DECLARATION

I declare that this thesis is my own work. It is being submitted for the degree of Master of Philosophy in Mathematics (Financial Mathematics) in the University of Mines and Technology, Tarkwa. It has not been submitted for any degree or examination in any other university.

…………………………………………………

(Signature of Candidate)

……………. Day of ……………………, 2021

ABSTRACT

The aim of this study was to develop an Artificial Neural Network (ANN) Model for predicting the Ghanaian Cedi to US Dollar rate and the Ghanaian Cedi to Great Britain Pound rate with inflation, nominal growth, monetary policy, interest rate, trade balance, gross international reserve, foreign currency deposit, broad money and US inflation. Three different ANN models: Back Propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN) and Generalized Regression Neural Network (GRNN) were employed for the study. The results were measured by the Performance Index (PI), Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE). For the Ghana Cedi - US Dollar rate, after careful and extensive training, validation and testing, the BPNN model was realised to be the adequate model for predicting the exchange rate with MAE of 0.28973, RMSE of 0.32274, PI of 0.10416, MAPE of 7% and a prediction accuracy (R^2) of 0.8460 as against the RBFNN which have MAE o f0.37265, 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 respectively. Also, BPNN model was at the same time identified as the sufficient model to predict the Ghana Cedi to Great Britain Pound rate with MAE of 0.31016, RMSE of 0.38542, PI of 0.14855, MAPE of 5.62% and a prediction accuracy (R^2) of 0.7912 as against the RBFNN which have MAE of 0.40857, RMSE of 0.51858, PI of 0.26893, MAPE of 7.02% and an R^2 of 0.3705, and the GRNN with MAE of 0.50627, RMSE of 0.73248, PI of 0.53653, MAPE of 8.48% and an R^2 of 0.2189 Respectively.

DEDICATION

I dedicate this thesis to my patron saint Archangel Michael, my child Archangel-Michael Attobrah and my family.

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

In recent years, the impact of economic variables such as inflation, interest rate, nominal growth, trade balance, gross international reserve, etc 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 (Frankel, 2015).

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 (Mankiw, 2000). It is noted that, Exchange rate either appreciates or depreciates (fluctuate), and defined currency appreciation and depreciation 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 (Highfill and Wojcikewych, 2011).

Alegidede and Ibrahim (2017) revealed that, exchange rate volatility leads to many reforms in most of the economies in the world for which Ghana is part.

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 (Kamasa, 2013). 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 pass, 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 (Assery and Peel, 1991; Choudhry, 2005; Wang and Barret, 2007; Doyle, 2001; Thorbecke, 2008; Bredin *et al*., 2003; Tenreyro, 2007; Jack *et al*., 2019; Belke and Setzer, 2003; Belke and Kaas, 2004; Galiani *et al*., 2003; Danne, 2006; Kasman *et al*., 2011; Servén, 2003; Kiyota *et al*., 2008; Fuentes, 2006).

Stavrakeva and Tang (2015) examined 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 cedi = 1.17 dollars. After February 1966, Ghana introduced the "new cedi", which took effect from 1967 to 2007 (Amoako-Agyeman and Mintah, 2014).

Amoako-Agyeman and Mintah (2014) further added that, decades of some unfavourable macroeconomic and structural fundamentals devalued the "new cedi", so that in 2007, the largest of the bank notes (¢20,000) had a value of about US$2. 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 GH¢1.00=US$1.09.

In an open economy, there is always exchange rate volatility. This volatility has effects on firms, since firms do not know the exact quantification of exchange rates fluctuations, they expose themselves. This is because of the factors that causes the exchange rate. The determinants of the exchange rate are the supply of dollars and pounds to Ghana and Ghana's demand for dollars and pounds (Seyram and Matuka, 2020).

Seyram and Matuka (2020) explained that, supply of dollars and pounds come mainly from dollars and pounds received from exports of goods, use of Ghanaian services by foreigners, investment flows into Ghana, remittance inflows, loans and grants, whiles, demand for dollars and pounds come mainly from payment of dollar and pounds for imports of goods, use of foreign services by Ghanaians, transfers of dividends and profits earned by foreigners investing in Ghana, interest and amortisation of loans.

However, outside these recognised channels for dollar and pound supply and demand, there could be in and out movements of dollars and pounds through other (unofficial) channels referred to as "capital flight". Though they may not be captured in official transactions records, these flows also ultimately affect the exchange rate (Seyram and Matuka, 2020).

Due to the impact of exchange rate volatility on economies, econometricians have modelled exchange rate as a dependent variable with major macroeconomic indicators as independent variables using Artificial Neural Network (ANN) Hall *et al*. (2010).

Artificial Neural Network is an aspect of Artificial Intelligence (AI), which is an aspect of computer science, applied in several studies including financial research, in solving some fundamental real-life problems over two decades since its inception (Brooks and Prokopczuk, 2013).

Most studies on the application of ANN in Financial Mathematics (Engineering) is concentrated on the US stocks and indexes (Kristjanpoller and Minutolo, 2015), whiles (Stephen, 2014) reiterate that, few studies have been done in Africa on ANN in relation to financial research.

However, none of these econometric models developed using ANN incorporated these major factors at the same time. Thus; gross international reserve, foreign currency deposit, monetary policy, interest rate, inflation, trade balance, broad money supply, nominal growth, and the inflation rate of the United States of America.

However, Bacchetta and Van-Wincoop (2004, 2006, 2013) opined that the poor performance of exchange rate models has been as a result of the omission of one or more of the factors mentioned earlier (gross international reserve, foreign currency deposit, monetary policy, interest rate, inflation, trade balance, broad money supply, nominal growth, and the inflation rate of the United States of America)

Therefore, the aim of this study was to develop an Artificial Neural Network (ANN) Model, which would incorporate these factors to predict the exchange rate in Ghana.

1.2 Statement of the problem

Over the past decade, not many researchers have devoted considerable resources to modelling exchange rate in Ghana, especially using Artificial Neural Network. In literature, there are several econometric models that have been developed for Ghana's financial sector since the 1970's (Aryeetey and Fosu, 2003).

However, studies have revealed that the best way to go in predicting exchange Rate is by using Artificial Neural Network or machine learning Faia and Monacelli, 2008; Bacchetta and Van-Wincoop, 2013; Stephen, 2014).

Due to the impact of exchange rate fluctuations on economies, econometricians have modelled exchange rate as a dependent variable with major macroeconomic indicators as independent variables using Artificial Neural Network Hall *et al*. (2010).

However, none of these econometric models developed using ANN incorporated these major factors at the same time. Thus; gross international reserve, foreign currency deposit, monetary policy, interest rate, inflation, trade balance, broad money supply, nominal growth, and the inflation rate of the United States dollar.

Therefore, the aim of this study is to develop an Artificial Neural Network Model, which will incorporate the aforementioned factors to predict the exchange rate in Ghana.

1.3 Research Objectives

The objectives of this research are to:

i. Determine the impact of macroeconomic indicators on the exchange rate of Ghana.
ii. Develop Artificial Neural Network model for predicting Exchange rate changes in Ghana.
iii. Test the predictive accuracy of the model.

1.4 Methods to be used

The methods to be used in this thesis are:

i. Multiple regression for assessing the impact of the microeconomic variables on exchange rate.
ii. BPNN, GRNN and RBFNN were used for predicting exchange rate.

iii. Mean Absolute Percentage Error (MAPE), Performance Index (PI), Mean Absolute Error (MAE) and Root Mean Error (RMSE) were used to check for the errors in the model.

1.5 Organisation of the Thesis

This thesis was divided into five chapters. Chapter 1 talks about the background of the study and the objectives of the research. Chapter 2 focuses on the literature review. In this chapter, related works on predicting exchange rate was reviewed with key interest in artificial neural networks. Chapter 3 considers the materials and methods, which was incorporated within the algorithms associated to neural network models identification, and the analysis of some statistical estimators. Chapter 4 detailed on research results and explanation of the results obtained from the generated algorithm as discussed in chapter 3. Finally, chapter 5 was on the conclusion and recommendation of the research.

CHAPTER 2

LITERATURE REVIEW

2.1 Overview

This chapter reviews the various literature and various theoretical concepts from other research works which are relevant to predicting exchange rate in Ghana between the US Dollar and Ghana Cedi (USD/GHS) and the Great Britain Pound and the Ghana Cedi (GBP/GHS) using Artificial Neural Network.

2.2 Related Research Works

In many developing countries, the exchange rates are determined by the foreign exchange markets. In Ghana, the Ghana cedi has experienced volatile exchange rates against leading currencies (e.g., the US dollar, the UK pound) since the year 2000. This is largely due to, some extent, the high import trading volumes and low export trading base in the fundamentals of the economy (Menkhoff, 2013).
According to Bayoumi and Eichengreen (1998), in computing exchange market pressure index a change in nominal exchange rate, foreign exchange reserves and interest rates should be included.

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 (Menkhoff, 2013).

In the standard Dornbusch (1976) model, unanticipated monetary policy shocks generate large variations in the exchange rate. Here, nominal shocks affect real exchange rate but only in the short-run. Because real exchange rate deviates from its long-run equilibrium path, extant studies on the cause of the deviations and results are largely torn between two schools. The first documents significant relationship between real exchange rate fundamentals including supply and demand factors where the former largely relate to the level of output capacity and expected to follow the Balassa–Samuelson hypothesis. This hypothesis assumes that productivity increases tradable sectors hence pushing up sector wages. This in effect puts an upward pressure on wages in the non–tradable sector and the economy as a whole.

Because productivity does not increase in response to wage rise, prices of non-tradable goods are expected to rise leading to increase in the relative price of non-tradable to tradable goods, hence, an appreciation of the domestic real exchange rate. The demand factors relate to the role of government expenditure while the external shocks reflect changes in terms of trade, trade openness and capital flows. The second strand identifies the effects of real shocks in exchange rate volatility.

Again, according to Bilson (1978), an increase in the rate of inflation will lead to an increase in demand for money and an increase in expenditure on goods which results in an increase in prices. The currency is expected to depreciate due to the price rise to maintain the purchasing power parity. This assertion is based on a simple theoretical monetary model fundamental to the behavioural equation of the monetary approach assumed to be of Cogan functional form.

McPherson and Rakovski (1998) researched on "Exchange Rates and Economic Growth in Kenya: An Econometric Analysis". Their objective was to determine the relationship between exchange rate and economic growth in Kenya based on the data for the period 1970 to 1996. They analysed the possible direct and indirect relationship between the real and nominal exchange rates and GDP growth. They derived these relationships in three ways: within the context of a fully specified (but small) macroeconomic model, as a single-equation instrumental variable estimation, and as a vector auto regression model. The estimation results from the three different settings showed that there was no evidence of a strong direct relationship between changes in the exchange rate and GDP growth.

Levy-Yeyati and Sturzenegger (2003) compared the economic track records of two different exchange rate regimes: the "Fixed Exchange Rate" and the "Free Floating Exchange Rate System", in maintaining economic performance. The paper considered relationships between exchange rate and inflation and between exchange rate and GDP in Bangladesh. The experiences of moving away from a currency board system to floating regime since 2003 offers a lesson worthy of attention from the point of view of efficiency of "Floating Rate System" in least developed countries. Floating exchange rate regime in Bangladesh contrasts with its neighbour's currency board system. Experiences in Bangladesh and abroad showed that all that a government needs in this regard is to maintain confidence in the currency, secure the currency's strength and ensure its full convertibility. As long as this is backed by sufficient reserve of the foreign exchanges and there is firm political and economic will, adoption of a successful free exchange rate regime is possible

Chen (2012) researched on “Real exchange rate and economic growth: Evidence from Chinese provincial data (1992-2008)”. His paper studied the role of the real exchange rate on economic growth and in the convergence of growth rates among provinces in China. Using data from 28 Chinese provinces for the period 1992-2008 together with dynamic panel data estimation, he found conditional convergence among coastal provinces and also among inland provinces. The results reported here confirm the positive effect of real exchange rate appreciation on economic growth in the provinces.

Fofanah (2020) investigated 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 their 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 albeit weakly. The difference in direction and magnitude of effect is not far-fetched from the differences in macroeconomic conditions prevailing in each country

Kwakye (2012) determined the equilibrium real exchange rate and real misalignment for Ghana from the period 1980 to 2010. He 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. His study 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.

Works on the Determinants of the Real Exchange Rate in Ghana: A Focus on Inflation Using a Bound Test Approach was considered by Immurana *et al*. (2013). Their 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.

Elsewhere, Mishra (2014) did study the empirical analysis of Rupee Fluctuations against US dollar in post liberalization period from 1991 to 2013 in India. His main focus was to find out the relationship between the exchange rate and its determinants in India and to determine whether and how far the exchange rate depreciates or appreciates due to an increase or decrease in the independent variables. In the model specified, exchange rate was the dependent variable and inflation, interest rate, foreign portfolio investment, foreign direct investment, current account, capital account, foreign exchange reserves, trade balance and invisibles (all in US$ million) were the independent variables. Multiple regression model – Backward elimination method was applied. The study found out that the respective effect of FDI, invisbles, interest rate and capital account on exchange rate is insignificant and the respective effect of forex reserves (+), current account balance (-), foreign portfolio investment (-), trade balance (+) and inflation (-) on exchange rate is significant.

Also, Ghafoor *et al*. (2014), investigated the dynamic relationship between nominal exchange rate and macroeconomic variables in Pakistan. 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.

Menkhoff (2013) studied Time Series Analysis of the Exchange Rate of the Ghanaian Cedi to the American Dollar. They also considered out-of-sample forecast for the next three years of the exchange rate. The time series models considered for their objective were the

Autoregressive Integrated Moving Average (ARIMA) and the Random walk model. They found modest differences between the two models based on the out-of-sample forecast. Interestingly, they deduced that, both models performed similarly based on forecasted values.

