary. Since the p-value of 0.99 exceeds the significance level of 0.05, there is insufficient evidence to reject the null hypothesis. Hence, it indicates a non-stationarity of the time series.

Table 4.5

KPSS Test for GDP Training Set Time Series

```
	KPSS Test for Level Stationarity

data:  training
KPSS Level = 1.2323, Truncation lag parameter = 3, p-value = 0.01
```

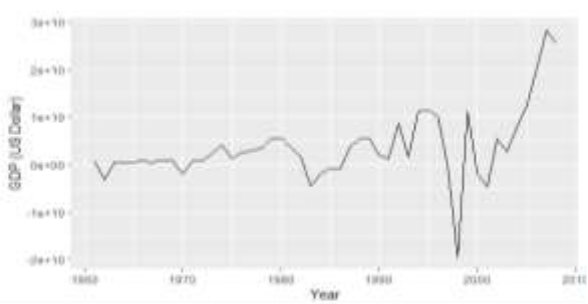
The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test is employed to assess the stationarity of a time series. Unlike the ADF and PP tests, the KPSS test examines the null hypothesis of stationarity rather than non-stationarity. Based on Table 4.5, the p-value is 0.01, which is lower than the specified significance level of 0.05, there is enough evidence to reject the null hypothesis of stationarity. Hence, it implies that the time series is non-stationary.

B. Differencing

1) First-Order Difference

Figure 4.5

GDP Training Set Time Series Plot (First-Order Differenced)



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The graph above displays the first-order difference of the GDP training set time series. The differenced series appears to exhibit a more linear pattern than the actual GDP graph, but there is a spiking trend at the end. To further analyze the graph, it must undergo additional stationarity tests.

2) Partial Autocorrelation Function (PACF) And Autocorrelation Function (ACF) Plots

Figure 4.6

PACF Plot of GDP Training Set Time Series (First-Order Differenced)

Table 4.6

PACF Values of GDP Training Set Time Series (First-Order Differenced)

```
Partial autocorrelations of series 'training_diff', by lag

     1      2      3      4      5      6      7      8      9     10     11     12     13     14     15
 0.493  0.038  0.031 -0.177  0.051 -0.187  0.114 -0.091 -0.110 -0.082  0.340  0.066  0.008 -0.087  0.073
    16
-0.078
```

The PACF Plot of the GDP Training set time series is shown in Figure 4.6. The PACF plot demonstrates a notable lag at order one and a significant lag occurring in the middle of the lag sequence. It indicates a correlation between the current observation and the observation in the middle of the sequence. This suggests a potential non-stationary pattern in the time series.

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Figure 4.7

ACF Plot of GDP Training Set Time Series (First-Order Differenced)

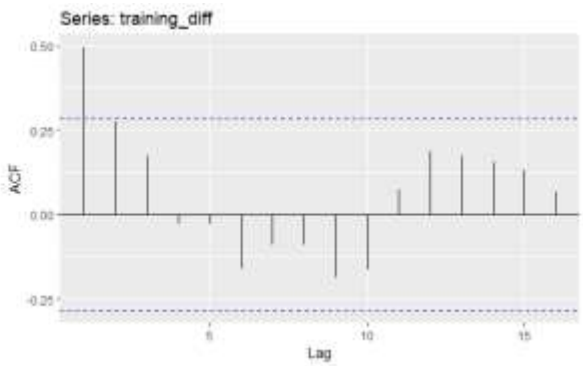

Table 4.7

ACF Values of GDP Training Set Time Series (First-Order Differenced)

```
Autocorrelations of series 'training_diff', by lag

     0      1      2      3      4      5      6      7      8      9     10     11     12     13     14
 1.000  0.495  0.275  0.173 -0.019 -0.028 -0.161 -0.081 -0.090 -0.188 -0.162  0.074  0.187  0.172  0.134
    15     16
 0.137  0.068
```

Figure 4.7 shows the autocorrelation function (ACF) plot of the first-order differenced time series for the GDP training set. The ACF plot reveals a gradual decrease in correlation as the lag increases. This pattern indicates the presence of non-stationarity in the time series.

