Print ISSN: 2054-0957 (Print),
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Forecasting Inflation Rate in the Philippines Using Seasonal Autoregressive Integrated Moving Average (SARIMA) Model

Shaina Jennifer T. Corpin, Joshua Nathaniel P. Marbella, Shairamagne Jade J. Kua, Romie C. Mabborang, Chedy T. Lamprea
Pamantasan ng Lungsod ng Maynila

doi: https://doi.org/10.37745/ejcsit.2013/vol11n21336 Published June 1, 2023

Citation: Corpin S.J.T.,Marbella J.N.P., . Kua S.J.J., Mabborang R.C., Lamprea C.T. (2023) Forecasting Inflation Rate in the Philippines Using Seasonal Autoregressive Integrated Moving Average (SARIMA) Model, *European Journal of Computer Science and Information Technology*, Vol.11, No.2, pp.13-36

ABSTRACT: *The Philippines has experienced a long period of rapid economic growth. However, inflation has now become a major concern, with the Philippines currently experiencing high inflation. High inflation is a threat to strong economic growth, particularly to people's purchasing power. This study aims to predict the inflation rate in the Philippines using Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The historical data on the inflation rate of the Philippines, comprising 135 observations from January 2012 to March 2023, was obtained from the official website of the Philippine Statistic Authority (PSA). The study followed the Box Jenkins Methodology, which consists of 4 stages: Identification, Estimation, Diagnostic Checking, and Forecasting to develop a SARIMA model. It was then revealed that the best SARIMA model for predicting the inflation rate in the Philippines is SARIMA* $(1,1,1)(0,0,1)_{12}$ *based on the following criteria: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQIC),* σ^2*, and the Highest Log Likelihood. This chosen model has a Mean Absolute Percentage Error (MAPE) of 8.17% which is within the acceptable range of 25%. This shows an indication that the forecast is acceptably accurate. The best SARIMA model was then used to forecast the inflation rate in the Philippines from April 2023 to March 2024, and based on the result of the forecasting, it appears that the inflation rate in the Philippines is expected to decline gradually over the next 12 months, from 6.93% in April 2023 to 4.85% in March 2024. These findings could provide insights that the government can use to make decisions about monetary policies and help the economy of the Philippines to improve.*

KEYWORDS: Box Jenkins methodology, inflation rate, monetary policies, seasonal autoregressive integrated moving average (SARIMA) model.

INTRODUCTION

The Philippines has undergone a prolonged period of robust economic growth, positioning it as one of the emerging economies in the Southeast Asian region. However, the country is currently facing the challenge of high inflation rates, which pose a significant threat to the sustainability of this growth and the purchasing power of its citizens. To mitigate the adverse effects of inflation, accurate predictions of future inflation rates are crucial for policymakers to formulate effective monetary policies and implement measures to stabilize the economy.

This research study aims to address the need for reliable inflation rate forecasting in the Philippines. By utilizing the Seasonal Autoregressive Integrated Moving Average (SARIMA) model, this research endeavors to provide accurate and timely forecasts of the inflation rate, offering insights that can inform decision-making and contribute to improving the country's economy.

Despite the importance of forecasting inflation, limited studies have focused specifically on the Philippines and its unique economic context. While several existing studies have employed SARIMA models to forecast inflation rates in various countries, there is a dearth of research in the Philippine context. Therefore, this research seeks to fill the existing research gap by applying the SARIMA model to historical inflation data from the Philippines.

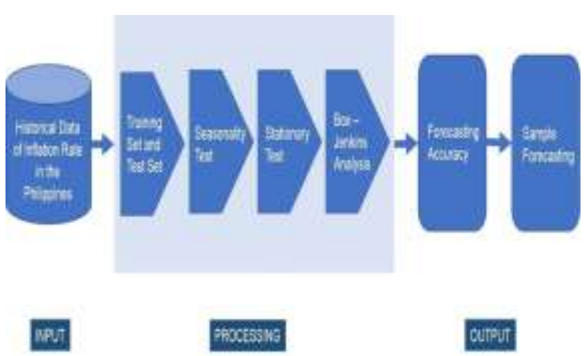
By conducting a comprehensive analysis of the historical inflation data and applying the Box Jenkins Methodology, this study intends to develop a SARIMA model specifically tailored to the Philippine context. The research aims to identify the optimal SARIMA model that provides accurate forecasts, enabling policymakers to anticipate and address inflationary pressures effectively.

The research findings will contribute to the existing body of knowledge by providing insights into the forecasted inflation trends for the Philippines. Moreover, the study's results will be valuable in informing policymakers about potential future inflation rates, facilitating the implementation of appropriate monetary policies to stabilize the economy and enhance the overall economic performance of the country.

The use of modern technologies, specifically programming languages, is of huge advantage in today’s forecasting opportunities. The researchers used Python programming language to perform a rolling forecast of the best SARIMA model after model selection, depending on the criteria in the Box-Jenkins model. Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) showing potential to be an Autoregressive (AR) or Moving Average (MA) model were listed and paired to test whether its values in the SARIMA program gives the best model according to different criteria namely: Akaike Info Criterion (AIC), Bayesian Info Criterion (BIC), Hannan-Quinn Info Criterion (HQIC), σ^2, and the Highest Log Likelihood. These values were compared and weighed to identify which model is the best fit for the Inflation Rate data in the Philippines, dating from January 2012 to March 2023. The Root Mean Squared Error (RMSE), a test that distinguishes how well will the model forecast a variable by averaging the difference between values predicted and the actual values of data, and the Mean Absolute Percentage Error (MAPE), a test that compares forecasting accuracy with different models of time-series by not allowing positive and negative errors from having conflict with one another, were also calculated after splitting the data to check whether the data is within 25% which is the accepted value of error for forecasting.

Conceptual Framework

Figure 1.1: Conceptual Framework for Forecasting Inflation Rate in the Philippines Using SARIMA Model



The data on the inflation rate of the Philippines was retrieved from Philippine Statistics Authority (PSA). The collected data was divided into two categories: the training set and the test set. The seasonality test is required to determine whether the time series data is seasonal on which the appropriate method depends. In addition, a stationary test was conducted to determine whether the data is stationary; if not, differencing will be applied. The Box- Jenkins Analysis was then implemented, which consists of four stages: model identification, model estimation, diagnostic checking, and forecasting. Forecasting accuracy was determined by calculating the difference

Vol.11, No.2, pp.13-36, 2023

Print ISSN: 2054-0957 (Print),

Online ISSN: 2054-0965 (Online)

Website: https://www.eajournals.org/

Publication of the European Centre for Research Training and Development -UK

between the actual value and the forecasted value of the test set in order to identify errors. After verifying minimal error, sample forecasts for the next 12 months from the end of the data were also generated using the best model.

