A Comparative Analysis of Artificial Neural Network and Autoregressive Integrated Moving Average Model on Modeling and Forecasting Exchange Rate

Mogari I. Rapoo, Diteboho Xaba

***Abstract*—**This paper examines the forecasting performance of Autoregressive Integrated Moving Average (ARIMA) and Artificial Neural Networks (ANN) models with the published exchange rate obtained from South African Reserve Bank (SARB). ARIMA is one of the popular linear models in time series forecasting for the past decades. ARIMA and ANN models are often compared and literature revealed mixed results in terms of forecasting performance. The study used the MSE and MAE to measure the forecasting performance of the models. The empirical results obtained reveal the superiority of ARIMA model over ANN model. The findings further resolve and clarify the contradiction reported in literature over the superiority of ARIMA and ANN models.

***Keywords*—**ARIMA, artificial neural networks models, error metrics, exchange rates.

I. Introduction

A time series is a sequential set of data points, measured typically over successive times (e.g. daily, weekly, monthly, quarterly, yearly, etc.) [1]. The objectives of time series methods are to describe and summarize time series data, fit low dimensional models, and make forecasts. There are two types of time series data; linear and non-linear. Linear time series involves simple models that describe the behavior of a series in terms of the past values. Furthermore, these linear methods are often employed to capture the dynamics and patterns in most financial time series data. Over decades, the linear methods have been in the forefront of research and used extensively in the time series forecasting. However, it has been found that these linear time series models usually leave certain aspects of the economic and financial data unexplained. Therefore, this case led to the introduction of non-linear models or methods.

A non-linear time series is any stochastic process that is not linear, meaning that non-linear time series are generated by non-linear dynamic equations. Several studies have revealed that linear models are relatively poor in terms of capturing certain financial data behavior or economic performance at certain points in time [5]. Moreover, most studies have shown that the financial time series data have a non-linear component and linear models have limitations to non-linearity [2].

M. I. Rapoo is with the North West University (Mafikeng Campus), Private Bag X2046, Mmabatho; South Africa, 2735 (phone: (018) 389-2656, e-mail: ishmael.rapoo@gmail.com).

D. Xaba is with the North West University (Mafikeng Campus), Private Bag X2046, Mmabatho; South Africa, 2735 (phone: (018) 389-2195, e-mail: Diteboho.Xaba@nwu.ac.za).

To model and forecast time series data is of the utmost importance as of the nature of the series. Most time series model have a shortcoming in modeling nonlinear series. However, the ANN model has this ability to learn the characteristics of the data. The ability of the ANN is to model the nonlinear process without having to specify the stochastic process beforehand. Consequently, in spite of the numerous appealing qualities of ANN models and the general agreement that ANN models ought to be more proper than conventional models, according to the literature, doubtlessly time series forecasts of ANN models in respect to other option models are sometimes not generally precise. This can also be for the reason that, for the estimation of the parameters of ANN, there is no rule of thumb to select them; the instant process follows trial and error methods.

Reference [4] conducted the study where they assessed the forecasting accuracy of the ANN model and traditional statistical models for agricultural price forecasting using real price data by taking into account the major limitations of the previous studies. Monthly price data from Jan 1980 to Dec 2010 were used. The results showed that the ANN is still superior to linear models. Also, the results were the same in the case of [11], [12].

Reference [10] undertook the study with the objective of investigating the function of neural networks and ARIMA model in predicting and measuring Tehram Stock Exchange general index and compared the prediction errors of the two models. Results suggest that the accuracy of neural network in predicting total index is markedly greater compared with the prediction of ARIMA models based on MSE, RMSE, and Theil's U-statistic. Moreover, according to the disturbance criteria rates, MAD, and MAPE, the performance of method ARIMA is better than ANN.

Reference [5] investigated whether ANN models offer any improvement in terms of exchange rate forecasting accuracy over the traditional used models. The results obtained in this paper indicate that ANN models can provide better forecast than random walk models and traditional models, such as ARMA and GARCH models.

Reference [14] stipulated that ANN is able to deal with daily and weekly data as well as the non-linearity present in exchange rate data. Looking at the findings of this world, research on the comparative study of ANN and ARIMA might, without a doubt, be a conclusion that the ANN model is outperforming the linear models most especially because of the non-linearity dynamics present in time series data.

International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:11, No:11, 2017

However, [15] found that, with the exchange rate, the best ARIMA linear model is found to be the random walk model.

References [9] and [15] conducted their study using hybrid models of ARIMA-ANN and ARIMA-Kalman and believed that the hybrid models improve forecasting accuracy. Reference [8] undertook the study to compare the performance of ANN and ARIMA models in forecasting of seasonal (monthly) time series, and the results show that the ANN are relatively better than ARIMA models in forecasting ability, but the nature of the data may influence the results.

