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UTILIZING TIME SERIES MODELS AND MACHINE LEARNING FOR CPI FORECASTING IN THE PHILIPPINES

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Abstract

Inflation is a pervasive economic challenge in many developing countries, including the Philippines. The Consumer Price Index (CPI) holds a pivotal role in shaping the nation's inflation dynamics. In the context of the Philippines, the CPI stands as a critical gauge, reflecting the average expenditures of households on essential goods and services. Inflation, characterized by a sustained increase in the general price levels of commodities and services, is influenced by a multitude of factors, encompassing monetary expansion, escalating production costs, and surges in demand for goods and services (Nopirin, 1987). To foster economic stability and make informed policy decisions, comprehending and effectively managing inflation through an in-depth analysis of the CPI becomes imperative.

1. INTRODUCTION

In many developing countries, inflation is a significant macroeconomic concern, and the Philippines is no exception. The Consumer Price Index (CPI) plays a crucial role in determining the nation's inflation rates. In the Philippine context, the CPI serves as a vital indicator, reflecting the average expenses of households for goods and services. Inflation, characterized by a sustained rise in the overall price level of goods and services, can be influenced by various factors, such as an increase in the money supply, rising production costs, or heightened demand for goods and services (Nopirin, 1987). Understanding and effectively managing inflation, through a thorough analysis of the CPI, is imperative for making informed economic policies and ensuring the country's economic stability.

The Philippine Statistics Authority (PSA) highlights that inflation continues to pose a significant threat to the country's macroeconomic stability. In August 2022, inflation in the Philippines declined to 6.3 percent, breaking a streak of five consecutive months of increase. In the report. 4.9 percent average inflation rate for the period of January up to August 2022 stood at, taking into account the inflation figure for August. In comparison, the official inflation rate for August 2021 was 4.4 percent. The ARIMA approach is frequently preferred in many studies for forecasting economic statistics like the Consumer Price Index (CPI). This choice is due to ARIMA effectiveness

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in short-term forecasting. However, it is important to acknowledge that ARIMA may have limitations when used for long-term forecasting, as it could generate constant results (Djawoto, 2010). The time series data initial characteristics, including identifying yearly seasonality and studying autocorrelation functions to uncover underlying patterns. ARIMA has shown effectiveness in making short-term predictions of stock prices, as highlighted in a study by (Adebiyi, Adewumi, and Ayo 2014). While ARIMA is a time series model designed for linear data, it is essential to acknowledge that not all time series phenomena are strictly linearly related. In fact, some phenomena exhibit nonlinear characteristics. To tackle these nonlinear problems, alternative methods are required, as emphasized in the research conducted (Janah, Sulandari, and Wiyono 2014). Artificial Neural Networks (ANNs) offer an alternative method for solving complex problems, as demonstrated in the research conducted (Fitriani, Ispriyanti, and Prahutama 2015). ANNs are designed to simulate the functioning of the human brains neural network, making them capable of handling various data patterns and relationships, as emphasized (Susilokarti, Arif, Susanto, and Sutiarso 2015).

An innovative approach was proposed, integrating ARIMA with multilayer perceptron's and support vector machines to enhance forecasting performance (Santos 2019),. This hybrid system proved to be promising in addressing complex forecasting tasks. The implied relationship between the consumer price index (CPI) and inflation suggests that as the index rises, the likelihood of experiencing higher inflation also increases. This relationship holds several implications, as inflation can have both positive and negative effects. While some levels of inflation can be beneficial for economic growth, excessive inflation can lead to economic instability. Moreover, the rate of inflation influences investors' decisions, impacting their choices in investment products and the timing of their investments. As a result, accurately predicting the CPI becomes crucial for guiding investors and financial institutions in their decision-making processes. Structural inflation, income disparities, and the adverse effects of inflation on low- and middle-income individuals are some of the challenges that arise from fluctuating inflation rates. Current literature predominantly focuses on conventional econometric models, thereby neglecting the exploration of the capabilities of machine learning models, such as artificial neural networks, random forests, and support vector machines, in enhancing the accuracy and robustness of CPI forecasts. This research gap calls for an in-depth investigation into the effectiveness of machine learning techniques as a viable alternative for improving CPI forecasting accuracy, considering their capacity to capture intricate nonlinear patterns, handle large datasets, and potentially mitigate the limitations of traditional methods.