Statement of the Problem

The study aims to predict the inflation rate in the Philippines on a monthly basis using the SARIMA model. It addresses the following research problems:

1. Which SARIMA model works best at predicting the inflation rate in the Philippines?
2. How accurate is the SARIMA model at predicting the inflation rate in the Philippines?
3. What will be the status of the inflation rate for the next 12 months based on the result of the SARIMA model?
4. What are the implications of accurate inflation rate forecasts obtained through the SARIMA model for policymakers, businesses, and the general public in the Philippines?

LITERATURE REVIEW

Box-Jenkins Model and SARIMA Model

The Box-Jenkins Model is a mathematical model that forecasts data ranges based on time series inputs. The Box-Jenkins Model was developed by two mathematicians, George Box, and Gwilym Jenkins. These two mathematicians explored the concepts which make up this model in a 1970 publication entitled "Time Series Analysis: Forecasting and Control." For forecasting purposes, the Box-Jenkins Model can examine several forms of time series data. Its method determines outcomes by comparing data points. The methodology enables the model to create forecasts by identifying patterns using autoregression, moving averages, and seasonal differencing. In addition, the Box- Jenkins Model is best suited for short-term forecasting of 18 months or less. One form of the Box-Jenkins model is the Autoregressive integrated moving average (ARIMA) model (Scott, 2022).

According to Brownlee (2019), ARIMA is one of the most extensively utilized forecasting algorithms for univariate time series data forecasting. However, while the approach may handle trend data, it cannot handle seasonal data, which is a time series with a regular cycle. SARIMA (Seasonal Autoregressive Integrated Moving Average) is an extension of ARIMA that allows for direct modeling of the seasonal component of the series. The notation for SARIMA is given as SARIMA (p, d, q) where p denotes the number of trend autoregression orders, d the number of trend difference orders, q the number of trend moving average orders, P is the number of seasonal autoregressive orders, D the number of seasonal difference orders, Q the number of seasonal moving average orders, and m stands for the number of time steps for a single seasonal period.

Rolling Origin

When selecting the most appropriate forecasting model or method for the data, forecasters typically divide the available sample into two parts: a training set and a test set, according to Svetunkov (2023). A common ratio is 80:20, which indicates that 80% of the data is used for training and 20% is used for testing (Roshan, 2022). The model is then estimated on the training set, and the performance of its predictions is assessed on the test set using some measure of error. It is referred to as "fixed origin" evaluation when this process is used just once. This, however, may give an inaccurate impression of the accuracy of predicting methods. As a result, it makes sense to use a more robust evaluation technique in which the model's performance is assessed multiple times rather than just once. One such technique is referred to as "rolling origin" evaluation (Svetunkov, 2023). Tashman (2000) defines rolling origin as an evaluation approach used in time series analysis. The forecasting origin is repeatedly moved forward by a specified number of observations in this technique, and forecasts are generated from each origin.

Inflation and Its Effects

According to Fernando (2023), the purpose of inflation is to assess the aggregate impact of price changes on a wide variety of goods and services. It enables a singular value to represent **the rise** in the price level of goods and services in an economy over time. Floyd (2023) stated that a general increase in prices over time affects customers' buying power since a given quantity of money will gradually be able to support less consumption. The buying power of consumers decreases whether inflation is 2% or 4%, regardless of the pace. This simply means that they lose it twice as quickly at a higher rate. Indeed, Editorial Team (2022) also stated that as the value of a currency falls due to inflation, people could need more money to meet their necessities. Additionally, as a result of inflation, consumers find it more challenging to save money. Additionally, investors are discouraged from investing in a country when there are unstable economic conditions with high inflation. Moreover, individuals earning the minimum salary are generally affected by inflation. When there is inflation, an employee's minimum salary may appear to be low when the cost of products and services rises. This is due to the fact that the government is unlikely to increase the minimum wage so that it corresponds with the inflation rate.

Aboy, Magalona, & Premacio (2022) believed that inflation has a significant impact on the country's economy. It is important not only to the government but also to the lifestyle of the average individual. It is essential to the decision-making processes of households, businesses, markets, and governments. Given the current significance of inflation to a nation, forecasting becomes more crucial. Accurate forecasting can make decisions more wisely, and preparedness can be strengthened. As a result, the researchers carried out a study that uses a Seasonal ARIMA (SARIMA) framework to model Philippine inflation rates. Monthly data from January 2015 to March 2020 were used for modeling. Based on the analysis, inflation in the Philippines follows a SARIMA $(\mathbf{0}, \mathbf{1}, \mathbf{0})(\mathbf{1}, \mathbf{1}, \mathbf{0})_{\mathbf{12}}$. The model has Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), and Theil Inequality Coefficient values of 1.189417, 1.012582, and 0.089779, respectively. Therefore, the model is adequate since the values are close to zero. It has also been demonstrated to be reliable in predicting inflation rates, with a 24-month forecast accuracy of 98.81058%.

In another study, Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) and Multi-layer Perceptron Neural Network (MLPNN) techniques were used by dela Cruz, Pamaylaon, and Largo (2019) to find a statistical model for forecasting the monthly Philippine inflation rate from January 2015 to December 2016. The data, comprising 336 data points used for this study, was taken from the Philippine Statistics Authority's Philippine Statistics Yearbook and the Bangko Sentral ng Pilipinas. The best model for each technique was determined using 324 of the observations (from January 1988 to December 2014), while the remaining 12 observations were utilized for validation. Based on the ACF and PACF plots, the Philippine Inflation Rate has a seasonal component and an overall decreasing tendency. For the ARIMA technique, R Statistical Software was used, and for the MLPNN technique, Zaitun Time Series. It was discovered that the best model for the ARIMA technique is ARIMA $(\mathbf{2}, \mathbf{1}, \mathbf{0})(\mathbf{0}, \mathbf{0}, \mathbf{1})_{\mathbf{12}}$, and the best model for the MLPNN is ANN$(\mathbf{48}, \mathbf{7}, \mathbf{1})$ with bipolar sigmoid function. The residuals of both models were found to be independent and both to be suitable. To evaluate which of the two approaches is more accurate in predicting the inflation rate in the Philippines, Mean Absolute Error (MAE) was identified. It was discovered that the ARIMA approach performed better than the MLPNN.

With the use of univariate historical data of the Philippines' inflation rates from 1960 to 2017, Delima & Lumintac (2019) were able to come up with a suitable ARIMA(p,d,q) model in forecasting the Philippines' inflation rate for the year 2018 to 2022. The traditional assignment of p, d, and q values using the correlograms' ACF and PACF plot and unit-root test data identification was observed. The best model was selected according to the lowest AIC as well as forecast error statistical tools like RMSE, MAE, and MAPE. The results demonstrated that when AIC is to be observed, ARIMA (1,0,0) is the best-fitted model. The Philippines' inflation rate is projected to be 7.05% by the end of 2018, rising to a maximum predicted value of 8.93% in 2022. With an estimate of 4.60% inflation in 2018, ARIMA (7,0,0) was found to be the most appropriate model using the forecast error criterion. Inflation was expected to be 5.21% over the following 12 months. The researchers believed that the findings of this study could be used by the government as guidance or input for monetary policies and decisions that could aid the Philippines' economy.

