

A Comparison of Forecast Behavior of Four Time Series Models on Nigeria's External Reserves

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Abstract

This article compared decomposition, Holt-Winters, ARIMA and Artificial neural networks (ANN) models for forecast accuracy and similarity on Nigeria's external reserves. Fitted adequate ARIMA model is ARIMA (1, 1, 1) while ANN (12, 7, 1) possessing minimum mean absolute error (MAE) of six ANN models fitted was chosen for forecasting. Holt-Winters model utilized parameter values 0.9, 0.3 and 0.3 for level, trend and season respectively. The parameters were selected such that MAE was minimal. Based on forecast mean square error of twelve out-of-sample forecasts, ARIMA performed best, followed by Holt-Winters and then, decomposition. ANN performed worst. Fitted ARIMA suggests an increasing trend for the series. With increasing lead time, Holt-Winters forecasts substantially tend to move in an opposite direction to each of decomposition and ARIMA forecasts. The article observes that for Nigeria's external reserves to attain high levels of the past there must be improved governance, security and infrastructure. The need to extend study to other economic series was recommended.

Keywords: ARIMA, External reserves, Time series, Forecasting, Nigeria, Artificial neural networks.

Introduction

Time series analysis whose ultimate goal is forecasting is a tool that utilizes past observations to predict for the future. The reliance on past observations remains regardless of the time series model adopted for forecasting. It does matter whether the fundamental approach like the decomposition model or more advanced techniques like SARIMA and its nonlinear counterparts like ARCH and GARCH or more recently developed approach of machine learning like artificial neural networks and support vector machines is adopted. The principle remains relying on perceived data generating process to project for the future.

Several reasons may inform the need to peep into what future values of a variable are likely to be. Usually, this is for planning purposes. A lot of important economic planning activities and decisions revolve around likely future values of economic variables. Planning is not restricted to only this. It is required in all aspects of human endeavor. For instance, estimates of future population of children under the age of 5 years could help in educational and health planning.

Time series modeling works in the literature include Kandananond (2012) that modeled demand forecasting, Otu, Osiju, Jude and Ifeyinwa (2014) and Nyaboke, Orwa and Joseph (2017) that modeled inflation rates, Adebisi, Adewumi and Ayo (2014), Merh, Saxema and Pardasani (2010) that modeled stock price and Etuk, Aboko, Victor-Edema and Dimkpa (2014) that modeled Nigerian monthly savings deposit rates. Recent works on forecasting include Bolarinwa and Bolarinwa (2021a, b, c and d) and Amaefula (2021).

This research intends comparing forecast behavior of ANN, decomposition, Holt-Winters and ARIMA models on Nigeria's external reserves with a view to recommending the most accurate. External

reserves are assets held on reserve in foreign currencies by a central bank to back liabilities. That is, to provide funding for servicing foreign currency liabilities and debt obligations.

Future projection of external reserves could for instance help government project borrowing capacity in the future since the size of external reserves is one of determinants for suitability for foreign loans from international lending organizations like the World Bank and the International Monetary Fund. The quantum of the external reserves is one of the indicators of the state of a nation's economy. Identifying a suitable model for forecasting such an important variable is therefore an effort in the right direction.

This article is arranged as follows: next section discusses the Methodology, followed by Results and Discussion. The last section concludes the article.

Methodology

Data

The data (sourced from CBN Bulletin (2020)) is Nigeria's external reserves in Millions of US Dollars covering January 2004 to December 2019. Data for January to December 2019 was set aside for model validation while the rest was modeled.

Model

Decomposition

It is based on the theory that the time series variable is made up of four effects (trend (T), seasonal (S), cyclical (C) and irregular (I)). The multiplicative version is of form

$$y_t = T.S.C.I \quad (1)$$

ARIMA

ARIMA (p, d, q) is of form

$$\phi_p(B)(1-B)^d y_t = \theta_q(B)\varepsilon_t \quad (2)$$

where p, d , and q represent the number of autoregressive parameters, the order of differencing and number of moving average parameters in the model respectively. Model was estimated by nonlinear least squares method and diagnostics utilized the Modified Box-Pierce (Ljung-Box) Chi-Square statistic.

Holt-Winters' (H-W)

The multiplicative version of the H-W model is of the form

$$l_t = \alpha \frac{y_t}{s_{t-p}} + (1-\alpha)(l_{t-1} + b_{t-1}) \quad (3a)$$

$$b_t = \beta(l_t - l_{t-1}) + (1-\beta)b_{t-1} \quad (3b)$$

$$s_t = \delta \frac{y_t}{l_t} + (1-\delta)s_{t-p} \quad (3c)$$

$$\hat{y}_{t+k} = (l_t + kb_t)s_{t-k-p} \quad (3d)$$

where $0 < \alpha < 1$; $0 < \beta < 1$ and $0 < \delta < 1$; α, β and δ are smoothing constants representing level, trend and the seasonal components respectively. l_t, b_t and s_t are smoothed estimates of the level, trend and the seasonal components at time t respectively. p is seasonality and equals 12 and 4

respectively for monthly and quarterly data. $\hat{y}_{t+k}$ is the k -step-ahead forecast. The parameters were obtained such that mean absolute error was minimized. This was achieved while α , β and δ were respectively 0.9, 0.3 and 0.3.

