Application of Time Series Analysis for Philippines' Inflation Prediction

Allemar Jhone P. Delima, Maria Tavita Q. Lumintac

Abstract*: This study established appropriate ARIMA (p,d,q) model in forecasting Philippines' inflation rate for the years 2018 to 2022 using the univariate historical data of the country's inflation rates from 1960-2017. In selecting the best model to be used in forecasting, the traditional assignment of p,d,q value using correlograms' ACF and PACF plot and unit-root test data identification were observed and is selected according to the model with lowest AIC and forecast error statistical tools such as RMSE, MAE, and MAPE. Findings showed that ARIMA(1,0,0) is the best-fitted model when AIC is to observe. The inflation rate in the Philippines is forecasted to be at 7.05% by the end of 2018 whereas the highest predicted value is 8.93% in 2022. Using the forecast error criterion, ARIMA(7,0,0) was identified to be the best fit having a prediction of 4.60% inflation rate in 2018. Looking forward, a 5.21% inflation rate in the next twelve months is projected. The government may use the results of this research as input and or a guide to monetary policies and decisions that may help improve the Philippine economic status.

***Index Terms*: ARIMA, Data mining, Forecasting, Inflation Prediction**

I. INTRODUCTION

Inflation has been a widely and unfavorably known topic discussed in the literature of economics that is most essential for both developing or industrialized country [1]. Inflation, as a unique country experience and a local problem [2], refers to the sustained economy-wide increase in the average prices of commodities, merchandises, and services that is resulted by the drop in a country's currency value. Price stability is depicted if the inflation rate is low, and high otherwise [3]. Inflation is caused by various reasons such as food prices [4], foreign price increase, and also by the rise in the monetary interest rate [5].

The Bangko Sentral ng Pilipinas serves as the Philippines' central bank that controls and craft policies on all monetary schemes in the country. These policies influence the dynamics of wage and commodity price in the entire nation [6].

The inflation rate is indeed an essential indicator of central banks' performance. Therefore, inflation forecasts are considered as important variables where policies with regards to monetary decisions are based. Aside from being an import variable for monetary policy decision making, it is one of the most-talk-about topics in the national macroeconomic policy debate [7].

Inflation prediction and determination display vast array in economic and technological literature. Forecasting, as one of the major points in econometric modeling, has two types. One is the famous statistical forecasting which can be based on historical data and the other one which is the economic forecasting that can be based on multivariate models, i.e., univariate models and multivariate models, respectively [8].

There is a continuous increase in the analysis of inflation in the past decades, therefore allowing different possibilities of extracting knowledge in it using different perspectives.

One of the famous methods in extracting interesting patterns and knowledge in data is called data mining [9], [10]. Data mining analytics such as neural network, classification, clustering, decision trees, time series analysis and more have become standard practice in disciplines such as business intelligence, sciences, finance, government, economics, and marketing. The use of such techniques will also impact social sciences and humanities in general [11].

This paper implemented the traditional ARIMA methodology, a type of time series analysis model, in predicting Philippines' inflation rate for years 2018-2022 using the historical univariate data of Philippines' yearly inflation from years 1960 to 2018. Various ARIMA models were observed, and the best model that will be used in predicting the inflation rate is selected from it.

II. RELATED LITERATURE

A wide academic and empirical literature on inflation and inflation-related researches are prevalent. A study in [12] examined the behavior of month-on-month (m-o-m) inflation and used applicable autoregressive-moving average (ARMA) model. Findings showed that adoption of BSP's inflation targeting policy was successful in anchoring inflation as its rate was characterized as mean-stationary by the time of adopting the inflation targeting policy.

