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FORECASTING THE PHILIPPINE INFLATION RATE USING BOX-JENKINS AUTOREGRESSIVE INTEGRATED MOVING AVERAGE AND MULTI-LAYER PERCEPTRON NEURAL NETWORK TECHNIQUES

by

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Forecasting the Philippine Inflation Rate Using Box-Jenkins Autoregressive Integrated Moving Average and Multi-Layer Perceptron Neural Network Techniques

Victor Paul J. dela Cruz[1 2], Geoffrey A. Pamaylaon[1 3] and Fe F. Largo, MSc[4]

ABSTRACT

This study was conducted to find a statistical model in forecasting the monthly Philippine Inflation Rate from January 2015 to December 2016 using Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) and Multi-layer Perceptron Neural Network (MLPNN) techniques. The data were retrieved from Bangko Sentral ng Pilipinas and Philippine Statistics Yearbook published by the Philippine Statistics Authority. There are 336 data points where 324 (from January 1988 to December 2014) of the observations were used to identify the 'best' model of each technique and the remaining 12 were used for validation. Philippine Inflation Rate exhibits a decreasing trend in general and has a seasonal component based on the ACF and PACF plots. R Statistical Software was utilized for ARIMA technique while Zaitun Time Series was used for MLPNN technique. It was found that $ARIMA(2,1,0) \times (0,0,1)_{12}$ is selected as 'best' model for ARIMA technique and $ANN(48,7,1)$ with bipolar sigmoid function is selected as 'best' model for the MLPNN. Both models were found to be adequate and their residuals were uncorrelated. Mean Absolute Error (MAE) was utilized to compare which of the two methods is better in forecasting the Philippine Inflation Rate. It was found out that ARIMA technique is a better technique compared to the MLPNN.

KEYWORDS

Inflation, Autoregressive Integrated Moving Average (ARIMA), Multi-Layer Perceptron Neural Network (MLPNN), Autocorrelation Function (ACF), Partial Autocorrelation Function (PACF) and Akaike Information Criterion (AIC)

INTRODUCTION

Inflation is one of the biggest issues not only for macroeconomics but also for government across the world. It affects the global trade market and their economic performance. It is also one of the factors affecting the contract price in the world market such as the price of the crude oil (Labonte, 2011). Government in every country makes the economic and monetary policies to control the inflation. According to Labonte (2011) and Chamberlin (2004), inflation is defined as a sustained or continuous rise in the general price level especially goods and services utilized with Consumer Price Index or CPI. Kennoh (2016) also added that the inflation could loss purchasing power and it also serves to transfer money from savers and investors to debtors.

According to McMahon (2014), forecasting the inflation rate is critical for financial planning for companies and individuals. Without an accurate gauge of the rate of inflation, forecasting actual expenses accurately would be a tough job. Forecasting the inflation rate is also critical in decision making for stock valuations.

With this, the researchers were motivated to study on Forecasting the Philippine Inflation Rate using Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) Model and Multi-layer Perceptron Neural Network (MLPNN) techniques, for which the researchers will determine the behavior and will identify the best model of the inflation rate in the Philippines.

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This study aims to: (a) identify the characteristic of Philippine Inflation Rate from January 1988 to December 2014; (b) identify the 'best' model for Box-Jenkins' ARIMA Model and MLPNN techniques; (c) identify which of the two technique is better in forecasting Philippine Inflation Rate.

SOME CONCEPTS OF TIME SERIES and ARIMA

Time series is a sequence of observation taken sequentially in time (Box, Jenkins & Reinsel, 1994; Montgomery, Johnson & Gardiner, 1990). It is a type of regression where the independent variable is the time and the dependent variable is the historical data to be forecasted.

ARIMA approach was first popularized by George E. P. Box and Gwilym Jenkins and referred to as Box-Jenkins ARIMA method. It provides a comprehensive set of tools for univariate time series model for identification, parameter estimation and forecasting. Successive values of the time series under consideration or of the input-output data are available for analysis for at least 50 and preferably 100 observations or more should be used to the said method.