3) Augmented Dickey-Fuller Test, Philipps-Perron, & Kwiatkowski-Phillips-Shmidt-Shin Tests

Table 4.8

ADF Test for GDP Training Set Time Series (First-Order Differenced)

```
        Augmented Dickey-Fuller Test

data:  training_diff
Dickey-Fuller = -1.6624, Lag order = 3, p-value = 0.7089
alternative hypothesis: stationary
```

The presented results of the Augmented Dickey-Fuller Test indicate a p-value of 0.7089, higher than the significance level of 0.05. This implies that the first-order difference, as assessed by the ADF test, remains non-stationary.

Table 4.9

PP Test for GDP Training Set Time Series (First-Order Differenced)

```
        Phillips-Perron Unit Root Test

data:  training_diff
Dickey-Fuller Z(alpha) = -25.865, Truncation lag parameter = 3, p-value = 0.01
alternative hypothesis: stationary
```

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The Phillips-Person Unit Root Test was used to develop the outcomes presented above. The p-value of 0.01 (<p=0.05) states that the null hypothesis of non-stationarity is rejected, in contrast to the consistent non-stationarity observed in the PACF, ACF, and Augmented Dickey-Fuller (ADF) test results, the Phillips-Perron (PP) test unexpectedly suggested stationarity. Hence, solely relying on the PP test's indication of stationarity is insufficient to conclude that the time series is stationary.

Table 4.10

KPSS Test for GDP Training Set Time Series (First-Order Differenced)

```
        KPSS Test for Level Stationarity

data:  training_diff
KPSS Level = 0.46262, Truncation lag parameter = 3, p-value = 0.05016
```

Table 4.10 presents the results of the Kwiatkowski-Phillips-Shmidt-Shin (KPSS) test conducted on the first-order difference of the GDP time series. With a p-value of 0.05016 (>p=0.05), the results fail to provide adequate evidence for rejecting the null hypothesis of stationarity. However, the PACF, ACF, and ADF tests' results specified the series' non-stationarity. It is necessary to proceed with second-order differencing to address any remaining non-stationarity.

4) Second-Order Difference

Upon performing differencing on the GDP training set time series, it is evident that the data exhibit non-stationary characteristics. Therefore, second-order differencing was employed to address the non-stationarity of the GDP training set time series after first-order differencing.

Figure 4.8

Plot of GDP Training Set Time Series (Second-Order Differenced)

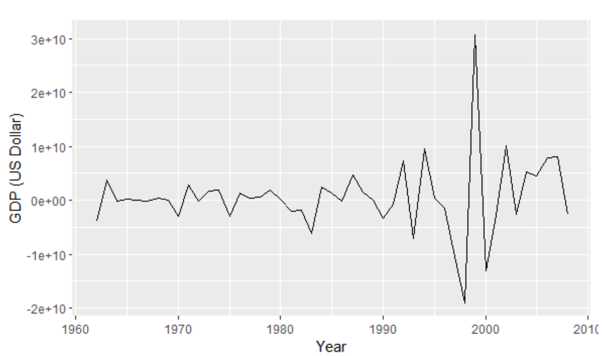

Figure 4.8 depicts the second-order difference of the GDP training set time series. The plot shows a more linear behavior without any significant trend or seasonality. Additionally, the dispersion of data points around the mean remains constant over time without displaying any systematic patterns or changes. As such, Figure 4.8 provides evidence of a stationary plot.

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5) Partial Autocorrelation Function (PACF) And Autocorrelation Function (ACF) Plots

Figure 4.9

PACF Plot of GDP Training Set Time Series (Second-Order Differenced)

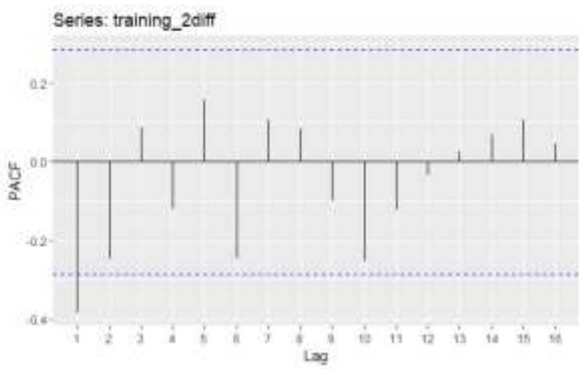

Table 4.11

PACF Values of GDP Training Set Time Series (Second-Order Differenced)

```
Partial autocorrelations of series 'training_2diff', by lag

     1      2      3      4      5      6      7      8      9     10     11     12     13     14     15
-0.385 -0.250  0.087 -0.121  0.157 -0.248  0.107  0.082 -0.100 -0.255 -0.123 -0.035  0.025  0.069  0.106
    16
 0.045
```

The Partial Autocorrelation Function (PACF) plot reveals a notable lag at the first order, where the lag value of -0.385 falls within the 95% confidence interval, as shown in Table 4.11. Subsequent lag values after the first order also remain within the confidence interval. Therefore, based on the PACF analysis, it suggests that the time series exhibits stationarity.

