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Forecasting Inflation, Exchange Rate, and GDP using ANN and ARIMA Models: Evidence from Pakistan

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ABSTRACT

Purpose: The purpose of this study is to specify an efficient forecast model for the accurate prediction of macroeconomic variables in the context of Pakistan.

Design/Methodology/Approach: We particularly investigate the comparative accuracy of Artificial Neural Network (ANN) and Autoregressive Integrated Moving Average (ARIMA) models-based predictions using monthly data of inflation, exchange rate, and GDP from 1990 to 2014.

Findings: According to our findings, the ANN-based forecasted inflation series is more precise as compared to ARIMA-based estimates. On the contrary, the ARIMA model outperforms the ANN model for exchange rate forecasts with the forecasted values being very close to the actual values. Further, ARIMA performs comparatively better in forecasting GDP with relatively smaller forecast error. On the whole, our findings suggest the ARIMA model provides appropriate results for forecasting exchange rates and GDP, while the ANN model offers precise estimates of inflation.

Implications/Originality/Value: Our findings have important implications for the analysts and policymakers highlighting the need to use appropriate forecasting models that are well aligned with the structure of an economy.

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Introduction

In recent years, much emphasis has been placed on gaining access to the reliable prediction of time series data in a wide range of domains. Forecasting has become a critical component of the economy and many analysts, researchers, and policymakers employ forecast models to predict future economic trends. It is even crucial in the context of developing countries such as Pakistan, where policymakers have to deal with frequent fluctuations in macroeconomic factors such as inflation, real output, exchange rates, etc. According to Svensson and Woodford (2004), the central bank is particularly in need of forecasting major macroeconomic factors for better policy decisions. Diegel and Nautz (2021) also contend that forecasts of inflation and real output contain critical information for devising an effective monetary policy. The need to forecast inflation, gross domestic product (GDP), and exchange rates as frequently as possible has become increasingly important for policymakers and other market participants. Huge imbalances in Pakistan's imports and exports lead the currency rate to vary rapidly, making it difficult for investors in the forex market to make a decision. In a similar vein, accurately forecasting inflation and GDP has substantial consequences for economic policymaking and investment decisions.

In order to make the optimal economic decisions, forecasting should be done with considerable caution, and the forecasting models used should be exceedingly efficient. The importance of forecasting models cannot be disregarded in order to have updated macroeconomic projections for implementing modern monetary policy based on market expectations (Woodford, 2000). A great effort has been exerted on anticipating various macroeconomic factors using both qualitative and quantitative models (Shahriar et al., 2021). There are many forecasting models, such as Autoregressive Integrated Moving Average (ARIMA) and the Artificial Neural Network (ANN) models that assist in identifying pure linear and nonlinear patterns respectively (Zhang et al., 2020; Balasmeh et al., 2019; Moghaddam et al., 2019; Matyjaszek et al., 2019). Shahriar et al. (2021) conducted research to forecast atmosphere-related factors and concluded that both ARIMA and ANN-based results are more accurate as compared to other forecasting models. Keeping this in mind, this study employs the ARIMA model and ANN model to forecast major macroeconomic variables such as inflation, GDP, and exchange rate in Pakistan. The current research tries to improve the overall forecasting process by addressing the main question that which forecasting model (ANN or ARIMA) produces better results for predicting macroeconomic variables in the context of Pakistan.

Literature Review

Many dynamic models have been developed to forecast macroeconomic variables in a variety of nations. It is critical to precisely estimate the consequences of numerous shocks to the economy by estimating the future dynamics of important aspects of the economy such as GDP, inflation, and exchange rates. Banerjee, Marcellino, and Masten (2004) investigated forecasting in acceding nations and supported the cautious application of models for forecasting macroeconomic variables. It is argued that ARIMA and ANN models have the adequate predictive capacity (Shahriar et al., 2021; Zhang et al., 2020; Balasmeh et al., 2019). Faisal (2012) argued that the ARIMA model is the best for forecasting inflation in Bangladesh. Salam, Salam, and Feridun (2006) investigated the prediction of inflation in underdeveloped countries and recommended that the simple ARIMA (1) model beats the other forecasting models. Olajide, Ayansola, Odusina, and Oyenuga (2012) suggested the ARIMA model (1,1,1) is the best model for projecting the inflation rate as it has the lowest root mean squared error (RMSE).

