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# Artificial Neural Network Model for Predicting Exchange Rate in Ghana: A Case of GHS/USD

**Joseph Acquah, Alex Emmanuel Nti, Isaac Ampofi, David Akorli**

Department of Mathematical Sciences, University of Mines and Technology, Tarkwa, Ghana

**Email address:**
jacquah@umat.edu.gh (J. Acquah)

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**Abstract:** In today's global economy, accuracy in predicting the foreign exchange rate or at least predicting the trend correctly is of crucial importance for any future investment and this is mostly achieved by the use of computational intelligence-based techniques as explored in this paper. The aim of this study was to develop an Artificial Neural Network (ANN) Model for predicting the GHS/USD with inflation, nominal growth, monetary policy, interest rate, trade balance, gross international reserve, foreign currency deposit, broad money as the major indicators for Exchange rate. Three different ANN models which are Back Propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN) and Generalized Regression Neural Network (GRNN) were developed and the results were measured by the Performance Index (PI), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). After extensive training, validation and testing of the data, the BPNN model was seen to be the adequate model for predicting the exchange rate with MAE of 0.28973, RMSE of 0.32274, PI of 0.10416 and MAPE of 7% and a prediction accuracy ($R^2$) of 0.8460 as against the RBFNN which have MAE of 0.37265, RMSE of 0.48472, PI of 0.2349, MAPE of 8.52% and an $R^2$ of 0.3744, and the GRNN with MAE of 1.06482, RMSE of 1.15444, PI of 1.33274, MAPE of 24.07% and an $R^2$ of 0.2987.

**Keywords:** Artificial Neural Network, Training, Validation, Performance Index, Mean Absolute Error, Generalized Regression Neural Network

## 1. Introduction

In recent years, the impact of economic variables such as inflation, interest rate, nominal growth, trade balance, gross international reserve, foreign currency deposit and broad money on exchange rates has been very important to policy making which has been put under test and have traditionally proven very difficult to model and predict [1].

Exchange rate is the price of one currency in terms of another currency. In an open economy, exchange rate is an important macroeconomic indicator, which plays significant role in the determination of the prices of goods and services [2]. It is noted that, Exchange rate either appreciates or depreciates (fluctuate), and this appreciation and depreciation can be explained as, “increase and decrease in a currency’s value, compared to other foreign exchange in the market".

This implies that, currency appreciation of exchange rate, makes import goods and services cheaper, and export goods expensive whiles, currency depreciation raises the price of import goods and services, whiles reducing prices of export goods and services, thereby raising the cost of raw materials and productivity, hence reducing profit of industries in the economy [3].

Ghana introduced major economic recovery reforms in the financial sector with the introduction of the Financial Sector Adjustment Programme (FINSAP) in the 1988 and beyond. The recovery programme introduced the jettison of free exchange rates as a preference to the free-floating regime practiced before 1988 [4]. Again, it is noted that, the transition was done with the view that, flexible exchange rate was the best approach to control the boom-and-burst disorder for the country to turn on the path of positive growth with the growth-enhancing effect arising from the exchange rate, investments, terms of trade, and trade volumes.

In a developed and developing economy, exchange rate volatility has effect on export, trade, inflation, employment, growth and investment [5-7]. Examine the link between monetary policy and exchange rate changes, focusing both on measures of conventional as well as unconventional monetary policies. They confirmed that a country's currency tends to appreciate when there are higher simultaneous and expected future policy rates in that country relative to others.

The inception of the cedi in July 1965 to replace the Ghana pound saw a higher in value than the US dollar. The exchange rate then was 1.00 GHS = 1.17 USD. After February 1966, Ghana introduced the "new cedi", which took effect from 1967 to 2007 [8]. Further added that, decades of some unfavorable macroeconomic and structural fundamentals devalued the "new cedi", so that in 2007, the largest of the bank notes (20,000 GHS) had a value of about 2 USD. In 2007, the "new cedi" was redenominated for the introduction of the "Ghana cedi" in such a way that it was higher in value than the US dollar at an exchange rate of 1.00 GHS = 1.09USD [8].

As part of one of the major policies by the Government of Ghana to provide economic discipline that will ensure the GHS is stable with the USD or at best appreciation with the USD, the Government of Ghana introduce the 1D1F to promote industrialization, the planting for food and jobs initiative, but these initiatives did not bring out the major economic discipline such as inflation, nominal growth, monetary policy, interest rate, trade balance, gross international reserve, foreign currency deposit, broad money. Therefore, there is the need to develop a model that incorporates these factors to predict the GHS/USD in order to make informed decision.

## 2. Related Research Work on Ann Model

Several researches have proposed several methodologies and procedures in forecasting or predicting exchange rate for many economies, but few have been done in the area of Artificial Neural Network [9]. Research on "Real exchange rate and economic growth: Evidence from Chinese provincial data (1992-2008)". The influence of the real exchange rate in economic growth and the convergence of growth rates among Chinese provinces was investigated in this article. He discovered conditional convergence among coastal and inland provinces using data from 28 Chinese provinces from 1992 to 2008, as well as dynamic panel data estimate. The results reported here confirm the positive effect of real exchange rate appreciation on economic growth in the provinces [10].

Investigating the effects of exchange rate volatility on output growth and inflation in the West African Monetary Zone (consisting of Ghana, The Gambia, Guinea, Liberia, Nigeria and Sierra Leone) following exchange rate regime shift. Results from the study revealed that, while exchange rate volatility is inflationary across all the countries, its effect on output growth differ. Specifically, volatility and depreciation in particular negatively affects real GDP growth in Liberia and Sierra Leone but positively impacts on output in the other countries [11].

The equilibrium real exchange rate and real misalignment for Ghana from the period 1980 to 2010. The employed the method of the Error Correction Model. Real effective exchange rate was his dependent variable in the model specified and the explanatory variables included were productivity, trade openness, real relative interest rate, government expenditure, terms of trade and foreign reserves. It was revealed that productivity, trade openness, real relative interest rate and foreign reserves had a significant negative (depreciating) impact on real exchange rate, whereas total government expenditure, terms of trade, domestic credit and fiscal deficit had a positive (appreciating) impact on real exchange rate. However, the effects of domestic credit and fiscal deficit on real exchange rate were statistically not significant [12].