The forecasted values showed that the exchange rate of the Ghana cedi to the American dollar will increase continuously in the next three (3) years. By their problem of study, they concluded that, the exchange rate between the Ghana Cedi and the US dollar was non-stationary. This means the process was not in statistical stability. The forecasts from the ARIMA and Random Walk models suggest that, in the absence of any structural changes, the upward trend against the US dollar might continue in the near future.

Ghafoor *et al*. (2014), studied an analysis of exchange rate: a case of Pakistani Rupee verses the US Dollar. The research aimed at studying the dynamic association between macro-economic variables and exchange rate in Pakistan. For this purpose, the study analysed quarterly time series of the relevant variables from 1998 quarter 1 to 2012 quarter 4. The study tests the proposed hypotheses using econometric models that are widely accepted and practiced in academic research in the areas of economics and finance. In the first place the study investigated as to whether all-time series variables (exchange rate and the set of seven (7) macroeconomic variables) were stationary or not. The study further investigated in multivariate form, the co-integration properties of the variables under investigation. Again, the study applied Granger-cause macroeconomic variables or vice versa in the multivariate form. Along this line, the study also applied the Granger-causality test in the bi-variate form to investigate the lead-lag relationship and hence established the direction of influence i.e., uni-directional. The study results suggested that, there was a long-run association between exchange rate and inflation at 10% significance level. The Granger-causality test suggested that, the direction of influence was more from inflation to exchange rate than from exchange rate to inflation (though both were statistically insignificant). The results from the Granger-causality test suggested that money supply led exchange rate i.e., money supply Granger-cause exchange rate (a uni-directional causality). The study reported finding that indicated bidirectional causality between exchange rate and total reserve less gold. A rise in the total reserve less gold caused exchange rate of Pak Rupee to appreciate and vice versa. The study also reported statistically significant inverse relationship between exchange rate and exports. The findings from the Granger-causality test suggested that, exchange rate and industrial production share statistically significant relationship. The study failed to report evidence to support Share price index in multi-variate co-integration test as well as Granger-causality test. Finally, the study reported that both balance of trade and exchange rate were cointegrated, and that, exchange rate Granger cause balance of trade in the short-run.

Alagidede and Ibrahim (2017), studied on the causes and effects of exchange rate volatility on economic growth: 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. Decomposing the shocks indicates that almost three quarters of exchange rate volatility were self-driven. The remaining one quarter or so was accounted for by the factors alluded to previously. The implication of the results is that, since exchange rate volatility is almost self-driven, unbridled interventions may not only exacerbate volatility, but may also be costly in terms of output and welfare. Improving exchange rate modelling and forecast at the central bank level, while incorporating the impact of asset prices in domestic monetary policy could improve both the transparency and functioning of the foreign exchange market.

Mwinlaaru and Ofori (2017) worked on Real Exchange Rate and Economic Growth in Ghana. The study sought to determine effect of real effective exchange rate on economic growth in Ghana using annual data from 1984 to 2014. Data were sourced from the databases of World Bank, Bank of Ghana annual bulletins, and Ghana Ministry of Finance and Economic Planning. Using the ARDL cointegration estimation technique, the study found that real exchange rate and economic growth are cointegrated. The result further suggests that real exchange rate exerts a positive and statistically significant effect on economic growth in both the long-run and short run. Thus, there is the need to ensure exchange rate stability in the Ghanaian economy to help boost economic growth

Havi (2019) 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.

Enu (2017) worked on the key drivers of the exchange rate depreciation in Ghana. His objective was to determine the key variables that influence the frequent exchange rate depreciation in Ghana, using time series data from the period of 1980 to 2015. The natural logarithm of all the variables and employed the Backward Elimination and Stepwise Regression method. His finding suggests that, export representing trade had been a variable which had significant negative effect on the exchange rate of the Ghana Cedi against the dollar during the years under review. The results suggest that, to ensure a stable Ghana Cedi, policies should be directed to grow the Ghanaian economy from an import-driven one to an export driven economy through massive investment in its key sectors of the economy.

ARIMA models have been used for forecasting different types of time series and have been compared with a benchmark model for its validity. Olatunji and Bello (2015) in their study found that the exchange rate follows a long-term trend with short-term fluctuation. Therefore, to capture the long-term trend, many authors had used Auto regressive Integrated Moving Average (ARIMA) model as proposed by Box-Jenkins, to forecast the exchange rate. Olatunji and Bello (2015) found evidence that ARIMA models performed well when compared to nonparametric and Markov switching models.

Plasmans *et al*. (1998) used macroeconomic models and artificial neural networks (ANN), a very powerful tool for detecting non-linear patterns, to test whether the underlying relationship was non-linear. They could not produce satisfactory monthly forecasts. On the contrary, Gradojevic and Caric (2009) modelled the exchange rate as depending non-linearly on its past values, and their model outperformed simple linear models, but they never compared it to a random walk. Panda and Narasimhan (2007) showed (using daily and weekly data) that ANNs are a more robust forecasting method than a random walk model. Hence, the application of ANNs to short-term currency behaviour was successful in numerous cases and the results suggest that ANN models may offer some advantages when frequent short-term forecasts are required (Gradojevic and Yang 2006).

Schmitz and watts (1970) used parametric modelling to forecast wheat yields in the United States, Canada, Australia and Argentina. The essence of this approach was that the data were used for identifying the estimation of the random components in the form of moving average and autoregressive process. It did not identify and measure the structural relationship as was attempted when forecasting with econometric models. They used exponential smoothing to forecast yields in United States and Canada. They also compared the forecasting accuracy between parametric modelling and exponential smoothing.

Kirby (1966) compared three different time-series methods viz., moving averages, exponential smoothing, and regression. He found that in terms of month-to-month forecasting, horizon was increased to six months. The regression models included was found to be the best method for longer-term forecasts of one year or more. Makridakis and Wheelwright 1977) found that econometric models were not entirely successful in improving the accuracy in forecasting.

Leuthold *et al*. (1970) in their study of forecasting daily hog price and quantities' used Theil's inequality coefficient for comparing the predicative accuracy of the different forecasting approaches.

Also, Rathnayake *et al*. (2017) worked on the macroeconomic factors which are determinants of real effective exchange rate (REER): evidence from ten selected countries in Asia. Two panel regression approaches namely fully modified ordinary least squares (FMOLS), dynamic ordinary least squares (DOLS) and fixed effects were applied using panel data over the period of 2002–2016. However, most of the independent variables were found to be important in the REER determination.

The empirical results showed that, the presence of a significant long-term association amongst the REER and seven macroeconomic determinants namely interest rate, inflation, trade balance, terms of trade, trade openness, foreign reserves and share price index and their significance remained the same in all models applied. However, trade balance had a positive connection with the REER while other significant variables had a negative association with the REER in long run. Moreover, the money supply (M2) and real gross domestic production (GDP) did not show a significant relationship with the REER.

In the work done by Ofori-Abeberese *et al*. (2017) on the Interaction between Public Sector Wage, Inflation and Exchange Rate Volatility in Ghana, the ARDL method was empirically used to determine whether the rising public sector wage bill and inflation have any impact on the value of the cedi over the period 1986 to 2014. They discovered that inflation, money supply, interest rate and public wage bill have significant impact on exchange rate in the Ghanaian economy. The outcome of their study postulated that, exchange rate determination in Ghana is also a fiscal phenomenon in spite of the significant and domineering role played by monetary expansion.

Appiah and Adetunde (2011) forecasted the exchange rate between the Ghana Cedi and the US Dollar by forecasting future rates using time series analysis. In their work, ARIMA model was developed using the Box Jenkins method of Time Series Analysis on the monthly data from 1994 to 2010.

The result showed that, the predicted rates were consistent with the depreciating trend of the observed series. Meanwhile, ARIMA (1,1,1) model was found as the most suitable model with least Normalised Bayesian Information Criterion (BIC) of 9.11, Mean Absolute Percentage Error (MAPE) of 0.915, Root Mean Square Error of (3.873 and a high value of R Square of 1.000. The estimation was done by Ljung-Box test, with (Q18) = 15.146, 16 DF and a p-value of 0.514 with no autocorrelation between residuals at different lag times. Finally, a forecast for a two-year period for 2011 and 2012 was calculated, which showed a depreciating of the Ghana Cedi against the US Dollar.

Sirait and Simatupang (2019) worked on exchange rate forecasting and Value-at-Risk Estimation on Indonesian currency using Copula Method. They preferred the clayton copula to the Frank and Gumbel copula, because the former has the highest log-likelihood values.

The study determined the future value and the value-at-risk estimation of four selected currencies, namely United States Dollar (USD), Australian Dollar (AUD), European Union Euro (EUR) and the Japanese Yen (JPY) against the Indonesian Rupiah (IDR). The Monte-Carlo simulation was implemented to estimate the future value of each currency relationship and integrating it with the concept from the copula method. The risk value estimation was conducted using value-at-risk (VaR) and the VaR estimation was within the ranges of 90%, 95% and 99% confidence interval.

It was noted that, each currency uses their regressive model to see if the selected exchange rates have the characteristics of a seasonal or non-seasonal pattern. The result showed that, JPY/IDR, and EUR/IDR relationships had the highest simulated loss and estimated risk values in each confidence interval.

Olakorede *et al*. (2018) also worked on integrated moving average model for the exchange rate between the Nigerian Naira and the US Dollar. The research fitted a univariate time series ARIMA model to the monthly data of exchange rate from 1980 to 2015. The Box-Jenkins Autoregressive Integrated Moving Average (ARIMA) model was estimated and the best fitted ARIMA model was used to obtain the post-sample forecasts for three years (2016 to 2019). The best model was selected using Auto. ARMA with the fitted model being ARIMA (0,1,1) with Akaike Information Criteria (AIC) of 2313.19, and Normalised Bayesian Information Criteria (BIC) of 2325.39. The model was further validated by Ljung-Box test with no significant Autocorrelation between the residuals at different lag times and subsequently by white noise of residuals from the diagnostic check performed, which clearly portrayed randomness of the standard error of the residuals, and no significant spike in the residual plots of ACF and PACF. Finally, the forecasted values indicated that, the Naira will continue to depreciate against the US Dollar between the periods under study.

Etuk and Nkombou (2014) modelled the monthly data from January 1997 to March 2013 on Central African Franc and the US Dollar (XAF-USD) exchange rates by SARIMA technique. The time plot showed an overall upward secular trend with no obvious regular seasonal component. As expected, it was shown that there was no stationarity as indicated by the Augmented Dicky Fuller (ADF) test.

By the development of ANN, researchers and investors are hoping that they can solve the mystery of exchange rate predictions. It has been proved that the ANN model, which is a type of non-linear model, is a strong alternative in the prediction of exchange rates. ANN is a very suitable method to find correct solutions especially in a situation which has complex, noisy, irrelevant or partial information (Kadilar *et al.*, 2009).

Along with ANN there are many approaches such as heuristic algorithms, soft computing methods, fuzzy inference systems and others for modelling. Conventional nonlinear techniques, such as Markov switching models which have been used for modelling. However, generally the results suggest that conventional nonlinear modelling does not improve exchange rate forecasts (Galeshchuk, 2016).

Olatunji and Bello (2015) also worked on a suitable model for the forecast of exchange rate in Nigeria (Nigeria Naira versus US Dollar). The Box-Jenkins ARIMA and ARMA methodology were used for forecasting the monthly data collected from January 2000 to December 2012. Result analysis revealed that, the series became stationary at first difference. The diagnostic checking also showed that ARIMA (1, 1, 2) and ARMA (1, 1) were appropriate or optimal model based on the Akaike's information criterion (AIC), Shcwarzt information criterion (SIC), and Hannan Quinn criterion (HQC). The performance of the models (ARIMA and ARMA model) for both in-sample and out-of-sample also shows that ARIMA (1, 1, 2) has Minimum Mean Error (ME), Mean Squared Error (MSE), Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), which indicates that ARIMA (1, 1, 2) model was the best or optimal model for the period forecasted.

In the work of Ngan (2016), Ngan forecasted foreign exchange rate by using ARIMA model with a case study of the Vietnam against the US Dollar (VND/USD) exchange rate. Data from the first day of 2013 to the last day of 2015 was employed whiles applying ARIMA model with four steps to forecast foreign exchange rate between VND/USD in the next twelve months of 2016. Forecasted foreign exchange data were compared with real foreign exchange rate in Vietnam and the results showed Arima model was suitable for estimating foreign exchange rate in Vietnam in short-time period.

Many hybrid models have been proposed by the previous researchers to ensure more efficient Artificial Intelligence (AI) and statistical models. For example, Pai and Lin (2005) used hybrid ARIMA and SVMs model in forecasting stock price. He *et al*., (2010) make prediction on exchange rate by using a slantlet denoising least squares support vector regression hybrid methodology. Yang and Lin (2011) combined empirical mode decomposition (EMD) and neural network to forecast exchange rate. The results of these studies show that a hybrid model can defeat single models in forecasting time series. Furthermore, recent studies on hybrid models of Least Square Vector Machine (LSSVM) with other suitable techniques or models show that the hybrid model can outperform another single model (Wei *et al*., 2019;

Asma'Mustafa and Ismail, 2016). Basically, these studies show that a hybrid model is developed to overcome the drawbacks of the single models and ensure that more accurate and effective model can be obtained to forecast time series data.