The model of the form ARIMA (p, d, q) is

$$\phi(B)(1-B)^d\tilde{z}_t = \theta(B)a_t$$

where $\phi(B)$ is the autoregressive, $\theta(B)$ is the moving average in their backshift notations, d is the number of times differencing was used on the original time series, $\bar{z}_t$ is the dependent variable and a_t is the error term. On other hand, the model of the Seasonal ARIMA form is

$$\Phi_P(B^s)\phi_p(B)(1-B)^d(1-B^s)^D\tilde{z}_t = \theta_q(B)\Theta_Q(B^s)a_t$$

where $\Phi_P(B^s) = 1 - \Phi_1 B^s - \Phi_2 B^{2s} - \cdots - \Phi_P B^{Ps}$, $\Theta_Q(B^s) = 1 - \Theta_1 B^s - \Theta_2 B^{2s} - \cdots - \Theta_Q B^{Qs}$,.

NEURAL NETWORK and MLPNN

According to Stergiou and Siganos (1996), ANN is information processing paradigm inspired by the way biological nervous system, such as the brain. The advantage of ANN technique is that it is capable of deriving meaning from complicated dataset that can be used to extract patterns and detect the complex trends. ANN is also capable of learning tasks based on the data and can create its own representation of the information during learning time.

MLPNN is the most popular type of neural networks in use today. The first and last layers are called input and output layers respectively, because they represent inputs and outputs of the overall network. The remaining layers are called hidden layers. There is currently no theoretical reason to use neural networks with any more than two hidden layers. In fact, for many practical problems, there is no reason to use any more than one hidden layer (Heaton, 2008). Figure 3 illustrates the way in which each neuron in an MLP processes the information.

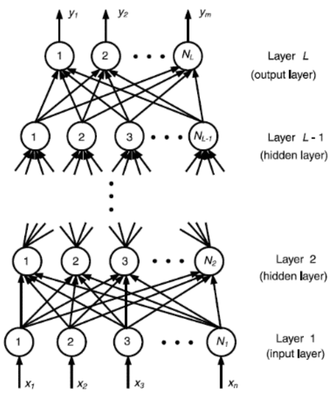

Figure 1. MLPNN Structure (Stergiou & Siganos, 1996)

METHODOLOGY

Figures 2 and 3 elaborate the procedures in obtaining an appropriate time series model using Box-Jenkins ARIMA and MLPNN techniques, respectively. To determine which technique is better in forecasting the Philippine Inflation Rate, the researchers compared the forecast accuracy of the two techniques through Mean Absolute Error (MAE)[5].