On the other hand, a paper in [7] compared the performance of factor models, vector auto regression, and autoregressive integrated moving average models in predicting 12 months horizon in Austrian harmonized index of consumer prices and other sub-indices in determining the source of inflation. The result showed that with the type of datasets and attributes they used, it turned out that factor models displayed the highest predictive accuracy used in forecasting sub-indices and that it can be improved if combined with other results of the other models.Meanwhile,

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forecasting inflation rate in Pakistan was done using Box Jerkins approach. The dataset used to forecast inflation was the historical data of price consumer index from years 1961-2012. The result showed that ARIMA(1,1,1) model was used to forecast the inflation for the year 2013 has a rate of 8.83% [13]. Moreover, a study in [14] used ARIMA(1,1,1) in modeling inflation rate in Botswana using the historical data of price consumer index from years 2001-2011. The incorporation of ARCH/GARCH model was observed as an improved result was depicted. The result showed that both ARIMA(1,1,1) and ARIMA(1,1,1) with GARCH (1,2) performed well in forecasting as their results in the 95% interval covered the actual price consumer index.

Further, in [15], ARIMA models for forecasting Bangladesh's inflation was observed. The result showed that ARIMA(1,0,0) is the most accurate model to forecast the inflation for five years having predicted an inflation rate of 4.40% in 2016 with a slightly increased rate in the next consecutive years.

Furthermore, the ARIMA(1,2,1) model was used in predicting Sudan inflation rates. The result showed that there is a forecasted increase in Sudan's inflation in the years 2017-2026 based on the historical data used, which is from years 1970-2016 [16]. Additionally, a study predicting inflation rates in Nigeria for the year 2017 was realized using ARIMA(1,2,1) model as this model was found to be the best based on the AIC, AICc and BIC statistical criteria. The forecasted value revealed that there is a predicted increase in the inflation rate in Nigeria, following the 95% confidence interval [17].

III. METHODOLOGY

A. Datasets

This study used Autoregressive Integrated Moving Average (ARIMA) model to forecast the inflation rates in the Philippines for the year 2018-2022 using the univariate historical data of Philippines' inflation rate from years 1960-2017. The datasets were obtained from the Philippine Statistics Authority, Trading Economics, and Banko Sentral ng Pilipinas.

B. Autoregressive Integrated Moving Average

The Autoregressive Integrated Moving Average model is used to forecast values in a time series manner through historical data and a series of errors' linear combination. The equation of the model is:

Error! Reference source not found. (1)

where the time index is represented by *t*, and the backshift operator as B, **Error! Reference source not found.** for autoregressive (AR)(p), **Error! Reference source not found.** for moving average (MA)(d), and **Error! Reference source not found.** for non-seasonal (I)(d) in the ARIMA(p,d,q) model and random shocks represented by **Error! Reference source not found.** [18].

C. Correlogram

The correlogram is a medium to graphically represent the value of the Autocorrelation Function (ACF) which is the moving average MA(q) of the model and autoregressive in the form of Partial Autocorrelation Function (PACF) which is the AR(p) of the model denoted as:

Error! Reference source not found. (2)

where **Error! Reference source not found.** denotes the ACF coefficient in lag *k*, and the observed period is expressed as *t*, while observation in period *t* is denoted by **Error! Reference source not found.**. The mean is denoted by **Error! Reference source not found.** , and lastly, observation in t-k is expressed as **Error! Reference source not found.** [18].

D. Akaike Information Criterion (AIC)

In [14], AIC was used to choose a better model of ARIMA(p,d,q) in forecasting. The model is denoted as:

Error! Reference source not found. (3)

where **Error! Reference source not found.** denote the estimates of squared residuals of the ARIMA. The size of observations within samples is represented by *T* and *n* for the parameters estimated. It is said that the model with the lowest AIC is better and should be used.