Works on the Determinants of the Real Exchange Rate in Ghana: A Focus on Inflation Using a Bound Test Approach was conducted. The study adopted an Autoregressive Distributed Lag (ARDL-Bounds Test) approach to co-integration to find out the determinants of the real exchange rate in Ghana by including inflation. Hence, the research developed a simple real exchange rate model for Ghana with the variables, Openness of trade, inflation and election year as a dummy variable on real exchange rate. The study found inflation to have a positive impact on the real exchange rate in the long run but a negative impact in the short run. Thus, the study concluded that openness of trade depreciates the real exchange rate in both the long run and the short run; whiles inflation depreciated the real exchange rate in the short run and appreciated the real exchange rate in the long run [14].

Also, the dynamic relationship between nominal exchange rate and macroeconomic variables in Pakistan was investigated. Exchange rate was the regress variable and the regressors were total reserves less gold, inflation through wholesale price index, imports, exports, industrial production, stock price index and money supply. The study period was from the first quarter of the year 1998 to the fourth quarter of the year 2012. Cointegration and Granger Causality tests were used for the estimations. The study determined that there is a long-run association between exchange rate and inflation at 10% significance level and the Granger-Causality test suggests that the direction of influence is more from inflation to exchange rate than from exchange rate to inflation; money supply granger-cause exchange rate; a bi-directional causality exists between exchange rate and total reserve; a bi-directional causality exists between exchange rate and industrial production and exchange rate granger-causes balance of trade in the short run [16].

Studies on the causes and effects of exchange rate volatility on economic growth was studied: Evidence from Ghana using annual data spanning 1980 to 2013, exploiting techniques from the time series literature. In their study, they identified that, while shocks to the exchange rate were mean reverting, misalignments tend to correct very sluggishly, with painful consequences in the short run as economic agents recalibrate their consumption and investment choices. Additionally, they noticed that, about three quarters of shocks to the real exchange rate were self-driven, and the remaining one quarter or so was attributed to factors such as government expenditure and money supply growth, terms of trade and output shocks. They concluded that, the short run output was the main driver of exchange rate fluctuations in Ghana. In the long run, however, exchange rate volatility is significantly influenced by government expenditure growth, money supply, terms of trade shocks, FDI flows and domestic output movements [13].

Researched on the determinants of currency crises in Ghana, He used monthly data from 1990 to 2016, whiles applying multinomial logistic regression by constructing a composite variable, exchange market pressure index which depicted the currency crisis environment in Ghana. He found that, due to the appreciation in exchange market pressure index growth rate of domestic credit and growth rate of output are significant determining factors of currency crises. As a result, increase in growth rate of domestic credit and increase in growth rate of output will reduce the probability of currency crisis. On the other hand, due to the depreciation in exchange market pressure index, broad money supply-reserves ratio is a significant determining factor of currency crisis occurring. As a result, decrease in broad money supply-reserves ratio will reduce the probability of currency crisis occurring. Hence, He concluded that, growth rate of domestic credit, broad money supply reserves and growth rate of output are significant determinants of currency crisis in Ghana [15].

Also worked on Foreign Exchange Prediction: A comparative Analysis of Foreign Exchange Neural Network (FOREXNN) and ARIMA Models, with the aim to model and predict the Nigerian foreign exchange rates against United States dollars and Chinese Yuan Renminbi using daily exchange rates from 18th April, 2007 to 3rd September, 2012. Foreign Exchange Neural Network (FOREXNN) models with back propagation training algorithm using descent gradient optimization technique and logistic activation function were developed and compared with Autoregressive Integrated Moving Average (ARIMA) on the basis of their predictive performance. The performance metrics considered for the evaluation of the models were mean square error (MSE) and mean absolute error (MAE). The results showed that FOREXNN models were superior to ARIMA models [17].

Worked on Inflation Forecasting in Ghana using Artificial Neural Network Model Approach. The work considered monthly series data from January 1991 to December 2010 to estimate and forecast for the period January 2011 to December 2011. The Nonlinear Autoregressive Network (NAR) model and Nonlinear Autoregressive with Exogenous Input Network (NARX) model were each trained with 20 hidden layer units, 1 output unit and LM backpropagation procedure. The forecast results remarkably indicated that both ANNs predict accurately with the NARX producing closer results than the NAR. The result of the ANNs were also compared with traditional time series models such as the AR (12) and VAR (14) which used the same set of variables. The basis of comparison was the out-of-sample forecast error (RMSFE). The results showed that, the RMSFE of the ANNs were lower than their econometric counterparts. Therefore, judging by the RMSFE criterion, it was concluded that, the comparative criterion forecast based on ANN models were more accurate [18].

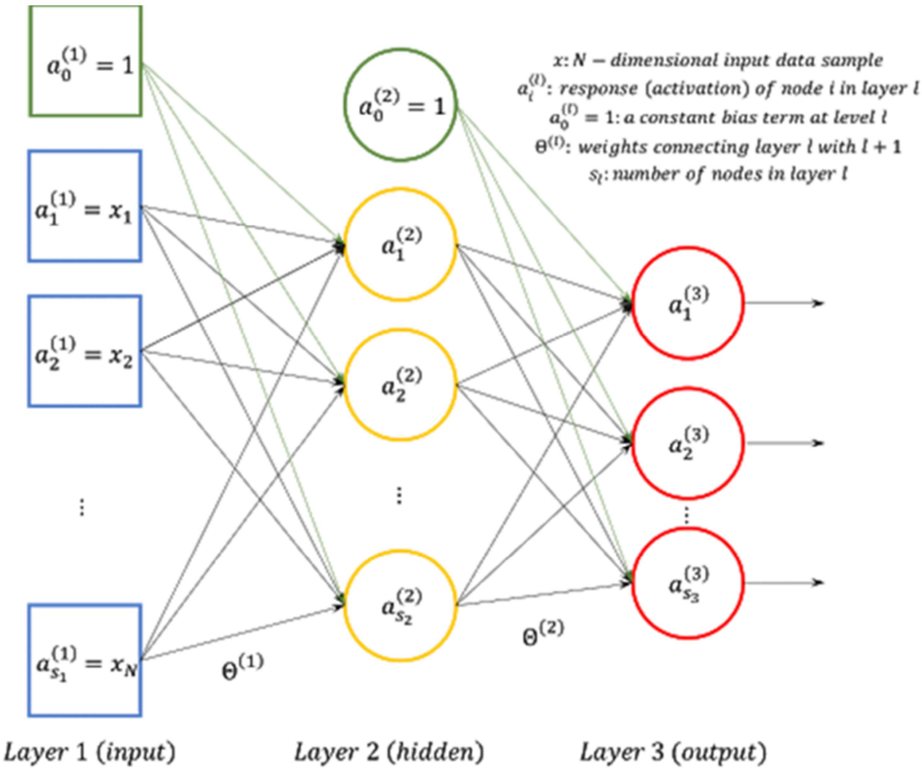


***Figure 1.*** *Back Propagation Neural Network.*

## 3. Developing Artificial Neural Network (Ann) Models

This section talks about the mathematical exactitudes of ANN models for predicting the exchange rate in Ghana. The ANN models considered are; Back Propagation neural Network (BPNN), Radial Basis Function Neural Network (RBFNN) and Generalized Regression Neural Network (GRNN).