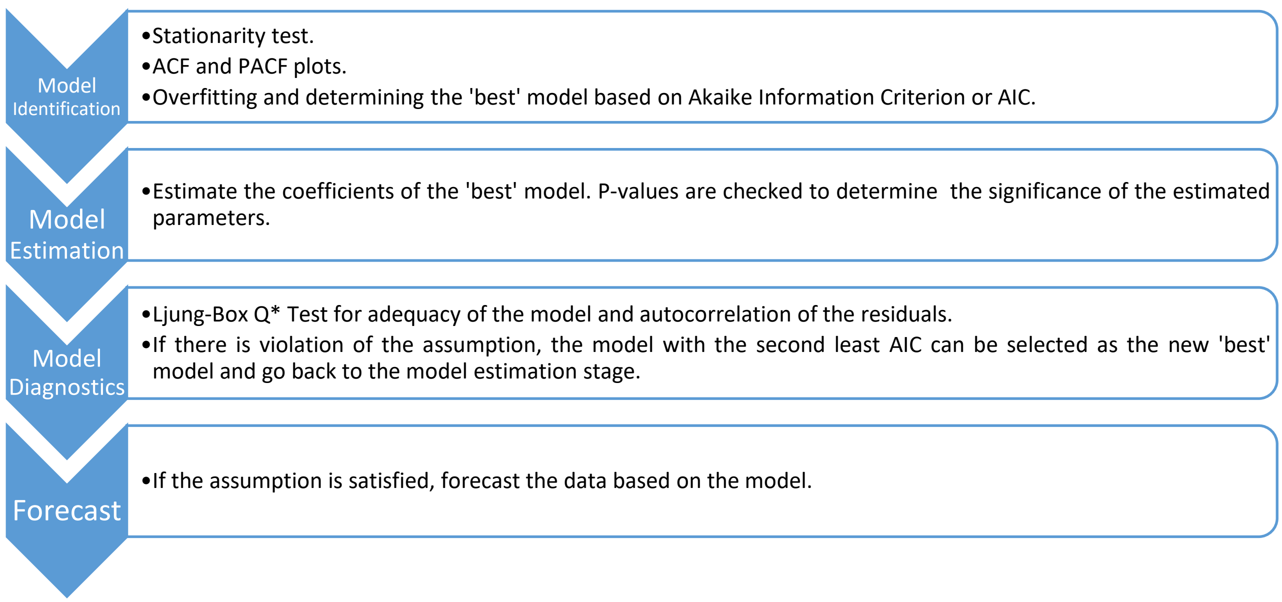

Figure 2. Procedures on Box-Jenkins' ARIMA model technique[6]

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[5] There were two data sources in this paper. The January 1988 to December 2005 dataset was taken from the Philippine Statistics Yearbook published by the National Statistics Office which can be found at the Philippine Statistics Authority Regional Office while the January 2006 to December 2014 dataset was taken from the website of Bangko Sentral ng Pilipinas (bsp.gov.ph).

[6] There were many tests to show series is stationarity. In this paper, the researchers used the Kwiatkowski, Phillipis, Schimdt and Shin (KPSS) Test. In overfitting, Overfitting of the tentative models was made to make sure that no any terms are left out of the model (Burke, 2012). This will be done by adding a parameter on AR and MA terms but not to increase these two terms simultaneously. The smallest AIC indicates the 'best' model of the series. Moreover, in order to determine the best model of the ARIMA, the researchers used R Statistical Software.

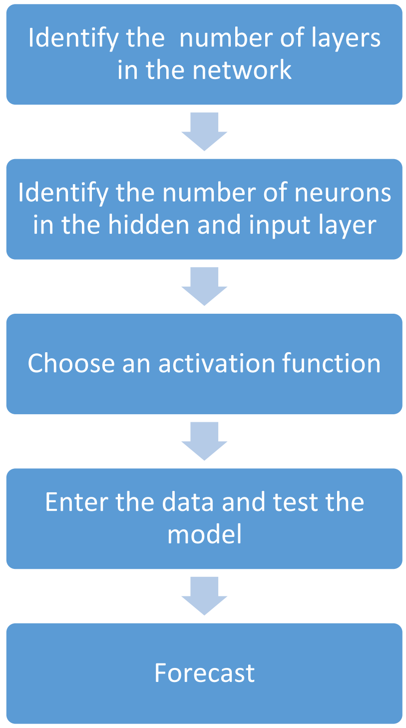


Figure 3. Procedures on MLPNN technique[7]

RESULTS AND DISCUSSION

Figure 4 shows the historical plot of monthly Inflation Rate in the Philippines with 324 observations using R Statistical Software. The plot showed a peak on March 1991 and the dip in August 2009. The average of the Inflation Rate in the Philippines from January 1988 to December 2014 is 7.0% with the variance of 15.2%. Moreover, inflation rate shows a general decrease in its values.

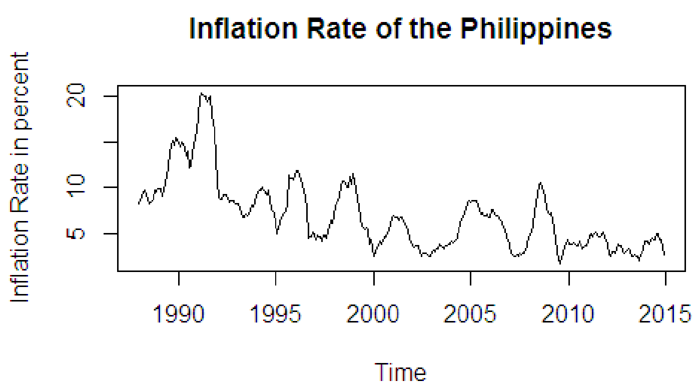


Figure 4. Historical Plot of Inflation Rate in the Philippines

[7] In order to find the number of neurons in hidden layer, the researchers used the Geometric Pyramid Rule proposed by Masters (as cited in Jha, n.d.; Lipae & Deligero, 2012) The formula was given is