On the contrary, Zhang, Patuwo, and Hu (1998) contend that ANN delivers better predicting outcomes because of its nonlinearity function. Panda and Narasimhan (2007) investigated three models based on neural network, linear autoregressive, and random walk and concluded that the neural network model performs better. They further suggested that the ANN-based forecasts are relatively better as they have substantially lower RMSE than that of the forecasts based on ARIMA models. Zou et al. (2007) studied the effectiveness of ARIMA and ANN models for forecasting Chinese grain prices. According to their findings, predictions based on ANN are more precise than that of the ARIMA model. Choudhury, Sarkar, and Mukherjee (2002) investigated engineering workforce forecasts using ARIMA and ANN models and found that the ANN model has a relatively lower average error. Önder, Bayır, and Hepşen (2013) investigated forecasting using ANN in the context of Turkey and concluded that the ANN model outperforms humans in predicting. Kamruzzaman and Sarker (2003) conducted a study on currency rate forecasting and compared both ARIMA and ANN models to predict the Australian dollar and found the ANN model to be more favorable.

Overall forecasting-related literature has inconsistent findings regarding the ARIMA and ANN models in different economies and also in the case of different economic factors within a particular economy. These mixed findings made us intrigued to further investigate these forecasting models in the context of Pakistan. We intend to decipher the predictive power of ARIMA and ANN models in forecasting GDP, exchange rate, and inflation in Pakistan.

Data and Methodology

The main focus of this study is to forecast three macroeconomic factors such as inflation, exchange rate, and GDP. We forecast these three variables using ANN and ARIMA models. We particularly conduct a comparison of these models to identify which model gives better estimates with smaller RMSE. We obtain monthly data on inflation, GDP, and exchange rates from 1990 to 2014. Inflation data is measured by the consumer price index (CPI), the exchange rate of Pakistan is taken in comparison to the US Dollars, and the data on GDP is taken in terms of real output.

Artificial Neural Network (ANN)

ANN is a well-known machine learning technique for analyzing complicated interactions between predictors and predictands (Shahriar et al., 2020). A neural network, often known as an artificial neural network, is a mathematical model inspired by biological brain networks. The working of the ANN model is based upon the neural system of the human body. First, it accepts data and then transforms it by adding some weights to it and then passes this information to the hidden layers which further transform data to give output or the forecast results. A neural network is made up of a network of interconnected artificial neurons that process information using a connectionist approach to computing. The number of layers and neurons at each layer may be simply altered due to its adjustable architecture. Furthermore, ANN does not require any previous assumptions, such as data stationarity, throughout the model-building process.

In an artificial neural network, a neuron is connected to other neurons. It receives information from one neuron and passes it to the other. After receiving the information, the weights are assigned to that information, and then it is passed further. ANN model-based forecasting is carried out in three layers, which are input, hidden, and output layers. The input layer is the raw data given to the network for processing. Then comes the hidden layer whose working depends upon the input units and the weights assigned between the input and hidden units. There can be several hidden layers in a model. The data on various variables is processed in this stage with the help of the following equation,

$$x = \frac{e^{2x} - 1}{e^{2x} + 1} \tag{1}$$

Where x is the variable and −1 to +1 is the limit provided for the data to fall within this range.

