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Are Neural Network Models Truly Effective at Forecasting? An Evaluation of Forecast Performance of Traditional Models with Neural Network Model for the Macroeconomic Data of G-7 Countries

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Abstract: Forecasting macroeconomic and financial data are always difficult task to the researchers. Various statistical and econometrics techniques have been used to forecast these variables more accurately. Furthermore, in the presence of structural break, linear models are failed to model and forecast. Therefore, this study examines the forecasting performance of economic variables of G7 countries: France, Italy, Canada, Germany, Japan, United Kingdom and United States of America using non-linear autoregressive neural network (ARNN) model, linear auto regressive (AR) and Auto regressive integrated moving average model (ARIMA) models. The economic variables are inflation, exchange rate and Gross Domestic Product (GDP) growth for the period from 1970 to 2015. To measure the performance of the considered model Root, Mean Square Error, Mean Absolute Error and Mean Absolute Percentage Error are used. The results show that the forecasts from the non-linear neural network model are undoubtedly better as compared to the AR and the Box–Jenkins ARIMA models.

Keywords: Macroeconomic variables, non-linear auto regressive neural network model, forecast comparison, G7 countries.

Introduction

Forecasting economic and financial variables plays an important role in decision making. Different statistical models are used to analyze and forecast these variables over the past several decades. Among them, autoregressive integrated moving average (ARIMA) model is one of the most important and widely used to forecast univariate time series data (Box and Jenkins, 1970). The ARIMA modeling technique depends on the lagged values of the series and lagged error terms. There is abundant literature discussed time series forecasting models and found that in case of short-run forecasting, the ARIMA models are more efficient as compared to the complex structural models. Currently Artificial neural networks (ANNs) have been widely used to predict various financial and economic time series data due to flexible nonlinear modeling. Khashei and Bijari (2010) compared the forecast accuracy of neural network and nonlinear autoregressive models and found that ANNs forecast more accurately than linear AR models. Because of data driven as well as self-adaptive capability, ANNs model is found to be most efficient in solving nonlinear behavior. Furthermore, Prybutok et al. (2000) compared the forecasting power of ANNs model with two statistical models i.e. regression model and traditional time series Box Jenkins ARIMA model. Whereas, Mitrea et al. (2009) investigated and compared the forecast performance of Moving Average, ARIMA, ANNs Feed-forward and nonlinear autoregressive network with exogenous inputs (NARX) models. They used inventory database of Panasonic Refrigeration Devices Company. According to their findings, the forecast of Neural Networks models is more reliable than the traditional linear time series models. In another study, Adebiyi et al., (2014) compared the forecasting performance of ARIMA and ANNs models, using the New York Stock Exchange data. According to their findings, the neural networks model gives superior forecast to the Box-Jenkins linear ARIMA model. Yavuz and Yilanci (2012) tested linearity in macroeconomic data of G 7 countries covering the period 1959Q1-1999 Q4. Aksoy and Ledesma (2008) method applied on the stationary data and observed that order of integration has uncertainty. To clarify the results another linearity test (Harvey et al., 2008) was used to explore which kind of unit root test is applicable to test the stationarity. Back propagation algorithm based ANNs is used to model Economic Growth of G7 countries by taking GDP as a function of land area of the country, cultivated land, population, enrollment rate, total capital formation, exports of goods and services, and the general government's final consumption of collateral and broad money by Wang et al. (2020). Results show that the Back Propagation Neural Networks model performs better based on various accuracy measures statistics in forecasting short-term GDP.

This study compares forecasting performance of two important traditional linear models namely AR and ARIMA and compared with the non-linear autoregressive neural network model for the G7 countries. Three well known economic key factors are included in this study namely exchange rate, inflation and GDP growth. These factors are not only in the estimation of economic strength and solidity but are also the sign of growth and development for any nation (Fraz and Fatima, 2016). Since, G-7 countries are the

Table 1 Unit root test.

Country	Inflation				Exchange rate				GDP Growth			
	ADF statistic		PP statistic		ADF statistic		PP statistic		ADF statistic		PP statistic	
	Level	1st diff	Level	1st diff	Level	1st diff	Level	1st diff	Level	1st diff	Level	1st diff
Canada	0.345	-6.925*	-1.813	-6.964*	-2.188	-4.141*	-1.762	-4.141*	-2.385	-7.858*	-2.030	-19.65*
France	-2.483	-9.165*	-2.336	-10.728*	-0.832	-6.096*	-0.831	-5.855*	-2.171	-7.875*	-1.873	-14.02*
Germany	-2.437	-5.510*	-2.437	-5.510*	-1.919	-5.506*	-1.319	-5.147*	-3.303	-	-3.093	-
Italy	-1.482	-7.072*	-1.639	-7.065*	-	-	-	-	-2.067	-9.128*	-3.120	-
Japan	-2.756	-7.559*	-2.752	-9.597*	-	-	-	-	-1.808	-8.787*	-2.471	-13.79*
UK	-2.071	-7.477*	-2.163	-8.901*	-	-	-	-	-3.068	-	-2.811	-
USA	-1.784	-7.313*	-2.271	-9.343*	-	-	-	-	-3.472	-	-3.472	-