$$N_h = \sqrt{N_i N_o}$$

where N_i is the number of input neurons and N_o is the number of output neurons.

Figure 4 also shows that the time series data is not stationary since it is evident in the plot that the series does not fluctuate near its mean value. To formally test whether this series is stationary or not, KPSS test for stationarity was used. The KPSS test is an upper tail test (Kwiatkowski, Phillips, Schmidt, & Shin, 1992). At 5% level of significance, the test statistic value for the Philippine Inflation Rate is 15.968 and the critical value for the test is 0.463. Since the computed value is greater than the critical value, this leads to rejection of H_o and it is concluded that the series has unit root. To make the series stationary, transformation of the series using first differencing was applied.

Figure 5 shows the plot of the transformed data of Philippine Inflation Rate. It can be observed that the transformed series is stationary since it can be seen that most of the transformed data points fluctuate near zero. To check formally whether the transformed series is stationary or not, KPSS test again is obtained.

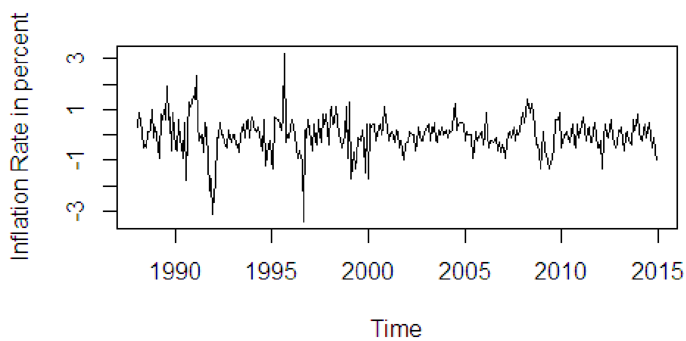


Figure 5. Plot of Transformed Data of Inflation Rate in the Philippines Using First Differencing

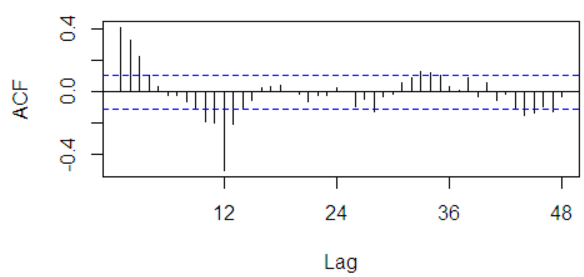
The value of test statistic is 0.0714. This value is less than the critical value which is 0.463 thus, there is insufficient evidence to conclude that the first differenced series has unit root. Therefore, the said transformed series is stationary.

Correlogram plots of the transformed inflation rate were obtained. Figures 6a and 6b show the Autocorrelation Function (ACF) and Partial Autocorrelation Function (PACF) plots, respectively. Critical values for white noise process is $\pm\frac{1.96}{\sqrt{T}}$, where T is the number of observations (Hyndman, 2013). Thus, the series is a white noise if ACF and PACF values are within the interval $[-0.11, 0.11]$ or within the broken blue lines. As shown in these plots, the differenced data exhibits white noise process since majority of the ACF and PACF values belong to the said interval.

Figure 6a shows that the ACF plot of the transformed data is exponentially decayed and has the sinusoidal wave-like behavior although there are spikes at lags 1 and 12 is observed. Figure 6b shows that the PACF of the transformed data cuts-off at second lag. Hence, it is second-order Autoregressive or $AR(2)$ component. Thus, the first tentative model is ARIMA (2, 1, 0).

