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Predicting Exchange rate Volatility in the Nigerian Financial Market Using Artificial Neural Network Technology

S. Suleiman[1], N. Shehu[2]

[1]Department of Mathematics, Usmanu Danfodiyo University,Sokoto, Sokoto State, Nigeria
[2]Department of Mathematics and Statistics, Federal University Birnin Kebbi, Kebbi State, Nigeria

Abstract Knowledge of volatility is of crucial importance in many areas. The variability in the foreign exchange markets means huge losses or profits by investors. Therefore, the idea of estimating the market fluctuations is thus is very significant as this can help investors plan well for their investment returns from the market. Due to complex nature of the financial markets, linearity assumption in the financial market variables may be unsatisfactory. Artificial neural network technology is a non-linear mathematical model which is widely applied in the prediction of financial variables due to its flexibility. In this research, a monthly data (1995-2017) for Naira/USD exchange rates were used. Different architectures of the artificial neural networks models were estimated but architectures (3, 6, 1) was chosen because it gives the minimum error rate. This means a network 0f three significant input variables, six hidden nodes and output neuron is chosen for the prediction. It shows that the predicted values compared very with actual values.

Keywords Volatility, Artificial Neural Network (ANN), Prediction

1. Introduction

The exchange rate and its volatility are key factors that influence economic activities in Nigeria. That is why foreign exchange (FX) market fluctuations have always attracted considerable attention in both the economics and statistics literature. Examining the FX market by volume reveals that global daily FX transactions exceeded $4 trillion in 2010; bigger than the annual value of global trade (Bank for International Settlement, 2010). The world"s total external reserves grew to $9.7 trillion in 2010, while Nigeria"s reserves peaked at $64 billion in 2008 before the global financial crisis and dropped to $31.7 billion in late–2011 (BIS, 2010; CBN, 2011). Exchange–rate volatility is swings or fluctuation over a period of time in exchange rate. There has been excessive volatility of the *Naira* against major exchange rates in Nigeria since the adoption of flexible exchange–rate regimes in 1986. Consequently sustained exchange rate volatility was thought to have led to currency crises, distortion of production patterns as well as sharp fluctuations in external reserve. Recently, currency debates have taken centre–stage with the euro–zone currency and sovereign debt crises, US dollar volatility, concerns about China"s currency rates and strengthening of the Japanese yen, among others.

Stock market volatility is one of the most important aspects of financial market developments, providing an important input for portfolio management, option pricing and market regulation [1].

An investor's choice of a portfolio is intended to maximize the expected return subject to a risk constraint, or to minimize his risk subject to a return constraint. An efficient model for forecasting of an asset's price volatility provides a starting point for the assessment of investment risk. To price an option, one needs to know the volatility of the underlying asset. This can only be achieved through modeling the volatility. Volatility also has a great effect on the macro-economy. High volatility beyond a certain threshold will increase the risk of investor loses and raise concerns about the stability of the market and the wider economy [2].

Financial time series modeling has been a subject of considerable research both in theoretical and empirical statistics and econometrics. Numerous parametric specifications of ARCH models have been considered for the description of the characteristics of financial markets. Engle [3] introduced the Autoregressive Conditional Heteroscedasticity (ARCH) for modeling financial time series while Bollerslev [4] came up with the Generalized ARCH (GARCH) to parsimoniously represent the higher order ARCH model while Nelson [5] introduced the Exponential GARCH to capture the asymmetric effect. Other specifications of the GARCH model includes: the TGARCH introduced by Zakoian [6], IGARCH by Engle and Bollerslev [3,4], the Quadratic GARCH (QGARCH) model introduced by Sentana [7], the GJR model by Glosten *et al.*, [8] just to mention but a few.

Nigerian Financial Market has experienced many researches as far as volatility modeling is concerned. Studies carried out in the Nigerian Financial Markets include, Amaefula and Asare [9], who used GARCH (1,1) with multivariate regressors to determine the impacts of Inflation Dynamics and Global Financial Crises on Stock Market Returns and Volatility: Evidence from Nigeria. Musa, *et al* [10], who examined Exchange rate volatility of Nigerian Naira against some major currencies in the world: An application of multivariate GARCH models. Oke and Azeez [11], who applied ARCH models on a Test of Strong-Form Efficiency of the Nigerian Capital Market. Bala and Asemota [12], Exchange–Rates Volatility in Nigeria: Application of GARCH Models with Exogenous Break.