In ANN model the data is first normalized between −1 to +1 for the purpose of bringing all the variables into proportion with one another. For that purpose, we employ the following equation,

$$Normalized\ Value = \left(\frac{current\ value - \max value}{\min value - \max value}\right) \tag{2}$$

Then comes the output layer, which results from the hidden layer. It depends upon the hidden layers and the weights assigned between the hidden and output layers. In ANN model data is divide into two parts. The first half data is taken as input data to train the model and the second half is set for forecasting results. We use the following function in order to compare output with the desired values.

$$E = \frac{1}{2} \Sigma_i \Sigma_p \left(t_{ip} - o_{ip}\right) 2 \tag{3}$$

This function compares output function of o_{ip} to a desired function of t_{ip} over the set of p training vectors and i output units.

Autoregressive Integrated Moving Average (ARIMA)

ARIMA is composed of autoregressive (AR), integrated (I), and moving average (MA) models. In order to run ARIMA model using the Box-Jenkins approach, three steps must be considered: identifying, estimating, and forecasting parameters (Tang et al., 2020; Mossad & Alazba, 2015). The identification stage begins with a time series data stationarity check. If stationarity in time series data is not found after the first attempt, the differencing (or power transformation) technique is repeated until non-stationarity is removed. If this procedure is performed d times, the integration order of the model is set to d. ARIMA is then applied to the resulting data.

Lags of differenced series appear in the forecasting equation as 'auto-regressive' terms, lags of estimate error appear as 'moving average' terms, and a time series that must be differenced to become stationary is referred to as an 'integrated' version of a stationary series. We estimate the ARIMA model through the Box Jenkins approach using the following equation,

$$Y_t = \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + \cdots + \varphi_p Y_{t-p} + \varepsilon_t + \theta_{t-1}\varepsilon_{t-1} + \theta_{t-2}\varepsilon_{t-2} + \cdots \theta_{t-q}\varepsilon_{t-q} \quad (4)$$

$$Y_t = c + \beta Y_{t-1} + \beta_2 Y_{t-2} \ldots + \varepsilon_t \quad (5)$$

Where Y_t be the actual data value and ε_t be the random error at any given time t.

Analysis and Discussion

The total data set period is divided into two sets, the input data set and the forecasted data. The first 10-year data from 1990 to 2000 is used as input data for forecasting and the remaining data set from 2001 to 2014 is used for the comparison of forecasted results. When we predict inflation values using the ANN model, we find predicted values to be very close to the actual values. Our findings regarding exchange rate forecast using the ANN model show some deviation from the actual data. While the forecasted results for GDP through the ANN model are much different from the actual data set. Hence, ANN predicts inflation precisely, while it has a moderate to low level of precision for exchange rate and GDP respectively.

Next, we employ the ARIMA model for estimating our main variables of concern. In order to estimate the ARIMA model, the data of all three variables are needed to be stationary. First of all, the log of data is taken and then the series is differenced on level one. The results of the Augmented Dickey-Fuller (ADF) test suggest all the variables are having unit root at level, but data becomes stationary at level 1.

Table 1: Augmented Dickey-Fuller Test (Unit root test)

Variables	ADF (levels)	Critical Values	ADF (first differences)	Critical Values
Inflation	1.43	3.45	7.52	3.45*
Exchange Rate	0.75	3.45	10.70	3.45*
GDP	0.21	3.45	16.42	3.45*

*At 5% level of significance (Source: Authors' compilation)

The autocorrelation function (ACF) and partial autocorrelation function (PACF) are used to obtain the values of AR and MA terms. After the estimation of equation (4), the results are tested for serial correlation and heteroscedasticity. Our findings reveal that there is no serial correlation and heteroscedasticity in the data. For inflation, the ARIMA model of (1,1,1) is estimated and for GDP the ARIMA model of (1,1,2) is estimated. In the case of exchange rate three ARIMA models (1,1,1), (1,1,2), and (1,1,3) are tested against each other, and out of three (1,1,1,) is found to be the most appropriate. Next, we use the ordinary least square (OLS) method after the data becomes stationary. We report our OLS-based results in Table 2.
Table 3 reported below displays monthly actual and predicted values based on the ANN and ARIMA