Aside from spike at lag 12 on ACF plot, large spikes for lags of multiples of 12 (which are 12, 24 and 36) can also be noticed on PACF plot as seen in Figure 6b. This implies that the Philippine Inflation Rate has a seasonal component. Hence, the second tentative model is ARIMA (2, 1, 0) × $(2, 0, 1)_{12}$ and the third tentative model is ARIMA (2, 1, 0) × $(0, 0, 1)_{12}$.

(a)



(b)

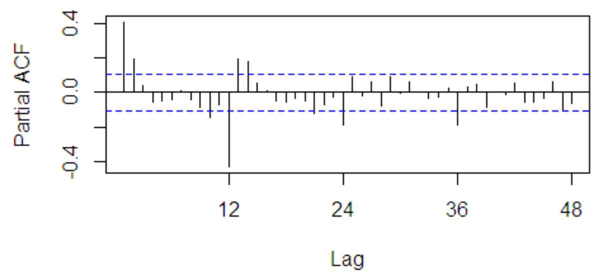


Figure 6. *ACF (a) and PACF (b) plots of Transformed Inflation Rate Using First Differencing*

Table 1 shows the tentative and overfitted models of the Philippine Inflation Rate through ARIMA technique. Also, it shows the Akaike Information Criterion (AIC) which will be used to determine the 'best' model of the said technique. From these models, ARIMA (2, 1, 0) × $(0, 0, 1)_{12}$ has the smallest AIC with the value of 490.22.

Table 1. Tentative and overfitted models of Philippine inflation rate through ARIMA technique

Tentative Models	AIC
ARIMA (2,1,0)	620.9
ARIMA (2, 1, 0) × $(2, 0, 1)_{12}$	492.56
ARIMA (2, 1, 0) × $(0, 0, 1)_{12}$	**490.22**
Overfitted Models	
ARIMA (3,1,0)	622.38
ARIMA (2,1,1)	622.59
ARIMA (3, 1, 0) × $(2, 0, 1)_{12}$	493.70
ARIMA (2, 1, 1) × $(2, 0, 1)_{12}$	493.95
ARIMA (2, 1, 0) × $(3, 0, 1)_{12}$	494.45
ARIMA (2, 1, 0) × $(2, 0, 2)_{12}$	494.13
ARIMA (3, 1, 0) × $(0, 0, 1)_{12}$	491.54
ARIMA (2, 1, 1) × $(0, 0, 1)_{12}$	491.76
ARIMA (2, 1, 0) × $(1, 0, 1)_{12}$	491.70
ARIMA (2, 1, 0) × $(0, 0, 2)_{12}$	491.78

Table 2 shows the coefficients of ARIMA (2, 1, 0) × $(0, 0, 1)_{12}$, as well as standard errors of the respective estimates, z and p-values. From this table, it is shown that all p-values are less than 0.05. Thus, it is concluded that the estimates of the respective parameters are significantly different from zero.

Table 2. Model estimates of 'Best' ARIMA model

Model	$\boldsymbol{AR}\ (\mathbf{1})$	$\boldsymbol{AR}\ (\mathbf{2})$	$\boldsymbol{SMA}\ (\mathbf{1})$
Estimate	0.3152	0.2007	-0.7005
Standard Error	0.0545	0.0546	0.0439
Z	5.7890	3.6736	-15.9665
p-value	7.081×10^{-9}	0.0002	$< 2.2 \times 10^{-16}$

Ljung-Box Q* Test was used to confirm whether the residuals of the 'best' model are uncorrelated. The number of lags to be obtained is 24 since the 'best' model is seasonal and the number of degrees of freedom for this model is 21 since it has three parameters in the model. The Q* value is 11.603 with p-value of 0.9497. Since 0.9497 is greater than 0.05, which is the level of significance, this implies that there is insufficient evidence to conclude that autocorrelation exists in the residuals of the 'best' model and thus, the said model is adequate.