There is a significant amount of research on volatility of stock markets in Nigeria. The focus of financial time series modeling has been on the ARCH model and its various extensions which is basically based on the assumption that the time series data has a linear correlation structure thereby ignoring the aspect of non-linearity in the dataset. Therefore, ARCH type models of those complex problems may not be satisfactory. Nonparametric models estimated by various methods such as Artificial Intelligence (AI), can be fit on a data set much better than linear models.

For many years, researchers have made extensive efforts to take advantage of Artificial Neural Network technology to optimize a decision making process, to process an extensive amount of information , and to forecast financial markets leading to an increase in investment return. But, in Nigerian context, such researches are scanty or unavailable.

Recently, Artificial Neural Networks (ANN) has been proposed as a promising alternative to time-series forecasting. A large number of successful applications have shown that neural networks can be a very useful tool for time-series modeling and forecasting [13-19]. The reason is that the ANN is a universal function approximator which is capable of mapping any linear or non-linear functions [20-21]. Neural networks are basically a data-driven method with few priori assumptions about underlying models. Instead they let data speak for themselves and have the capability to identify the underlying functional relationship among the data. In addition, the ANN is capable of tolerating the presence of chaotic components and thus is better than most methods. This capacity is particularly important, as many relevant time-series possess significant chaotic components.

2. Volatility models

Let y_t be stock price at time t. Then

$$r_t = 100(ln\, y_t - ln\, y_{t-1}) \quad (1)$$

denotes the continuously compounded daily returns of the underlying assets at time t.

The most widely used model for estimating volatility is ARCH (Auto Regressive Conditional Heteroscedasticity) model developed by Engle(1982). Since the development of the original ARCH model, a lot of research has been carried out on extensions of this model among which GARCH [16] and is defined as $r_t = \mu_t + \varepsilon_t, \varepsilon_t = \sigma_t z_t$, and

$$\sigma_t^2 = \omega + \sum_{i=1}^{P} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 \quad (2)$$

$\omega, \alpha_i, \beta_j$ are non-negative parameters to be estimated , z_t is an independently and identically distributed (i.i.d.) random variables with zero mean and unit variance and ε_t is a serially uncorrelated sequence with zero mean and the conditional variance of σ_t^2 which may be nonstationary, the GARCH model reduces the number of parameters necessary when information in the lag(s) of the conditional variance in addition to the lagged ε_{t-i}^2 terms were considered, but was not able to account for asymmetric behavior of the returns.

Because of this weakness of GARCH model, a number of extensions of the GARCH (p,q) model have been developed to explicitly account for the skewness or asymmetry. The popular models of asymmetric volatility includes, the exponential GARCH (EGARCH) model by Glosten *et al.,* [8].

The GJR-GARCH (p, q) model was introduced by Donaldson and Kamstra [22] to allow for allows asymmetric effects. The model is given as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{P} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k \varepsilon_{t-k}^2 I_{t-k}^- \quad (3)$$

Where I_t^- (a dummy variable)=1 if $\varepsilon_t < 0$ & 0 otherwise.

In the GJR-GARCH model, good news $\varepsilon_{t-i} > 0$ and bad news, $\varepsilon_{t-i} < 0$, have differential effects on the conditional variance; good news has an impact of α_i while bad news has an impact of $\alpha_i + \gamma < 0$. If $\gamma_i > 0$, bad news increases volatility, and there is a *leverage effect* for the ith −order.if $\gamma \neq 0$, the news impact is asymmetric Glosten *et al.*, [8]. The exponential GARCH (EGARCH) model advanced by Nelson, [5] is the earliest extension of the GARCH model that incorporates asymmetric effects in returns from speculative prices. The EGARCH model is defined as follows:

$$log\sigma_t^2 = \omega + \sum_{j=1}^{P} \alpha_i \left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}} - E(\frac{\varepsilon_{t-i}}{\sigma_{t-i}})\right| + \sum_{j=1}^{q} \beta_j log\sigma_{t-j}^2 + \sum_{k=1}^{r} \gamma_k (\frac{\varepsilon_{t-k}}{\sigma_{t-k}}) \quad (4)$$