Artificial Neural Networks (ANN)

This is a machine learning approach to modeling time series. It has high capacity for handling nonlinear series unlike decomposition, ARIMA and H-M that are linear models. The relationship between the input y_{t-i} ($i=1, 2, \dots, p$) and the output y_t for a one-output layer feedback model has the form

$$y_t = g \left[\alpha_0 + \sum_{j=1}^h \alpha_j f \left(\beta_{0j} + \sum_{i=1}^p \beta_{ij} y_{t-i} \right) \right] \quad (4)$$

where

α_i and β_{ij} ($i = 0, 1, 2, \dots, p; j = 1, 2, \dots, h$) are model parameters often called *connection weights*; f and g are respectively activation functions for hidden and output layers. Six ANN models were fitted and one with least mean absolute error was selected for forecasting.

PERFORMANCE CRITERION

Out-of-sample forecast accuracy was compared using the mean square error (mse) defined

$$mse = \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n} \quad (5)$$

where n is number of forecasts involved.

Forecasts Similarity Assessment Tools

A total of 36 out-of-sample forecasts were generated using each model. Similarity of forecasts from different models was assessed through paired t-test and linear correlation analysis. Since 4 models were involved, 6 such comparisons were carried out. Only the first 12 of the 36 out-of-sample forecasts whose true values were available (Data set aside for model validation) were used in computing forecast mse that formed the basis for comparing forecast accuracy. The entire 36 forecasts were however, used for performing t-tests and correlation analysis.

Results and Discussion

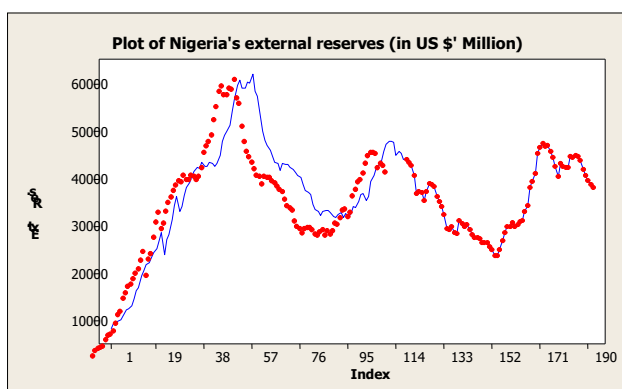


Fig. 1. Plot of Nigeria's external reserves in Millions of US Dollar

Fig. 1 is plot of the original data covering January 2004 – December 2019. The plot displays swings whose duration seems irregular.

Table 1. Forecasts and mean square errors

T	True value	MODEL			
		ANN	DECOMPOSITION	HOLT-WINTERS	ARIMA
181	42515.7	40064.3	39249.2	41288.7	42578.7
182	42329	39040.2	39334.9	40360.8	42599.7
183	44793.1	37698.7	39437.5	40271.7	42651.4
184	44474.3	37392.8	39194.3	39897	42728.2
185	44898.4	36992.2	38792.8	39008.7	42825.8
186	44747	35757.8	38549.4	38773.7	42940.5
187	43971.9	34790.7	39080.6	39129.7	43069.2
188	42062.4	34353.9	39465.6	39004.2	43209.2
189	40689.9	33687.5	39167.2	38880.3	43359.2
190	39614.8	31753.2	39163.5	38212.5	43516.8
191	38799.6	31437.3	39253.2	38550.8	43680.8
192	38092.7	31216	38943	38068.5	43850.1
MSE		51388815	15500278	12937169	8060555

Fitted ANN model is ANN (12, 7, 1), it was selected from six ANN models fitted but was selected based on its possessing the minimum mean absolute error. ARIMA model fitted is ARIMA (1, 1, 1). Holt-Winters model utilized 0.9, 0.3 and 0.3 for level, trend and seasons parameters. ARIMA records the least mse (computed based on 12 out-of-sample forecasts) and hence, has highest forecast accuracy, followed by Holt-Winters, then decomposition and lastly, artificial neural networks. It is surprising that the most sophisticated of the four models being artificial neural networks performed worst. This is not a general statement in any way.

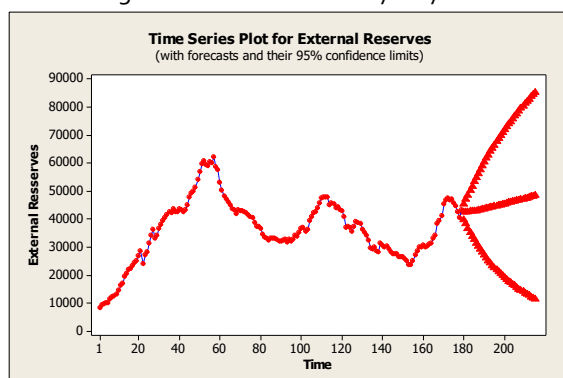


Fig. 2. Plot of original data and ARIMA forecasts for January 2019-December 2021

Having outperformed other models, ARIMA forecasts for 36 months are displayed in Figure 2. The plot suggests upward trend in foreign reserves over the forecast horizon, all factors being constant. The highest reserves were recorded in 2008 probably due to price of crude oil on the international market and the feat is yet to be repeated since then. The forecasts have not suggested that it will reach those points in the near future, at least not within period covered by the forecasts. This calls for concern. It means that a brilliant intervention will be required to attain highest of levels of foreign reserves attained in the past. As to whether the present administration possesses the potentials to make such happen is another topic for discussion. Achieving this means deliberate attempt at