Figure 4.10

ACF Plot of GDP Training Set Time Series (Second-Order Differenced)

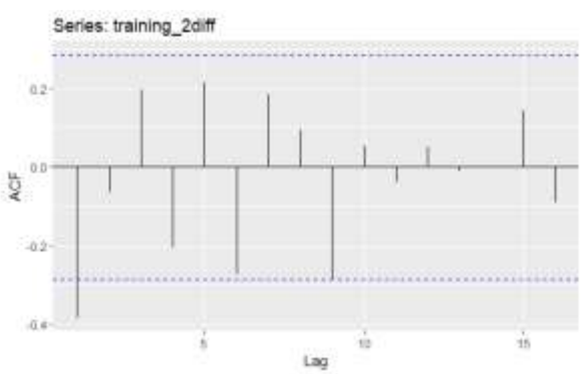

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Table 4.12

ACF Values of GDP Training Set Time Series (Second-Order Differenced)

```
Autocorrelations of series 'training_2diff', by lag

     0      1      2      3      4      5      6      7      8      9     10     11     12     13     14
 1.000 -0.385 -0.084  0.198 -0.206  0.214 -0.274  0.183  0.094 -0.287  0.054 -0.099  0.093 -0.022  0.000
    15     16
 0.143 -0.093
```

The Autocorrelation Function (ACF) plot in Figure 4.10 exhibits lag values of order 1 and 9 that lie outside the 95% confidence interval. Table 4.12 provides the corresponding autocorrelation values, with orders 1 being -0.385 and 9 being -0.287. Additionally, the gradual decay observed in the autocorrelation values indicates the absence of a significant correlation between consecutive observations as the time lag increases. These findings align with the characteristics of a stationary time series, thus suggesting that the analyzed time series displays stationarity.

6) Augmented Dickey-Fuller Test, Philipps-Perron, & Kwiatkowski-Phillips-Shmidt-Shin Tests

Table 4.13

ADF Test for GDP Training Set Time Series (Second-Order Differenced)

```
        Augmented Dickey-Fuller Test

data:  training_2diff
Dickey-Fuller = -3.8538, Lag order = 3, p-value = 0.02377
alternative hypothesis: stationary
```

Table 4.13 presents the results of the Augmented Dickey-Fuller test with a p-value of 0.02377 (<p=0.05), implying sufficient evidence to reject the null hypothesis of non-stationarity. Therefore, after performing second-order differencing, the time series attains stationary.

Table 4.14

PP Test for GDP Training Set Time Series (Second-Order Differenced)

```
        Phillips-Perron Unit Root Test

data:  training_diff
Dickey-Fuller Z(alpha) = -25.865, Truncation lag parameter = 3, p-value = 0.01
alternative hypothesis: stationary
```

The Phillips-Perron Unit Root Test reveals a p-value of 0.01 (<p=0.05), providing sufficient evidence to reject the null hypothesis of non-stationarity. Consequently, the conclusion can be drawn that the time series exhibits stationarity.

Figure 4.15

KPSS Test for GDP Training Set Time Series (Second-Order Differenced)

```
        KPSS Test for Level Stationarity

data:  training_2diff
KPSS Level = 0.15162, Truncation lag parameter = 3, p-value = 0.1
```

Table 4.15 displays the outcomes of the Kwiatkowski-Phillips-Shmidt-Shin test. The obtained p-value of 0.1 is higher than the significance level of 0.05, indicating strong evidence in favor of the null hypothesis of stationarity. Therefore, based on the KPSS test, it can be concluded that the time series is stationary.

C. Selection of Optimal ARIMA Model using AIC, AICc and BIC Criteria

The selection of the appropriate ARIMA (p, d, q) model involves determining the values for p, d, and q, which respectively represent the AR process, the number of differencing operations, and the MA process. The lag order of 1 is identified as significant for the autoregressive (AR) process or (p) model. Additionally, lag orders of 1 and 9 are significant for the moving average (MA) process or (q) model. As the time series undergoes double differencing, the value of 2 is assigned to the differencing component or (d) model.