Rashid and Waqar (2016) worked on exchange rate forecasting using Modified Empirical Mode Decomposition (EMD) and Least Square Vector Machine (LSSVM), where a modified EMD-LSSVM model for exchange rate forecasting was developed. The research indicated that, exchange rate data requires a model that can capture the non-stationary and non-linearity. Hence the reason for the usage of the empirical mode decomposition (EMD) in combination with least squares support vector machine (LSSVM) model in order to forecast daily US dollar and the New Taiwan Dollar (USD or TWD) exchange rate. The EMD was used to decompose exchange rate data behaviours which were non-linear and nonstationary. LSSVM has been successfully used in non-linear regression estimation problems and pattern recognition. However, its input number selection is not based on any theories or techniques. In their proposed model, the exchange rate was first decomposed by using EMD into several simple intrinsic mode oscillations called intrinsic mode function (IMF) and a residual. Then, Permutation distribution clustering (PDC) was used to cluster the IMF and the residual into few groups according to their similarities in order to improve the LSSVM input. After that, LSSVM was used to forecast each of the groups and all the forecasted value were summed up in order to obtain the final exchange rate forecasting value where the best number of inputs for the LSSVM was determined by using partial autocorrelation function (PACF). The result showed that the modified EMD-LSSVM (MEMD-LSSVM) outperforms single LSSVM and hybrid model of EMD-LSSVM. Again, with the implementation of decomposition strategy via EMD to the exchange rate data, the non-linear and non-stationary behaviour of the exchange rate data was addressed effectively and the hidden pattern of the data was revealed for better understanding resulting in improving the forecasting accuracy. This was proven with better forecasting result produced by EMD-LSSVM compared to LSSVM. The implementation of PDC in clustering the IMFs and residual resulting from EMD into several groups showed that the proposed MEMD-LSSVM model outperforms LSSVM and EMDLSSVM. Thus, it can be concluded that PDC gave contribution to improve the input for LSSVM in the proposed MEMD-LSSVM.

Tlegenova (2015) modelled and forecasted exchange rate between US Dollar and that of Kazakhstan Tenge (USD/KZT), the European Union Euro and the Kazakhstan Tenge

(EUR/KZT), and the Singapore Dollar and the Kazakhstan Tenge (SGD/KZT) using time series by comparing the actual data with forecasts using time series over the period from 2006 to 2014. The study's goal was to apply the ARIMA model for forecasting of yearly exchange rates of the currencies under consideration. Hence, the ARIMA technique was presented, and three main steps for constructing the model were identified, namely, Identification, Estimation, and Model checking. The accuracy of the forecast was compared with Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Squared Error (RMSE). Results showed that the MAPE values for all three currencies were the smallest, i.e., the most effective.

In the work of Leung *et al.* (2017) on the application of neural networks to an emerging financial market: forecasting and trading the Taiwan stock index, it was emphasised that, neural networks have drawn noticeable attention from many computers and operations researchers in the last decade. While some previous studies have found encouraging results with using this artificial intelligence technique to predict the movements of established financial markets, it was interesting to verify the persistence of this performance in the emerging markets. The rapid growing financial markets are usually characterized by high volatility, relatively smaller capitalization, and less price efficiency, features which hindered the effectiveness of those forecasting models developed for established markets. Therefore, the study attempted to model and predict the direction of return on the Taiwan Stock Exchange Index, one of the fastest growing financial exchanges in developing Asian countries. The approach was based on the notion that, trading strategies guided by forecasts of the direction of price movement may be more effective and lead to higher profits. The Probabilistic Neural Network (PNN) was used to forecast the direction of index return after it was trained by historical data. The forecasts were applied to various index trading strategies, of which the performances were compared with those generated by the buy and hold strategy, and the investment strategies guided by the forecasts estimated by the random walk model and the parametric Generalized Methods of Moments (GMM) with Kalman filter. Empirical results show that the PNN-based investment strategies obtain higher returns than other investment strategies examined in the study.

Gallo (2014) worked on Artificial Neural Networks in Financial Modelling, where it was explained that, Artificial Neural Network deals with generating, in the fastest times, an implicit and predictive model of the evolution of a system. In particular, it derives from experience its ability to be able to recognize some behaviours or situations and to "suggest" how to take them into account. The work illustrated an approach to the use of Artificial Neural Networks for Financial Modelling; the work aimed to explore the structural differences (and implications) between one- and multi- agent and population models. In one-population models, ANNs were involved as forecasting devices with wealth-maximizing agents (in which agents made decisions so as to achieve a utility maximization following non-linear models to do forecasting), while in multi-population models' agents did not follow predetermined rules, but tend to create their own behavioural rules as market data were collected. In particular, it was important to analyse diversities between one-agent and one-population models. In fact, in building one-population model it was possible to illustrate the market equilibrium endogenously, which was not possible in one-agent model where all the environmental characteristics were taken as given and beyond the control of the single agent. A particular application which was aimed to study was the one regarding "customer profiling", in which (based on personal and direct relationships) the "buying" behaviour of each customer could be defined, making use of behavioural inference models such as the ones offered by Artificial Neural Networks.

Brooks (1997) shows that the improvements in performance obtained from using linear and non-linear univariate time-series models are very small over forecasts generated by a random walk model. Gradojevic and Yang (2006) claim that ANNs outperform random walk and linear models based on a number of recursive out-of-sample forecasts. The authors proved that ANNs perform better than other linear models in terms of percentage of correctly predicted exchange rate changes. Boero and Marrocu (2002) did a comparative study of the forecasting performance of different models of three traded exchange rates (the French franc, the German mark and the Japanese yen) against the US dollar. Three non-linear models, mainly a two-regime SETAR, a three regime SETAR and a GARCH-M model were compared and contrasted against two linear models, primarily AR and random walk processes. The results showed that the advantages of non-linear models over linear ones lie in the criteria used to assess forecast accuracy. The authors concluded by stating that in their analysis non-linear models generated more forecasting gains than linear ones.

Adewole *et al*. (2011) worked on Artificial Neural Network Model for Forecasting Foreign Exchange Rate. He argued that, the present statistical models used for forecasting cannot effectively handle uncertainty and instability nature of foreign exchange data. Hence, an artificial neural network foreign exchange rate forecasting model (AFERFM) was designed for foreign exchange rate forecasting to correct some of these problems. The design was divided into two phases, namely: training and forecasting. In the training phase, back propagation algorithm was used to train the foreign exchange rates and learnt how to approximate input. Sigmoid Activation Function (SAF) was used to transform the input into a standard range [0, 1]. The learning weights were randomly assigned in the range [-0.1, 0.1] to obtain the output consistent with the training. SAF was depicted using a hyperbolic tangent in order to increase the learning rate and make learning efficient. Feed forward Network was used to improve the efficiency of the back propagation. Multilayer Perceptron Network was designed for forecasting. The design was implemented using matlab and visual studio because of their supports for implementing forecasting system. The system was tested using mean square error and standard deviation with learning rate of 0.10, an input layer, 3 hidden layers and an output layer. The best-known related work, Hidden Markov foreign exchange rate forecasting model (HFERFM) showed an accuracy of 69.9% as against 81.2% accuracy of AFERFM. This shows that the new approach provided an improved technique for carrying out foreign exchange rate forecasting

Mbaga and Olubusoye (2014) 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.

Econ and Hadrat (2015) 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.

del Rosario Martinez-Blanco *et al.*, (2016) researched on the Generalized Regression Neural Networks with Application in Neutron Spectrometry, the aim of the research was to apply a generalized regression neural network (GRNN) to predict neutron spectrum using the rates count coming from a Bonner spheres system as the only piece of information. In the training and testing stages, a data set of 251 different types of neutron spectra, taken from the International Atomic Energy Agency compilation, were used. Fifty-one predicted spectra were analysed at testing stage. Training and testing of GRNN were carried out in the MATLAB environment by means of a scientific and technological tool designed based on GRNN technology, which was capable of solving the neutron spectrometry problem with high performance and generalization capability. This computational tool automates the pre-processing of information, the training and testing stages, the statistical analysis, and the postprocessing of the information. In the work, the performance of feed-forward backpropagation neural networks (FFBPNN) and GRNN were compared in the solution of the neutron spectrometry problem. From the results obtained, it was observed that, despite very similar results, GRNN performed better than FFBPNN because the former could be used as an alternative procedure in neutron spectrum unfolding methodologies with high performance and accuracy.

Bal and Demir (2017) researched on Forecasting TRY/USD Exchange Rate with Various Artificial Neural Network Models. In the study, the exchange rate between the Turkish Lira and the US Dollar (TRY/USD) forecast was modelled with different learning algorithms, activations functions and performance measures. Various Artificial Neural Network (ANN) models for better forecasting were investigated, compared and the obtained forecasting results interpreted respectively. The results of the application showed that Variable Learning

Rate Backpropagation learning algorithm with tan-sigmoid activation function had the best performance for TRY/USD exchange rate forecasting.

Chaudhuri and Ghosh (2016) worked on Artificial Neural Network and Time Series Modelling Based Approach to Forecasting the Indian Rupee and US Dollar Exchange Rate in a Multivariate Framework. To forecast the exchange rate, two different classes of frameworks were used. Namely, Artificial Neural Network (ANN) based models and Time Series Econometric models. Multilayer Feed Forward Neural Network (MLFFNN) and Nonlinear Autoregressive models with Exogenous Input (NARX) Neural Network were the approaches that were used as ANN models. Generalized Autoregressive Conditional Heteroskedastic (GARCH) and Exponential Generalized Autoregressive Conditional Heteroskedastic (EGARCH) techniques were the ones that were used as Time Series Econometric methods. During the process of generating results, it was observed that both sets of techniques generated useful and efficient predictions of the exchange rate. The application of both MLFFNN and NARX including the use of various backpropagation algorithms were quite unique and the non-linear relationship between the exchange rate and the explanatory variables were effectively captured. From the technique point of view, it is observed that the predictive performance of MLFFNN did not depend on the number of neurons in the hidden layer, but was sensitive to the backpropagation algorithms. For the NARX model, neither the number of neurons, nor the training algorithms, significantly affected the performance. In the econometric modelling, four different approaches namely, GARCH (1,1,), GARCH (2,2), EGARCH (1,1) and EGARCH (2,2) were used and the results obtained were reported to have been satisfactory. Within the framework, the results indicated that, although the two different approaches were quite efficient in forecasting the exchange rate, MLFNN and NARX were the most efficient.

Gradojevic and Yang (2000) worked on the Application of Artificial Neural Networks to Exchange Rate Forecasting: The Role of Market Microstructure Variables. Artificial neural networks (ANN) were employed for high-frequency Canada/U.S. dollar exchange rate forecasting. ANN outperformed random walk and linear models in a number of recursive out-of-sample forecasts. The inclusion of a microstructure variable and order flow, substantially improved the predictive power of both the linear and non-linear models. Two criteria were applied to evaluate the model performance: root-mean squared error (RMSE) and the ability to predict the direction of exchange rate moves. ANN was consistently better in RMSE than random walk and linear models for the various out-of-sample set sizes. Moreover, ANN performed better than other models in terms of percentage of correctly predicted exchange rate changes (PERC). The empirical results suggested that, optimal ANN architecture is superior to random walk and any linear competing model for high-frequency exchange rate forecasting.

Recently, Wohl and Kennedy (2018) in their study exhibited an extreme starter endeavour to examine international trade with neural network and the traditional trade gravity model approach. The findings showed that, the neural network has a high degree of accuracy in prediction compared to RMSE within the gravity model. The work pointed out that, neural networks have the nonlinear functional capability to withstand chaos and noise in most datasets (Du and Zhang, 2018) and comparatively are more robust and have high adaptability owing to a large number of inter connectivity within its processing element (Piermartini and Yotov, 2016).

Pourebrahim *et al*. (2018) in their work on a comparison of neural networks and gravity models in trip distribution concluded that neural networks outperform gravity models when data is scarce. Invariably in large datasets, evidence shows that gravity models outperform neural networks but they point out with less certainty in respect to the latter.

Furthermore, Elif (2014) compares neural networks to a panel gravity model approach and stated that both models give a satisfactory result that modified gravity model of bilateral trade which was analysed, explained the variation in bilateral exports among European countries. The panel gravity model provided an advantage of explaining the individual effect of independent variable on bilateral trade and showed their significance as well. The neural networks in another dimension with a similar independent variable accordingly gave a 97% variation showing much superiority to the traditional panel gravity model data analysis. The application of Neural Networks to One Belt One Road (OBOR) was justified by the fact that, neural networks have the benefit of comprehensively predicting dichotomous outcomes as shown in fields such as medicine Alaloul *et al*. (2018), also it has the capability to handle complex non-linear relationships between the dependent and independent variables. This therefore falls in line with a bilateral relationship which has a similar dichotomous characteristic, with the host proponent country, China and its partners who have subscribed to participate in this trade arrangement.

2.3 The ANN Model

Artificial Neural Networks (ANNs) are a class of machine learning algorithms that draw inspiration from biological neural systems. Artificial Neural Network is a parallel, distributed information processing structure consisting of processing elements interconnected via unidirectional signal channels called connection weights. Although modelled after biological neurons, ANNs are much simplified and bear only superficial resemblance. Every ANN consists of a set of units (or neurons) and a set of connections between them. The individual processing unit in ANNs receives input from other sources or output signals of other units and produces it to give output. Each neuron is basically just a mathematical function Φ (the activation function) that takes as parameter the activation "a", which is a weighted sum of all the incoming signals to the neuron. The value of Φ(a) is the outgoing signal of the neuron. It is important to note that the activation parameter of a given neuron is a weighted sum of all its incoming signals:

$$a = \sum w_i x_i \tag{2.1}$$

The w_i is the weight of the incoming connection i, and x_i is the signal value that was sent by the neuron on the other side of that connection. It's clear that the higher the weight of the connection, the more influence it will have on the neuron. In correspondence with the Hebbian principles, it therefore seems intuitive that we can simulate adaptation by adjusting the values of these weights.

The exact nature of the activation function Φ(a) can be defined in several different ways. One very simple and somewhat common approach is to use a step function which is either 1 or 0 based on whether the activation "a" is greater than some constant threshold.

CHAPTER 3

MATERIALS AND METHODS

3.1 Overview

This chapter extensively describes ANN models explored in this study. It also talks about the prediction of the Exchange rate in Ghana in relation to the US Dollar and the Great Britain pound. The various methods which predict exchange rate in Ghana with their assumptions were also discussed in this chapter.