Inflation influences all parts of the economy, from customer spending, business speculation, and work rates to taxpayer-supported initiatives, charge strategies, and loan fees. Since it can lower the value of investment returns, it is essential to understand inflation when investing. With expansion rising as of late following quite a while of relative quiet to its most elevated level in forty years, financial backers might profit from realizing the variables driving expansion, the effect on their portfolios, and moves toward consideration as the speculation scene shifts. Pufnik and Kunovac (2006) did a study on short-term forecasting of inflation in Croatia using Seasonal ARIMA, where they found out that the most accurate predictions of CPI developments are acquired by first anticipating the index's components and then aggregating them in the overall index, given a somewhat longer time horizon (three to twelve months) in the seasonal models they constructed. The results of the study imply that the test data should only have a limit of three to twelve months in order for the Seasonal ARIMA Model's forecasting to be more exact and accurate.

Since the growth of inflation affects the money supply and monetary government, banks and institutions started to model and forecast the subject to lower their expenditures and focus on gains in the future as time passes by. In general, forecasting inflation helps both the corporate and private sectors with their financial planning. On a business level, inflation has an impact on the real cost of costs and stock prices. Investors can consequently better identify risks and make hedging investments by forecasting changes. Koop and Korobilis (2012) forecasted the inflation rate of the US using quarterly data based on the generalized Phillips curve. The authors used Dynamic Model Averaging, which is like an SMA Model of a Seasonal ARIMA, where they used the moving average as their reference for forecasting. The results of their study suggest that their models extend conventional approaches by allowing for the set of predictors for inflation to change over time after the investigation of the use of DMA and DMS methods for forecasting US inflation.

Saz (2011) tested the efficacy of SARIMA Models for forecasting the inflation rate of Turkey, where the suggested SARIMA model was created using a methodical modeling approach by the Hyndman-Khandakar (HK) algorithm's stepwise selection process. The study's findings point to a single, superior SARIMA model that accurately and sparingly represents the Turkish inflation process. SARIMA $(0,0,0)(1,1,1)_{12}$, a seasonal autoregressive moving average model with one degree of seasonal integration for the intrinsic stochastic seasonality, one seasonal autoregressive, and one seasonal moving average element, served as the model's illustrative example. Seasonal differencing served as the SARIMA Model in this investigation. When the data still cannot be made stationary despite several stationarity tests, seasonal differencing is applied. The evolution of changes from one season to the next is the seasonal difference of a time series. Seasonal differencing simply uses the value that was recorded during the same season the previous year as the "index" that is removed from each time series value. This is the most fundamental type of seasonal adjustment. Therefore, seasonal differencing often removes the majority of the trend as well as the overt indicators of seasonality from a dataset.

Robert, Mohamed, and Abdel-Fattah (2002) performed a study on the evaluation of a functional time series model for forecasting inflation in Uganda where they explored Box-Jenkins' Auto-Regressive Integrated Moving Average (ARIMA) and Seasonal Autoregressive Integrated Moving Average (SARIMA) methodologies to evaluate the FTS method of forecasting the general CPI where their accuracies are compared and validated using Mean Squared Error (MSE), Root Mean Square Error (RMSE), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC) criteria. The results of their study indicated that the SARIMA model outperformed the ARIMA model based on the MAPE, MSE, and RMSE forecast accuracy, proving that Uganda's general inflation rates had seasonality components. The findings further confirm that the main causes of inflation in the Ugandan economy are the general CPI, international coffee prices, international oil/fuel prices, and currency rates. A relative error metric called mean absolute percentage error utilizes absolute values to prevent positive and negative mistakes from canceling one another out and relative errors to let you compare forecast accuracy amongst time-series models, while the Root Mean Squared Error (RMSE) calculates the typical difference between values that a model predicts and actual values. It gives an estimate of the model's accuracy or how well it can forecast the desired number.

Batini (2004) did research on price stabilization in Nigeria where the author used the historical performance of monetary policy in Nigeria and the comparative benefits of several monetary policy options that Nigeria may use in the future after the numerous operational obstacles that impede the implementation of monetary policy now have been resolved. In this study, it was found that nominal interest rates should be for inflation to stabilize near its low, long-run target rate. A suitable guideline for an explicit inflation objective minimizes volatility between actual inflation and the long-term aim. Price stability reduces inflation volatility, which lowers market uncertainty and interest rates and encourages investment. It helps make the financial system more stable. It promotes stability and social cohesiveness.

Fahrudin and Sumitra (2019) also conducted a study to forecast Bandung City's inflation based on

CPI. The forecasting results were used as a guide for calculating the one-month living expenses of a single worker. In this analysis, the SARIMA method was used to forecast the inflation rate using time series data. The researchers believed that the SARIMA method could produce forecasting results that could track the movement of actual inflation rate data. The researchers were able to select SARIMA$(1,0,1)(1,0,1)_{11}$, the model with the lowest MAD of 0.141, MSE of 0.025, and MAPE 0.42%, based on a comparison of the overall SARIMA models. It demonstrates that the SARIMA method's inflation forecasting results are extremely reliable and accurate. The KHL value generated from inflation predicting calculations is close to actual data, allowing it to be used as a reference for a single worker in need of one month.

Synthesis

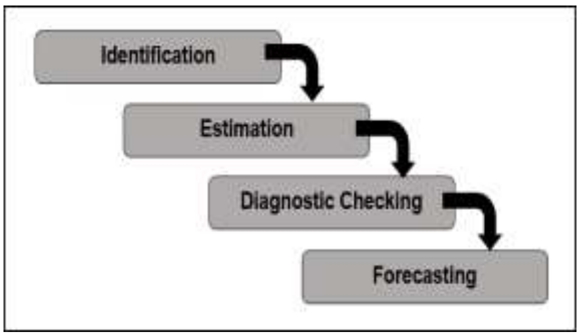
The level restriction of all the research presented and tackled thus far is to find the most appropriate model to improve forecasting techniques through candidate selection. Mostly, the approach of other studies is through using the ARIMA model where they render the data stationary at the first difference and perform the test, after identifying the Autocorrelation Function (ACF) and the Partial Autocorrelation Function (PACF). This study compared the use of the best ARIMA model to the best Seasonal ARIMA model which showed better results with the latter option. The time series must be stationary before using the appropriate procedures in the Box-Jenkins Model. The same forecasting technique uses regression analyses on time series data and is based on the idea that things that happened in the past affect what will happen in the future. The authors of the study took a different approach and performed a rolling forecast of the inflation rate of the Philippines from 2012-2023 using the best SARIMA model. The SARIMA model $(1,1,1)(0,0,1)_{12}$ was found to be the fittest for the rolling forecast. Other studies mostly use ARIMA for forecasting since the data in the country they were experimenting with were non-seasonal and did not proceed with a more complex forecasting representation. After the authors split the data into 80% training and 20% testing, and rendering the data stationary, ACF and PACF values were used to indicate spikes and seasonal spikes for forecasting. The forecasting origin was updated repeatedly on the data, where predictions were generated from each origin. The method made it possible to generate several forecast errors for time series, which improved the researchers' comprehension of the models' capabilities. The analyzed papers were helpful to the researchers since they provided evidence that it is feasible to estimate future market inflation rates. This research used the appropriate methodology to give a thorough performance review to ensure price stability and find answers to issues that may arise in the economy, enterprises, and the country.