Where $\omega, \alpha_i, \beta_j$ and γ_k are constant parameters. The EGARCH (p,q) model, unlike the GARCH (p, q) model, indicates that the conditional variance is an exponential function, thereby removing the need for restrictions on the parameters to ensure positive conditional variance. The asymmetric effect of past shocks is captured by the γ coefficient, which is usually negative, that is, cetteris paribus positive shocks generate less volatility than negative shocks Longmore and Robinson [23]. The leverage effect can be tested if γ < 0. If γ ≠ 0, the news impact is asymmetric.

The asymmetry power ARCH (APARCH) model of Ding *et al*., [24] also allows for asymmetric effects of shocks on the conditional volatility. Unlike other GARCH models, in the APARCH model, the power parameter of the standard deviation can be estimated rather than imposed, and the optional γ parameters are added to capture asymmetry of up to order r. The APARCH (p, q) model is given as:

$$\sigma_t^{\delta} = \omega + \sum_{j=1}^{P} \alpha_i (|\varepsilon_{t-i}| - \gamma_i \varepsilon_{t-i})^{\delta} + \sum_{j=1}^{q} \beta_j log\sigma_{t-j}^{\delta} \quad (5)$$

where δ >0, i γ ≤1 for i =1, …, r, γi = 0 for all I > r, and r ≤ p If γ ≠ 0, the news impact is asymmetric.

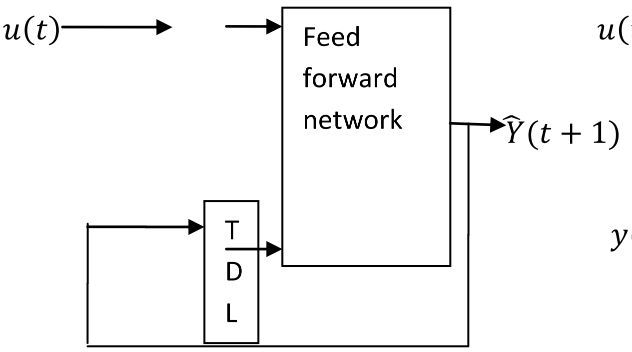
The introduction and estimation of the power term in the APARCH model is an attempt to account for the true distribution underlying volatility. The idea behind the introduction of a power term arose from the fact that, The assumption of normality in modeling financial data, which restricts *d* to either 1 or 2, is often unrealistic due to significant skewness and kurtosis Longmore and Robinson [23]. Allowing *d* to take the form of a free parameter to be estimated removes this arbitrary restriction.

3. Neural Network Autoregressive with Exogenous Input (NNARX)

NNARX is a recurrent dynamic network, with feedback connections enclosing several layers of the network. The NNARX model is based on the linear ARX model, which is commonly used in time-series modelling and forecasting. The NNARX model can be represented as follows:

$$y(t) = f(y(t-1), y(t-2) \dots, y(t-n), u(t-1), u(t-2), \dots, u(t-n)) \quad (6)$$

Where the next value of the dependent output signal $y(t)$ is regressed on previous values of the output signal and previous values of an independent (exogenous) input signal. The output is feed backed to the input of the feed-forward neural network as part of the standard NNARX architecture as shown in Fig 2. Since the true output is available during the training, we could create a series parallel architecture in which the true output is used instead of feeding back the estimated output as shown in Fig 3. This has two advantages, first is that the input to the feed-forward network is more accurate, second is that the resulting network has purely feed-forward architecture and static back propagation can be used for training.