3.2 Artificial Neural Networks

Artificial neural networks (ANNs) are a class of machine learning algorithms that draw inspiration from biological neural systems. Artificial Neural Network is a parallel, distributed information processing structure consisting of processing elements interconnected via unidirectional signal channels called connection weights. Although modelled after biological neurons, ANNs are much simplified and bear only superficial resemblance.

Some of the major attributes of ANNs are:

- It exploits nonlinearity meaning that there exist a simple nonlinear equation connecting inputs to outputs.
- Input–output mapping: ANN's can undergo a learning process in which the inputs are fed with an idea of what the expected output is going to be. If the expected outputs are quite different from the actual output, the parameters in the system can be adjusted such that for a given set of inputs we can obtain the output that is closer to the expected output. This might not be achieved directly; hence there is a continuous adjustment of the parameters such that the difference between the actual and expected is small.
- Adaptivity: the free parameters can be adapted to changes in the surrounding environment.
- Evidential Response: Gives response with confidence levels and decisions with a measure of confidence.

- Fault Tolerance: Cases where a particular connection is not functioning, the network still works.
- VLSI implementation: Using the Very Large-Scale Integrated Circuit, it is possible to integrate a large number of neurons together.

3.2.1 The Artificial Neurons

Every ANN consists of a set of units (or neurons) and a set of connections between them. The individual processing unit in ANNs receives input from other sources or output signals of other units and produces an output as shown in figure 3.1.

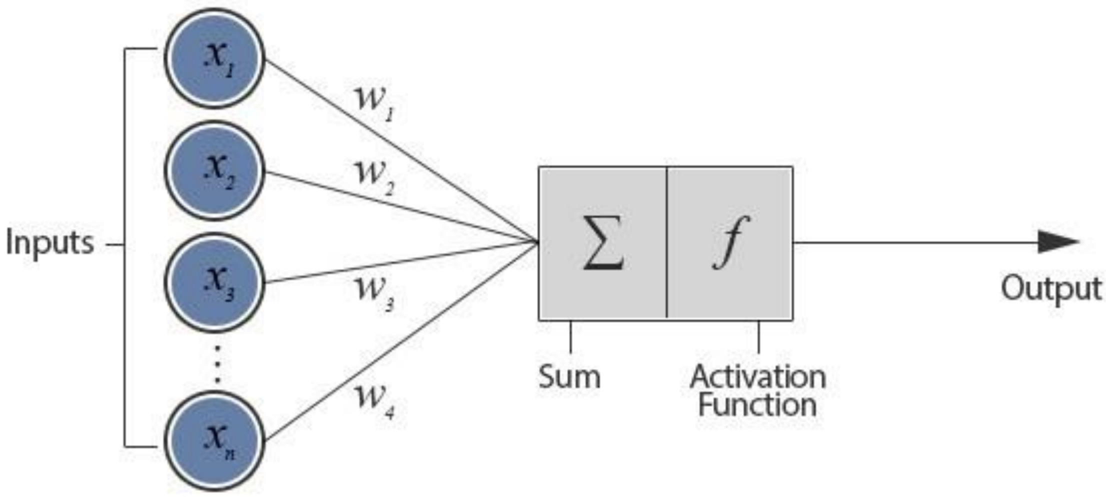

Figure 3.1 Schematic Diagram an ANN model

Source: (Lahiri and Ghanta, 2009)

Each neuron is basically just a mathematical function for example Φ (the activation function) that is taken as a parameter with activation function "a", which is a weighted sum of all the incoming signals to the neuron. The value of Φ (a) is the outgoing signal of the neuron. It is important to note that the activation parameter of a given neuron is a weighted sum of all its incoming signals given as Equation (3.1)

$$a = \sum w_i x_i \tag{3.1}$$

The w_i is the weight of the incoming connection i and x_i is the signal value that was sent by the neuron on the other side of that connection. It is clear that the higher the weight of the connection, the more influence it will have on the neuron. In correspondence with the

Hebbian principles, it is therefore possible to simulate adaptation by adjusting the values of these weights

The exact nature of the activation function Φ (a) can be defined in several different ways. One very simple and somewhat common approach is to use a step function which is either 1 or 0 based on whether the activation function "a" is greater than some constant threshold μ, as indicated in Equation (3.2)

$$\Phi(a) = \begin{cases} 1 & \text{if } a > \mu \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

While this approach works well enough in many situations, it is clear that more information could be produced by each neuron if the activation function is continuous instead of just binary. This is because a binary function Φ means the neuron can only take on one of two states, whereas a continuous function Φ means it can take on any number of different values. One of the most popular choices of continuous activation functions is the symmetric sigmoid function, defined as Equation (3.3)

$$\Phi(a) = \tanh(k \times a) \tag{3.3}$$

Here k is a scaling factor which determines how steep the curve is. The resulting value is bound to the range [−1, +1]. Figure 3.2 shows the shape of the symmetric sigmoid function with k = 1.

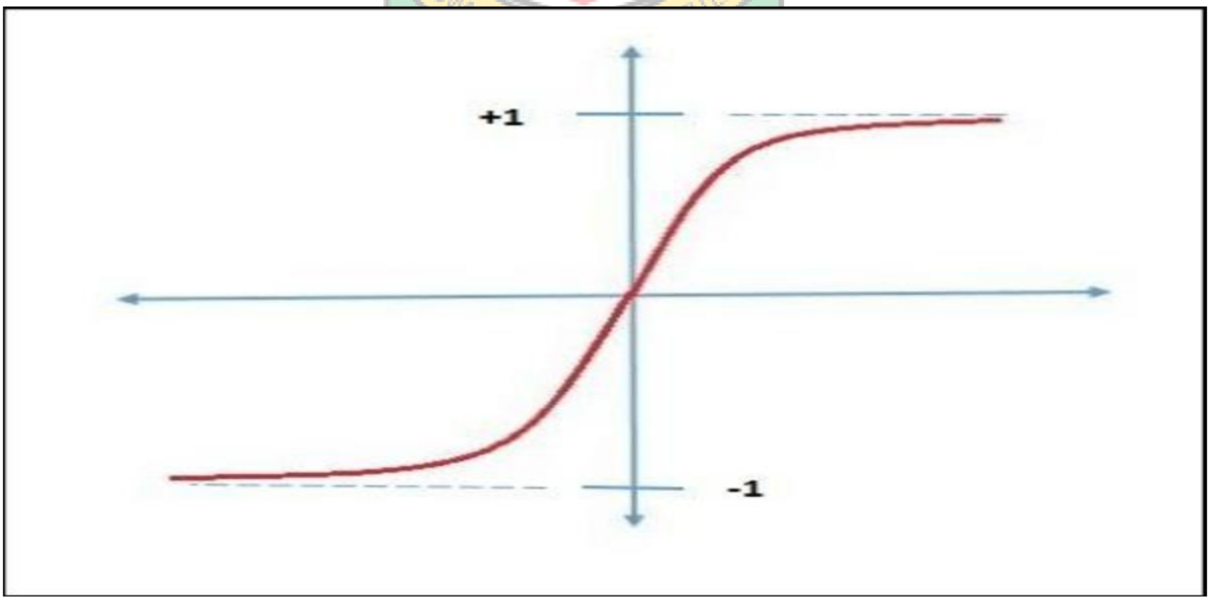

Figure 3.2 The symmetric sigmoid activation function (with k = 1)

Source: (Sibi *et al.*, 2013)

3.2.2 Network Architecture Layers

Considering how a network of the neurons operates in unison. The standard way of designing ANNs is to group the neurons into N layers, including one input layer, one output layer, and up to several hidden (internal) layers (Sethi, 1990). A typical network architecture layers is illustrated in Figure 3.3. For instance, a given neuron in one layer might not necessarily be connected to all the neurons in the next. This is what we call a sparse network. A complete network is one in which any given neuron is always connected to every neuron in the next layer.

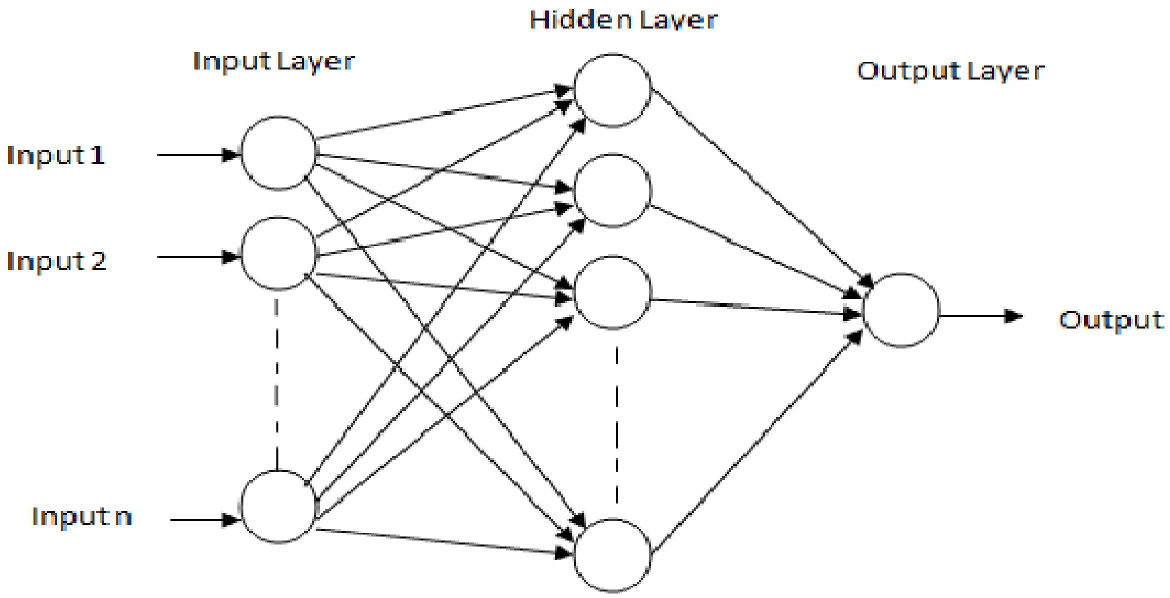

Figure 3.2 Illustrative mode of Network Architecture

Source: (Tarsauliya *et al*, 2011)

3.2.3 The Input Layer

The input layer can be thought of as the "sensor organ" of the ANN. It is where we set the parameters of the environment (i.e., the information we want the ANN to make a decision about). The neurons in this layer have no incoming connections, since their values are set from an external source. The outgoing connections send these values to the neurons of the next layer in the hierarchy.

3.2.4 The Hidden Layer(s)

In between the input and output layers, we have a series of one or more “hidden” layers. The reason we call them hidden is that, they are invisible to any external processes that interact with the ANN. The neurons in these layers have both incoming connections from the preceding layer and outgoing connections to the succeeding layer, and work just as described earlier in this section. The hidden layers can be thought of as the “cognitive brain” of the network.

3.2.5 The Output Layer

The output layer holds the end result of the computations of the ANN model. If the input layer holds the parameters of a problem, the information gathered can be interpreted as the proposed solution. The neurons in this layer have no outgoing connections, because their Φ-values are read directly by whatever external process is using the network.

3.2.6 Adaptation of Neural Network

The aspect of neural networks is their ability to learn. Most newly programmed neural networks are not able to perform their task with the desired accuracy at once. The network behaviour is adapted in learning or training process. During this process, the network is iteratively provided with a set of input patterns together with the corresponding output patterns until it produces the desired output. This set of input patterns and corresponding output patterns is called a training set. During training, the network may change the values of its parameters according to the applied learning rule. The purpose of training a neural network on a certain task depends on important assumption.

After the training phase, the neural network is assumed to perform its task satisfactory on previously unencountered input patterns: the training is useful only if the knowledge gained from training patterns generalises to other input patterns. It is important for the training set to be representative for all input patterns on which the network will perform its task.

Two conditions have to be fulfilled regarding the representativeness of training patterns:

i. The training patterns must belong to the class of patterns which the network is expected to process.

ii. The training pattern must be selected from input space according to the distribution in which all input patterns occur in it. A network cannot be expected to predict correctly when it is trained on a training set with too many outliers.

The memorization of patterns and the subsequent response of the network can be categorized into two general paradigms: Associative Mapping and Auto-association Mapping.

Associative mapping is a mapping in which the network learns to produce a particular pattern on the set of input units whenever another particular pattern is applied on the set of input units.

Auto-association mapping is also an input pattern associated with itself, usually, the states of input and output units coincide

3.3 Types of Artificial Neural Networks

Artificial neural networks are computational models that work similarly to the functioning of a human nervous system. There are several kinds of artificial neural networks. These types of networks are implemented based on the mathematical operations and a set of parameters required.

Some of the neural networks are, Back Propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN), Generalized Regression Neural Network (GRNN), Convolutional Neural Network (CNN), etc.

For the purposes of this research, BPNN, RBFNN and GRNN were considered and utilised to achieve the said objectives of the study.

3.4 Develop 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).

3.5 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 3.4 Illustrates Architecture of Back Propagation Neural Network.