Table 2: OLS Results of ARIMA Model

Variables	Coefficient	T stats	SB Criteria	Adjusted R square	P Value
Inflation	0.000489	0.059659	−1.241815	0.058706	0.9525
Exchange Rate	0.005539***	4.304812	−5.925910	0.175342	0.0000
GDP	1.19E+09***	3.362950	45.43771	0.416712	0.0009

*at 5% level of significance (Source: Authors' compilation)

forecast models. The results show that the ANN model outperforms the ARIMA model. The ANN model's outputs are closer to the actual values. As a result, it is stated that when it comes to forecasting inflation in Pakistan, the ANN outperforms the predictions generated by ARIMA model.

Table 3: Comparison of the Forecasted Results for Inflation

Month	Actual Inflation	Forecast by ANN	Forecast By ARIMA
Sep	10.46	10.52276	13.71202
Oct	10.97	10.98097	13.61534
Nov	10.19	10.24095	13.52145
Dec	9.75	9.758775	13.43029
Jan	10.10	10.2111	13.34178
Feb	11.05	11.17155	13.25584
Mar	10.79	10.82237	13.17240
Apr	11.27	11.31508	13.09138
May	12.29	12.31458	13.01271
Jun	11.26	11.3163	12.93633
Jul	9.60	9.6864	12.86217
Aug	9.06	9.13248	12.79217
Sep	8.79	8.85153	12.72026
Oct	7.66	7.70596	12.65237

(Source: Authors' compilation)

This can also be seen from the Figure 1 in which actual and ANN based predicted values overlap while ARIMA based forecasted values are overstated at all points.

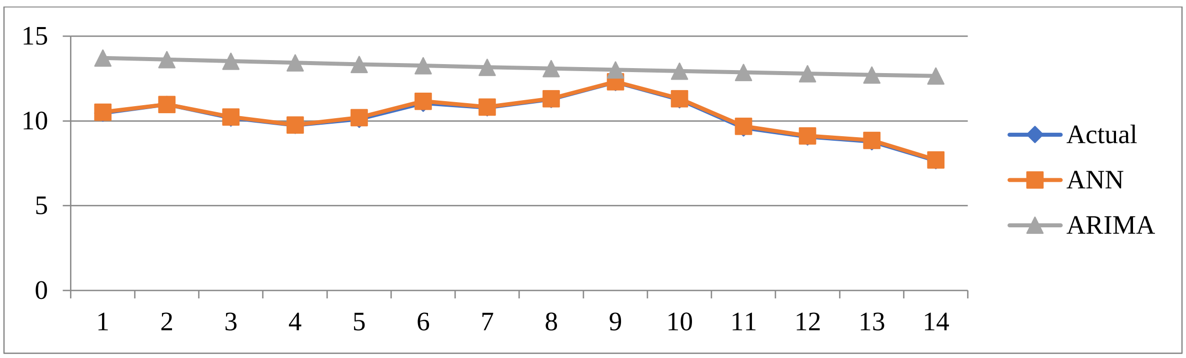

Figure: 1 Forecasted Inflation using ANN and ARIMA vs Actual Values (Source: Authors' compilation)

Following are the results of the two proposed models' forecasts of exchange rates. Table 4 shows that the calculated value of forecast for exchange rate via ARIMA is more appropriate than that of ANN model.

Table 4: Comparison of the Forecasted Results for Exchange Rates

Month	Actual Exchange Rate	Forecast by ANN	Forecast By ARIMA
Sep	87.4744	113.5418	88.68153
Oct	86.9655	87.48728	89.01041
Nov	86.9316	94.75544	89.33991
Dec	89.3402	97.11279	89.67001
Jan	90.1357	101.2224	90.00073
Feb	90.6186	117.6229	90.33207
Mar	90.7135	91.2578	90.66402
Apr	90.6345	98.7916	90.99660
May	91.2605	99.20016	91.32979
Jun	94.1151	96.27973	91.66360
Jul	94.3779	97.20921	91.99803
Aug	94.4660	102.9679	92.33308
Sep	94.5877	98.37123	92.66876
Oct	95.3487	113.5418	93.00506

(Source: Authors' compilation)

The results shown in Figure 2 suggest that the ARIMA model overlaps the actual exchange rates and performs better as compared to the ANN model in terms of forecasting exchange rates.