METHODOLOGY

Research Design

This study adopts a quantitative research approach to forecast the inflation rate in the Philippines using the Seasonal Autoregressive Integrated Moving Average (SARIMA) model. The research design involves the analysis of historical data and the application of statistical techniques to develop a predictive model.

Figure 3.1: The Box- Jenkins Model



The Box-Jenkins Model was employed in this study to identify the best SARIMA model for forecasting the inflation rate in the Philippines. Box-Jenkins is divided into 4 stages: Identification, Parameters Estimation, Diagnostics Checking, and Forecasting.

Identification – It involves identifying the appropriate order of the seasonal and non-seasonal ARIMA components by observing the correlogram from autocorrelation function (ACF) and partial autocorrelation function (PACF) plots.
Estimation – Various statistical criteria were used to choose the best SARIMA model for a given time series during the estimation phase of the Box-Jenkins model. The Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), Hannan-Quinn Information Criterion (HQIC), σ^2, and log-likelihood were the criteria used for this study.
Diagnostic checking – At this stage, the residuals of the fitted model are checked to ensure that they are white noise.
Forecasting – After the model has been validated, it was used to forecast the test set, assess its accuracy, and forecast future observation.

Data Gathering

The data on the Philippines' inflation rate used in this study was obtained from the official website of the Philippine Statistic Authority (PSA), psa.gov.ph. PSA is the Philippine government's central statistical authority in charge of collecting, compiling, analyzing, and publishing statistical data. PSA adheres to international statistical standards and best practices to guarantee the reliability and accuracy of its data. 135 observations were taken from the PSA's monthly summary inflation report, which covered the period from January 2012 to March 2023.

Data Preprocessing

Splitting of the Data – Data splitting is a crucial step in the forecasting of time series data since it enables the researchers to assess how effectively the selected model predicts new data. The time series data for this study was split into two sets: training set, which contains 80% of the data, and test set, which contains 20% of the data. The train set was utilized to fit the model and generate predictions for each item in the test set.

Seasonality Test – To find out whether the time series data is seasonal, the researchers conducted seasonal decomposition using an additive model which decomposes a time series into its trend, seasonal, and residual components by assuming that the time series can be modeled as the sum of these three components. The seasonality can be detected by visually examining theseasonal component for regular patterns or cycles that repeat at fixed intervals. If the seasonal component exhibits regular patterns or cycles, then it indicates the presence of seasonality in the time series.

Stationary Test – ACF and PACF plot is performed to find out whether a time series is stationary or non-stationary. The researchers also conducted an Augmented Dickey-Fuller (ADF) test to confirm if the times series data is stationary.

H_0: The time series has a unit root. The series is non-stationary.

H_a: The time series has no unit root. The series is stationary.

The hypotheses are tested at 0.05 significance level. If p-value < 0.05, reject the null hypothesis and conclude that the times series is stationary.

Differencing – When the time series appears to be non-stationary, differencing is done to remove the trend and/or seasonal components from the data, making it stationary. Differencing involves subtracting the current observation of the series and the previous observations. The ADF test, ACF, and PACF plot were again performed to confirm stationarity and to determine if additional differencing is required to achieve stationarity.

RESULTS AND DISCUSSION

Plotting Time Series

The Plot of the Inflation Rate

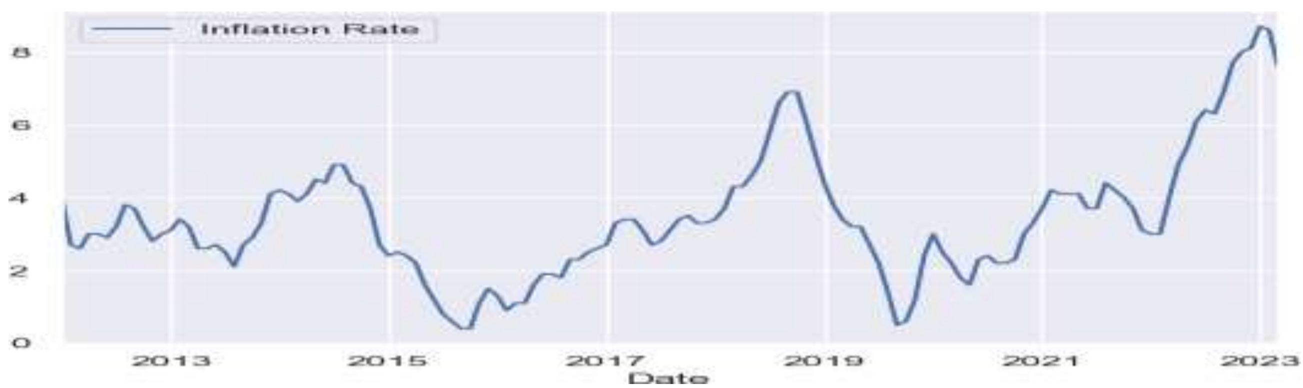
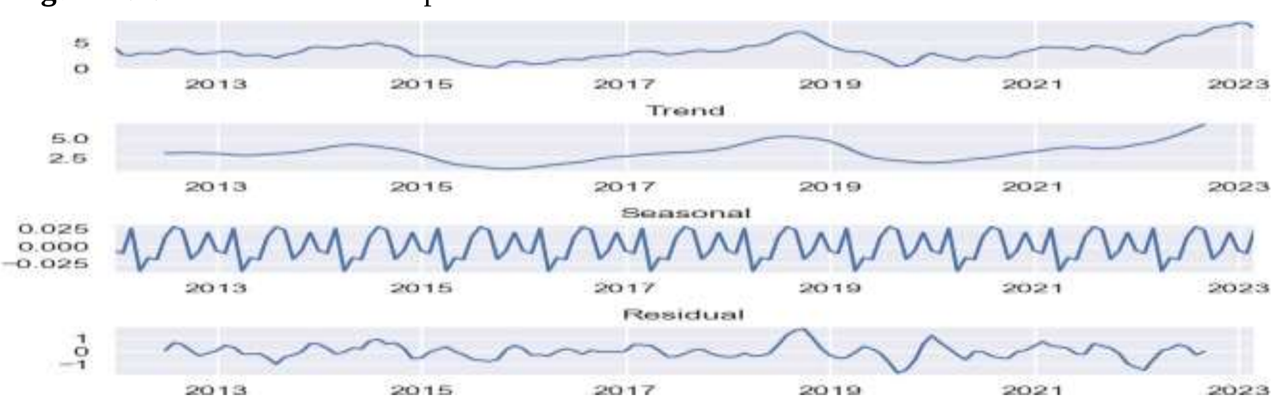