*A. Back Propagation Neural Networks (BPNN)*

Back propagation is a short form for "backward propagation of errors. Back propagation is the core of neural net training. It is a standard method of training artificial neural networks. In this method, the wights of the neural network are adjusted based on the neural net on the error rate obtained in the previous iteration. Correct tuning of the weights helps to reduce error rates and to make the model reliable by increasing its generalization. This method helps to calculate the gradient of a loss function with respects to all the weights in the network. Figure 1 illustrates Architecture of Back Propagation Neural Network.

B. Back Propagation Neural Network Algorithm

The BPNN algorithm is a popular technique adequate to accomplish many learning problems. Inputs $x$, arrive through the preconnected path, and is modelled using real weights $W$. The weights are usually randomly selected. BPNN algorithm consists of two processes which are feed forward and back propagation. In feed forward step, the data which the network receives from outside are conveyed from input layer at output layer, and in back propagation step the error term of the network is transferred from output layer to the first layer. This algorithm is based on delta learning rule in which the weight adjustment is done through Mean Square Error (MSE) of the response to the sample input, [19]. The set of these sample patterns are repeatedly presented to the network until the error value is minimized. The back-propagation algorithm has emerged as one of the widely used learning procedures for multilayer networks [20]. The training algorithm used in the back-propagation network is as follows:

Step 1: Initially set the weights to small random values.

Step 2: While stopping condition is false, do step 3 to step 10.

Step 3: For each training pair do step 4 to step 9.

Step 4: Each input unit receives the input signal $x_i$ and broadcasts it to all nodes in the hidden layer.

Step 5: The activation model, $M_{inj}$ is computed by the relation given as Equation (1)

$$M_{inj} = Z_{mj} + \sum_{i=1}^{n} x_i w_{ij} \tag{1}$$

and the activation function $M_j$ is obtained as Equation (2)

$$M_j = f(M_{inj}) \tag{2}$$

where, $Z_{mj}$ is a bias on hidden unit *j*, $x_i$ represents input vector, $w_{ij}$ denotes the weight connection between input layer to hidden layer, and $f$ represents the activation function.

Step 6: For each output node $(y_k, k = 1,2,...r)$, $q_{ink}$ is computed by the relation given as Equation (3)

$$q_{ink} = Z_{oj} + \sum_{j=1}^{p} M_j a_{jk} \tag{3}$$

and Output unit $q_k$ is obtained as Equation (4)

$$q_k = f(q_{ink}) \tag{4}$$

$Z_{oj}$ is the bias output unit $j$, $a_{jk}$ represents the weight which connect node $j$ in the hidden layer to node $k$ in the output layer.

Step 7: Compute $\delta_k$ for each output neuron $(q_k, k = 1,...,v)$, where $\delta_k$ is define by Equation (5)

$$\delta_k = (t_k - q_k) f(q_{ink}) \tag{5}$$

where $t$ =target vector and $\delta_k$ is the error at output unit $k$.

Step 8: After receiving delta values from the step 7 above, each hidden unit $(M_j, j = 1,..., p)$ then calculates the sum of its delta input given by Equation (6)

$$\delta_{inj} = \sum_{k=1}^{m} \delta_j a_{jk} \tag{6}$$

and $\delta_j$ by Equation (7)

$$\delta_j = \delta_{inj} f(M_{inj}) \tag{7}$$

where, $\delta_j$ is the error at hidden unit $j$.

Step 9: Update the values of its bias and weights at each output unit $(q_k, k = 1,...v)$. Weight correction is done and this is given by Equation (8)

$$w_{inj}(new) = w_{ij}(old) + \Delta w_{ij} \tag{8}$$

and bias estimator is given by Equation (9)

$$\Delta a_{jk} = \alpha \delta b_k \tag{9}$$

where $\alpha$ denotes the learning rate and formula for updating of bias is given by Equation (10)

$$\Delta z_{mk} = \alpha \delta_k \tag{10}$$

and new bias estimator is obtained as Equation (11)

$$a_{jk}(new) = a_{jk}(old) + \Delta z_{mk} \tag{11}$$

such that $z_{mk}(new)$ is obtained as indicated in Equation (12)

$$z_{mk}(new) = z_{mk}(old) + \Delta z_{mk} \tag{12}$$

To update the values of its bias and weight at each hidden unit $(m_j, j = 1,...,p)$, formula for weight correction is given by Equation (13)

$$\Delta w_{ij} = \alpha \delta_j x_i \tag{13}$$

Formula for bias correction is given by Equation (14)

$$\Delta z_{mj} = \alpha \delta_j \tag{14}$$

therefore, $w_{ij}(new)$ is obtained as indicated in Equation (15)

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij} \tag{15}$$

and… $z_{mj}(new)$ is given as Equation (16)

$$z_{mj}(new) = z_{ij}(old) + \Delta z_{jk} \tag{16}$$

Step 10: Then test the stopping condition. The stopping condition may be minimized of errors, number of epochs etc.

*C. Radial Basis Function Neural Network (RBFNN)*

Radial basis functions are powerful techniques for interpolation in multidimensional space. RBF is a function which is built into a distance criterion with respect to a centre. Thus, it considers the distance of a point with respect to the centre. Radial basis functions have been applied in the area of neural networks where they are used as a replacement for the sigmoidal hidden layer transfer characteristic in multi-layer perceptron.

RBFN networks have two layers of processing. First, input is mapped onto each RBFNN in the 'hidden' layer, the output of these features is taken into consideration while computing the same output in the next time-step which is basically a memory. The RBFNN chosen is usually a Gaussian function. Figure 2 is a diagram that represents the distance calculating from the center to a point in the plane similar to a radius of the circle. RBFNN have the advantage of not suffering from local minima in the same way as Multi-Layer Perceptrons. This is because the only parameters that are adjusted in the learning process are the linear in nature from the hidden layer to output layer. Linearity ensures that the error surface is quadratic and therefore has a single easily found minimum. The trained model depends on the maximum reach or the radius of the circle in classifying the points into different categories. If the point yet to be classified is in or around the radius, the likelihood of the new point falling into that class is high. There can be a transition while changing from one region to another and this can be controlled by the beta function.