Research Elaborations

The first step involves conducting tests for trend, seasonality, and stationarity, which will be further explained in the methodology section. If the data is found to be non-stationary, appropriate transformations are applied. Moving on to the second step, two models were employed for the study:

ARIMA (Autoregressive Integrated Moving Average) and ANN (Multi-Layer Perceptron's). As indicated in Figure 1, each model follows distinct steps in its application. Once the models are calculated, the next phase involves integrating them and comparing their performance using metrics such as RMSE, MAPE. The objective of this study is to enhance the forecasting capabilities of the conventional ARIMA model by integrating it with ANN, specifically MLPs, for predicting the consumer price index in different regions of the Philippines. Through this hybrid ARIMA-ANN approach, we aim to leverage the strengths of both methods to achieve more accurate and reliable time series forecasts. By combining the ANN's ability to capture intricate non-linear patterns with ARIMA's expertise in modeling linear and autoregressive components, we intend to demonstrate that the hybrid model outperforms the standalone ARIMA model in terms of forecast accuracy and predictive performance. The Consumer Price Index (CPI) plays a vital role in measuring inflation and provides valuable insights into the standard of living and socio-economic development of the population. Accurate modelling of inflation through scientific analysis of goods and services costs is essential for effective control and management of price increases (V. Hostryk & S. Dolinskyi, 2021). (Zahara 2020) highlights the significant role of accurate prediction results in informing government policies and emphasizes the indispensability of economic forecasting in the economic sector.

The Consumer Price Index (CPI) stands as a critical economic indicator, providing valuable data on consumer-paid prices for goods and services. This study utilizes both the ARIMA time series model and Artificial Neural Network (ANN), specifically Multilayer Perceptron's (MLPs), for machine learning model treatment. The data obtained is quantified and evaluated to fulfill the study objectives. The primary goal of this study is to enhance the forecasting capabilities of the conventional ARIMA (AutoRegressive Integrated Moving Average) model by incorporating Artificial Neural Networks (ANN), particularly Multilayer Perceptrons (MLPs). Through this hybrid ARIMA-ANN approach, the study aims to capitalize on the strengths of both methods to achieve more precise and reliable time series forecasts. The hybrid ARIMA-ANN model shows promise as a robust technique in time series analysis, with potential for enhancing forecasting tasks, as previously demonstrated in relevant literature (Lai, 1998; Zhang et al.,2001).

2. RESULTS AND FINDINGS

To verify if hybrid ARIMA-ANN model consistently outperforms the standalone ARIMA model, delivering more accurate and reliable forecasts over an extended forecast horizon. The integration of Artificial Neural Networks (ANN) using Multilayer Perceptron (MLP) in the ARIMA models improved the accuracy of the fitted and forecasted values. RMSE and MSE values for the Hybrid ARIMA-ANN models are lower compared to the original Box-

Jenkins/ARIMA models, validating the goal of enhancing accuracy through ANN integration.

Table 1. Summary Metrics of Box-Jenkins Models

CPI	**Model Type**	**Stationary R-Squared**	**R-Squared**	**RMSE**	**MAPE**	**MAE**	**Normalized BIC**	**Ljung Box Q**	**Sig.**
Philippines	ARIMA(1,1,0)	0.196	0.994	0.379	0.279	0.297	-1.796	18.363	0.366
NCR	ARIMA(1,1,0)	0.196	0.994	0.379	0.279	0.297	-1.796	17.703	0.408
CAR	ARIMA(0,1,1)	0.287	0.994	0.374	0.273	0.287	-1.819	10.431	0.885
Region I	ARIMA(0,1,1)	0.151	0.991	0.461	0.323	0.341	-1.405	10.476	0.882
Region II	ARIMA(0,1,1)	0.181	0.988	0.631	0.443	0.474	-0.775	17.309	0.434
Region III	ARIMA(0,1,1)	0.093	0.99	0.556	0.387	0.419	-1.029	12.037	0.798
Region IVA	ARIMA(0,1,0)	0	0.988	0.551	0.432	0.459	-1.12	20.018	0.332