Reference [13] study compared ARIMA and ANN in forecasting the prices of groundnut oil in Mumbai from Jan 1994 to July 2010. The results showed that the ANN performed better than the ARIMA model in forecasting the prices. In [6], forecasting accuracy of ANN model and traditional statistical models was assessed. The results show that ANN is still superior to linear models. Furthermore, hybrid models were observed to produce more accurate results than these models independently.

The study investigated the accuracy of ANN model to that of traditionally used models in terms of exchange rate forecasting. The results obtained revealed that ANN can provide better forecast than random walk model and traditional models, such as ARIMA and GARCH models [3].

The objective of the study is to examine the forecasting accuracy of the two models (ARIMA and ANN) in modeling and forecasting exchange rate. The paper is constructed as follows: methodology and analysis in section II. Section III is the summary and conclusions.

II. Methodology and Analysis

In this section, forecasting methods are introduced which are ARIMA and nonlinear ANN models respectively. These models will be under appropriate assessment. Lastly, model diagnostic tests will be performed.

A. ARIMA (p, d, q) Model

The study used monthly data of South African exchange rate obtained from the Reserve Bank. The data have the period of 1960/01 to 2016/02, which is total of 674 observations. The series has an upward trend, with fluctuations in the series apparent. Fig. 1 is the plot of the non-stationary series.

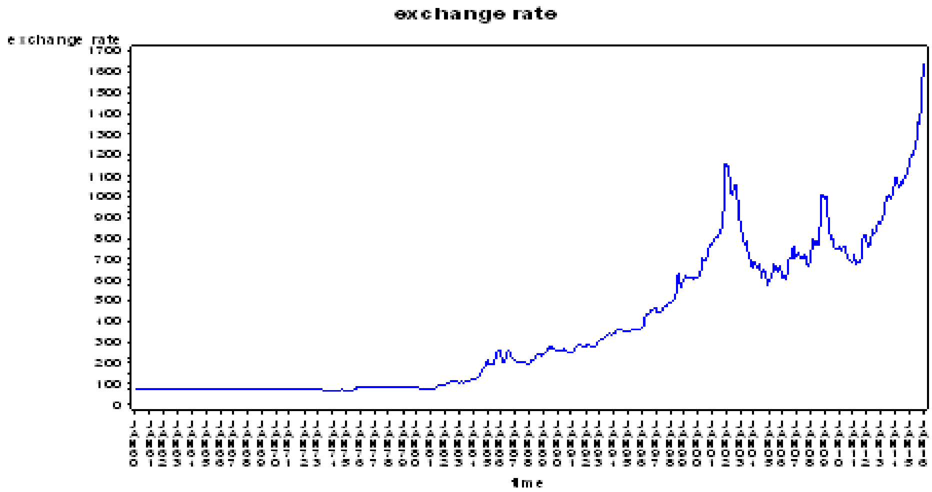

Fig. 1 The plot of South African exchange rate

In assessing the data for stationary or non-stationary, the ADF test is employed in the study. At levels, the series is on-stationary. Thereby, the study first differenced the series to make it stationary at first difference. The ADF test results will be reported under appendix section. The best ARIMA model estimated using maximum likelihood using both PACF and ACF is ARIMA (1, 1, 0).

TABLE I
Estimated ARIMA Model for Monthly Series

Statistic	South African Exchange rate
Model Identification	ARIMA (1,1,0)
Model Coefficient	0.33388
Model Equation	$(1-0.33388B)(1-B)X_t = \varepsilon_t$
BIC	5.859

Table I presents the estimated ARIMA model. For the selection of the model, the minimum information criterion was employed. The stochastic process of the ARIMA model can be presented in the following form:

$$\hat{X} = \beta_0 + \beta_1 X_{t-1} + ... + \beta_p X_{t-p} - \alpha_1 u_{t-1} - \alpha_q \varepsilon_{t-q} - ... - \alpha_1 \varepsilon_{t-1} + \varepsilon_t, \quad (1)$$

given that $\varepsilon_t = X_t - \hat{X}_t$ is the difference between the actual and forecasted value of the series, respectively.

B. Testing for Nonlinearity

Linearity of the error term is one of the assumptions in time series analysis that must be assessed. According to this assumption, the error term must be identically and independently distributed (iid). The study uses the Brock, Dechert, and Scheinkman (BDS) test to assess the assumption, where this test is dominant in this regard. Table II presents the

International Journal of Business, Human and Social Sciences
ISSN: 2517-9411
Vol:11, No:11, 2017

results of the BDS test. According to the results, the null hypothesis is rejected, and hence, the series of the exchange rate is nonlinear. To further confirm the findings, the cumulative sum test is used to test stability of the series.