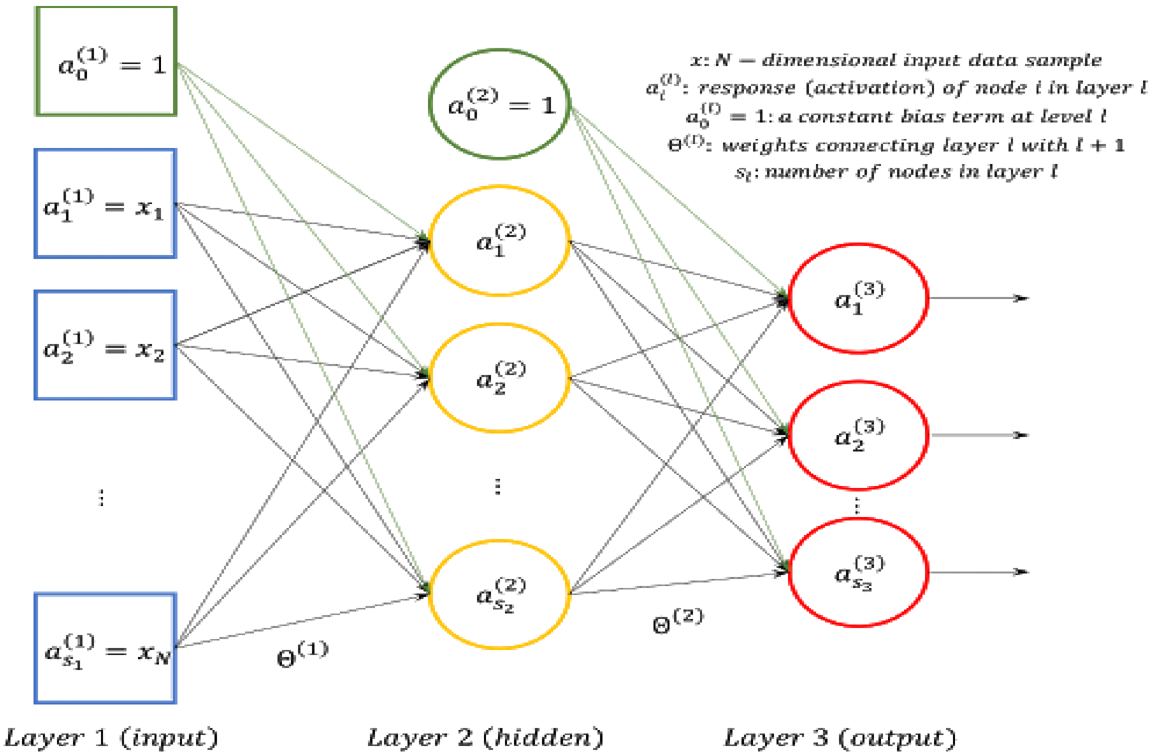

Figure 3.3 Diagram of Back Propagation Neural Network

Source: (Malinov *et al*., 2000)

3.5.1 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, Lavanya and Parveentaj (2013). 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 (Attalla and Hagazy, 2003). 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 (3.4)

$$M_{inj} = Z_{mj} + \sum_{i=1}^{n} x_i w_{ij} \tag{3.4}$$

and the activation function M_j is obtained as Equation (3.5)

$$M_j = f(M_{inj}) \tag{3.5}$$

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 $(y_k, k = 1, 2, ...r), \dots$ q_{ink} is computed by the relation given as Equation (3.6)

$$q_{ink} = Z_{oj} + \sum_{j=1}^{p} M_j a_{jk} \tag{3.6}$$

and Output unit q_k is obtained as Equation (3.7)

$$q_k = f(q_{ink}) \tag{3.7}$$

Here, 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 output layer.

Step 7: Compute δ_k for each output neuron $(q_k, k = 1,...,v)$, where δ_k is define by Equation (3.8)

$$\delta_k = (t_k - q_k) f(q_{ink}) \tag{3.8}$$

where $t =$ target vector and δ_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 (3.9)

$$\delta_{inj} = \sum_{k=1}^{m} \delta_j a_{jk} \tag{3.9}$$

and …by Equation (3.10)

$$\delta_j = \delta_{inj} f(M_{inj}) \tag{3.10}$$

where, δ_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 (3.11)

$$w_{inj}(new) = w_{ij}(old) + \Delta w_{ij} \tag{3.11}$$

and … is given by Equation (3.12)

$$\Delta a_{jk} = \alpha \delta b_k \tag{3.12}$$

where α denotes the learning rate and formula for updating of bias is given by Equation (3.13)

$$\Delta z_{mk} = \alpha \delta_k \tag{3.13}$$

and … is obtained as Equation (3.14)

$$a_{jk}(new) = a_{jk}(old) + \Delta z_{mk} \tag{3.14}$$

such that $z_{mk}(new)$ is obtained as indicated in Equation (3.15)

$$z_{mk}(new) = z_{mk}(old) + \Delta z_{mk} \tag{3.15}$$

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 (3.16)

$$\Delta w_{ij} = \alpha \delta_j x_i \tag{3.16}$$

Formula for bias correction is given by Equation (3.17)

$$\Delta z_{mj} = \alpha \delta_j \tag{3.17}$$

Therefore, … $w_{ij}(new)$ is obtained as indicated in Equation (3.18)

$$w_{ij}(new) = w_{ij}(old) + \Delta w_{ij} \tag{3.18}$$

and … $z_{mj}(new)$ is given as Equation (3.19)

$$z_{mj}(new) = z_{ij}(old) + \Delta z_{jk} \tag{3.19}$$

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

3.6 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 3.5 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.

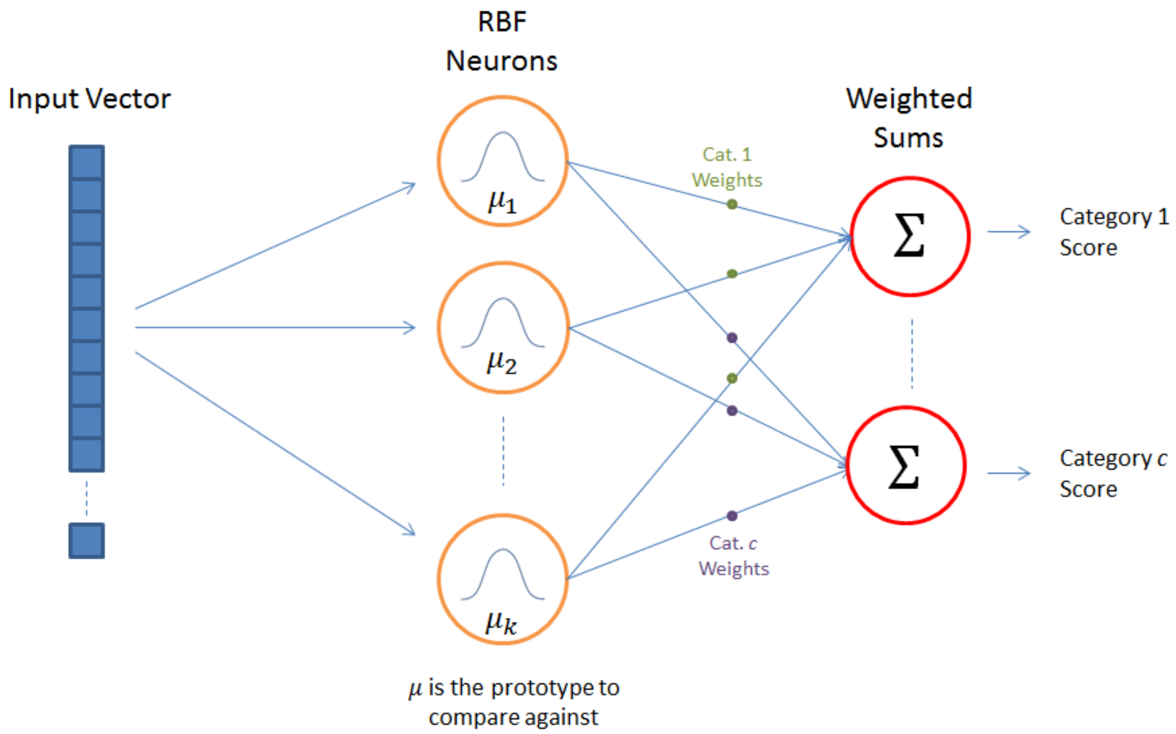

Figure 3.4 Distance from the Centre to a Point

Source: (Singh and Parhi, 2011)

3.6.1 Radial Basis Function Neural Network Algorithm

The standard RBFNN consists of three layers: an input layer, a hidden layer, and an output layer. Figure 3.6 shows a schematic representation of the RBF network. The number of the nodes in the input and output layers is decided by the research objects. In this work, the number of nodes is nine. The nodes in the input layer and output layer represent the vector from an input space to a desired network response, respectively. Through a defined learning algorithm, the error between the actual and desired response is minimized by optimization criterions.

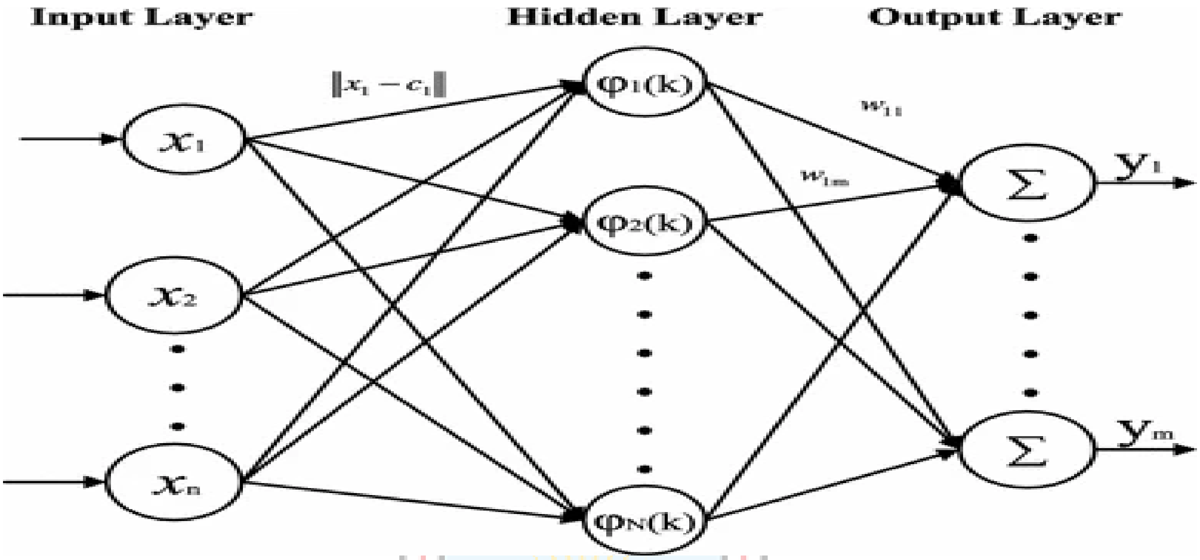

Figure 3.5 Schematic representation of RBF neural network

Source: (Nazir *et al*. 2019)

From Figure 3.6, the i^{ih} output node of the RBFN network can be expressed as indicated in Equation (3.20)

$$y_i = \sum_{k=1}^{N} y_k(\|x - \mu_k\| w_{ik}), 1 = 1, 2, ..., m \tag{3.20}$$

where $x = [x_1, x_2, \ldots, x_n]^T$ is an input value; n is the number of input node; y_k is the centre of the kth RBF node in the hidden layer, $k = 1, 2, \ldots, N$, and N is the number of hidden nodes. The norm function also $\|x - u_k\|$ denotes Euclidean distance between u_k and x; $\varphi k|| \cdot || \varphi k|| \cdot |$ is the nonlinear transfer function of the k^{th} RBFNN node; w_{ik} is the weighting value between the kth RBF node and the ith output node; and m is the number of output nodes.

Deducing from Equation (3.20), it is evident that, the output of the network is computed as a weighted sum of the hidden layer outputs. The nonlinear output of the hidden layer is described as $\varphi k|| \cdot || \varphi k|| \cdot ||$, which are radial symmetrical. A gaussian function is usually used to describe RBFNN function and it is defined as Equation (3.21)

$$\varphi_i(x) = \exp\left(\frac{-1}{2\sigma_i^2}\left(\|x - x_i\|^2\right)\right) \text{ for } i = 1, 2, \ldots, n \tag{3.21}$$

The output neuron is a summing unit which produces the output as a weighted sum of the hidden layer as shown by Equation (3.22)

$$Y(x) = \sum_{i=1}^{h} w_i \varphi(x) \tag{3.22}$$

3.7 Generalized Regression Neural Network (GRNN)

Generalized Regression Neural Network (GRNN) is a variation to Radial Basis Function Neural Network (RBFNN). GRNN was proposed by Specht (1991). 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.

GRNN is made of input, hidden, summation, division layer and output layers as shown in Figure 3.7.

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.