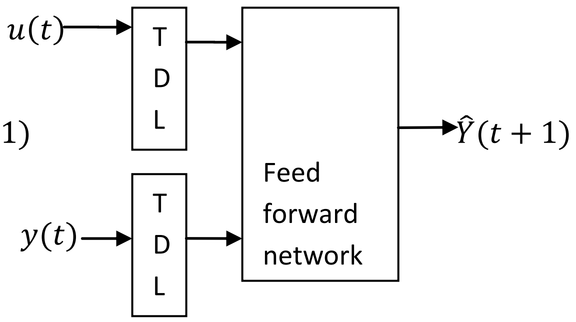


Figure 1: Parallel architecture of NNARX *Figure 2: Series Parallel architecture of NNARX*

Dynamic networks can be trained in the same gradient-based algorithm that is applied in back propagation. Although the method of training is same with static networks but the performance of this algorithm in dynamic networks is different from static networks because the gradient is computed in a more complex way.

4. Proposed Artificial Neural Network Model

In this paper, the underlying concept of the proposed model is that there are some explanatory factors other than historical prices that affect the future price returns volatility in the Market. We will predict volatility of price returns of Naira/USD exchange rate with a number of market variables which affect the price returns of the exchange rate. Selection of the input variables will depend on the knowledge of which ones affect volatility significantly. Some endogenous variables related to the historical performance of the returns are also used. These may include price returns, squared price returns, price, price squared, etc. The exogenous variables will also be used that may include some macro-economic variables which likely influence price returns. Both the endogenous and exogenous variables will be used as the input variables to the ANN model and the standard deviation as a measured of volatility is used as target output for training the network.

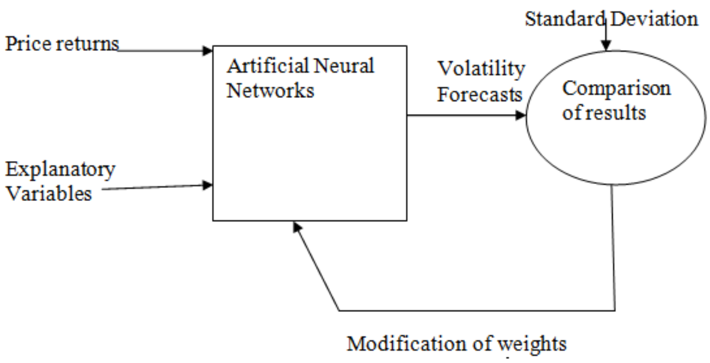


Figure 3: Schematic representation of the proposed model

5. Results and Discussion

In order to reduce the complexity of the neural network and to enhance the predicting performance, a linear regression model was used to select the significant predictors of the Naira/USD exchange rate volatility.

Table 1: Regression coefficients of the predictors

Model		**Unstandardized Coefficients**		**Standardized Coefficients**	**T**	**Sig.**
		B	**Std. Error**	**Beta**		
	(Constant)	1.003	1.493		0.672	0.503
	COP	-13.241	1.361	-2.56	10.395	0.001
	CPI	-0.003	0.008	-0.088	-0.341	0.734
1	Price	-0.015	0.027	-0.313	-0.533	0.595
	Sq. Price	0.000	0.000	0.560	0.803	0.423
	returns	49.977	2.949	2.660	16.949	0.000
	Sq. returns	52.239	3.092	2.670	16.894	0.000

The results shows that while crude oil price (COP), Price Returns and Price Returns Squared are significantly affecting volatility, Consumer Price Index(CPI), Price and Price Squared are not significant predictors of the volatility.

During training process some parameters were used at different values of nodes in the hidden layer in order to determine the best architecture of the network that guarantee at least good prediction. Table 2 is obtained when

Table 2: The determination of the number of nodes in the hidden layer

Nodes	Error	Threshold reached
1	167.6572	0.009924
2	167.5491	0.007699
3	149.2278	0.008135
4	149.4092	0.008822
5	149.03264	0.008564
6	148.7505	0.009292
7	148.9823	0.005994
8	148.8678	0.008081
9	148.9367	0.009984