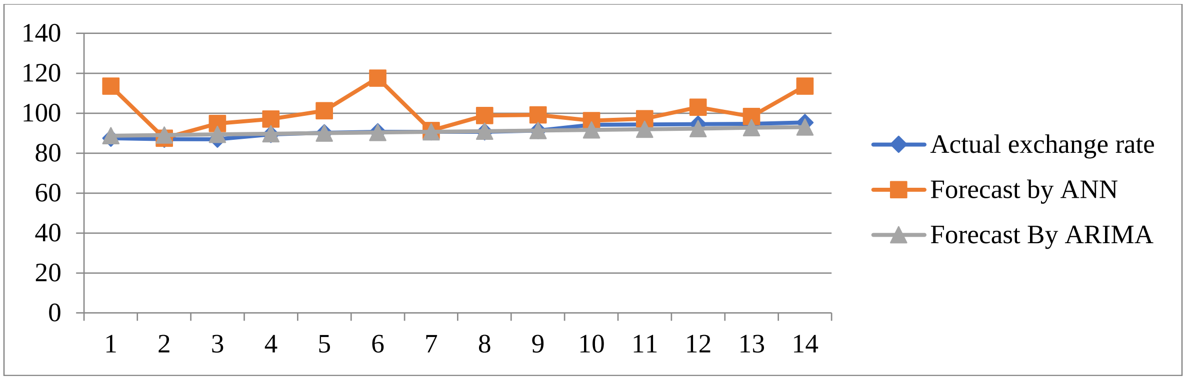

Figure: 2 Forecasted Exchange Rate using ANN and ARIMA vs Actual Values (Source: Authors' compilation)

Finally, the results of the GDP forecast using the ANN and ARIMA models show that both models fail to predict the data precisely. The ANN forecast is much higher than the actual GDP data, whereas the ARIMA model forecast is lower than the actual data. However, when compared to the ANN model forecast, the ARIMA model-based forecast is relatively closer to the actual data, as shown in Table 5 and Figure 3 below.

Table 5: Comparison of the Forecasted Results for GDP

Month	Actual GDP	Forecast by ANN	Forecast By ARIMA
Sep	514,878,658,905.28	543196985145.07	507633378336.7774
Oct	515,895,133,370.30	538594519238.59	508678999549.5299
Nov	516,957,073,034.14	522126643764.48	509748565652.3368
Dec	518,064,746,567.68	533606688964.71	510842172721.1059
Jan	515,913,341,735.14	538097615429.76	498332551080.5258
Feb	517,105,698,900.15	534687292662.75	499543843382.9812
Mar	518,344,372,240.47	530266292802.00	500827664578.9181
Apr	519,629,677,489.23	536309790136.64	502184498882.9353
May	520,961,942,893.93	538674648952.32	503614832023.8135
Jun	522,341,509,355.96	586589515006.74	505119151278.233
Jul	523,240,712,468.16	570332376590.30	506096225329.9612
Aug	524,185,540,802.02	565072012984.57	507097142631.3374
Sep	525,176,232,083.38	576643502827.55	508121941782.1055
Oct	514,878,658,905.28	543196985145.07	509170680368.525

(Source: Authors' compilation)