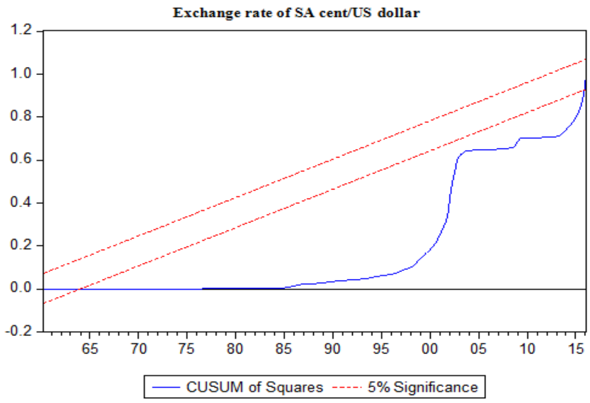

Fig. 2 CUSUM test of stability

In the above figure, CUSUM test introduced by [4] is employed to assess the stability of series of exchange rate. Any measure outside the two critical bends is associated with instability of parameters or variance. Based on Fig. 2, there is evidence that there is no stability in the exchange rate series as the movement of the series is outside the two critical lines of the plot.

C. ANN Model

An ANN is basically a nonparametric attempt to model the human brain. ANN acts like a human brain, trying to recognise regularities and patterns in the data. They can learn from experience and can generalize based on their previous knowledge. Furthermore, their power originates from the parallel preparing of the information from the data. No assumption of the model structure is required in the model building process. Rather, the network model is to a great extent determined by the attributes of the data. Reference [15] mentions that single concealed layer feed-forward network is the most generally utilized model structure for time series modeling and forecasting. The relationship between the output (y_t) and inputs $(y_{t-1};\cdots;y_{t-p})$ has the following mathematical representation:

$$y_t = \alpha_0 + \sum_{j=1}^{q} \alpha_{ig}\left(\beta_{0j} + \sum_{i=1}^{p} \beta_{ij} y_{t-i}\right) + \varepsilon_t \qquad (2)$$

where $\alpha_j\,(j = 0,1,\ldots, q)$ and $\beta_{ij}(i = 0,1,\ldots, p;\ j = 1,2,\ldots,q)$ are the model parameters. The study employed the unipolar sigmoid function as the hidden layer transfer function or activation function:

$$g(x) = \frac{1}{1+e^{-x}} \qquad (3)$$

Transfer functions such as the sigmoid are commonly used for time series data because they are nonlinear and continuously differentiable which are desirable properties for network learning [7].

TABLE II
PERIODS OF ANN AND ARIMA ON TESTING AND TRAINING SET

Models	Series	Training set	Testing set
ANN	1960/01-2016/02 (674)	1960/01-1994/04 (412)	1994/05-2016/02 (262)
ARIMA	1960/01-2016/02 (674)	1960/02-2016/02 (673)	NA

Note: numbers inside the parenthesis indicates the number of observations some observations are lost due to differencing

The study selected the network which consists of one input layer, two hidden layers, and one output layer at a learning rate, momentum and maximum iterations of 0.01, 0.1, and 10 000 respectively. This model is used for in-sample forecasting. When ANN has been used, the accuracy of forecasting improves as the number of iterations increases, because this model can recognize the pattern of the past observation of the exchange rate.

TABLE III
IN-SAMPLE COMPARISON OF FORECASTING PERFORMANCE

MODELS	MSE	MAE
ANN	814.76447	19.33074
ARIMA	382.94811	9.398694

Considering the results shown in Table III, the traditional linear model of ARIMA has outperformed the ANN model. The error in ARIMA model is almost half of that in ANN model. This has also proven the ability of ARIMA model to perform in time series forecasting.

III. CONCLUSION

Monthly dataset of exchange rate covering the periods of 1960/01 to 2016/02 was modeled using both linear and non-linear models in ARIMA and ANN, respectively. For the series shown non-stationary at levels, the widely used test of ADF was employed to induce stationary in the series. Thereby, the series became stationary at first difference to make forecasting possible. Based on the value of BIC and minimum information criteria method, the selected model of ARIMA was ARIMA (1.1.0), and some of the diagnostic checks were not satisfied. However, the in-sample forecast has shown a close relationship as the selected model showed a satisfactory mimic of the original series of the exchange rate.

In the case of ANN, the test for non-linearity was conducted for confirmation of the choices of the model. The tests of BDS and CUSUM are employed respectively, and the results obtained showed that the series of exchange rate is both non-linear and unstable. The study selected the network which consists of one input layer, two hidden layers, and one output layer at a learning rate, momentum and maximum iterations of 0.01, 0.1 and 10 000, respectively. The study conducted the in-sample forecast of the two models to assess the performance of the models. The forecasting performances were assessed based on the error metrics of MSE and MAE. The error metrics showed that the ARIMA model outperformed the ANN model, as the error metric statistics of the ANN were larger than that one of ARIMA.