*Significant at 1% level of significance

Note: ADF statistics stands for Augmented Dickey-Fuller and PP statistics stands for Phillips-Perron test statistic

most developed countries; therefore, the best forecast performance either from AR, ARIMA or neural network model for each macroeconomic variable could give a significant and reliable time series econometric model to the researchers, economists and policy makers. It would also be beneficial for other countries i.e. developed, developing and underdeveloped countries (Fraz et al. 2019). Performance of the models is accessed by root mean square error (RMSE), mean absolute error (MAE) and mean absolute percentage error (MAPE).

Section 2 presents the data descriptions and methodology. Whereas, data analysis, results and discussion are presented in section 3. Lastly, the conclusion is presented in section 4.

Materials and Methods

Data Description

Yearly data of exchange rate, inflation and GDP growth are used in this study. The macroeconomic indicators from Italy, Canada, Japan, France, Germany, USA and UK were obtained. Time span of all the time series variables are different as it depends on the convenience of obtain ability for each indicator. All selected variables covered the time period till 2015. Canada, Japan, and UK are the only exchange rates which are under consideration in this study. The main reason to pick these three G7 countries is because of exchange rate in US dollar from IMF. All the macroeconomic indicators show non-linear behavior generally. Exchange rate and inflation, specifically following nonlinear behavior. The linear AR, ARIMA and non-linear ANNs model used to cover by this study are discussed.

Autoregressive Model

For most of the time series data, linear models are used to estimate the models and for using in forecasting.

Generally, AR, MA, and ARMA models are commonly used. Linear AR model is used for empirical study which is the part of Box and Jenkins (1970) process. The autoregressive process of order p is expressed as follows:

$$X_t = \sum_{j=1}^{p} \theta_j X_{t-j} + w_t \quad (1)$$

where $w_t \sim N(0, \sigma^2)$

Autoregressive Integrated Moving Average Model

Basically, an ARIMA process is a method of

Table 2 Forecast Evaluation statistics

Countries	Forecast method	Inflation			Exchange rate			GDP growth		
		RMSE	***MAE***	***MAPE***	***RMSE***	***MAE***	***MAPE***	***RMSE***	***MAE***	***MAPE***
Canada	AR	2.019	1.831	178.664	0.330	0.298	27.211	2.330	1.781	97.562
	ARIMA	2.410	2.212	209.126	0.278	0.250	22.814	2.283	1.742	95.446
	NN	0.640	0.468	58.686	0.202	0.178	16.227	2.217	1.581	86.143
France	AR	0.749	0.627	139.307	-	-	-	1.364	1.005	82.855
	ARIMA	1.214	1.090	169.796	-	-	-	2.828	2.480	407.715
	ANNs	1.730	1.314	196.221	-	-	-	2.506	1.866	211.192
Germany	AR	1.727	1.567	227.273	-	-	-	-	-	-
	ARIMA	1.466	1.259	202.012	-	-	-	-	-	-
	ANNs	1.099	0.968	68.286	-	-	-	-	-	-
Italy	AR	2.995	2.579	1168.357	-	-	-	-	-	-
	ARIMA	3.463	3.078	1292.187	-	-	-	-	-	-
	ANNs	1.612	1.268	679.395	-	-	-	-	-	-
Japan	AR	3.023	2.849	3248.125	23.188	17.966	19.317	3.340	2.592	524.917
	ARIMA	2.849	2.696	2821.823	31.684	25.804	27.360	3.307	2.601	553.472
	ANNs	2.270	2.132	2533.385	27.184	24.966	23.823	3.300	2.491	523.823
UK	AR	3.046	2.693	77.877	0.074	0.068	11.290	-	-	-
	ARIMA	2.809	2.600	81.019	0.065	0.060	10.186	-	-	-
	ANNs	1.135	0.919	45.500	0.048	0.037	6.629	-	-	-
USA	AR	1.870	1.477	328.949	-	-	-	-	-	-
	ARIMA	1.947	1.500	339.950	-	-	-	-	-	-
	ANNs	1.501	1.101	270.115	-	-	-	-	-	-

regression analysis that measures the power of one dependent variable related to other changing variables. This process has a characteristic root on unit circle. Taking a difference on non-stationary time series data, the usual ARMA technique transformed into Box-Jenkins ARIMA *(p,q)* models. Since 1970, ARIMA modeling technique is popular to forecast any time series data either related to economy or finance.