Figure 4.1: The Plot of the Inflation Rate

Figure 4.1 represents a line graph of the time series data of the monthly inflation rate from January 2012 to March 2023, comprising 135 observations. The graph depicts how the inflation rate fluctuates over time. The highest recorded inflation rate since then was 8.7% in January 2023, with 0.4% being the lowest which was in September and October 2015.

SEASONALITY TEST

Figure 4.2: Time Series Decomposition



European Journal of Computer Science and Information Technology
Vol.11, No.2, pp.13-36, 2023
Print ISSN: 2054-0957 (Print),
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Figure 4.2 shows the result of seasonal decomposition using an additive model conducted by the researchers to detect seasonality. It can be observed that the seasonal component exhibits regular patterns or cycles, which indicates the presence of seasonality in the time series. This confirms that Seasonal Autoregressive Integrated Moving Average (SARIMA) model is the appropriate forecasting model to be used in predicting the monthly inflation rate in the Philippines.

STATIONARY TEST

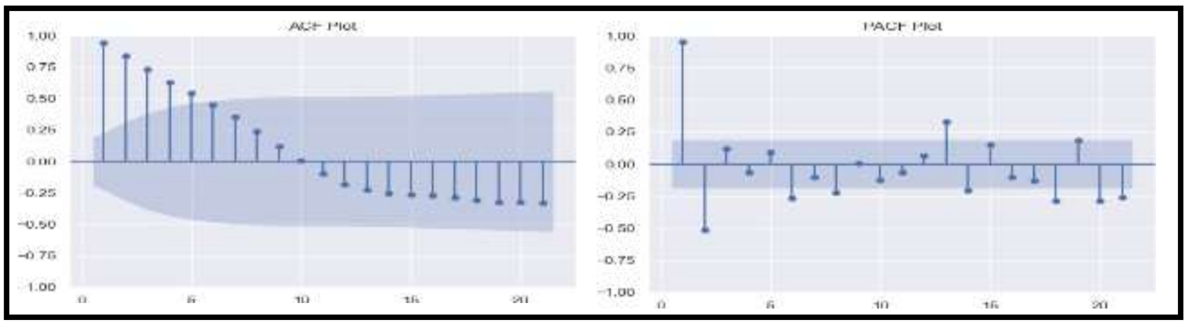


Figure 4.3: Inflation Rate Correlogram

Blue bars on Auto Correlation Function (ACF) and Partial Autocorrelation Function (PACF) plot shown in Figure 4.3 is the error bands or the 95% confidence interval, and any lag within these bars is not statistically significant.

It can be seen above that the ACF plot shows a slow decay as the lag increases, and the PACF plot shows a significant spike at lag 1, and higher lags are significant but decreasing spikes indicating the presence of the trend. These findings signify a non-stationary time series.

Table 4.1: Augmented Dickey-Fuller (ADF) Test

ADF	-2.356269
p-value	0.154461
Number of lags	13
Number of Observations	94.00000
Critical Value (1%)	-3.501912
Critical Value (5%)	-2.892815
Critical Value (10%)	-2.583454

To confirm that the time series is non-stationary, the researchers also conducted an Augmented

European Journal of Computer Science and Information Technology
Vol.11, No.2, pp.13-36, 2023
Print ISSN: 2054-0957 (Print),
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Dickey-Fuller (ADF) Test, and the result shows a p-value of 0.154461 > 0.5 which accepts the null hypothesis confirming that the time series is non-stationary.

Transforming to Stationary: Differencing

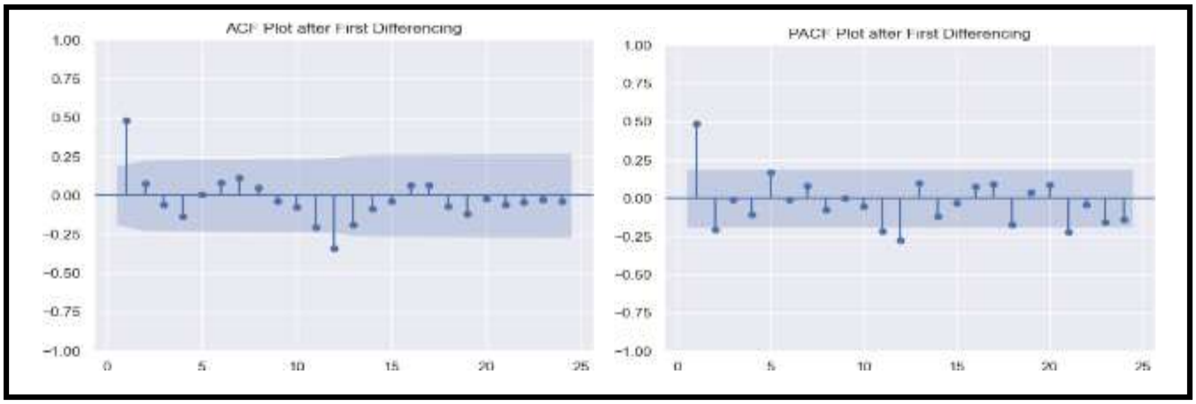


Figure 4.4: Correlogram of Inflation Rate after First Differencing

It can be observed from the ACF and PACF plot that the majority of the lags fall within the confidence interval, which indicates that the differenced time series data already attained stationary.

Table 4.2: Augmented Dickey-Fuller (ADF) Test for Differenced Inflation Rate

ADF	-3.132613582
p-value	0.024231906
Number of lags	12
Number of Observations	94.000000
Critical Value (1%)	-3.501912385
Critical Value (5%)	-2.892815255
Critical Value (10%)	-2.583453861

The result from the ADF test conducted to differenced time series data shows a p- value of 0.024 < 0.05 which rejects the null hypothesis. This concludes that the differenced time series data is now stationary.