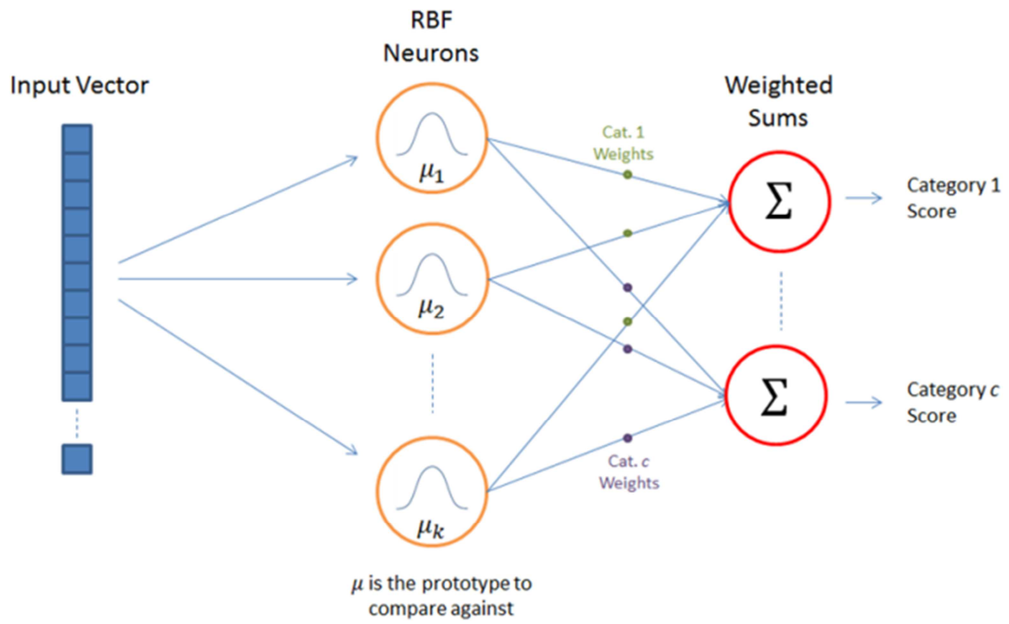


***Figure 2.*** *Distance from the Centre to a Point.*

D. Generalized Regression Neural Network (GRNN)

Generalized Regression Neural Network (GRNN) is a variation to Radial Basis Function Neural Network (RBFNN). GRNN represents an improved technique in the neural networks based on nonparametric regression. The idea is that, every training sample will represent a mean to a radial basis neuron. GRNNs are single-pass associative memory feedforward type of ANNs, and uses normalized Gaussian kernels in the hidden layer [21].

GRNN is made of input, hidden, summation, division layer and output layers as shown in Figure 3. When GRNN is trained, it memorizes every unique pattern. This is the reason why it is single-pass network and does not require any back-propagation algorithm. After training GRNN with adequate training data, it is able to generalize new inputs. GRNN advantages include its quick training approach and its accuracy.

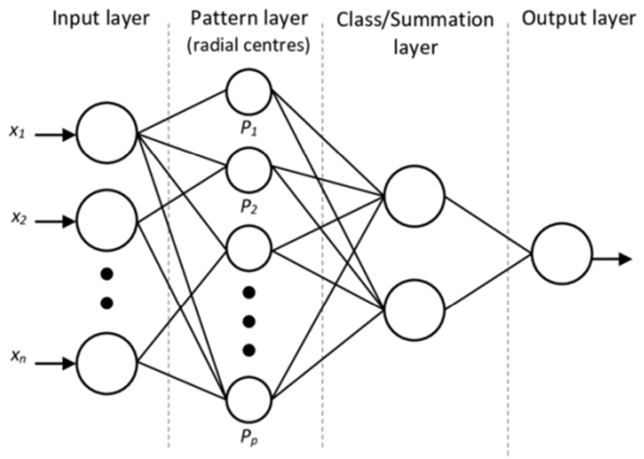


***Figure 3.*** *Generalized Regression Neural Network Architecture.*

# 4. Multiple Linear Regression

Multiple regression is an extension of simple linear regression. It is used when we want to predict the value of a variable based on the value of two or more other variables. The variable we want to predict is called the dependent variable (or sometimes, the outcome, target or criterion variable).

The general multiple linear regression (also known as the regression model) can be written in the population as given by Equation (17)

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \ldots + \alpha_n x_n + \varepsilon \tag{17}$$

where $y =$ dependent variable (Exchange rate), $\alpha_0 =$ intercept, $\alpha_1, \alpha_2, \ldots \alpha_n =$ coefficients (true values) $x_0, x_1, \ldots x_n =$ Independent variables (Macroeconomic Factors considered).

A. Ordinary Least Squares (OLS)

Ordinary least squares are a type of linear least squares method for estimating the unknown parameters in a linear regression model. OLS chooses the parameters of a linear function of a set of explanatory variables by the principle of least squares: minimizing the sum of the squares of the differences between the observed dependent variable (values of the variable being observed) in the given dataset predicted by the linear function.

Geometrically, this is seen as the sum of the squared distances, parallel to the axis of the dependent variable, between each data point in the set and the corresponding point on the regression surface. The smaller the differences, the better the model fits the data. The resulting estimator can be expressed by a simple formula, especially in the case of a simple linear regression, in which there is a single regressor on the right side of the regression equation.

The OLS estimator is consistent when the repressors are exogeneous, and by the Gauss Markov theorem optimal in the class of linear unbiased estimators when the errors are homoscedastic and serially uncorrelated. Under these conditions, the method of OLS provides minimum variance mean unbiased estimation when the errors have finite variance. Under the additional assumption that the errors are normally distributed, OLS is the maximum likelihood estimator. The OLS method minimizes the sum of squared residuals, and leads to a closed-form expression for the estimated value of the unknown parameter vector β given by Equation (18)

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T y \tag{18}$$

{\displaystyle {\hat {\boldsymbol {\beta}}}=(\mathbf {X} ^{\mathsf {T}}\mathbf {X})^{-1}\mathbf {X} ^{\mathsf {T}}\mathbf {y}}, where y {\displaystyle \mathbf {y}}is a vector whose *i*th element is the *i*th observation of the dependent variable, and {\displaystyle \mathbf {X}}x is a matrix whose $_{\text{ij}}$ element is the *i*th observation of the $j^{th}$ independent variable.{\displaystyle (\mathbf {X} ^{\mathsf {T}}\mathbf {X})^{-1}\mathbf {X} ^{\mathsf {T}}} The estimator is unbiased and consistent if the errors have finite variance and are uncorrelated with the regressors given by Equation (19)

$$E\left[X_j \varepsilon_i\right] = 0 \tag{19}$$

where $x_j$ is the transpose of row *j* of the matrix $x$. It is also efficient under the assumption that the errors have finite variance and are homoscedastic, meaning that the expression given by Equation (20)

$$E\left[\varepsilon_i^2 \middle| x_i\right] \tag{20}$$

does not depend on *i*.