Region IVB	ARIMA(0,1,1)	0	0.178	0.99	0.618	0.439	-0.815	9.685	0.916
Region V	ARIMA(0,1,0)	0.178	0.99	0.618	0.406	0.439	-0.815	9.685	0.916
Region VI	ARIMA(0,1,1)	0	0.989	0.506	0.361	0.383	-1.288	13.4	0.767
Region VII	ARIMA(0,1,1)	0.17	0.993	0.557	0.42	0.456	-1.025	14.855	0.606
Region VIII	ARIMA(0,1,0)	0	0.137	0.99	0.505	0.359	-1.222	7.606	0.974
Region IX	ARIMA(0,1,0)	0	0.954	0.873	0.589	0.617	-0.199	4.415	1
Region X	ARIMA(0,1,0)	0	0.992	0.447	0.339	0.358	-1.538	18.322	0.435
Region XI	ARIMA(1,1,0)	0.171	0.987	0.553	0.408	0.43	-1.041	6.989	0.984
Region XII	ARIMA(0,1,0)	0	0.989	0.606	0.419	0.446	-0.929	14.74	0.68
Region XIII	ARIMA(1,1,0)	0.139	0.991	0.52	0.363	0.384	-1.163	9.19	0.934
BARMM	ARIMA(0,1,0)	0	0.989	0.453	0.31	0.328	-1.509	12.037	0.845

The ARIMA (1,1,0) for Philippines, NCR, Region XI, and Region XIII model is applied for predicting the monthly consumer price index (CPI). The ARIMA (1,1,0) model indicates that it includes a first-order differencing component (d = 1), which helps in achieving stationarity and correcting the trend, and a moving average (MA) component of order q = 0, implying there is no need for additional moving average terms. The AR component is not explicitly mentioned here, but it is implicitly included as ARIMA (1,1,0) indicates the presence of an autoregressive (AR) component of order p = 1. For Regions IV-A, V, VIII, IX, X, XII, and BARMM, ARIMA (0,1,0) is the suitable model in fitting and forecasting the CPI. This indicates that autoregressive and moving average terms are not needed. For CAR, Regions I, III, III, IV-B, VI, and VII, the SPSS expert modeler applied the ARIMA (0,1,1) for forecasting and fitting the CPI values. This suggests that an Autoregressive Component is not applicable to these time series data. By looking at the results of the modelling phase performed by SPSS Modeler, the 3 different BoxJenkins models were applied widely across different CPI's. This suggests that those Regions that share the same Box-Jenkins models display similar characteristics in terms of the progression and variation of values as shown during the exploratory phase of inspecting the individual CPI's per Region. Moreover, this gives an insight that those Regions with same BoxJenkins model may also expect to have the same properties in terms of their individual economic indicators that one way or another directly or indirectly influence the CPI values.

The models' performances are evaluated using various metrics such as the stationary Rsquared, R-squared, RMSE (Root Mean Squared Error), MAPE (Mean Absolute Percentage Error) Error), MAE (Mean Absolute Error), Normalized BIC (Bayesian Information Criterion), Ljung-Box Q statistic, and significance (Sig.) level. The R-squared values for both stationary and non-stationary data are high, indicating that these models generated by the SPSS expert modeler can explain a significant portion of the variability in the CPI data. The RMSE, MAPE, and MAE values are relatively low, suggesting that the model's predictions are close to the actual values. The Ljung-Box Q statistic checks the residuals' autocorrelation, and the significance. (Sig.) level helps in determining the presence of residual autocorrelation. Lower values of the Ljung-Box Q statistic and higher significance (Sig.) levels indicate better model fit. All Box Jenkins model flagged nonsignificant Ljung-Box Q statistics, suggesting that all of the respective Box-Jenkins models per Regions best fit their respective CPI.

Table 2. Model Specifications and Performance Metrics of the Hybrid Models

CPI	**Activation Function-Hidden Layer**	**Activation Function-Output Layer**	**Error Function**	**Initial Lamda**	**Initial Sigma**	**SSE-Training**	**Relative Error Training**	**SSE - Testing**	**Relative Error Testing**
Philippines	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.137	0.007	0.042	0.006
NCR	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.344	0.02	0.276	0.014
CAR	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.121	0.006	0.037	0.012
Region I	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.141	0.008	0.062	0.012
Region II	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.302	0.018	0.11	0.008
Region III	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.175	0.009	0.145	0.018
Region IVA	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.18	0.009	0.137	0.064
Region IVB	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.184	0.009	0.119	0.016
Region V	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.276	0.015	0.087	0.014