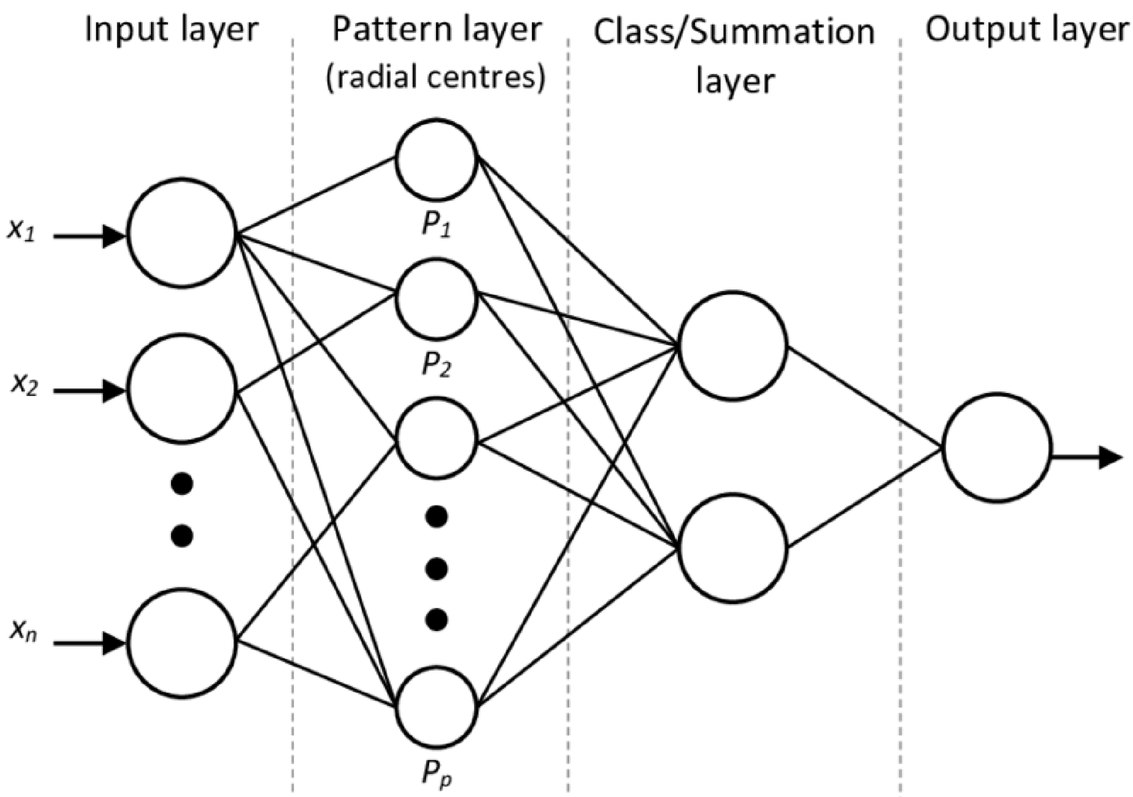

Figure 3.6 Generalised Regression Neural Network Architecture

Source: (Brooks and Tucker, 2015)

3.7.1 Generalized Regression Neural Network (GRNN) Algorithm

The generalized regression neural network (GRNN) was proposed by Specht (1991), with the theoretical basis of nonlinear regression analysis. As shown in Figure 3.8, the GRNN constitutes four components, namely: the input layer, the pattern layer, the summation layer and the output layer.

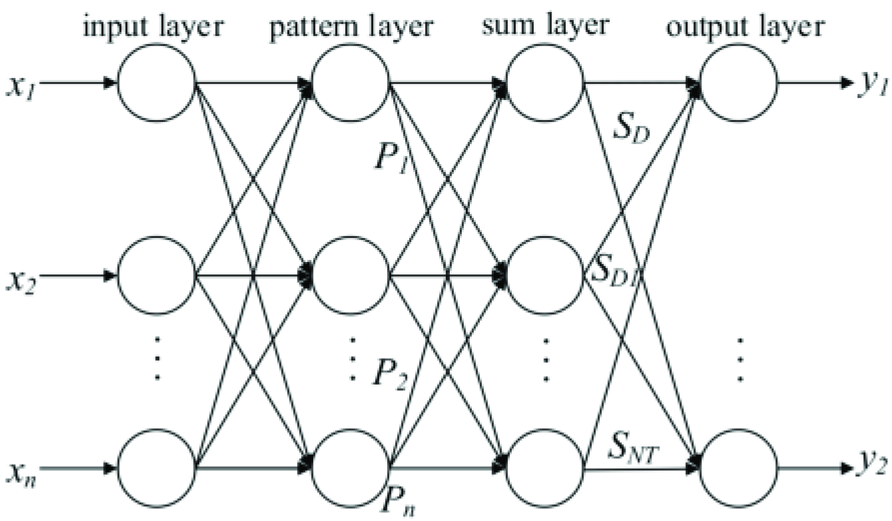

Figure 3.7 The Structure of the Generalized Regression Neural Network (GRNN)

Source: (Lin *et al*, 2018)

The input layer is where the original variables enter the network corresponding to the neurons one by one and are submitted to the next layer.

The pattern layer in GRNN is the component where nonlinear transformation is applied to the values received from the input layer. The transfer function of the i^{th} neuron in the pattern layer is given as Equation (3.23)

$$P_i = \exp\left[{-(x - x_i)^T (x - x_i)} \middle/ {2\sigma^2} \right] \quad \forall\ i = 1, 2, \ldots, n \tag{3.23}$$

where **x** represents input variable, $\mathbf{x}_i$ is the learning sample corresponding to the ith neuron; and σ is the smoothing parameter.

The summation layer is where the sum and weighted sum of the pattern outputs are calculated. The summation layer contains two types of neurons, in which one neuron SA makes arithmetic summation of the output of all pattern layer neurons, and the connection weight of each neuron in the pattern layer to this neuron is 1. Its transfer function is given as Equation (3.24)

$$S_D = \sum_{i=1}^{n} P_i \tag{3.24}$$

The outputs of all neurons in the pattern layer were weighted and summed to gain the other neurons S_{NJ} in the summation layer. The transfer function of the other neurons in the summation layer is given as Equation (3.25)

$$S_{NJ} = \sum_{i=1}^{n} y_{ij} P_i \qquad j = 1, 2, \ldots, k \tag{3.25}$$

where y_{ij} is the connection weight between the i^{th} neuron in the pattern layer and the j^{th} neuron in the summation layer.

The output layer is where the forecasting results can be derived. The output of each neuron is given by Equation (3.26)

$$y_j = \frac{S_{NJ}}{S_D} \qquad \text{j=1,2,...,k} \tag{3.26}$$

where y_j is the output of the j^{th} neuron.

3.8 Designing ANN models

Designing ANN models follows a number of systemic procedures. In general, there are five basics steps: (1) collecting data, (2) preprocessing data, (3) building the network, (4) train, and (5) test performance of model as shown in Figure 3.9

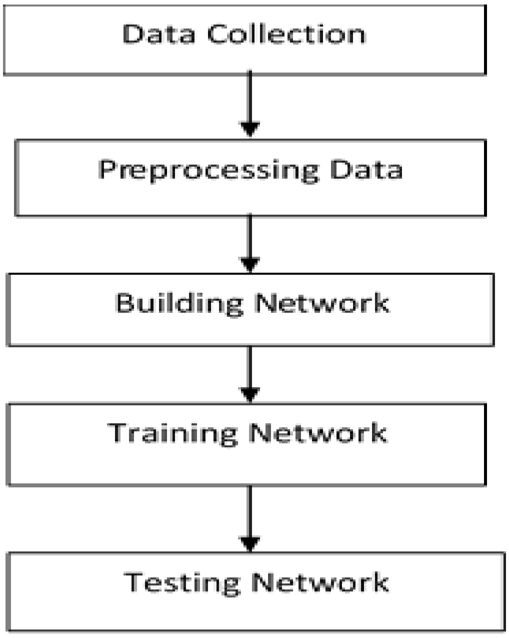

Figure 3.8 Basic Flow for Designing Artificial Neural Network Model

3.8.1 Data collection

Collecting and preparing sample data is the first step in designing ANN models. The data used to build the model usually comes from multiple datasets. In particular, three datasets are commonly used in different stages of the creation of the model.

The model is initially fit on a training dataset, which is a set of examples used to fit the parameters (e.g. weights of connections between neurons in artificial neural networks) of the model. The model (e.g. a neural net or a naive Bayes classifier) is trained on the training dataset using a supervised learning method, for example using optimization methods such as gradient descent or stochastic gradient descent. In practice, the training dataset often consists of pairs of an input vector (or scalar) and the corresponding output vector (or scalar), where the answer key is commonly denoted as the target (or label). The current model is run with the training dataset and produces a result, which is then compared with the target, for each input vector in the training dataset. Based on the result of the comparison and the specific learning algorithm being used, the parameters of the model are adjusted. The model fitting can include both variable selection and parameter estimation.

3.8.2 Data Pre-Processing

After data collection, three data preprocessing procedures are conducted to train the ANNs more efficiently. These procedures are:

i. solve the problem of missing data
ii. normalize data and
iii. randomize data.

The missing data are replaced by the average of neighboring values during the same month. Normalization procedure before presenting the input data to the network is generally a good practice, since mixing variables with large magnitudes and small magnitudes will confuse the learning algorithm on the importance of each variable and may force it to finally reject the variable with the smaller magnitude (Tymvios *et al*., 2008).

3.8.3 Building the network

At this stage, the designer specifies the number of hidden layers, neurons in each layer, transfer function in each layer, training function, weight/bias learning function, and performance function. In this work, Back Propagation Neural Network, Radial Basis Function and Generalized Regression Neural Networks were used.

3.8.4 Training the network

During the training process, the weights are adjusted in order to make the actual outputs (predicated) close to the target (measured) outputs of the network.

3.8.5 Testing and validating the network

The next step is to test the performance of the developed model. At this stage unseen data are exposed to the model. Additionally, graph is plotted between the actual output and the predicted output so that a comparison can be made. The performance of the models is discussed in detail in chapter 5.

3.8.6 Performance Evaluation Index

In order to evaluate the performance of the developed ANN models quantitatively, and to verify whether there is any underlying trend in performance of ANN models, by determining which forecasting model outperforms the other models, statistical analysis involving the coefficient of determination (R^2) and error measures such as the Performance Index (PI), Mean Absolute Error (MAE), the Root Mean Square Error (RMSE) and Mean Absolute Percentage Error are employed.

The smaller the values of the error indicators (PI, RMSE and MAE, MAPE), the better the forecasting performance. The error indicators really reflect the overall error of the prediction model and the degree of error dispersion. The smaller the values of these three indicators, the more concentrated the distribution of errors. These four error indexes are defined as follows:

The Coefficient of Determination, R^2

The coefficient of determination is perhaps the most widely used measure of the goodness of fit of relationship, showing how well a developed model predicts a given set of observations. The value of R^2 varies from 0 to 1; a value of zero would indicate that no variability has been explained, whereas a value of one would imply that all of the residuals are zero and the developed model fits perfectly through all of the observed points. In general, a high value of R^2 means we have a good fit, and a low value means we have a poor fit. R^2 is estimated using Equation (3.27)

$$R^2 = 1 - \frac{\sum_i \left(y_i - \hat{y}_i\right)^2}{\sum_i \left(y_i - \hat{y}\right)^2} \tag{3.27}$$

where y_i is the i^{th} observed value; y is the mean of the observed time series data; $\hat{y}_i$ is the i^{th} predicted value.

Performance Index (PI)

The performance Index (PI) measures the performance of the developed networks as the Mean Square Error (MSE). MSE is a frequently used measure of the differences between predicted values by a model or an estimator and the values observed. The performance index is expressed as Equation (3.28)

$$PI = MSE = \frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2 \tag{3.28}$$

Where y_i is the i^{th} observed value; $\hat{y}_i$ is the i^{th} predicted value; n is the sample size.

Mean Absolute Error (MAE)

Mean Absolute Error (MAE) is a model evaluation metric. The mean absolute error of a model with respect to a test set is the mean of the absolute values of the individual prediction errors on over all instances in the test set. MAE is given by Equation (3.29)

$$PI = MAE = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{3.29}$$

Where y_i is the ith observed value; $\hat{y}_i$ is the ith predicted value; n is the sample size.

Root Mean Square Error (RMSE)

The Root Mean Square Error (RMSE) is a frequently used measure of the difference between values predicted by a model and the values actually observed from the environment that is being modelled. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power. The RMSE of a model prediction is defined as the square root of the mean squared error as shown in Equation (3.30)

Root Mean Square Error (RMSE) provides information on the short-term performance which is a measure of the variation of predicated values around the measured data. The lower the RMSE, the more accurate is the estimation.

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(y_i - \hat{y}_i\right)^2} \tag{3.30}$$

Where y_i is the ith observed value; $\hat{y}_i$ is the ith predicted value; n is the sample size.

Mean Absolute Percentage Error (MAPE)

The mean absolute percentage error, also known as mean absolute percentage deviation (MAPD), is the measure of prediction accuracy of a forecasting method in statistics, for example in trend estimation. Additionally, it is also used as a loss function for regression problems in machine learning.

MAPE finds the absolute of the difference between actual value and the forecast value. The absolute value in this calculation is summed for every forecasted point in time and divided by the number of fitted points *n*, and then multiplied by 100%.

It usually expresses the accuracy as a ratio defined by the formula given by Equation (3.31)

$$\mathrm{MAPE} = \frac{1}{n}\sum_{t=1}^{n}\left|\frac{A_t - F_t}{A_t}\right| \times 100\% \tag{3.31}$$

Where A_t is the actual value and F_t is the forecast value.

3.9 Multiple 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 (3.32)

$$y = \alpha_0 + \alpha_1 x_1 + \alpha_2 x_2 + \ldots + \alpha_n x_n + \varepsilon \tag{3.32}$$

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)

3.9.1 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: minimising 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 (3.33)

$$\hat{\beta} = \left(X^T X\right)^{-1} X^T y \tag{3.33}$$

where y is a vector whose *i*th element is the *i*th observation of the dependent variable, and x is a matrix whose $_{ij}$ element is the *i*th observation of the j^{th} independent variable. The estimator is unbiased and consistent if the errors have finite variance and are uncorrelated with the regressors given by Equation (3.34)

$$E\left[X_j \varepsilon_i\right] = 0 \tag{3.34}$$

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 (3.35)

$$E\left[\varepsilon_i^2 | x_i\right] \tag{3.35}$$

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 β.

The condition of homoscedasticity can fail with either experimental or observational data. If the goal is either inference or predictive modelling, the performance of OLS estimates can be poor if multicollinearity is present, unless the sample size is large

3.9.2 Instrumental Variables (IV)

Instrumental variable is performed when the regressors are correlated with the errors. In this case, there is a need for some auxiliary instrumental variables z_i such that expected value is indicated in Equation (3.36)

$$E\left[z_i \varepsilon_i\right] = 0 \tag{3.36}$$

If **z** is the matrix of instruments, then the estimator can be given in closed form as indicated in Equation (3.37)

$$\hat{\beta} = \left(X^T Z (Z^T Z)^{-1} Z^T X\right)^{-1} X^T Z \left(Z^T Z\right)^{-1} Z^T y \tag{3.37}$$

3.9.3 Generalized Method of Moments (GMM)

The usual approach when facing heteroskedasticity of unknown form is to use the generalized method of moments (GMM). GMM makes use of the orthogonality conditions to allow for efficient estimation in the presence of heteroskedasticity of unknown form.