The condition that the errors are uncorrelated with the regressors will generally be satisfied in an experiment, but in the case of observational data, it is difficult to exclude the possibility of an omitted covariate z that is related to both the observed covariates and the response variable. The existence of such a covariate will generally lead to a correlation between the regressors and the response variable, and hence to an inconsistent estimator of $\beta$. The condition of homoscedasticity can fail with either experimental or observational data.

# 5. Results and Discussion

A. Data Set

Data on monthly average of Ghana's exchange rate in US Dollar to Cedis (USD/GHS) and monthly measurement of Ghana's Monetary Policy (MP) in Percentage (%), Interest Rate (IR) in percentage (%), Inflation (INF) in percentage (%), Nominal Growth (NG) in percentage (%), Broad Money Supply (BMS) in millions of GHS, Gross International Reserves (GIR) in million US$, Foreign currency deposit (FCD) in million GHS, USA inflation (INFA) in percentage (%) and Trade Balance (TB) in Million US$ for 171-month period from January, 2005 to March 2019 were obtained through the Bank of Ghana's treasury and the market historical interbank foreign exchange rate.

B. Multiple Linear Regression

Ordinary least squares, instrumental variable and generalized method of moment were used to ascertain true statistical values to determine the impact of Monetary policy, nominal growth, broad money supply, gross international reserve, foreign currency deposit, trade balance, interest rate, inflation, all in Ghana and USA inflation on the exchange rate in Ghana. The result is presented in Table 1.

***Table 1.*** *The impact of macroeconomic indicators on exchange rate (USD-GHS).*

| **Dependent variable is Exchange Rate (USD-GHS)** | | | | |
|---|---|---|---|---|
| **Predictor Variable** | **OLS** | **IV** | **IV-GMM at lag 2** | **IV-GMM at lag 4** |
| Log of Growth Rate (Nominal) | -0.2200*** | -0.5312*** | -0.5517*** | -0.4902*** |
| US Inflation | 0.0721*** | 0.0876*** | 0.0887*** | 0.0857*** |
| Log of Inflation Rate | -0.3472* | -0.2615 | -0.2430 | -0.2083 |
| Log of Interest Rate | -0.5480*** | -0.5467*** | -0.5522*** | -0.5933*** |
| Log of Broad Money Supply | 1.5812*** | 1.5972*** | 1.6280*** | 1.6885*** |
| Log of Gross International Reserve | -1.0993*** | -1.1327*** | -1.1722*** | -1.2389*** |
| Log of Foreign Currency Deposit | -0.0657*** | -0.0771*** | -0.0787*** | -0.0776*** |
| Log of Monetary Policy Rate | 1.9301*** | 1.6311*** | 1.5651*** | 1.5309*** |
| Trade Balance | 0.0004** | 0.0003* | 0.0003 | 0.0003 |
| Constant | -5.5605*** | -3.9140*** | -3.6651*** | -3.7516*** |
| F-Statistic/Wald Chi-squared Statistic | 483.97 | 411.46 | 406.70 | 434.87 |
| p-value | 0.0000 | 0.0000 | 0.0000 | 0.0000 |
| R-squared | 0.9522 | 0.9472 | 0.9468 | 0.9489 |

It is normally advisable to run the routine OLS regression model in order to examine the impact of one or more predictor variables on a response variable since OLS estimates are by construction unbiased and consistent if all assumptions of a linear regression model are satisfied. In view of this, we obtain the estimates of the effect of some macroeconomic indicators on exchange rate (USD-GHS) as shown in Table 1 using the OLS estimator. Under column (2) in Table 1, all estimates are statistically significant at the 1% significant level except for trade balance and inflation rate which are significant at the 5% and 10% levels respectively. All variables except for US inflation and trade balance are logged in order to reduce the variance in their values. Variance for US inflation was already relatively low so taking logarithm will not result into major changes in its values. Trade balance has negative values so taking logarithm will result into the missing data problem which will unnecessarily reduce the sample size.

The negative coefficient of nominal growth rate, inflation rate, interest rate, gross international reserves and foreign currency deposit depict a reverse relationship between macroeconomic indicators and exchange rate (USD-GHS). This shows that, as nominal growth rate, inflation rate, interest rate, gross international reserves and foreign currency deposit increase, the exchange rate decrease. Technically, for the estimate of the effect of nominal growth rate on exchange rate; it implies that as the nominal growth rate increases by 10%, then exchange rate will decrease by 0.022% with all other variables remaining constant. If inflation increases by 10%, then exchange rate will decrease by roughly 0.035%; if interest rate increases by 10%, then exchange rate will go down by 0.055% keeping constant every other variable.

Gross international reserves and foreign currency deposit also have estimates of -1.0993 and -0.0657 respectively implying that exchange rate declines by nearly 0.11% and 0.07% when gross international reserves and foreign currency deposit rise by 10%. However, US inflation, broad money supply, monetary policy rate and trade balance have positive signs implying their direct relationship with exchange rate. For instance, a 10% increase in US inflation increases exchange rate by 0.007% with all other variables held fixed. A 10% increase in each of broad money supply and monetary policy rate increase the exchange rate by approximately 0.16% and 0.19% respectively. Trade balance has a very little/marginal impact on exchange rate in Ghana as shown by its relatively smaller estimate.

*C. Analysis of Back Propagation Neural Network (BPNN)*

This section presents the result of BPNN algorithm on the exchange rate (GHS/USD). Table 2 has three sections and these are, architecture (Arch.) which indicates the number of neurons in the input layer, the training which also represents the neurons in the hidden layer, and the testing part representing the neurons in the output layer. The Architecture is the neuron at which optimality is identified by the empirical analysis of the errors. The training network section contains the coefficient of determination with the following error estimates. Thus, Performance Index (PI), Mean Absolute Error (MAE), and Root Mean Squared Error (RMSE). Whiles, the testing network also contains Performance Index (PI), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE) and the Mean Absolute Percentage Error which will be used as a benchmark for selecting the adequate model for predicting the exchange rate in Ghana.