Region VI	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.199	0.011	0.047	0.007
Region VII	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.135	0.007	0.066	0.011
Region VIII	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.206	0.011	0.073	0.01
Region IX	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	1.125	0.062	1.791	0.052
Region X	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.203	0.01	0.031	0.011
Region XI	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.285	0.015	0.117	0.027
Region XII	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.233	0.014	0.114	0.009
Region XIII	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.182	0.009	0.094	0.011
BARMM	Hyperbolic Tangent	Identity	Sum of Squares	0.000001	0.0001	0.291	0.015	0.043	0.012

The input covariate wherein the ANN will be trained are the fitted and forecasted CPI values from the Box-Jenkins models, with the observed CPI per Regions were used as the Dependent Variables. The purpose of integrating an ANN through Multilayer Perceptron in the Box-Jenkins Models is to further lower the RMSE and MSE values which will ensure that the fitted and forecast values are getting closer to the observed values. The ANN model uses the hyperbolic tangent as the activation function in the hidden layer and the identity function in the output layer. It employs the sum of squares as the error function. The model is trained and tested using SSE (Sum of Squared Errors) values and relative errors for both training and testing phases. Several measures, including SSE Training, Relative Error Training, SSE-Testing, and Relative Error-Testing, are used to evaluate the performance of the ANN model. SSE stands for the sum of squared errors (measured separately for the training and testing phases) between the predicted and actual CPI values. Relative error values, on the other hand, provide a thorough assessment of the model's performance by providing information about the precision of the model's predictions during both training and testing.

Table 3. Summary table for Accuracy Metrics-RMSE and MSE

CPI	MSE-ARIMA	MSE-MLP	RMSE-ARIMA	RMSE-MLP
Philippines	80.05909091	79.62490909	47574582	8.923279055
NCR	54.79527273	53.36327273	02382909	7.305016956
CAR	76.18908364	75.07113091	28635841	8.66435981
Region I	87.98545455	86.35763636	80056212	9.292880951
Region II	115.9745455	114.9050909	76914785	10.71937922
Region III	88.13759636	86.02806545	88162566	9.27513156
Region IVA	83.58090909	82.61836364	42259518	9.089464431
Region IVB	148.2607273	147.3107273	17623617	12.13716307
Region V	145.3611691	142.8057291	05658198	11.95013511
Region VI	84.38858182	83.89572909	86325806	9.159461179
Region VII	44.16072727	43.41635455	45353811	6.589108782
Region VIII	80.73597091	79.66956182	85319744	8.92578074
Region IX	46.27472727	46.13424909	02552997	6.792219747
Region X	95.61748182	95.41718545	78419188	9.768172063
Region XI	82.96210545	81.65519091	08353608	9.036326184
Region XII	107.3027527	107.2420213	10.3587042	10.35577236
Region XIII	91.40850545	88.70479945	60779542	9.418322539
BARMM	106.5025	101.7139836	32000484	10.08533508

For the RMSE (Root Mean Squared Error) and MSE (Mean Squared Error) are both commonly used performance metrics to assess the accuracy of predictions or forecasts in various fields, including statistics, machine learning, and data analysis. These accuracy metrics are undeniably sound in evaluating the fitted values generated by the Hybrid ARIMA-ANN models for each Regions' CPI. Upon inspection, it can be clearly seen that the RMSE and MSE values across all MLP (Hybrid ARIMA-ANN) models are relatively lower compared to those of the fitted values from the original Box Jenkins/ARIMA models. These results further validate the primary goal of this analysis wherein the fitted values are to be made more accurate through the integration of ANN in the ARIMA models.