$$X_t = \sum_{j=1}^{p} \theta_j X_{t-j} + \sum_{j=1}^{q} \beta_j w_{t-j} + w_t \qquad (2)$$

Nonlinear Autoregressive Neural Network Model

The salient features of macroeconomic time series data are high variations and sudden fluctuations, which make difficult to use a liner model. A nonlinear autoregressive neural network can be used for the forecast purpose of the macroeconomic time series. A discrete non-linear autoregressive neural network model can be expressed as:

$$y_t = h(y_{t-1}, y_{t-2}, y_{t-3}, \dots, y_{t-p} + e_t \qquad (3)$$

y_t *is a* time series at time *t*. The function *h (·)* is unknown and neural network training approximate the required function by optimizing the weights of network as well as the neuron bias. Here, $e_{(t)}$ is the approximation error for the time series *y* at time *t (for details,* see Ruiz et al. (2016).

Results and Discussion

Data Analysis

The traditional famous unit root tests namely Augmented Dickey-Fuller and Phillips-Perron test are employed to check the stationary in the time series data (Table 1). All the macroeconomic time series are stationary at first difference except for the GDP growth of Germany, UK, and USA. Therefore, these macroeconomic time series are excluded since the aim of this study is to compare the forecast of AR, ARIMA and ARNN models. Firstly, the all data are divided into in-sample and out-of-sample. The forecasted values are compared with the observed values after estimation of the time series model by using data up to year 2000. While the period 2001 to 2015 is used to evaluate the forecast of models.

The aim of present study is to check whether the ARNN model gives reliable and superior forecast to the historic linear time series models. Therefore, three forecast accuracy criteria's MAPE, RMSE and MAE are used (Table 2). Forecast from the nonlinear ARNN model completely dominates the linear AR and Box-Jenkins ARIMA models on the basis of forecast measures such as RMSE, MAE and MAPE. Whereas, the macroeconomic inflation variable, the forecast performance ARNN model is superior to the other models for all the G7 countries except France. Furthermore, the macroeconomic variable namely inflation, the forecast performance of linear AR model is far better as compared to the linear ARIMA model as well as Non-linear NN model. In contrast, for the exchange rate data, the forecasting performance of non-linear ARNN model is quite better as compared to AR and ARIMA models for Canada and UK. Similarly, the forecast performance of linear AR model is best among the two remaining models for the Japan. Lastly, the empirical analysis shows that non-linear ARNN process performs better than other two linear process for the selected macroeconomic variable namely GDP growth for the countries namely Canada and Japan. While for France, similar results were obtained from its inflation. The forecast performance of linear AR model is superior to the ARIMA and non-linear ARNN model. Over all approximately, 80% finding in this study reveals that the forecast performance of auto regressive neural network model is superior to the other two linear models, namely AR and ARIMA models. Still, 20% results are in favor of linear models for the cases of inflation, exchange rate and GDP growth of France and Japan. But the forecast performance of linear AR models for these countries are not much superior as compared to the non-linear ARNN model. It concluded that the non-linear ARNN models are the best as compared to linear AR and ARIMA models to handle the nonlinearity in the data and providing better forecast performance as compared to linear models.

Conclusion

It is not an easy task to forecast the macroeconomic time series containing nonlinearity and breaking points. In this comparative study, forecast performance of AR, ARIMA and nonlinear ARNN models are evaluated. The ARNN models are the most outstanding time series models for forecast purpose. It is found that ARNN models are designed to explore the sudden shocks and variations in the time series data. Various forecasting measures i.e. RMSE, MAE, and MAPE are used to verify the results. The empirical results show that eighty percent results favor heavily the prediction performance of nonlinear ARNN models. Remaining 20% results show that the forecast performance of linear AR model is better in cases of inflation, GDP growth and exchange rate of few G7 countries. The findings of this study suggest that the forecast performance of nonlinear ARNN models is superior to the conventional Box-Jenkins ARIMA and AR models for all the macroeconomic time series data in the presence of nonlinearity. Overall, the forecast performance of non-linear ARNN model is dominant approximately in all cases of macroeconomic time series data for the G-7 countries. Results are similar to the results of Adebiyi (2014), Ruiz et al. (2016) as well as Mitrea et al. (2009). It is suggested that researchers should work on the data which contains the seasonality component of time series data from more countries.

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