Figure 7 shows the graphical representation of predicted and actual Inflation Rate in the Philippines. The black mark represents the actual values while the green one is the predicted values (from January 1988 to December 2014) based on the 'best' model. The figure shows that the behavior between predicted and actual inflation rate is almost consistent. At the same figure, the blue mark represents the projected inflation rate from January 2015 – December 2016. The computed values for one-year forecast are shown in Table 3. It shows that the forecasted values are increasing and the confidence interval widens in every step of the forecast.

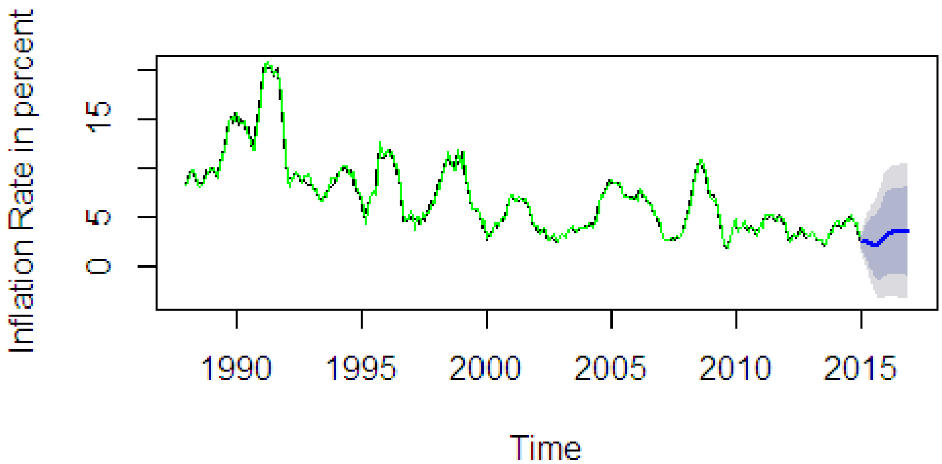


Figure 7. Predicted Values versus Actual Inflation Rate in the Philippines based on 'Best' ARIMA model

Table 3. Forecast and Actual Values of Philippine Inflation Rate using the 'Best' ARIMA Model from January 2015 to December 2016

Month	Actual	Forecast	Lower 95% Confidence Interval	Upper 95% Confidence Interval
January 2015	2.4	2.3998	1.4122	3.3874
February 2015	2.5	2.3724	0.7406	4.0042
March 2015	2.4	2.5012	0.2191	4.7833
April 2015	2.2	2.4899	-0.3867	5.3664
May 2015	1.6	2.2107	-1.2147	5.6361
June 2015	1.2	2.2665	-1.6629	6.1960
July 2015	0.8	1.9909	-2.4038	6.3856
August 2015	0.6	2.0214	-2.8047	6.8474
September 2015	0.4	2.1029	-3.1255	7.3313
October 2015	0.4	2.1756	-3.4301	7.7814
November 2015	1.1	2.5709	-3.3906	8.5325
December 2015	1.5	2.9317	-3.3669	9.2303
January 2016		3.1248	-3.3156	9.5651
February 2016		3.2580	-3.2803	9.7963
March 2016		3.3388	-3.2640	9.9416
April 2016		3.3910	-3.2616	10.0436
May 2016		3.4236	-3.2696	10.1169
June 2016		3.4444	-3.2844	10.1732
July 2016		3.4575	-3.3037	10.2188
August 2016		3.4658	-3.3259	10.2576

September 2016	3.4711	-3.3500	10.2921
October 2016	3.4744	-3.3751	10.3239
November 2016	3.4765	-3.4009	10.3539
December 2016	3.4778	-3.4271	10.3827

The actual inflation rate is generally decreasing from the first to the third quarter of the year 2015 due to slower price increase of food items, as well as the cheaper price of electricity and domestic petroleum products (Bangko Sentral ng Pilipinas, 2015). However, from October 2015, the actual Inflation Rate started to increase for about 0.7%. This is due to higher prices of food items because of the seasonal demand nearing Christmas Season, the adverse impact of typhoons *Lando, Nona* and *Onyok* that visited the country and non-food inflation increases as prices of service-related CPI components accelerate (Bangko Sentral ng Pilipinas, 2015).