promoting none oil export. Unfortunately the operating environment must be the right one to achieve improvements in productive activities in any economy. A situation where power supply remains epileptic, roads in bad shape, and insecurity worsening by the day cannot be said to be the right environment where manufacturing activities could thrive. It is when the environment is right that productive activities will thrive, export will receive huge boost and external reserves will dramatically improve.

Banditry must be deliberately fought and those found wanting be made to face the full wrath of law so as to discourage others from indulging in same or other violent crimes. Internet fraudsters must be sought after, arrested and prosecuted so that the international community can have confidence once again in transacting genuine businesses with Nigerians. Corruption in all its ramifications must also be fought, ill-gotten wealth should no longer be celebrated as presently the case and institutions must be strengthened and be allowed to freely operate.

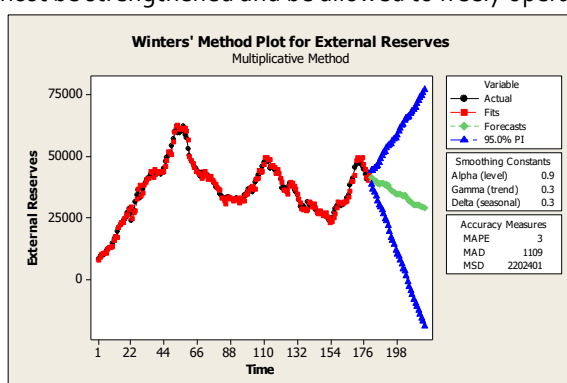


Fig. 3. Plot of original data and Holt-Winters' forecasts for January 2019-December 2021

The plot of H-W forecasts (Fig. 3) paints a gloomy scenario for future sizes of Nigeria's external reserves as it portrays a downward trend. Despite the model's being second in forecast performance, its behavior is contrary to that of ARIMA.

Table 2. P-values for paired t-tests

	ANN	DECOMP	H-W	ARIMA
ANN	-	0.000	0.008	0.000
DECOMP	0.000	-	0.000	0.000
H-W	0.008	0.000	-	0.000
ARIMA	0.000	0.000	0.000	-

Paired t-tests conducted on 36 months forecasts to investigate similarity in forecasting behavior of the models revealed results in Table 2. The p-values suggest that no pair of the models has produced forecasts whose means are not significantly different. Out of the six comparisons, only one of the p-values is non-zero, yet significant at 5% level. So, all the tests are highly significant. This is only corroborating the scenario exhibited by widely differing mse's in Table 1. So the models have not generated similar forecasts but have rather generated significantly differing forecasts.

Table 3. Pearson's correlation coefficients between forecasts

	ANN	DECOMP	H-W	ARIMA
ANN	1	-0.195 (0.254)	0.343 (0.041)	-0.291 (0.085)
DECOMP	-0.195 (0.254)	1	-0.646 (0.000)	0.647 (0.000)

H-W	0.343 (0.041)	-0.646 (0.000)	1	-0.990 (0.000)
ARIMA	-0.291 (0.085)	0.647 (0.000)	-0.990 (0.000)	1

The observed correlation coefficients were also computed based on 36 forecasts (See Table 3). Enclosed in parentheses are the p-values. Forecasts from ANN and those of each of decomposition and ARIMA models have shown insignificant negative linear correlation (indicative of dissimilarity) at 5% level. However, significant correlation was recorded between ANN and Holt-Winters forecasts. Correlation between decomposition and each of Holt-Winters and ARIMA is also significant, although the forecasts from decomposition move in opposite direction to those of Holt-Winters (implication of negative correlation of -0.646). A very strong, negative, highly significant correlation between Holt-Winters and ARIMA suggests that their forecasts substantially tend to move in opposite directions confirming scenarios portrayed in Figures 2 and 3. This suggests marked dissimilarity in forecasts behavior of the two models.

Conclusion

This article has compared for forecast performance, decomposition, Holt-Winters, ARIMA and artificial neural networks models on Nigeria's external reserves. It is found that

1. ARIMA performed best, followed by Holt-Winters, then, decomposition and lastly, ANN based on forecast mean square error. Hence, ARIMA (1, 1, 1) is recommended for forecasting Nigeria's external reserves.
2. Each model yields significantly different forecasts from others.
3. With increasing lead time, Holt-Winters forecasts substantially tend to move in opposite direction to each of decomposition and ARIMA forecasts.

The need to compare the models on other economic series is hereby, suggested.

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