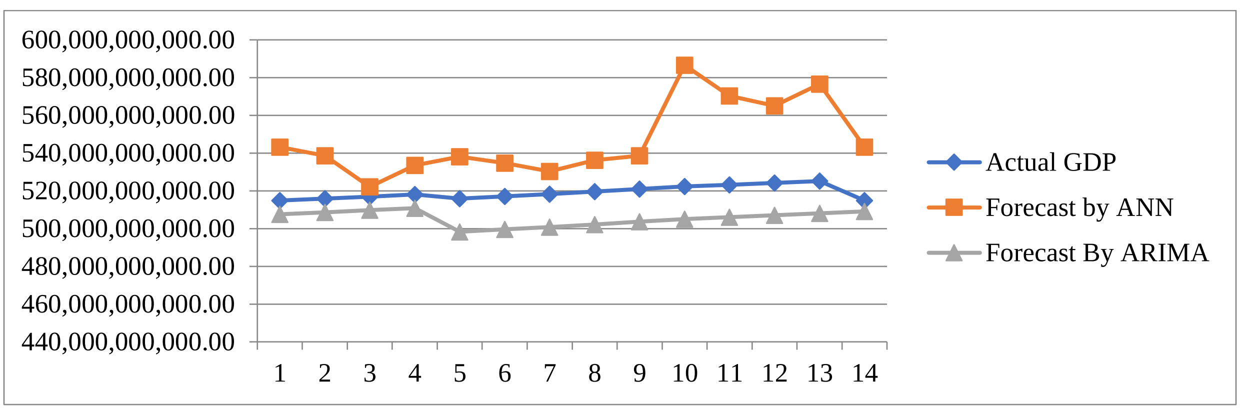

Figure: 3 Forecasted GDP using ANN and ARIMA vs Actual Values (Source: Authors' compilation)

The overall results show that ANN outperforms the ARIMA model in terms of inflation prediction, while the ARIMA model performs better in predicting exchange rate and GDP.

Next, we estimate the independent samples t-test that compares the means of two distinct groups based on ANN and ARIMA forecasts for our three forecasted variables. The results of the independent sample t-test for the three variables are reported below in Table 6.

Table: 6 Independent Sample T-test

Variables	Groups	N	Mean	SD	T	Df	Sig
Inflation	ANN	23	−.062	.04	10.58	44	.000*
	ARIMA	23	−2.90	1.29			
Exchange Rate	ANN	27	−8.12	7.61	−5.56	52	.001*
	ARIMA	27	.33	2.10			
GDP	ANN	21	−3.40	1.68	−11.97	40	.000*
	ARIMA	21	1.17	4.99			

*at 5% level of significance (Source: Authors' compilation)

According to t-test, the variation in each group is significant, and the mean value of ANN and ARIMA model is significantly different from each other. It suggests that the predicted values of GDP, inflation, and exchange rate under both models are significantly different.

Conclusion

This study on forecasting macroeconomic variables is conducted in the context of Pakistan, using monthly data on inflation, exchange rate, and GDP from 1990 to 2014. We investigate the comparative accuracy of ANN and ARIMA model-based predictions. Our findings show that when the prediction accuracy of the ANN model is compared to that of the ARIMA model, the results vary depending on different macroeconomic factors. Our findings suggest that in the Pakistani economy, the ARIMA model outperforms the ANN model for predicting exchange rates. In the case of inflation, however, our findings show that the ANN model's estimates are significantly better than those of the ARIMA model. The anticipated outcomes for GDP based on both the forecasting models are not precisely in line with the actual statistics. When we examine closely, we can see that the outcomes of the ANN model are further away from the real data, and the ARIMA projections are substantially closer to the actual data. As a result, ARIMA performs considerably better in terms of GDP forecasting, with a lower forecasting error. Overall, our findings suggest that the ARIMA model provides more appropriate results for forecasting exchange rates and GDP, while the ANN model outperforms the ARIMA model for predicting inflation.

Our findings have crucial implications for analysts and policymakers, emphasizing the need of using proper forecasting models that are well linked with the structure of a specific country. The forecasted results of these models may differ across nations and even for various economic aspects within the economy due to changes in economic structure. Future scholars should probe other forecasting models (perhaps hybrid models) capable of estimating GDP and other time series data with even reduced forecasting error.

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