Identification

The autocorrelation function (ACF) from Figure 4.4 displays a significant change in the lags 1 and 12, with corresponding values of .480 and -.339, respectively. Lags 1 and 12 embody the possible values for the Moving Average (MA) Component. The partial autocorrelation function (PACF) displays a significant change on the lags 1, 2, 11, 12, and 21, with corresponding values .485, -.206, -.217, -.274, and -.220, respectively. Lags 1, 2, 11, 12, and 21 are the possible values for the Autoregressive (AR) Component. Seasonal spikes at lag 12 in the ACF values of the differenced data indicated a Seasonal Moving Average (SMA) of 1. Seasonal spikes at lag 12 in the PACF values of the differenced data indicated a Seasonal Autoregressive (SAR) of 1.

Therefore, the candidates for Seasonal ARIMA (SARIMA) Models for the Inflation Rate are:

SARIMA $(1,1,1)(1,0,1)_{12}$

SARIMA $(1,1,1)(0,0,1)_{12}$

SARIMA $(1,1,1)(1,0,0)_{12}$

SARIMA $(2,1,1)(1,0,1)_{12}$

SARIMA $(2,1,1)(0,0,1)_{12}$

SARIMA $(2,1,1)(1,0,0)_{12}$

SARIMA $(11,1,1)(1,0,1)_{12}$

SARIMA $(11,1,1)(0,0,1)_{12}$

SARIMA $(11,1,1)(0,0,1)_{12}$

Estimation

Table 4.3: Best Model Determination

SARIMA Model	AIC	BIC	HQIC	σ^2	Log Likelihood
SARIMA $(1,1,1)(1,0,1)_{12}$	82.078	95.442	87.496	0.1096	-36.039
SARIMA $(1,1,1)(0,0,1)_{12}$	80.44	91.132	84.774	0.11	-36.22
SARIMA $(1,1,1)(1,0,0)_{12}$	87.302	97.993	91.636	0.1207	-39.651
SARIMA $(2,1,1)(1,0,1)_{12}$	82.614	98.651	89.115	0.108	-35.307
SARIMA $(2,1,1)(0,0,1)_{12}$	80.885	94.249	86.302	0.1084	-35.442
SARIMA $(2,1,1)(1,0,0)_{12}$	88.416	101.78	93.833	0.1195	-39.208
SARIMA $(11,1,1)(1,0,1)_{12}$	84.226	124.318	100.479	0.0889	-27.113
SARIMA $(11,1,1)(0,0,1)_{12}$	82.402	119.821	97.571	0.0885	-27.201
SARIMA $(11,1,1)(1,0,0)_{12}$	94.296	131.715	109.465	0.1049	-33.148

Vol.11, No.2, pp.13-36, 2023

Print ISSN: 2054-0957 (Print),

Online ISSN: 2054-0965 (Online)

Website: https://www.eajournals.org/

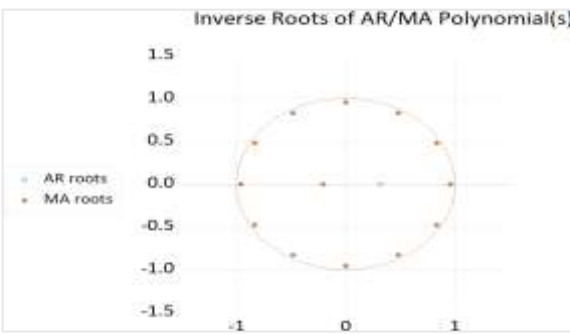
Publication of the European Centre for Research Training and Development -UK

Feasible SARIMA Models were selected by observing ACF and PACF plot from Figure 4.4. Although lag 12 and 21 of PACF values are significant, they are not counted as valid SMA and SAR Models, for they are already in both the seasonal and non-seasonal autoregressive and moving average components. It can be observed from Table 4.3 that the model with the lowest AIC, BIC, and HQIC values is the SARIMA $(1,1,1)(0,0,1)_{12}$ Model. This suggests that the model best fit for forecasting is the SARIMA $(1,1,1)(0,0,1)_{12}$ Model.

DIAGNOSTIC CHECKING (CHECKING OF RESIDUALS)

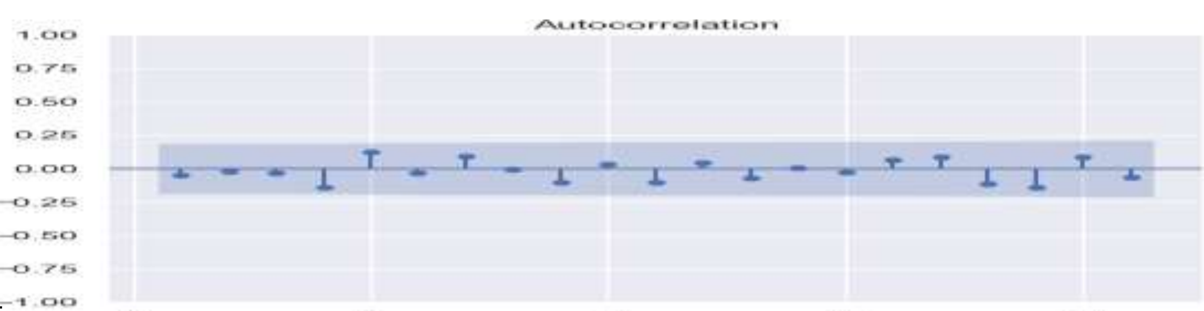
Invertibility

Figure 4.5: Unit Circle for Stable Univariate Process



Upon examining of ARMA structure of the SARIMA model $(1,1,1)(0,0,1)_{12}$, it is seen that the roots were seen within the unit circle. Herewith, the ARMA Structure is concluded as invertible hence the SARIMA model $(1,1,1)(0,0,1)_{12}$ is a good model.

Autocorrelation Plot



4

Figure 4.6: Autocorrelation of Residual

European Journal of Computer Science and Information Technology
Vol.11, No.2, pp.13-36, 2023
Print ISSN: 2054-0957 (Print),
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

As seen in the figure above, points are contained within the interval showing that no outlier has been observed. With this, the model is concluded as efficient and non-bias

Ljung-Box Test

Table 4.4: Ljung Box Test for the Residual of SARIMA $(1,1,1)(0,0,1)_{12}$

lb_stat	lb_pvalue
16.53227	0.739039

The Ljung Box-Test was applied to the residuals to check the independence of the SARIMA $(1,1,1)(0,0,1)_{12}$ model. As the rule states, if the p-value is larger than 0.05, then the model states that the fit is fine and there are no further adjustments. Otherwise, if it shows a lack of fit, then adjustments should be made. Herewith, p-value = 0.739039, which states that the SARIMA model concluded from the best model significantly fit for the data and forecasting could proceed seamlessly.

Forecasting Test Set

After the best SARIMA model has been validated, test forecasting is made to determine how well this model predicts new data.