The potential model candidates are ARIMA (1,2,1) and ARIMA (1,2,9). The optimal model selection is based on various criteria such as log-likelihood, Akaike Information Criterion (AIC), Akaike Information Criterion with correction, and Bayesian Information Criterion (BIC). These criteria are utilized to determine the model that best fits the data.

Table 4.16

Criterion Scores for Each ARIMA Model (AIC, AICc, and BIC)

CRITERIA	ARIMA (1,2,1)	ARIMA (1,2,9)
LOG-LIKELIHOOD	-1127.22	**-1120.96***
AIC	**2260.44***	2263.92
AICC	**2260.639***	2268.232
BIC	**2265.986***	2284.269

Table 4.16 presents the time series model candidates and their corresponding selection criteria. Among these models, ARIMA (1,2,1) stands out with lower scores in the AIC, AICc, and BIC measures, scoring 2260.44, 2260.639, and 2265.986, respectively. This indicates that ARIMA (1,2,1) performs better than the other models regarding the goodness of fit and model complexity. Consequently, ARIMA (1,2,1) is deemed the most suitable model for further validation and analysis in the subsequent ARIMA process.

D. Diagnostic Test

1) Invertibility – ARMA Structure

Figure 4.11

Inverse Roots for ARMA Structure

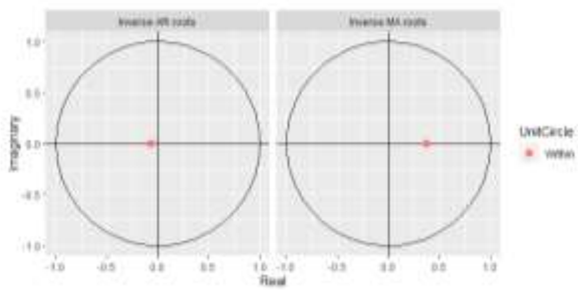
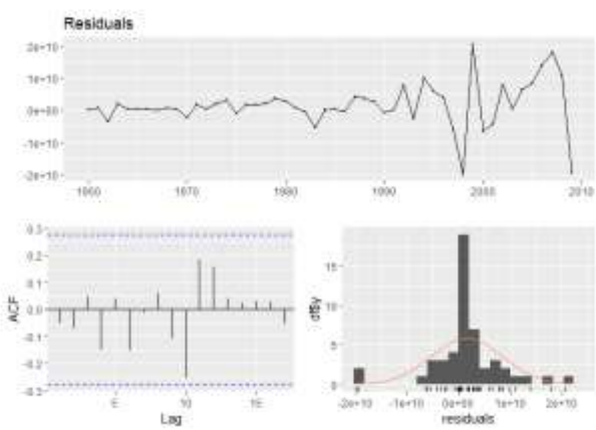


Figure 4.11 portrays the ARMA structure of the ARIMA (1,2,1) model, indicating that the inverse roots of both AR and MA components are situated within the unit circle. This suggests that the model is invertible and satisfies the diagnostic criteria. As a result, the model is considered appropriate for forecasting purposes.

2) Independence of Residuals – Ljung Box Test

Figure 4.12

Residuals of ARIMA (1,2,1) model



The residuals provide valuable information about the performance and accuracy of the model. Figure 4.12 illustrates the plotted residuals, the autocorrelation function (ACF), and the distribution of ARIMA (1,2,1). The plotted residuals graph portrays a more linear pattern, indicating that the model is unbiased in its prediction. Additionally, the ACF plot lags are independent, showing the independence of residuals. The residuals are normally distributed, which indicates that the model has successfully captured the underlying patterns and variability in the time series.

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Table 4.17

Ljung-Box Test for the Residuals of ARIMA (1,2,1)

```
        Box-Ljung test

data:  model1_residuals
X-squared = 0.046422, df = 1, p-value = 0.8294
```

Since the p-value of 0.8294 exceeds the significance level of 0.05, the null hypothesis of no autocorrelation in the residuals is accepted. Therefore, the residuals can be considered independent, and the data has no significant remaining autocorrelation structure.

E. Forecast Evaluation

1) Actual and Forecasted Value

Following the completion of diagnostic tests, the rolling origin forecast technique was utilized to obtain a test forecast for the gross domestic product in the Philippines from 2009 to 2021.