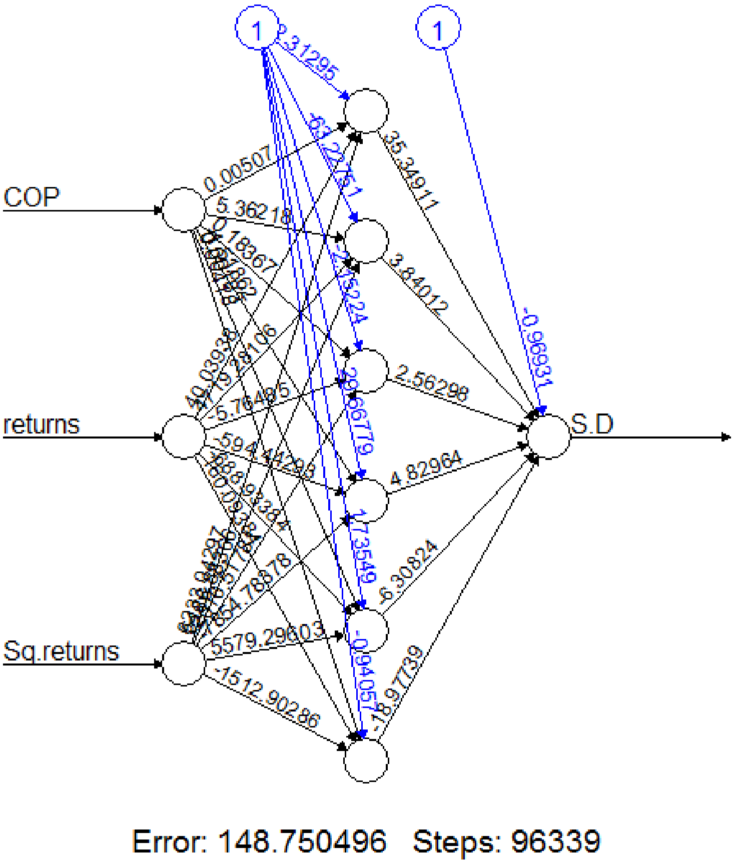


Figure 3: Artificial Neural Network Diagram

The back propagation training algorithm is used with learning rate of 0.01. It can be observed that the error of the network reduces with the increase in number of nodes for the hidden layer. At nodes 5 and 6, the level of error for the network dropped and continued to fluctuate; therefore node 6 seems to have the lowest and is therefore chosen as most appropriate for the prediction. The topology structure (3, 6, 1) of the ANN can be used to predict the volatility of Naira/USD exchange rate.

The networks after being trained with above parameters, the topology of (3, 6, 1) was selected as a result of minimizing the level of error. In about 96339 steps of iterations, the ANN converged with some estimates using step max algorithms. The estimates were depicted in the network diagram as shown figure 3. In the network; intercept to hidden neuron 1 is negatively related to volatility estimates, crude oil price is positively related to the output neuron, returns and square returns were positively influencing hidden neuron 1. Similarly, the network contains the importance of these explanatory variables to output neuron through other five hidden nodes. However, table 3 contains predicted output of the proposed model of the first six values of the explanatory variables and the output values for the response variable. It is clear that, the proposed model output compares very well with target output indicating good fit.

Table 3: Predicted artificial neural network values

s/n	COP	Returns	Sq.returns	nn-output	Target output
1	16.92	0.064773029	0.00419554500	0.99999999798	0.98456
2	17.54	0.016828721	0.00028320600	0.99984210983	0.95459
3	17.24	-0.010910874	0.00011904700	0.59804129151	0.62933
4	18.84	0.001859197	0.00000345661	0.10602191527	0.10607
5	18.71	-0.001484597	0.00000220403	0.07856129361	0.08485
6	17.58	0.001486805	0.00000221059	0.08246073899	0.08485

6. Summary and Conclusion

Different architectures of the Artificial Neural Network were evaluated using Naira/USD monthly exchange rates (1995-2014) data. Price of the exchange rates, square of the price, returns of the price, square returns of the price were the endogenous variables proposed for the network. Similarity, crude oil price and consumer price index were proposed exogenous variables to the network. Linear regression model was used as means of selecting significant variables to the network. Crude oil price, returns and squared returns were shown as significant variables and they were used in the training of the network. The standard deviation as an estimate of volatility is used as a response variable in order to train the network. The architectures (3, 6, 1) was selected for the prediction because it minimum the error. The proposed model predicts the response variable very well indicating good fit.

Reference

[1]. Poon, S.H. and C. Granger (2003). Forecasting volatility in financial markets: a review, *Journal of Economic Literature*, XLI, 478-539.