Consider a more general framework: an instrumental variables estimator implemented using the Generalized Method of Moments (GMM) has a conventional IV estimators such as two-stage least squares (2SLS) being special cases of this IV-GMM estimator. The model is given by Equation (3.38)

$$y = X\beta + u,\ u \sim (0, \Omega) \tag{3.38}$$

with X (N × k) and define a matrix Z (N × V) where V ≥ k. This is the Generalized Method of Moments IV (IV-GMM) estimator.

The V instruments give rise to a set of V moments:

$$g_i(\beta) = Z_i^{'} u_i = Z_i^{'}(y_i - x_i\beta),\ i = 1, N \tag{3.39}$$

where each g_i is a V-vector. The method of moments approach considers each of the V moment equations as a sample moment, which is estimated by averaging over N given by Equation (3.40)

$$\bar{g}(\beta) = \frac{1}{n}\sum_{i=1}^{N} z_i\left(y_i - x_i\beta\right) = \frac{1}{N} Z^{'} u \tag{3.40}$$

The GMM approach chooses an estimate that solves the equation given as (3.41)

$$\bar{g}\left(\hat{\beta}_{GMM}\right) = 0 \tag{3.41}$$

If V = k, the equation to be estimated is said to be exactly identified by the order condition for identification: that is, there are as many excluded instruments as included right-hand endogenous variables. The method of moment's problem is then k equations in k unknowns, and a unique solution exists, equivalent to the standard IV estimator given by Equation (3.42)

$$\hat{\beta}_{iv} = (Z^{'}X)^{-1} Z^{'} y \tag{3.42}$$

In the case of overidentification (**V** > k) we may define a set of k instruments as Equation (3.43)

$$\hat{x} = Z(Z^{'}Z)^{-1} Z^{'} X = P_z X \tag{3.43}$$

which gives rise to the two-stage least squares (2SLS) estimator given by Equation (3.44)

$$\hat{\beta}_{2SLS} = (\hat{X}^{'} X)^{-1} \hat{X}^{'} y = (X^{'} P_z X)^{-1} X^{-1} P_z y \tag{3.44}$$

which despite its name is computed by this single matrix Equation.

In the 2SLS method with overidentification, the V available instruments are “boiled down" to the k needed by defining the P_Z matrix. In the IV-GMM approach, that reduction is not necessary. All instruments are used in the estimator. Furthermore, a weighting matrix is employed so that we may choose $\hat{\beta}_{GMM}$ so that the elements of $\bar{g}(\hat{\beta}_{GMM})$ are as close to zero as possible. With V > k, not all moment conditions can be exactly satisfied, so a criterion function that weights them appropriately is used to improve the efficiency of the estimator.

The GMM estimator that minimizes the criterion is given by Equation (3.45)

$$J\left(\hat{\beta}_{GMM}\right) = N\,\bar{g}\left(\hat{\beta}_{GMM}\right)' W\,\bar{g}\left(\hat{\beta}_{GMM}\right) \tag{3.45}$$

where W is a V × V symmetric weighting matrix.

Solving the set of FOCs, we derive the IV-GMM estimator of an over identified equation given by Equation (3.45)

$$\hat{\beta}_{GMM} = \left(X'ZWZ'X\right)^{-1} X'ZWZ'y \tag{3.46}$$

which will be identical for all W matrices which differ by a factor of proportionality. The optimal weighting matrix, chooses $W = S^{-1}$ where S is the covariance matrix of the moment conditions to produce the most efficient estimator given by Equation (3.47)

$$S = E\left[Z'uu'Z\right] = \lim_{N\to\infty} N^{-1}\left[Z'\Omega Z\right] \tag{3.47}$$

With a consistent estimator of S derived from 2SLS residuals, we define the feasible IV-GMM estimator as Equation (3.48)

$$\hat{\beta}_{FEGMM} = \left(X'Z\hat{S}^{-1}Z'X\right)^{-1} X'Z\hat{S}^{-1}Z'y \tag{3.48}$$

where FEGMM refers to the feasible efficient GMM estimator.

CHAPTER 4

RESULTS AND DISCUSSIONS

4.1 Overview

This chapter contains the results and the discussion of the impact of the macroeconomic indicators (independent variables) on exchange rate, and the various neural networks approximations employed in this study to predict the exchange rate between the US Dollar and Ghana Cedi (USD/GHS) and the Great Britain Pound and Ghana Cedi (GBP/GHS), and finally selecting the efficient ANN models.

4.2 Data Used

A secondary data on monthly average measurement data of Ghana's exchange rate in US Dollar to Cedis (USD/GHS) and GBP to Cedi (GBP/GHS), and monthly measurement data 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.

4.3 Multiple 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.

Tables 4.1 and 4.2 were the outcomes of the impact on the Dollar and the Cedi, respectively when the data was analysed.

Table 4.1 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***
Std. error of the estimate of Growth Rate	(0.0788)	(0.1560)	(0.1601)	(0.1405)
US Inflation	0.0721***	0.0876***	0.0887***	0.0857***
Std. error of the estimate of inflation	(0.0195)	(0.0224)	(0.0230)	(0.0210)
Log of Inflation Rate	-0.3472*	-0.2615	-0.2430	-0.2083
Std. error of Inflation rate	(0.1958)	(0.1962)	(0.2007)	(0.1954)
Log of Interest Rate	-0.5480***	-0.5467***	-0.5522***	-0.5933***
Std. error of the estimate of Interest Rate	(0.0984)	(0.1105)	(0.1135)	(0.1069)
Log of Broad Money Supply	1.5812***	1.5972***	1.6280***	1.6885***
Std. error of the estimate of broad money supply	(0.1125)	(0.1097)	(0.1097)	(0.1095)
Log of Gross International Reserve	-1.0993***	-1.1327***	-1.1722***	-1.2389***
Std. error of the estimate of gross international reserve	(0.1891)	(0.1814)	(0.1800)	(0.1759)
Log of Foreign Currency Deposit	-0.0657***	-0.0771***	-0.0787***	-0.0776***
Std. error of the estimate of foreign currency deposit	(0.0165)	(0.0183)	(0.0185)	(0.0180)
Log of Monetary Policy Rate	1.9301***	1.6311***	1.5651***	1.5309***
Std. error of the estimate of monetary policy rate	(0.2835)	(0.3085)	(0.3125)	(0.3042)
Trade Balance	0.0004**	0.0003*	0.0003	0.0003
Std. error of the estimate of trade balance	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-5.5605***	-3.9140***	-3.6651***	-3.7516***
	(0.9013)	(1.1602)	(1.1508)	(1.0889)
Observations	171	170	169	167
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
Under identification Test (LM Statistic)		30.340	33.731	36.060
		0.0000	0.0000	0.0000
Overidentification Test (Hansen J Statistic)			0.3010	1.5360
			0.5832	0.6741
Endogeneity Test (Chi-squared Statistic)		6.9180	7.7560	7.8120
		0.0085	0.0054	0.0052

Table 4.1 shows the results of the impact of the macroeconomic variables in column (1) on the exchange rate between the U.S. dollar and the Ghana cedi. Column (2) shows the estimates from Ordinary Least Squares (OLS). Column (3) shows the estimates from the Instrumental Variable (IV) estimation technique. Column (4) shows the estimates from the IV-Generalized Method of Moments (IV-GMM) estimation technique with two lags of log of nominal growth rate as instruments for a suspected endogenous nominal growth rate. Similarly, column (5) shows the IV-GMM estimates with four lags of log of nominal growth rate instrumenting for nominal growth rate. Standard errors which are robust to the presence of heteroskedasticity and significant correlation is shown in parentheses. *** represents statistical significance of the estimates at the 1% alpha level, ** represents statistical significance of the estimates at the 5% alpha level and * represents statistical significance of the estimates at the 10% alpha level.

Table 4.2 The Impact of Macroeconomic Indicators on Exchange Rate (GBP-GHS)

Dependent variable is Exchange Rate (GBP-GHS)				
Predictor Variable	**OLS**	**IV**	**IV-GMM at lag 2**	**IV-GMM at lag 4**
Log of Growth Rate (Nominal)	0.1488	0.4179	0.0131	0.0247
Std. error of the estimate of Growth Rate	(0.1250)	(0.3956)	(0.1433)	(0.1288)
US Inflation	-0.0428	-0.0559	0.0156	0.0141
Std. error of the estimate of US inflation	(0.0593)	(0.0706)	(0.0261)	(0.0251)
Log of Inflation Rate	0.2821	0.2271	0.0456	0.0542
Std. error of inflation rate	(0.2633)	(0.2140)	(0.1498)	(0.1387)
Log of Interest Rate	0.1037	0.0940	-0.0249	-0.0294
Std. error estimate of the of interest rate	(0.1375)	(0.1343)	(0.0914)	(0.0861)
Log of Broad Money Supply	0.6363***	0.6602***	0.5181***	0.5386***
Std. error estimate of broad money supply	(0.1452)	(0.1615)	(0.0900)	(0.0874)
Log of Gross International Reserve	-0.4257	-0.4390	-0.1408	-0.1633
Std. error estimate of gross international reserve	(0.3216)	(0.3235)	(0.1662)	(0.1588)
Log of Foreign Currency Deposit	-0.0070	0.0027	-0.0357**	-0.0350**
Std. error estimate of foreign currency deposit	(0.0290)	(0.0380)	(0.0148)	(0.0143)
Log of Monetary Policy Rate	-0.1272	0.0663	0.3155	0.2857
Std. error estimate of monetary policy rate	(0.4990)	(0.3130)	(0.2235)	(0.2109)
Trade Balance	0.0002	0.0003	0.0001	0.0001
Std. error estimate of trade balance	(0.0002)	(0.0002)	(0.0001)	(0.0001)
Constant	-2.2063	-3.4879***	-3.3190***	-3.2912***
	(1.3400)	(0.6823)	(0.7565)	(0.7141)
Observations	171	170	169	167
F-Statistic/Wald Chi-squared Statistic	435.01	182.29	129.41	134.82
p-value	0.0000	0.0000	0.0000	0.0000
R-squared	0.3227	0.3089	0.2856	0.2818
Under identification Test (LM Statistic)		30.340	33.731	36.036
		0.0000	0.0000	0.0000
Overidentification Test (Hansen J Statistic)			1.1740	1.1670
			0.2785	0.7609
Endogeneity Test (Chi-squared Statistic)		0.9410	0.0420	0.0140
		0.3321	0.8378	0.9042

Table 4.2 shows the results of the impact of the macroeconomic variables on the exchange rate between the Great Britain pound and the Ghana cedi. Column (2) shows the estimates from Ordinary Least Squares (OLS). Column (3) shows the estimates from the Instrumental Variable (IV) estimation technique. Column (4) shows the estimates from the IV-Generalized Method of Moments (IV-GMM) estimation technique with two lags of log of nominal growth rate as instruments for a suspected endogenous nominal growth rate. Similarly, column (5) shows the IV-GMM estimates with four lags of log of nominal growth rate instrumenting for nominal growth rate. Standard errors which are robust to the presence of heteroskedasticity and serial correlation are shown in parentheses. *** represents statistical significance of the estimates at the 1% alpha level, ** represents statistical significance of the estimates at the 5% alpha level and * represents statistical significance of the estimates at the 10% alpha level.

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 4.2 using the OLS estimator. Under column (2) in Table 4.2, all estimates are statistically significant at the 1% alpha level except for trade balance and inflation rate which are significant at the 5% and 10% alpha 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 suggest that these macroeconomic indicators have a reverse relationship with exchange rate (USD-GHS). The negative sign reveals that, as the variables 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.

Under column (2) in Table 4.2, the total number of observations used in the estimation is 171 with an overall F-Statistic of 483.97 and 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. Consequently, the null hypothesis of joint insignificance is rejected in favour of the alternative hypothesis of joint significance. This further shows that, overall, the model is a good fitting model and fits better than a model with an imposed restriction. Lastly, under column (2), the R-squared value implies that 95.22% of the variations in exchange rate are accounted for by variations in the explanatory variables (macroeconomic indicators). Approximately 4.78% of the variation in exchange rate are left unexplained by the explanatory variables.

Problems of endogeneity arise when one or more explanatory variables are correlated with the error term of a regression model. In our case, all the macro indicators in our model may not pass the exogeneity test based on the assumption that a good number of the macro indicators are correlated to some extent with GDP which is in the error term and might just serve as a proxy for it. The nominal growth rate poses a huge problem of endogeneity to the researcher since it is highly correlated with GDP than any other macro indicator in our data. Unfortunately, if there are problems of endogeneity, then the OLS estimates obtained in column (2) are biased, inconsistent and less informative and may tend to either underestimate or overestimate the actual impacts on exchange rate. An intuitive approach to rectify the occurrence of an endogeneity problem in regression is to use an instrumental variable estimation technique which we have employed and the results are summarized under column (3) of Table 4.2.

Results from column (3) are obtained by instrumenting for nominal growth rate using just one lag of nominal growth rate. Clearly, we can observe that OLS estimate of nominal growth rate is really biased and underestimated the actual impact on exchange rate since the IV estimate is larger than the OLS estimate in absolute value terms. This substantial difference between the estimates from the two estimation strategies is as a result of the endogeneity of nominal growth rate. Now, exchange rate decreases by approximately 0.05% when nominal growth rate declines by 10% which is quite a significant decline relative to the decline recorded from using the OLS estimator under column (2). With the exception of nominal growth rate, all other estimates under columns (2) and (3) have nearly the same magnitude except for inflation rate and the monetary policy rate with substantial difference in estimates. Under the IV estimation, all variables are highly significant excluding trade balance which is marginally significant at the 10% alpha level and inflation rate being statistically insignificant. Interpretation of the rest of the results follows the same way as we did under column (2).