Figure 4.13

Test Forecast of Gross Domestic Product Time Series

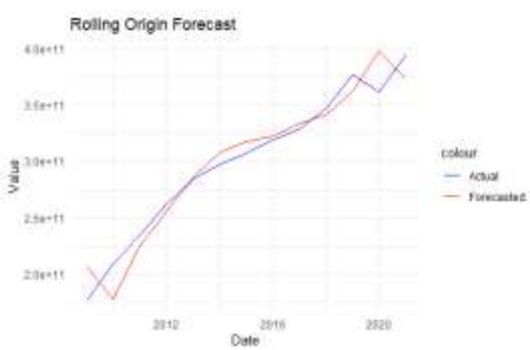

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Table 4.18

Test Forecast of Gross Domestic Product Time Series

date	actual	forecasted
2009	175974711592	206464373752
2010	208368726861	176950641875
2011	234216930370	224355203007
2012	261920509951	255095938631
2013	283902728261	285575383954
2014	297483247101	307240132298
2015	306446140629	317350187912
2016	318626761493	322401046885
2017	328480867143	333619822983
2018	346842094175	341673163933
2019	376823278561	362255544005
2020	361751116293	397632686567
2021	394086401171	372947994972

The model's accuracy was evaluated by comparing the forecasted GDP values to the actual data for the same period. Based on the findings in Figure 4.12, the model projected the GDP to be 175,974,711,592 US Dollars in 2009. It gradually increased, reaching 394,086,401,171 US Dollars by the end of 2021, with slight fluctuations observed in 2010 and 2021.

2) Error Measures

Table 4.19

Error Measures for Test Forecast of Gross Domestic Product Time Series

MODEL	MAPE	R-SQUARED	SIGMA SQUARED
ARIMA (1,2,1)	5.38	0.92	3.956e+19

The ARIMA (1,2,1) model exhibits a MAPE of 5.38%, implying that, on average, the forecasted values differ from the actual values by approximately 5.38%. This level of deviation is within an acceptable range, indicating a satisfactory fit of the model. The R-squared value of 0.92 shows that the model fits the data well and effectively captures the patterns and trends. The sigma squared value is 3.956e+19, which indicates a significant variance or dispersion in the data points. The value suggests that the data points are widely spread out from the mean, and the dataset has significant variability.

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Based on the evaluation of MAPE, R-squared, and sigma squared, it is determined that ARIMA (1,2,1) is a valid model for forecasting the gross domestic product of the Philippines. Therefore, ARIMA (1,2,1) is considered the most suitable ARIMA model for GDP forecasting in the Philippines.

3) Sample Forecast

Figure 4.14

Sample Forecast of Gross Domestic Product Time Series (2022-2029)

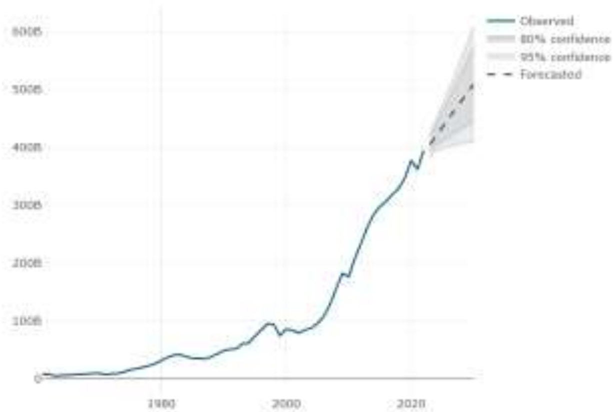

Table 4.20

Sample Forecast of Gross Domestic Product Time Series (2022-2029)

Forecasts:

	Point Forecast	Lo 80	Hi 80	Lo 95	Hi 95
2022	404644900246	392543507594	416746292897	386137417287	423152383204
2023	420379631046	402458363182	438300898910	392971417038	447787845053
2024	434883997773	410219146417	459548849130	397162362809	472605632737
2025	449680815811	417892252648	481469378974	401064403803	498297227819
2026	464408119653	424989694739	503826544567	404122841061	524693398245
2027	479151946668	431637942165	526665951171	406485547522	551818345813
2028	493891846208	437828946391	549954746024	408151039935	579632652480
2029	508632679288	443587093739	573678264838	409154040692	608111317884

Figure 4.14 presents the sample forecast of the Philippines' gross domestic product for the upcoming 8-year period. In the realm of economic projections, the forecasted Gross Domestic Product (GDP) in the Philippines unveils a compelling narrative (see Table 4.20). From 2022 to 2029, the GDP of the Philippines in US dollars escalates progressively, reaching remarkable milestones: 404,644,900,246 in 2022, 420,379,631,046 in 2023, 434,883,997,773 in 2024, 449,680,815,811 in 2025, 464,408,119,653 in 2026, 479,151,946,668 in 2027, 493,891,846,208 in 2028, and finally culminating at a stunning 508,632,679,288. This captivating trajectory unveils a tale of consistent economic growth and resilience.