[2]. Hongyu, P and Zhichao, Z.(2006). Forecasting Financial Volatility: Evidence from Chinese Stock Market. Working paper in economics and finance No. 06/02. University of Durham. United Kingdom.

[3]. Engle, R.F. (1982). Autoregressive Conditional Heteroskedasticity with Estimates of the Variance of U.K inflation, *Econometrica*, 50, 987-1008.

[4]. Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroscedasticity. *Journal of econometrics*,31, 307-327.

[5]. Nelson, D.B. (1991). Conditional heteroskedasticity in asset returns: a new approach. *Econo-metrica* 59, 347-370.

[6]. Zakoian, J.M. (1994). Threshold Heteroskedastic Models. *Journal of Economic Dynamics and Control*. 18, 931-955.

[7]. Sentana, E. (1995). Quadratic ARCH models. *Review of Economic Studies*. 62 (4), 639-661.

[8]. Glosten, L., Jagannathan, R, and Runkle, D. (1993). On the Relation between the Expected Value and the Volatility of the Nominal Excess Return on Stocks. *Journal of Finance*, 48, 1779-1801.

[9]. Amaefula C.G. and Asare B.K., The Impacts of Inflation Dynamics and Global Financial Crises on Stock Market Returns and Volatility. Evidence from Nigeria, *Asian Economic and Financial Review*, 4(5):641-650.

[10]. Musa T, Yakubu M., and Gulumbe S. U (2014), Exchange rate volatility of Nigerian Naira against some major currencies in the world: An application of multivariate GARCH models. *International Journal of Mathematics and Statistics Invention,* 2(6), 52-65.

[11]. Oke, Micheal Ojo, Azeez B.A. (2012), A Test of Strong-Form Efficiency of the Nigerian Capital Market, *Business Systems Review,* 1, 11-26

[12]. Bala D. A., and Asemota J. O. (2013), Exchange–Rates Volatility in Nigeria: Application of GARCH Models with Exogenous Break, *CBN Journal of Applied Statistics, 4, 89*-116.

[13]. Wong W.K., Min Xia, and W.C.Chu (2010), Adaptive Neural Network Model for time Series Forecasting. *European Journal of Operational Research Journal* 207,807-816.

[14]. Celik, A.E., Karatepe, Y., 2007. Evaluating and forecasting banking crises through neural network models: an application for Turkish banking sector. *Expert Systems with Applications* 33, 809–815.

[15]. Wang, T., Chien, S., 2006. Forecasting innovation performance via neural networks–a case of Taiwanese manufacturing industry. *Technovation* 26, 635–643.

[16]. Sahoo, G.B., Ray, C., 2006. Flow forecasting for a Hawaii stream using rating curves and neural networks. *Journal of Hydrology* 317, 63–80.

[17]. Singh, P., Deo, M.C., 2007. Suitability of different neural networks in daily flow forecasting. *Applied Soft Computing* 7, 968–978.

[18]. Barbounis, T.G., Teocharis, J.B., 2007. Locally recurrent neural networks for wind speed prediction using spatial correlation. *Information Science* 177, 5775–5797.

[19]. Bodyanskiy, Y., Popov, S., 2006. Neural network approach to forecasting of quasiperiodic financial time series. *European Journal of Operational Research* 175, 1357–1366.

[20]. Cybenko, G., 1989. Approximation by superpositions of a sigmoidal function. Mathematics of Control, *Signals, and Systems* 2, 303–314.

[21]. Funahashi, K., 1989. On the approximate realization of continuous mappings by neural networks. *Neural Networks* 2, 183–192.

[22]. Donaldson R. G., and Kamstra M., (1997) "An artificial neural network-GARCH model for international stock return volatility", *Journal of Empirical Finance*, vol. 4, no. 1, pp. 17-46.

[23]. Longmore, R., and W. Robinson. 2004. "Modelling and Forecasting Exchange Rate Dynamics: An Application of Asymmetric Volatility Models". Bank of Jamaica. Working Paper WP2004/03

[24]. Ding, Z. R.F. Engle and C.W.J. Granger. 1993. "Long Memory Properties of Stock Market Returns and a New Model". *Journal of Empirical Finance*. 1. 83 – 106.