Table 4.5: Test Forecasts of Inflation Rate

Date	Actual	Forecasted
January 2021	3.7	3.483244
February 2021	4.2	3.938863
March 2021	4.1	4.134331
April 2021	4.1	4.255310
May 2021	4.1	4.285276
June 2021	3.7	3.999154
July 2021	3.7	3.581872
August 2021	4.4	3.771256
September 2021	4.2	3.952268
October 2021	4	3.824047

November 2021	3.7	3.298927
December 2021	3.1	2.871482
January 2022	3	2.699542
February 2022	3	2.611318
March 2022	4	2.767318
April 2022	4.9	4.609661
May 2022	5.4	4.768626
June 2022	6.1	4.874393
July 2022	6.4	6.356446
August 2022	6.3	6.162407
September 2022	6.9	6.440253
October 2022	7.7	7.122825
November 2022	8	7.063962
December 2022	8.1	7.178123
January 2023	8.7	7.957655
February 2023	8.6	7.913370
March 2023	7.6	7.409889

Table 4.5 shows the comparison of the predicted inflation rate for the test set of January 2021 to March 2023 with the actual rate. The accuracy of the result will be evaluated by getting its forecast error.

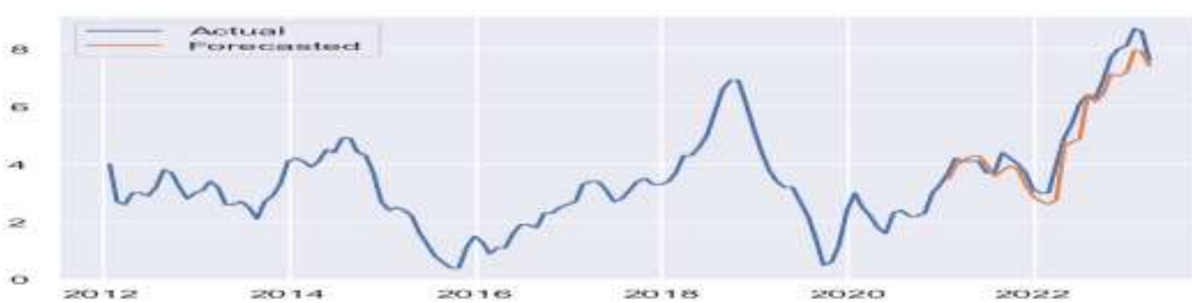


Figure 4.7: The Plot of Test Forecasts of the Inflation Rate

Figure 4.7 illustrates a line graph constructed from the values listed in Table 4.5 comparing the predicted rate of inflation, marked in orange, to the actual inflation rate, highlighted in blue, from January 2021 to March 2023. It can be observed from the graph that the predicted inflation rate is

Print ISSN: 2054-0957 (Print),
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

relatively close to the actual rate, and this will be confirmed by getting its forecast error.

Forecasting Accuracy

Table 4.6: Error Measures for Test Forecast of Inflation Time Series

MAE	0.4339378
MAPE	0.0836730
RMSE	0.5468734

It can be observed from Table 4.6 that Mean Absolute Percentage Error (MAPE) is equal to 8.37%, which is less than the accepted value of 25%. Moreover, values concluded from Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE), which are 0.4339 and 0.5469, respectively, implying that the model performs better.

Sample Forecast

Table 4.7: Sample Forecasts of Inflation Rate

Date	Forecasted
April 2023	6.933335
May 2023	6.578575
June 2023	6.174782
July 2023	5.963299
August 2023	5.844909
September 2023	5.626562
October 2023	5.178055
November 2023	4.934040
December 2023	4.934914
January 2024	4.505322
February 2024	4.545531
March 2024	4.846221

European Journal of Computer Science and Information Technology
Vol.11, No.2, pp.13-36, 2023
Print ISSN: 2054-0957 (Print),
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

The table shows the expected inflation rate from April 2023 to March 2024. The outcome reveals that the inflation rate will continue to decline over the next 12 months.

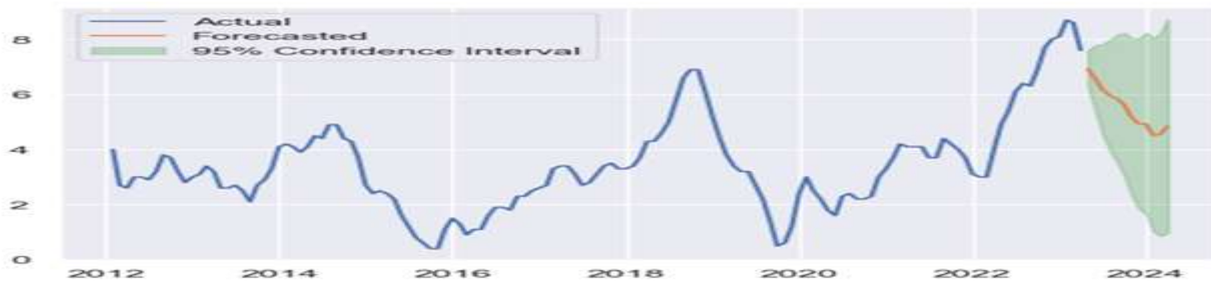


Figure 4.8: The Plot of the Forecasted Inflation Rate

The figure illustrates a line graph generated based on the values shown in Table, with the actual inflation rate highlighted in blue and the predicted inflation rate for the next 12 months highlighted in orange.

IMPLICATIONS

Accurate inflation rate forecasts obtained through the SARIMA model can have several implications for policymakers, businesses, and the general public in the Philippines. The implications and potential impact on various sectors are as follows:

Agriculture: A declining inflation rate can lead to increased profitability for the agriculture sector and an improvement in agricultural growth, which in turn helps to ensure food security for the population. Lower inflation may also result in stable food prices.

Education industry: The education industry may benefit from lower inflation rates. It may result in lower inflation-adjusted expenses for educational institutions and families, making education more accessible. By lowering the cost of education for families and children, this may increase access to high-quality education.

Healthcare Sector: Lower inflation can lower healthcare expenditures, including medicines, equipment, and services. This can make healthcare services more affordable. It may increase public health and medical access as a result.

European Journal of Computer Science and Information Technology
Vol.11, No.2, pp.13-36, 2023
Print ISSN: 2054-0957 (Print),
Online ISSN: 2054-0965 (Online)
Website: https://www.eajournals.org/
Publication of the European Centre for Research Training and Development -UK

Infrastructure Sector: Infrastructure project costs can benefit from a declining rate of inflation. Infrastructure projects may become more practical and economical by controlling construction costs, particularly those for materials and labor. This may support economic growth and infrastructure completion. This helps the government improve infrastructure development goals and improves the economy.