E. Forecast Evaluation

In [19], forecast evaluation was done using the various forecast error statistical tools which are modeled as follows:

Root Mean Squared Error (RMSE) (4)

$$R.M.S.E. = \sqrt{\sum_{t=T+1}^{T+h} (\hat{y}_t - y_t)^2 / h}$$

Mean Absolute Error (MAE) (5)

$$M.A.E. = \sum_{t=T+1}^{T+h} |\hat{y}_t - y_t| / h$$

Mean Absolute Percentage Error (MAPE) (6)

$$M.A.P.E. = 100 \times \sum_{t=T+1}^{T+h} \left| \frac{\hat{y}_t - y_t}{y_t} \right| / h$$

where the sample of the forecast is **Error! Reference source not found.** and **Error! Reference source not found.** denotes the actual value together with **Error! Reference source not found.** which is the forecasted value within the period *t*. It is mentioned that the smaller the value of the error, depicts a better model for forecasting ability.

IV. RESULTS AND DISCUSSION

The study was anchored on the concept of [17] but differed in the model as identified from training the datasets.

The experimental result for forecasting inflation rates in the Philippines using ARIMA Algorithm was implemented in R Studio using R Language. The graphical representation for correlogram was obtained using GRETL Software. In order to come up with an optimal ARIMA(p,d,q) model to be used in forecasting, the ACF and PACF must be observed as well as the stationarity of the data. After each test, results are recorded and are indexed in the table to compare each corresponding results visually. Fig. 1 shows the time series plot of Philippine inflation rates from the year 1960-2017.

A. Graphical and Statistical Methods

Fig. 2 depicts the correlogram plot of both moving average (MA)(q) and autoregressive (AR)(p) models denoted by ACF and PACF, respectively for lags 1 to 15. The figure can be interpreted as the spike of ACF do not decay to zero unlike the spikes of PACF which quickly decay to zero. This denotes an autoregressive (AR)(p) process while moving average (MA)(q) component is turned to zero. Meanwhile, the p-value of the differenced data is equal to 0.0001 so we reject the null hypothesis of the unit root. So d in the ARIMA(p,d,q) model is equal to zero.