The forecasted GDP has important implications for the Philippines, including economic planning, policy-making, and decision-making by various stakeholders. The forecasted GDP can provide insights into the future growth and development of the country, influencing investment decisions, government strategies, and overall economic stability.

IMPLICATIONS

The research findings suggest that the gross domestic product in the Philippines is projected to increase until 2029. This indicates a higher chance of job opportunities as people will have more money to spend on goods and services. A growing GDP can attract domestic and foreign investments, fostering innovation and further driving economic growth. Additionally, the increased GDP can lead to higher tax revenues for the government, offering policymakers greater financial means to invest in public infrastructure, social welfare programs, education, and healthcare. However, GDP can affect the inflation rate in different ways. If the increase in GDP results in a greater demand for goods and services without a proportional rise in their supply, it can cause prices to go up, leading to inflation. Conversely, if the GDP growth is accompanied by enhanced productivity and efficiency, it may contribute to price stability or even deflationary conditions.

CONCLUSION

In this study, we investigated the suitability and accuracy of ARIMA models for forecasting the Gross Domestic Product (GDP) in the Philippines. Through rigorous evaluation and analysis, we have reached several important conclusions.

Firstly, based on various selection criteria such as AIC, AICc, and BIC, we have determined that the ARIMA (1,2,1) model is the best-suited model for GDP forecasting in the Philippines. Additionally, diagnostic tests including invertibility, independence of residuals, and the Ljung-Box test have confirmed the accuracy of the ARIMA (1,2,1) model in capturing the patterns and trends of the GDP data.

Furthermore, we assessed the accuracy of the ARIMA (1,2,1) model by employing various metrics. The Mean Absolute Percentage Error (MAPE) revealed an average deviation of approximately 5.38% between the forecasted and actual GDP values, indicating a satisfactory fit of the model. The high R-squared value of 0.92 demonstrated that the ARIMA (1,2,1) model effectively captured around 92% of the variability in the GDP data, signifying a strong relationship between the model's predictions and actual GDP values. Additionally, the significant sigma squared value suggested wide dispersion and variability in the GDP data, reflecting diverse observations influenced by various economic factors.

Based on the evaluation of the MAPE, R-squared, and sigma squared metrics, we can confidently conclude that the ARIMA (1,2,1) model is a valid choice for GDP forecasting in the Philippines. Its accuracy, as indicated by the low MAPE and high R-squared value, demonstrates its ability to capture underlying patterns in the GDP data. However, it is important to consider the significant variability indicated by the sigma squared value when interpreting the model's forecasts. The sigma squared value, which represents the variance or dispersion in the data points, is found to be

3.956e+19. This value suggests a significant variability in the GDP data. The wide spread of the data points from the mean indicates that the dataset encompasses diverse observations, possibly influenced by various economic factors and external influences.

Regarding the forecasted GDP for the Philippines between 2022 and 2029, our analysis suggests a positive outlook with a steady growth trajectory. Starting at 404,644,900,246 in 2022, the GDP is projected to increase annually, reaching 508,632,679,288 by 2029. These forecasts provide valuable insights for economic planning, policy-making, and decision-making by various stakeholders in the Philippines.

In conclusion, based on the evaluation of the ARIMA (1,2,1) model and the forecasted GDP figures, our findings support the suitability and accuracy of the ARIMA (1,2,1) model for GDP forecasting in the Philippines. This model can serve as a valuable tool for economic analysis, policy formulation, and strategic decision-making, contributing to the overall growth and development of the Philippine economy in the coming years.

FUTURE RESEARCH

The researchers recommended incorporating relevant exogenous factors that could impact the GDP of the Philippines into the forecasting model. By including such factors, the model can better capture the complex dynamics influencing the GDP. It is advisable to evaluate alternative forecasting models for GDP to assess their performance and compare them with the ARIMA model. The forecasted GDP values can be utilized to inform policy decisions and plan future economic development initiatives.

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