From Table 2, the results of the Training data show that, architecture 9-23-1 has the minimum performance index (PI= 0.00060) with the estimated error values for MAE=0.01301 and RMSE= 0.02449. Architecture 9-23-1 being the optimal has estimated $R^2$ value of 99.91%. This shows that, the independent variables which are Ghana's inflation, monetary policy, interest rate, nominal growth, broad money supply, inflation of United State of America, foreign currency deposit and trade balance could explain 99.91% of the Exchange rate between GHS/USD.

However, the introduction of new data set to the trained models to predict, showed that, architecture 9-1-1 predicted adequately on new set of data than the other twenty-nine architectures including architecture 9-23-1 which was touted to be the adequate model at the training. From the results in Table 2, it is noted that, the test performance error estimates being PI of 0.10416, MAE of 0.28973, RMSE of 0.32274 and a MAPE of 7 percent were the least achieved error when the data was tested.

Therefore, the network architecture 9-1-1 is accepted as the optimal model for BPNN architecture, and can be used for predicting the exchange rate between the US Dollar and the Ghana Cedi.

***Table 2.*** *Summary of competing BPNN architecture for dollar and cedi.*

| Arch. | Train | | | | Test | | | |
|---|---|---|---|---|---|---|---|---|
| | PI | RMSE | MAE | R^2 | PI | RMSE | MAE | MAPE |
| 1 | 0.01582 | 0.12579 | 0.09614 | 0.97605 | 0.10416 | 0.32274 | 0.28973 | 6.99621 |
| 2 | 0.00359 | 0.05995 | 0.04673 | 0.99456 | 24.71170 | 4.97109 | 4.62230 | 105.12256 |
| 3 | 0.00198 | 0.04447 | 0.02982 | 0.99701 | 1.27350 | 1.12850 | 1.07504 | 24.56177 |
| 4 | 0.00116 | 0.03405 | 0.02594 | 0.99825 | 0.37726 | 0.61421 | 0.54393 | 12.71734 |
| 5 | 0.00168 | 0.04101 | 0.02653 | 0.99745 | 1.55279 | 1.24611 | 1.15173 | 26.14606 |
| 6 | 0.00393 | 0.06268 | 0.02756 | 0.99405 | 3.18684 | 1.78517 | 1.73665 | 40.32229 |
| 7 | 0.00096 | 0.03101 | 0.01888 | 0.99854 | 0.62359 | 0.78968 | 0.67112 | 16.13485 |
| 8 | 0.00161 | 0.04009 | 0.01771 | 0.99757 | 1.58068 | 1.25725 | 1.08572 | 25.76820 |
| 9 | 0.00209 | 0.04577 | 0.01693 | 0.99683 | 0.30763 | 0.55464 | 0.48271 | 11.26373 |
| 10 | 0.00221 | 0.04698 | 0.01637 | 0.99666 | 0.46145 | 0.67930 | 0.59399 | 13.73928 |
| 11 | 0.00125 | 0.03533 | 0.01404 | 0.99811 | 0.55303 | 0.74366 | 0.54208 | 12.78181 |
| 12 | 0.00359 | 0.05992 | 0.02005 | 0.99457 | 4.39147 | 2.09558 | 1.82748 | 40.84174 |
| 13 | 0.00141 | 0.03755 | 0.00974 | 0.99787 | 0.49536 | 0.70382 | 0.58494 | 13.91890 |
| 14 | 0.00379 | 0.06155 | 0.01996 | 0.99427 | 0.78976 | 0.88868 | 0.77369 | 17.41656 |
| 15 | 0.00212 | 0.04608 | 0.01398 | 0.99679 | 3.27849 | 1.81066 | 1.53309 | 34.12564 |
| 16 | 0.00088 | 0.02970 | 0.01496 | 0.99867 | 0.54585 | 0.73882 | 0.64001 | 15.05977 |
| 17 | 0.00108 | 0.03282 | 0.01161 | 0.99837 | 3.33404 | 1.82593 | 1.62915 | 36.67532 |
| 18 | 0.00153 | 0.03917 | 0.01567 | 0.99768 | 0.14040 | 0.37469 | 0.25571 | 5.74043 |
| 19 | 0.00313 | 0.05594 | 0.01538 | 0.99526 | 4.61977 | 2.14936 | 1.74823 | 38.79844 |
| 20 | 0.00533 | 0.07301 | 0.02005 | 0.99193 | 4.85611 | 2.20366 | 1.98075 | 44.72879 |
| 21 | 0.00070 | 0.02644 | 0.01731 | 0.99894 | 3.92340 | 1.98076 | 1.72679 | 38.57599 |
| 22 | 0.00112 | 0.03344 | 0.01445 | 0.99831 | 2.68579 | 1.63884 | 1.42918 | 32.15933 |
| 23 | 0.00060 | 0.02449 | 0.01301 | 0.99909 | 1.23055 | 1.10930 | 0.99376 | 22.80280 |
| 24 | 0.00153 | 0.03906 | 0.01550 | 0.99769 | 0.88388 | 0.94015 | 0.77101 | 18.66347 |
| 25 | 0.00613 | 0.07828 | 0.02140 | 0.99073 | 3.83651 | 1.95870 | 1.65937 | 37.05947 |
| 26 | 0.00205 | 0.04526 | 0.01536 | 0.99690 | 4.31733 | 2.07782 | 1.87062 | 42.11731 |
| 27 | 0.00078 | 0.02799 | 0.01376 | 0.99881 | 0.18104 | 0.42548 | 0.35838 | 8.48782 |
| 28 | 0.00064 | 0.02532 | 0.01391 | 0.99903 | 0.80690 | 0.89828 | 0.78882 | 17.71723 |
| 29 | 0.00171 | 0.04133 | 0.01684 | 0.99741 | 0.26605 | 0.51580 | 0.42238 | 10.00391 |
| 30 | 0.00121 | 0.03484 | 0.01409 | 0.99816 | 1.31567 | 1.14702 | 1.01206 | 24.06793 |

D. Validation of the Models

To further ascertain the appropriate technique for predicting the exchange rate between the GHS/USD, the predictive performance of the selected optimal network architectures for the various techniques are assessed. Figure 4, Figure 5 and Figure 6 show the graphical representation of the optimal architectures for the BPNN, RBFNN and the GRNN during the training stage, whiles Figure 7 shows the graph of the adequate (BPNN) model which was able to predict better than the test of RBFNN and GRNN models when new data sets were introduced (test stage). The asterisks (***) on the graphs indicate the graph of the observed values, whiles the continuous line (-) indicate the graph of the predicted trend.

The variance accounted for by the trained models are also shown in Table 3, from Table 3, the GRNN of architecture (spread) of 0.2 accounted for the highest proportion of variance explained during the training stage. Thus, $R^2$ of 99.87% implies that, the model could predict 99.87% accuracy at the training stage.