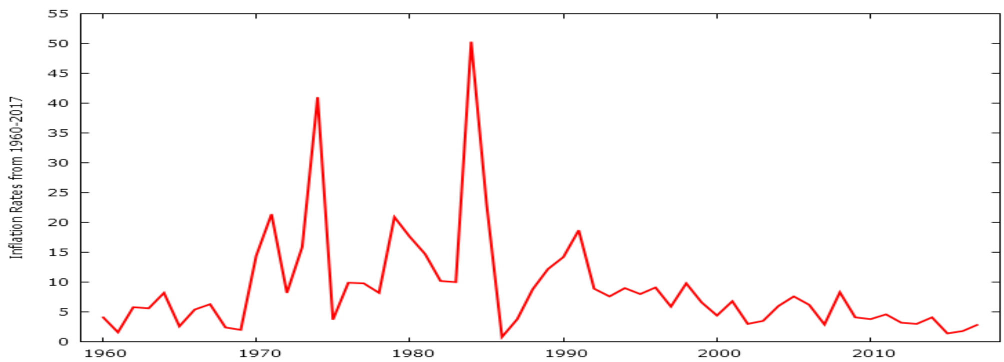

Fig. 1. The plot of Philippines' inflation rates from the year 1960-2017

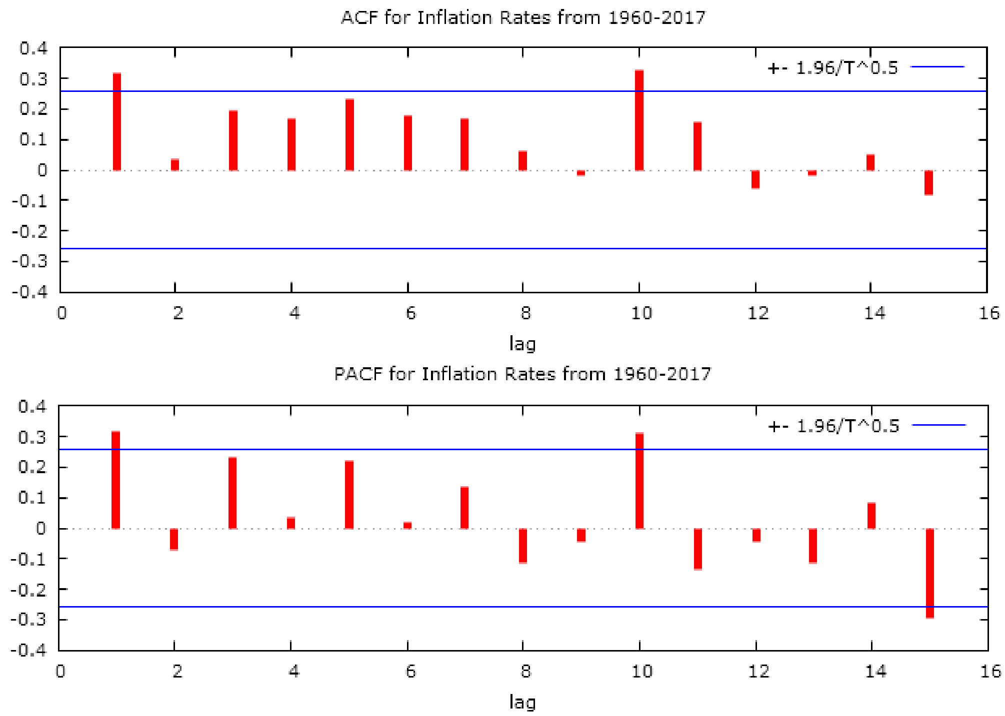

Fig. 2. The plot of ACF and PACF of inflation rates.

The initial possible model to be used is now either ARIMA(1,0,0), (2,0,0), (3,0,0), (4,0,0), (5,0,0), (6,0,0), (7,0,0), (8,0,0) ,(9,0,0) ,(10,0,0) ,(11,0,0), and (12,0,0) but will depend as to which model has the lowest Akaike Information Criterion (AIC) and forecast error evaluation.

Table 1. ARIMA model order selection using AIC

ARIMA Model	Log Likelihood	AIC

**** 1,0,0 ****	**-204.79**	**415.59**
2,0,0	-204.66	417.33
3,0,0	-203.08	416.17
4,0,0	-203.03	418.06
5,0,0	-201.53	417.05
6,0,0	-201.49	418.98
7,0,0	-200.85	419.70
8,0,0	-200.6	421.21
9,0,0	-200.58	423.16
10,0,0	-197.57	419.15
11,0,0	-197.24	420.47
12,0,0	-197.15	422.31

Table 2. ARIMA model order selection using forecast error evaluation

ARIMA Model	RMSE	MAE	MAPE	MASE
1,0,0	8.25734	4.894173	108.1174	0.8575711
2,0,0	8.238096	4.916713	105.0682	0.8615205
3,0,0	8.005526	4.954888	95.35074	0.8682097
4,0,0	7.997172	4.955867	94.69344	0.8683813
5,0,0	7.774946	4.678554	85.94786	0.8197897
6,0,0	7.769755	4.618543	85.09686	0.8092743
7,0,0	**7.122695**	**4.425908**	**81.39852**	**0.7755203**
8,0,0	7.637166	4.439781	83.89896	0.7779511
9,0,0	7.633957	4.49484	85.228	0.7875988
10,0,0	7.190662	4.54428	82.06365	0.7962617
11,0,0	7.142519	4.577564	83.6508	0.8020939
12,0,0	7.130545	4.554218	82.05142	0.7980031

As shown in Table 1, the ARIMA(1,0,0) appeared to be the statistically appropriate model to forecast the inflation based on the AIC. Meanwhile, it is gleaned in Table 2 that ARIMA(7,0,0) has the lowest error values based on forecast error evaluation statistical tools.