APPENDIX

TABLE IV
ADF TEST AT LEVEL(S)

		t-Statistic	Prob.*
ADF test statistic		1.428066	0.9991
Test critical values:	1% level	-3.440120	
	5% level	-2.865742	
	10% level	-2.569065	

TABLE V
ADF TEST AT FIRST DIFFERENCE

		t-Statistic	Prob.*
ADF test statistic		-4.361772	0.0004
Test critical values:	1% level	-3.440120	
	5% level	-2.865742	
	10% level	-2.569065	

TABLE VI
MODEL IDENTIFICATION: ACF AND PACF PLOTS AT FIRST DIFFERENCE

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
.|** |	.|** |	1	0.320	0.320	69.419	0.000
.|. |	.|. |	2	0.073	-0.033	73.073	0.000
.|. |	.|. |	3	0.045	0.035	74.438	0.000
.|. |	|. |	4	0.049	0.029	76.065	0.000
|. |	|. |	5	-0.020	-0.051	76.350	0.000
|. |	|. |	6	-0.057	-0.041	78.584	0.000
.|. |	.| |	7	0.034	0.073	79.371	0.000

TABLE VII
BDS TEST FOR NONLINEARITY

Dimension	BDS Statistic	Std. Error	z-Statistic	Prob.
2	0.046259	0.000572	80.91110	0.0000
3	0.047208	8.39E-05	562.9033	0.0000
4	0.046562	9.77E-06	4766.520	0.0000
5	0.045851	1.05E-06	43823.42	0.0000
6	0.045161	1.08E-07	416966.4	0.0000

REFERENCES

[1] Adhikari, R. and Agrawal, R. K., 2013. An introductory study on time series modeling and forecasting. *arXiv preprint arXiv:1302.6613.*

[2] Binner*, J. M., Bissoondeeal, R. K., Elger, T., Gazely, A. M. and Mullineux, A. W. 2005. A comparison of linear forecasting models and neural networks: an application to Euro inflation and Euro Divisia. Applied economics, 37(6), pp.665-680.

[3] Bissoondeeal, R. K., Binner, J. M., Bhuruth, M., Gazely, A. and Mootanah, V. P. 2008. Forecasting exchange rates with linear and nonlinear models. Global Business and Economics Review, 10(4), pp.414-429.

[4] Brown, R. L., Durbin, J. and Evans, J. M. 1975. Techniques for testing the constancy of regression relationships over time. Journal of the Royal Statistical Society. Series B (Methodological):149-192.

[5] Clements, M. P., Franses, P. H. and Swanson, N. R. 2004. Forecasting economic and financial time-series with non-linear models. International Journal of Forecasting, 20(2), pp.169-183.

[6] Jha, G. K. and Sinha, K. 2013. Agricultural price forecasting using neural network model: An innovative information delivery system. Agricultural Economics Research Review, 26(2), pp.229-239.

[7] Kaastra, I. and Boyd, M. 1996. Designing a neural network for forecasting financial and economic time series. Neurocomputing, 10(3), pp.215-236.

[8] Kihoro, J. M., Otieno, R. O. and Wafula, C. 2004. Seasonal time series forecasting: A comparative study of ARIMA and ANN models. AJST, 5(2).

[9] Liu, H., Tian, H. Q. and Li, Y. F. 2012. Comparison of two new ARIMA-ANN and ARIMA-Kalman hybrid methods for wind speed prediction. Applied Energy, 98, pp.415-424.

[10] Nourbakhsh, F., Rostami, A., Arshadi, A., Sarlak, A. and Almasi, M. 2013. Comparative Study of Artificial Neural Networks ANN and ARIMA Method, in Predicting the Overall Index of Tehran Stock Exchange. Journal of Basic and Applied Scientific Research, 3(3), pp.319-324

[11] Oyewale, A. M. 2013. Evaluation of artificial neural networks in foreign exchange forecasting. American Journal of Theoretical and Applied Statistics, 2(4), pp.94-101.

[12] Pedram, M. and Ebrahimi, M. 2014. Exchange Rate Model Approximation, Forecast and Sensitivity Analysis by Neural Networks, Case of Iran. Business and Economic Research, 4(2), p.49.

[13] Singh, A. and Mishra, G.C. 2015. Application of Box-Jenkins method and Artificial Neural Network procedure for time series forecasting of prices. Statistics in Transition new series, 1(16), pp.83-96.

[14] Stokes, A. 2011. Forecasting exchange rates using neural networks: A trader's approach.

[15] Zhang, G. P. 2003. Time series forecasting using a hybrid ARIMA and neural network model. Neurocomputing, 50, pp.159-175.