Figure 7 shows the predictions between the BPNN models on the test data. Although all the selected optimal architectures performed well, comparing the performance and the error measures arising from the prediction from the test data in Table 3 indicates that, the BPNN architecture (9-1-1) produced the least error estimate values with PI of 0.10416, MAE of 0.28973, RMSE of 0.32274 and MAPE of 7%.

Therefore, the BPNN architecture (9-1-1) is selected as the adequate model with a better accuracy for predicting the exchange rate between the US Dollar and the Ghana Cedi, hence, the back propagation neural network with architecture 9-1-1 is the best model for predicting the USD/GHS exchange rate.

***Table 3.*** *Model performance for GHS/USD.*

| Network | Arch. | spread | MAPE | PI | MAE | RMSE | $R^2$ | Ranking |
|---|---|---|---|---|---|---|---|---|
| BPNN | 9-1-1 | --- | 7.00 | 0.10416 | 0.28973 | 0.32274 | 0.8460 | 1 |
| RBFNN | 9-8-1 | 1.0 | 8.52 | 0.23495 | 0.37265 | 0.48472 | 0.3744 | 2 |
| GRNN | --- | 0.2 | 24.07 | 1.33274 | 1.06482 | 1.15444 | 0.2987 | 3 |

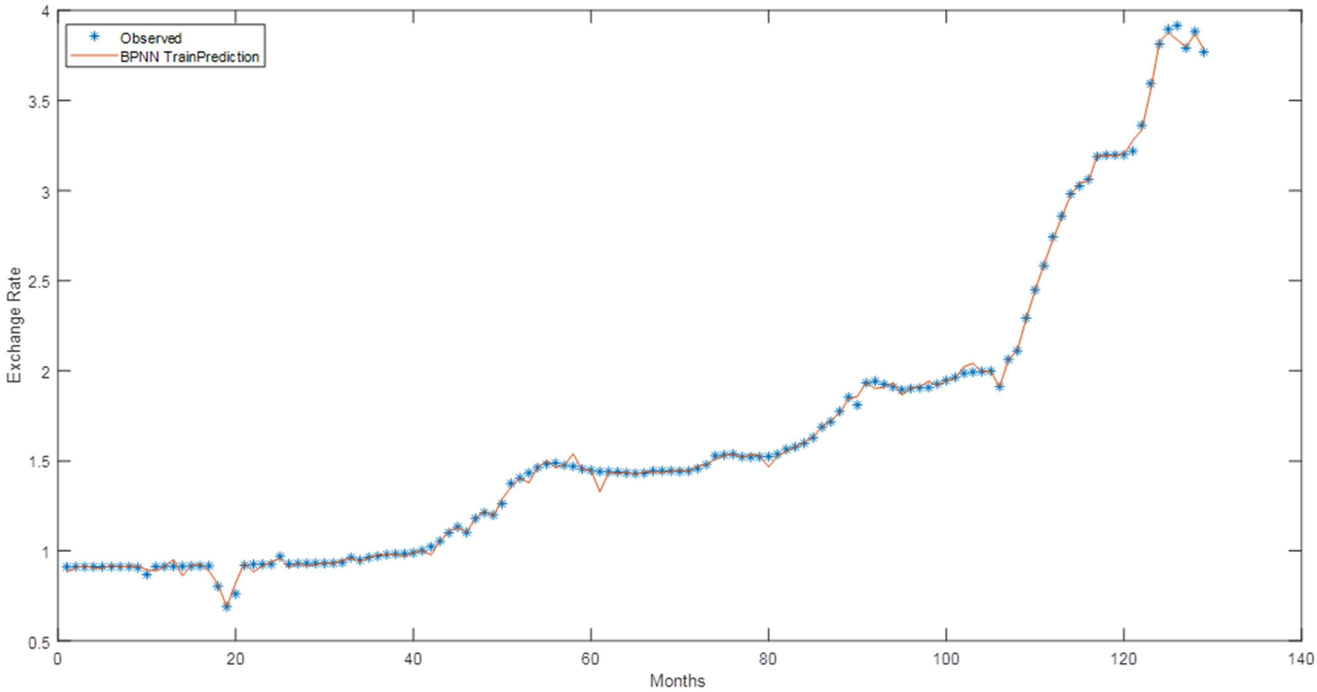


***Figure 4.*** *BPNN Indicating Training Performance of Selected Architecture.*

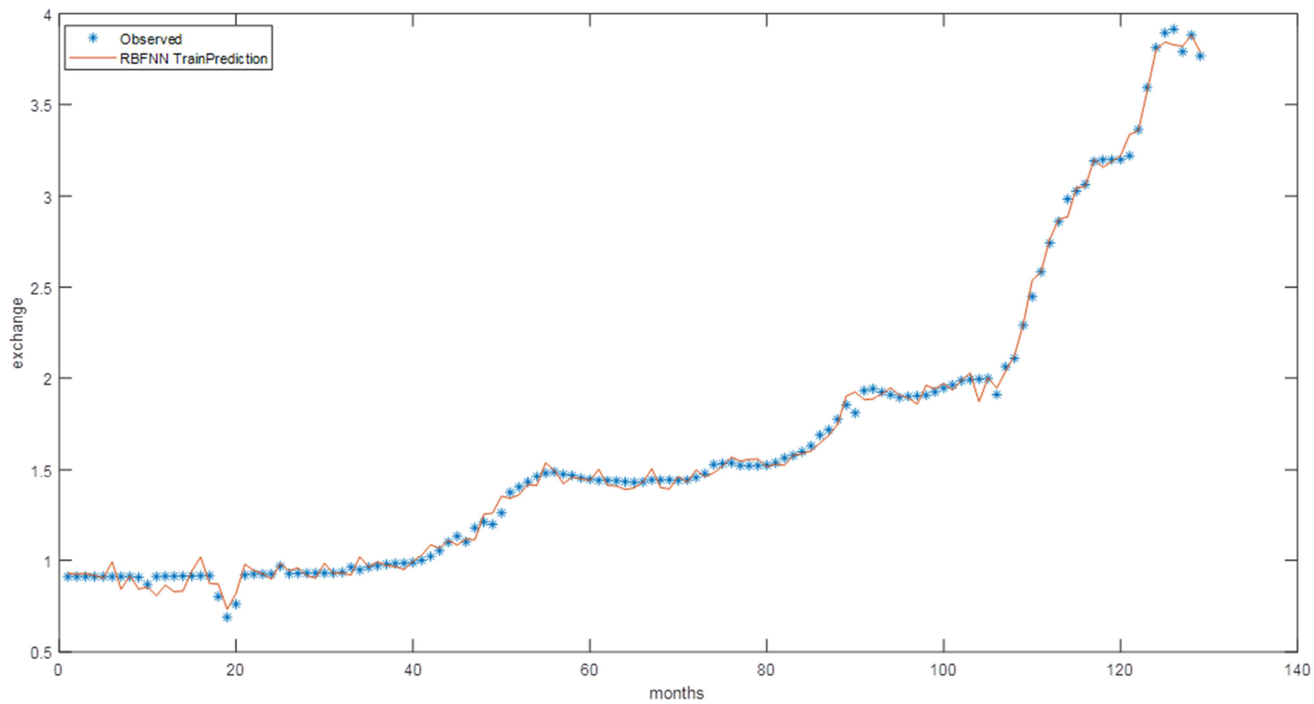


***Figure 5.*** *RBFNN Indicating Training Performance of Selected Architecture.*

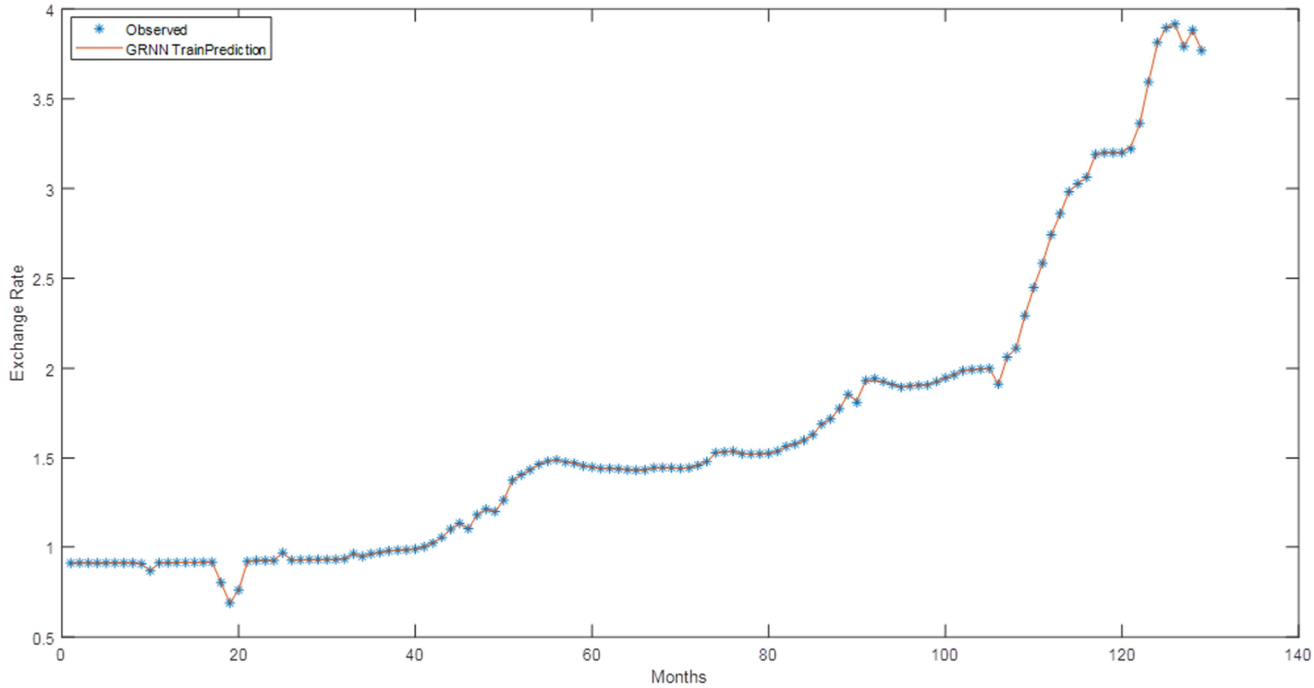


***Figure 6.*** *GRNN Indicating Training Performance of Selected Architecture.*

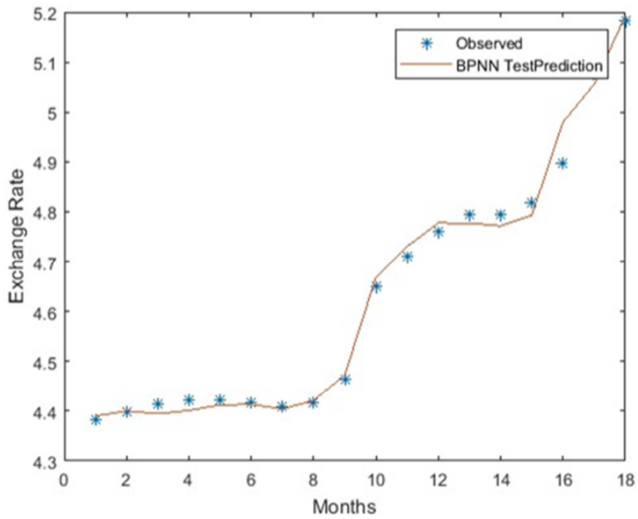