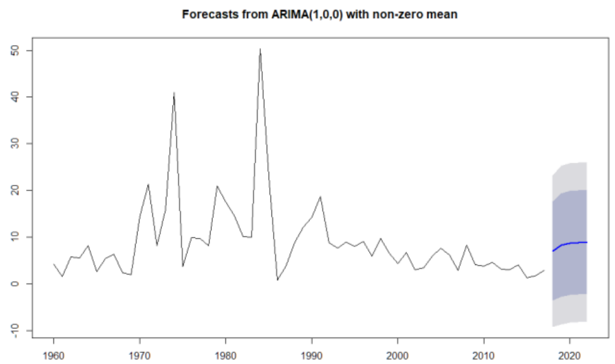

Fig. 3. Forecasted inflation for 2018-2022 using ARIMA(1,0,0)

Table 3. Forecasted value of inflation with a 95% interval

Year	Forecast	Lo 95	Hi 95
2018	7.051026	-9.133063	23.23512
2019	8.356701	-8.609112	25.32252
2020	8.767392	-8.273814	25.80860
2021	8.896572	-8.152075	25.94522
2022	8.937204	-8.112178	25.98659

Fig. 3 showed the plot of forecasted inflation using the ARIMA(1,0,0) model, which has the lowest AIC value. It is evident in Fig. 3 that there is a slight increase in the trend of forecasted inflation rates for the year 2018-2022. The highest forecasted inflation rate of 8.93% is expected in 2022. On the other hand, Table 3 showed the specific value of predicted inflation rates with 95% confidence interval.

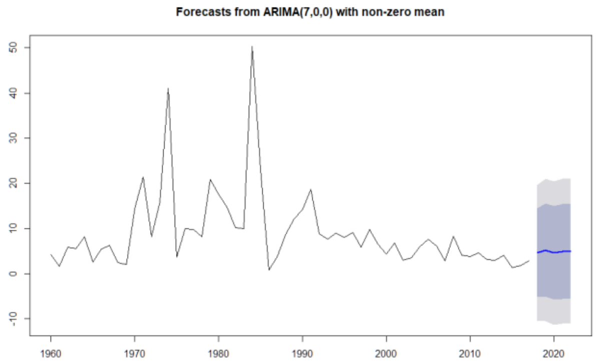

Fig. 4. Forecasted inflation for 2018-2022 using ARIMA(7,0,0)

Table 4. Forecasted value of inflation with a 95% interval

Year	Forecast	Lo 95	Hi 95
2018	4.600281	-10.43793	19.63849
2019	5.219721	-10.56228	21.00172
2020	4.615383	-11.25520	20.48597
2021	4.934603	-11.08459	20.95380
2022	5.099671	-10.98232	21.18166

Fig. 4 showed the forecasted inflation using ARIMA(7,0,0), which is the model that best fit according to the forecast error evaluation criterion. An increase in inflation is depicted from 2018-2019 and a slight decrease in the succeeding years until 2022. The specific value of inflation for the next five years having a 95% confidence interval is showed in Table 4.

V. CONCLUSION

In this paper, an attempt to come up with an optimal ARIMA(p,d,q) model to forecast the inflation rate of the Philippines for the year 2018-2022 was done. The use of time series analysis, particularly the ACF, PACF, stationary properties of the data, AIC, and forecast evaluation criteria were instrumental in coming up with the best-fitted model to forecast the inflation rates. Results showed that the best ARIMA model to be used based on AIC criterion is the ARIMA(1,0,0) while ARIMA(7,0,0) was determined to be the best fit when the forecast evaluation criteria such as RSME, MAE, and MAPE are to be considered. Using ARIMA(1,0,0) model, the forecast shows a slight and steady increase for the next five years with an expected inflation rate of 7.05% at the end of this quarter while an increasing and decreasing trend in inflation is depicted using ARIMA(7,0,0) model with the highest inflation expected in 2019.

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