Table 4. Forecasted CPI's from September - December 2022

CPI	**Sep.2022**	**Oct.2022 - ARIMA**	**Nov.2022**	**Dec.2022**	**Sep. 2022 MLP**	**Sept.2022 MLP**	**Nov 2022 MLP**	**Dec 2022 MLP**
	ARIMA Forecast	**Forecast**	**ARIMA Forecast**	**ARIMA Forecast**	**Forecast**	**Forecast**	**Forecast**	**Forecast**
Philippines	116.7	117.1	117.5	117.8	115.7	115.9	116.1	116.3
NCR	113.8	114.2	114.6	114.9	113.1	113.3	113.5	113.7
CAR	116.34	116.68	117.01	117.35	115.96	116.19	116.4	116.62
Region I	117.1	117.4	117.8	118.1	116	116.3	116.5	116.7
Region II	118.4	118.8	119.2	119.6	117.6	117.9	118.1	118.3
Region III	118.58	118.95	119.31	119.67	117.89	118.16	118.41	118.66
Region IVA	116.6	117	117.3	117.7	115.5	115.7	115.9	116.1
Region IVB	121	121.4	121.8	122.2	120.3	120.6	120.9	121.3
Region V	121.75	122.19	122.63	123.07	120.22	120.5	120.77	121.03
Region VI	117.56	117.93	118.29	118.65	116.96	117.19	117.41	117.62
Region VII	112.68	112.96	113.24	113.52	111.44	111.51	111.58	111.64
Region VIII	116.84	117.2	117.56	117.92	115.99	115.99	116.33	116.48
Region IX	115.22	115.54	115.86	116.18	114.09	114.2	114.3	114.39
Region X	117.47	117.83	118.2	118.57	117.37	117.68	117.97	117.97
Region XI	118.51	118.94	119.33	119.72	118.19	118.39	118.57	118.73
Region XII	119.39	119.79	120.18	120.57	118.83	119.13	119.42	119.7
Region XIII	118.58	118.96	119.34	119.72	118.26	118.55	118.83	119.1
BARMM	115.65	116	116.35	116.7	114.52	114.73	114.93	115.12

Using the ARIMA and ANN (Multilayer Perceptron) machine learning models developed, the forecasted Consumer Price Index (CPI) for each region, including the CPI of the Philippines as a whole, was presented. Notably, Regions IV and V exhibited relatively higher CPI values compared to other regions in terms of year-on-year changes. Conversely, Regions IX and NCR showed relatively lower CPI among all regions considered in the analysis. The high CPI values in Regions IV and V can be influenced by various factors, as evident from the raw data and PSA reports. The headline inflation rate at the regional level showed a slightly faster growth in November 2022 compared to October. The housing, water, electricity, gas, and other fuels with 6.7 percent inflation, and food and nonalcoholic beverages with 10.5 percent inflation were primarily the main driven by the acceleration of other commodity groups, it implies that the said commodities were the major contributing factor in the increase of the consumer price index. These commodity groups, along with other fixed expenses, significantly influence the prices of goods and services in these regions. For Bicol Region, the inflation rate in February 2022 slightly increased to 2.8% from 2.7% in the previous month, while inflation in February the previous year was higher at 7.2%. Similarly, in Region V (Bicol region). Based on the raw data provided by the PSA (Philippines Statistics Authority) the following were the main contributor such as housing, water, electricity, gas, and Other Fuels category saw an increase of 5.1% from 4.1%, which also contributed to the upward movement of other commodity groups.

According to the recent report from the Philippine Statistics Authority (PSA) in 2023, the overall downtrend in inflation can be attributed to various factors. One of the primary drivers of this downtrend were housing, water, electricity, gas, and other fuels category as well, which recorded a lower inflation rate of 1.8 percent in April 2023, compared to 5.6 percent in March. This category had a significant impact on the overall decrease in inflation during April 2023. Another contributing factor to the decelerated inflation was the food and non-alcoholic beverages category, which registered an inflation rate of 6.5 percent in April, down from 7.7 percent in previous months. Similarly, the transport category played a role in the inflation deceleration, with an inflation rate of 4.2 percent in April, compared to 6.5 percent in previous periods.

In July 2022, it was the second-lowest inflation in the region for the National Capital Region (NCR). The following commodities, such as housing, water, electricity, gas, and other fuels index, which declined to 3.6 percent from 5.9 percent in the previous month, were significantly responsible for the reduction of inflation in NCR during that time. Indicators of health at 1.3 percent and of personal care and other goods and services at 2.0 percent showed lower annual growth.

Moreover, the factors that influenced the inflation trend were external, such as the world economy and currency exchange. These external factors also played a role in shaping the overall inflation dynamics during the given period.

3. CONCLUSIONS

The study successfully developed and evaluated Hybrid ARIMA-ANN models for forecasting the CPI of the Philippines and its regions for 2022. The models demonstrated promising accuracy in capturing the underlying patterns in the CPI data, providing valuable insights into the economic indicators' influence on CPI values. The integration of ANN in ARIMA models significantly improved the accuracy of the forecasts, making it a suitable approach for future CPI predictions.

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