***Figure 7.*** *BPNN Indicating Test Performance of Selected Architecture.*

# 6. Conclusion and Recommendation

## *6.1. Conclusion*

This paper sought to determine the impact of macroeconomic factors on the exchange rate of Ghana, and to develop an ANN model for predicting the exchange rate in Ghana. The impact of the macroeconomic variables (monetary policy, nominal growth rate, broad money supply, gross international reserve, foreign currency deposit, USA inflation, trade balance, interest rate and inflation) on exchange rate have been established by the study, as shown in Table 1. The results in totality show a significant effect on almost all of the predicted variables examined. The results further proved that all predictor estimates were statistically significant at the 1% level except for trade balance and inflation rate which are significant at the 5% and 10% alpha levels respectively.

Also, the overall F-Statistics of 483.97 for the GHS/USD obtained had a p-value of 0.0000. This implies that, apart from the individual statistical significance of the variables, jointly, all the variables in the model are statistically significant since the p-value is smaller than 0.05.

ANN models for predicting the exchange rates (USD-GHS) were obtained. The optimal performance model for the USD-GHS was obtained at architecture 9-1-1. The predictive accuracy of the models was ascertained using the mean absolute error, performance index, root mean squared error and the mean absolute percentage error which can be found in Table 2.

## *6.2. Recommendation*

It is recommended that, investors, policy makers, researchers and academicians interested in predicting exchange rate in Ghana should use the back propagation neural model for determining the trends. For the special case of predicting the exchange rate between the GHS/USD, the backpropagation neural network model at architecture 9-1-1 should be used.

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