Philippine Economy: If the 12-month predicted inflation rate decreases, it may suggest price stability or a promising future for the national economy. It maintains consumer spending power and business confidence, promoting economic stability. It could foster an atmosphere that encourages investment and economic progress. Lower inflation can lead to price stability, increase consumer buying power, and foster an atmosphere that is favorable for economic growth.

Politics: If inflation is under control and declining, it may favorably affect the political environment and demonstrate competent economic management on the part of the government. It exemplifies efficient economic administration and can increase public confidence in the government's programs, which promotes political stability.

Public Administration and Governance Sector: Lower inflation reduces budget demands on government organizations. It can improve budget and financial management, improving service delivery and governance. It may help the government prioritize public services, infrastructure, and human capital development.

Public Transportation Sector: Lower inflation might stabilize transportation costs, including fuel and operations expenses. It can lower public transportation fares making it more affordable for the commuter.

Social Welfare Sector: A lower inflation rate may help secure the purchasing power of social welfare programs, ensuring that support for vulnerable people continues to be adequate. It lessens the chance that the value of cash transfer programs and subsidies, which are essential for social welfare, would be diminished.

These implications assume that other macroeconomic conditions remain stable. Because of the complexity and interdependence of the economic situation, the actual results may differ depending on a number of factors, including government policies, external shocks, and global economic trends.

CONCLUSION

In conclusion, the tendency of the inflation rate to decline is a positive indicator for the economy since it could increase consumer purchasing power, leading to increased consumption and economic growth. With lower inflation, businesses can plan more confidently. Investors desire steady, predictable inflation rates; therefore, lower inflation attracts foreign investment. Education, transportation, and healthcare services could also become affordable. However, the decreasing inflation rate forecasts do not always mean a straightforward positive indicator because if inflation falls too low, it can lead to deflation, which leads to reduced business profits and increased unemployment, which can all have a negative impact on the economy. Therefore, while the decline in forecasted inflation rates in the Philippines may suggest a period of decelerating inflation, it's important to continue monitoring economic developments and take a comprehensive view of the economy to completely understand the impacts of these changes. Overall, the study may provide insights that the government can use to make decisions about monetary policies and help to improve the Philippine economy.

REFERENCES

Aboy, J. B., Magalona J.R, & Premacio, D.Y. (2022, December 5). *Modelling Monthly Inflation in the Philippines using Seasonal Autoregressive Integrated Moving Average (ARIMA).* Open Access Journals. DOI: 10.4172/JSocSci.8.S2.002

Batini, N. (2004, June 1). *Achieving and Maintaining Price Stability in Nigeria.* International Monetary Fund (IMF). https://papers.ssrn.com/Sol3/papers.cfm?abstract_id=878921

Brownlee, J. (2019, August 21). *A Gentle Introduction to SARIMA for Time Series Forecasting in Python.* Machine Learning Mastery. https://machinelearningmastery.com/sarima-for-time-series-forecasting-in-python/

Dela Cruz,V.P., Pamaylaon G., Largo, F. (2019). *Forecasting the Philippine Inflation Rate Using Box-Jenkins Autoregressive Integrated Moving Average and Multi-Layer Perceptron Neural Network Techniques.* Philippine Statistics Authority. https://psa.gov.ph/sites/default/files/3.2.1%20Forecasting%20the%20Philippine%20Inflation%20Rate%20Using%20Box-Jenkins%20Autoregressive%20Integrated%20Moving%20Average%20and%20Multi-Layer%20Perceptron%20Neural%20Network%20Techniques.pdf

Deima, A.J., & Lumintac, M.T. (2019). *Application of Time Series Analysis for Philippines' Inflation Prediction*. Research Gate. https://www.researchgate.net/publication/333559369_Application_of_Time_Series_Anal ysis_for_Philippines'_Inflation_Prediction

Fahrudin, R., & Sumitra, I. D. (2019). Forecasting Inflation Using Seasonal Autoregressive Integrated Moving Average Method for Estimates Decent Living Costs. *IOP Conference Series: Materials Science and Engineering, 662(2).* https://doi.org/10.1088/1757-899x/662/2/022062

Fernando, J. (2023). *Inflation: What it is, How it Can Be Controlled, and Extreme Examples.* Investopedia.
https://www.investopedia.com/terms/i/inflation.asp

Floyd, D. (2023, March 14). *10 Common Effects of Inflation.* Investopedia. https://www.investopedia.com/articles/insights/122016/9-common-effects-inflation.asp

Indeed, Editorial Team. (2022, October 1). *What Is Inflation? (With Causes, Types, Pros, and Cons).* Indeed, Career Guide.
https://ca.indeed.com/career-advice/career-development/what-is-inflation

Koop, G., & Korobilis, D. (2012). Forecasting Inflation using Dynamic Model Averaging. *International Economic Review, 53(3), 867–886.* https://doi.org/10.1111/j.1468-2354.2012.00704.x

Philippine Statistics Authority (2018, January 5). *Summary Inflation Report Consumer Price Index (2006=100): December 2017.* https://psa.gov.ph/statistics/survey/price/summary-inflation-report-consumer-price-index-2006100-december-2017

Philippine Statistics Authority (2023). *Summary Inflation Report Consumer Price Index (2018=100): March 2023.* https://psa.gov.ph/statistics/survey/price/summary-inflation-report-consumer-price-index-2018100-march-2023

Pufnik, A., & Kunovac, D. (2006). *Short-Term Forecasting of Inflation in Croatia with Seasonal ARIMA Processes.* Working Papers 16, The Croatian National Bank, Croatia. https://ideas.repec.org/p/hnb/wpaper/16.html

Robert, E., Mohamed, A., & Abdel-Fattah, M. (2002). Evaluation of a Functional Time Series Model for Forecasting Inflation in Uganda. *Journal of Statistics Applications & Probability, 11(2), 523–534.* https://doi.org/10.18576/jsap/110213

Roshan, J. (2022, April 4). Optimal Ratio for Data Splitting. *Wiley Online Library, 15(4), 531-538.* https://onlinelibrary.wiley.com/doi/10.1002/sam.11583

Saz, G. (2011, May 20). The Efficacy of SARIMA Models for Forecasting Inflation Rates in Developing Countries: The Case for Turkey. *International Research Journal of Finance and Economics, 62, 111-142.* https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1845643

Scott, G. (2022, August 30). *Box-Jenkins Model: Definition, Uses, Timeframes, and Forecasting.* Investopedia.
https://www.investopedia.com/terms/b/box-jenkins-model.asp

Svetunkov, I. (2023, April 2). *Rolling Origin*. The R Project for Statistical Computing. https://cran.r-project.org/web/packages/greybox/vignettes/ro.html

Tashman, L. (2000). Out-Of-Sample Tests of Forecasting Accuracy: An Analysis and Review.

International Journal of Forecasting, 16(4), 437–450. https://www.sciencedirect.com/science/article/abs/pii/S0169207000000650?via%3Dihub