For MLPNN process, the identification of the number of neurons in the input layer is heuristic in nature. Thus in this study, the researchers decided to use 12, 24, 36 and 48 neurons in the input layer of four different models. The selection of the number of neurons in the input layer was based on the study of Lipae and Deligero (2012). Moreover, the researchers utilized the Geometric Pyramid rule to identify the number of neurons in the hidden layer which were 4, 5, 6 and 7, respectively. Each of these models was tested with four different activation functions (Semi-linear, Sigmoid, Bipolar Sigmoid, Hyperbolic Tangent) which gave a total of 16 models. Upon running the analysis, the researchers used the default setting in Zaitun Time Series for learning rate, momentum, and maximum number of iterations of 0.05, 0.5, and 10000, respectively. The model with the least Mean Square Error (MSE) and Mean Absolute Error (MAE) will be chosen as the 'best' MLPNN model. As shown in Table 4, ANN(48,7,1) with bipolar sigmoid function as activation function has the smallest MSE and MAE.

Table 4. MSE and MAE of the MLPNN Models for the Philippine Inflation Rate

Model	Activation Function	MSE	MAE
ANN(12,4,1)	Semi-linear	23.50565	3.22651
	Sigmoid	0.44384	0.49983
	Bipolar Sigmoid	0.31846	0.42093
	Hyperbolic Tangent	0.62532	0.61098
ANN(24,5,1)	Semi-linear	20.49447	2.94138
	Sigmoid	0.40946	0.45031
	Bipolar Sigmoid	0.21639	0.35090
	Hyperbolic Tangent	0.59485	0.67263
ANN(36,6,1)	Semi-linear	14.03995	2.76147
	Sigmoid	0.38833	0.47739
	Bipolar Sigmoid	0.16600	0.30624
	Hyperbolic Tangent	0.66066	0.38309
ANN(48,7,1)	Semi-linear	9.52899	2.25771
	Sigmoid	6.83829	0.42277
	Bipolar Sigmoid	**0.16390**	**0.30539**
	Hyperbolic Tangent	0.28461	0.39634

The residuals of the 'best' model are tested for autocorrelation through Ljung-Box Test and yielded a p-value of 0.0561. With this result, it can be concluded that the residuals are uncorrelated.

It can be observed from Table 5 that the ARIMA method has the least MAE with the value of 0.9325 compared to the MLPNN technique with the value of 1.5821. Hence, the ARIMA method is the better technique in forecasting the Philippine Inflation Rate than MLPNN technique.

Table 5. Actual and Forecast Values of 'Best' Model Using Two Techniques

Month	Actual	Forecast based on ARIMA(2, 1, 0) × $(0, 0, 1)_{12}$	Absolute Error	Forecast based on ANN(48, 7, 1) with Bipolar Sigmoid Function	Absolute Error
January 2015	2.4	2.3998	0.0002	2.6291	0.2291
February 2015	2.5	2.3724	0.1276	2.8770	0.3770
March 2015	2.4	2.5012	0.1012	3.3197	0.9197
April 2015	2.2	2.4899	0.2899	3.2358	1.0358
May 2015	1.6	2.2107	0.6107	2.9426	1.3426
June 2015	1.2	2.2665	1.0665	2.9158	1.7158
July 2015	0.8	1.9909	1.1909	2.8220	2.0220
August 2015	0.6	2.0214	1.4214	2.8438	2.2438
September 2015	0.4	2.1029	1.7029	2.8447	2.4447
October 2015	0.4	2.1756	1.7756	3.0189	2.6189
November 2015	1.1	2.5709	1.4709	3.2227	2.1227
December 2015	1.5	2.9317	1.4317	3.4125	1.9125
MAE		**0.9325**		**1.5821**	

The researchers concluded that both ARIMA and MLPNN techniques are appropriate in forecasting the Inflation Rate although ARIMA method is better technique in forecasting Philippine Inflation Rate.

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