There is an overall F-Statistic of 411.46 with a p-value of 0.0000 implying an overall good fitting model since the variables are jointly statistically significant at the 1% alpha level.[1] Moreover, 94.72% of the variations in exchange rate are explained by the variation in the explanatory variables. The Lagrange Multiplier (LM) Statistic under the under-identification test is 30.340 with a p-value of 0.0000 implying an overwhelming evidence against the null hypothesis of under identified instruments. Here our model is exactly identified since the number of instrumental variables is equal to the number of endogenous variables. The Chi-squared Statistic for the endogeneity test is 6.9180 with a p-value of 0.0085 suggesting a clear evidence against the null hypothesis of exogeneity of nominal growth rate. Apart from intuitively explaining that the nominal growth rate is endogenous, statistical test has exonerated our intuitive reasoning and hence the justification for using an IV estimator.

The IV-GMM estimates in columns (4) and (5) are obtained by instrumenting for the nominal growth rate using two lags and four lags of nominal growth rate respectively. If the number of instruments is more than the number of endogenous variables; the case for columns (4) and (5), then the IV estimates are no longer efficient compared to the IV-GMM estimates. The IV-GMM estimator employs all the moment conditions and computes a more efficient estimate than the IV estimate which only uses one instrument at a time for one endogenous variable. Clearly from column (4), the estimate of the nominal growth rate increased slightly in absolute value terms from estimate in column (3). It implies that, a 10% increase in nominal growth rate will result into roughly a 0.06% decline in exchange rate with all other variables remaining constant. The estimate of nominal growth rate is also highly statistically significant and so is every other variable with the exception of inflation rate and trade balance. Estimate of nominal growth rate in column (5) has a smaller absolute value than in column (4) although it is highly statistically significant. Similarly, in column (5), all the predictor variables are statistically significant apart from inflation rate and trade balance.

The models in columns (4) and (5) are statistically stable given that all the variables are jointly significant with F-Statistics of 406.70 and 434.87 respectively and p-values of 0.0000 each. For each of column (4) and column (5), approximately, 95% of all variations in exchange rate are explained by variations in the explanatory variables. Furthermore, in columns (4) and (5), there is an overwhelming evidence against the null hypothesis of under identification since the p-values are each less than 0.05. Since there is no empirical evidence of under identification and the models are not exactly identified, then it is conservative to test for overidentification using the Hansen Test. The Hansen J Statistic shown in columns (4) and (5) are respectively 0.3010 and 1.5360 with p-values of 0.5832 and 0.6741 respectively. The p-values reveal enormous evidence for the null hypothesis which revealed that the instruments are overidentified thereby making the IV-GMM estimates more reliable and justified than the IV and OLS estimates in columns (2) and (3) respectively. Moreover, there is great evidence against the null hypothesis of exogeneity of the nominal growth rate since the p-values of the Chi-squared Statistic are less than 0.05. This in addition justifies/solidifies our reason for employing the IV and IV-GMM estimators. Consequently, the IV estimates are more reliable than OLS estimates while the IV-GMM estimates are also more reliable than the IV estimates. Subsequently, the IV-GMM model to now choose from largely depends on educational guesses.

The results from Table 4.2 follows the same interpretations as in Table 4.1 but there are few issues in Table 4.2 that need to be ironed out relating to Table 4.1. When we compare the estimates of the nominal growth rate which is an endogenous variable, we realize that OLS and the two IV-GMM estimates differ substantially from the IV estimate in column (3). Since we do not know the exact or true values of the effect of these macroeconomic indicators on exchange rate and more specifically nominal growth rate, we can say very little or nothing about the accuracy or unbiasedness of these estimates. However, we can conclude that the IV-GMM estimator is a bit redundant when we regress exchange rate (GBP-GHS) on the macroeconomic indicators. This is evident from the endogeneity test of nominal growth rate which reveals quite a considerable evidence for the null hypothesis indicating that nominal growth rate is an exogenous variable. Endogeneity test for column (3) shows evidence for the null hypothesis and thus making the IV estimator in this scenario quite invalid as well. This shows that adopting the traditional OLS estimation strategy might just well be the best approach to take when exchange rate (GBP-GHS) is the response variable.

4.4 Data Analysis of USD/GHS

This section focuses on the result by the Back Propagation Neural Network (BPNN), Radial Basis Neural Network (RBNN), and the Generalised Regression Neural Network (GRNN) technique employed in this study to predict the exchange rate between the US Dollar and the Ghana Cedi. In this study, 121months data points were used for training the network, whiles 42 months data points were used for testing the network.

4.4.1 Analysis of Back Propagation Neural Network (BPNN)

This section presents the adequate result by the BPNN algorithm on the exchange rate of US Dollar and the Cedi. Table 4.3 has three sections. Thus, 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 4.3, 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 the USD and the Ghana Cedi.

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 4.3, 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 4.3 Summary of Competing BPNN Architecture for Dollar and Cedi

	Train				Test			
Arch.	**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

4.4.2 Radial Basis Function Neural Network (RBFNN)

Table 4.4 shows the results for the network approximation using RBFNN technique. The spread and the maximum number of neurons were set from 1.0 and 30 respectively so as to allow for an averagely smoother approximation. After computing several iterations (i.e., starting from neuron 1 to 30), the results of the training data showed that, architecture 9-2-1 has the minimum PI of 0.00194, MAE of 0.03418 and RMSE of 0.04410, and a corresponding R^2 of 99.71%.

The ability of architecture 9-2-1 to adequately train the data set gave an estimated R^2 value of 99.71% shows that, the independent macroeconomic factors (inflation, monetary policy, interest rate, nominal growth, broad money supply, inflation of United State of America, foreign currency deposit and trade balance) could explain 99.71% of the Exchange rate between the USD and the Ghana Cedi, hence, the model has best future prospect when introduced to a new data set for prediction.

However, the provision of the test data to the models proved that, architecture 9-8-1 was the most sufficient network architecture to predict the exchange rate of the US Dollar and the Cedi with PI of 0.23495, MAE of 0.37265, RMSE of 0.48472 and a MAPE of 8.52 percent. Thus, 9-8-1 network architecture is the adequate RBFNN architecture model for predicting the exchange rate between the US Dollar and the Ghana Cedi.

Table 4.4 Summary of Approximated RBFNN Architecture for Dollar and Cedi

Arch.	Train				Test			
	PI	RMSE	MAE	R^2	PI	RMSE	MAE	MAPE
1	0.00482	0.06944	0.04608	0.99270	4.49425	2.11996	2.04176	46.71289
2	**0.00194**	**0.04410**	**0.03418**	**0.99706**	5.60358	2.36719	2.20573	49.97501
3	0.00248	0.04977	0.03720	0.99625	6.08699	2.46718	2.27659	51.54341
4	0.00353	0.05940	0.04116	0.99466	7.71900	2.77831	2.48209	55.71504
5	0.00371	0.06089	0.04225	0.99439	4.18273	2.04517	1.80996	40.70419
6	0.00403	0.06348	0.04432	0.99390	4.46400	2.11282	1.83924	41.15499
7	0.00274	0.05231	0.04008	0.99586	4.40308	2.09835	1.78932	40.03626
8	0.00374	0.06112	0.04716	0.99435	**0.23495**	**0.48472**	**0.37265**	**8.52457**
9	0.00355	0.05956	0.04438	0.99463	3.95253	1.98810	1.73035	38.90469
10	0.00325	0.05704	0.04330	0.99508	7.30730	2.70320	2.29992	51.39691
11	0.00411	0.06411	0.04597	0.99378	0.98453	0.99224	0.84528	19.09929
12	0.00453	0.06734	0.04983	0.99314	0.36937	0.60776	0.44763	10.32440
13	0.00367	0.06057	0.04610	0.99445	3.52422	1.87729	1.65948	37.40202
14	0.00362	0.06013	0.04523	0.99453	2.67423	1.63531	1.38398	30.92875
15	0.00362	0.06019	0.04527	0.99452	2.65879	1.63058	1.37975	30.83096
16	0.00368	0.06066	0.04645	0.99443	1.02120	1.01054	0.85089	19.10287
17	0.00368	0.06068	0.04647	0.99443	1.01743	1.00868	0.84876	19.05753
18	0.00368	0.06070	0.04648	0.99442	1.01438	1.00716	0.84695	19.01906
19	0.00374	0.06118	0.04720	0.99433	0.82593	0.90881	0.75631	17.07784
20	0.00374	0.06119	0.04721	0.99433	0.82463	0.90809	0.75488	17.04777
21	0.00375	0.06120	0.04721	0.99433	0.82356	0.90750	0.75364	17.02169
22	0.00375	0.06121	0.04721	0.99433	0.82266	0.90701	0.75256	16.99893
23	0.00375	0.06121	0.04721	0.99433	0.82190	0.90659	0.75161	16.97895
24	0.00375	0.06122	0.04721	0.99433	0.82125	0.90623	0.75077	16.96132
25	0.00397	0.06301	0.04619	0.99399	2.45726	1.56756	1.35303	30.38958
26	0.00397	0.06302	0.04620	0.99399	2.45764	1.56769	1.35297	30.38743
27	0.00397	0.06303	0.04621	0.99399	2.45797	1.56779	1.35290	30.38545
28	0.00397	0.06304	0.04622	0.99399	2.45827	1.56789	1.35285	30.38364
29	0.00397	0.06304	0.04623	0.99398	2.45853	1.56797	1.35279	30.38196
30	0.00398	0.06305	0.04623	0.99398	2.45877	1.56805	1.35274	30.38042

NB: Optimal values are bolded

4.4.3 Generalised Regression Neural Network (GRNN)

Table 4.5 shows the results from the network approximation using GRNN technique. Similar to the RBFNN technique, the architecture sets are classified as spread. The spread was varied from 0.1 to 3.0 so as to allow for a closer fit of the measured data. As observed, a spread of 0.1 at the training stage produced the least values in terms of performance index (PI= 0.00000) with MAE of 0.00055, RMSE 0.00201 and a corresponding high R^2 value of 100.00%. During the test stage, spread 0.2 proved to be adequate with a PI of 1.33274, MAE of 1.06482, RMSE of 1.15444 and MAPE of 24.07% as shown in Table 4.5. Therefore, the GRNN network architecture with spread of 0.2 is optimal and regarded as the adequate GRNN architecture for predicting the Dollar Cedi exchange rate in Ghana.

Table 4.5 Summary of Approximated GRNN Network Architecture for Dollar and Cedi

Spread (Architecture)	Train				Test			
	PI	RMSE	MAE	R^2	PI	RMSE	MAE	MAPE
0.1	**0.00000**	**0.00201**	**0.00055**	**0.99999**	1.33263	1.15439	1.06576	24.09938
0.2	0.00086	0.02937	0.00998	0.99869	**1.33274**	**1.15444**	**1.06482**	**24.07439**
0.3	0.00242	0.04917	0.02229	0.99634	1.34288	1.15883	1.06921	24.17466
0.4	0.00368	0.06068	0.03274	0.99443	1.38451	1.17665	1.08552	24.54271
0.5	0.00488	0.06983	0.04273	0.99262	1.47349	1.21388	1.11847	25.28022
0.6	0.00651	0.08066	0.05473	0.99015	1.59476	1.26284	1.16215	26.25973
0.7	0.00887	0.09416	0.06779	0.98658	1.72132	1.31199	1.20775	27.29269
0.8	0.01245	0.11157	0.08189	0.98116	1.84636	1.35881	1.25381	28.35029
0.9	0.01876	0.13698	0.09969	0.97160	1.97544	1.40550	1.30278	29.48909
1.0	0.03033	0.17416	0.12323	0.95409	2.11520	1.45437	1.35624	30.74266
1.1	0.04902	0.22140	0.15197	0.92581	2.26927	1.50641	1.41489	32.12653
1.2	0.07457	0.27308	0.18396	0.88713	2.43815	1.56146	1.47785	33.61975
1.3	0.10508	0.32416	0.21643	0.84096	2.62017	1.61869	1.54345	35.18110
1.4	0.13818	0.37173	0.24725	0.79085	2.81249	1.67705	1.60988	36.76662
1.5	0.17193	0.41464	0.27622	0.73978	3.01195	1.73550	1.67568	38.33971
1.6	0.20497	0.45274	0.30336	0.68977	3.21553	1.79319	1.73981	39.87346
1.7	0.23650	0.48632	0.32818	0.64204	3.42045	1.84945	1.80153	41.34914
1.8	0.26611	0.51586	0.35074	0.59723	3.62420	1.90373	1.86036	42.75408
1.9	0.29362	0.54187	0.37115	0.55559	3.82449	1.95563	1.91597	44.08007
2.0	0.31902	0.56482	0.38970	0.51716	4.01936	2.00483	1.96817	45.32234
2.1	0.34236	0.58512	0.40644	0.48182	4.20717	2.05114	2.01688	46.47901
2.2	0.36378	0.60314	0.42143	0.44941	4.38668	2.09444	2.06209	47.55047
2.3	0.38340	0.61919	0.43490	0.41972	4.55704	2.13472	2.10388	48.53898
2.4	0.40136	0.63353	0.44726	0.39252	4.71775	2.17204	2.14238	49.44809
2.5	0.41782	0.64639	0.45855	0.36762	4.86861	2.20649	2.17778	50.28229
2.6	0.43290	0.65795	0.46884	0.34479	5.00969	2.23823	2.21026	51.04661
2.7	0.44674	0.66838	0.47827	0.32385	5.14122	2.26743	2.24003	51.74629
2.8	0.45944	0.67782	0.48686	0.30462	5.26358	2.29425	2.26732	52.38660
2.9	0.47113	0.68639	0.49471	0.28693	5.37723	2.31889	2.29231	52.97265
3.0	0.48188	0.69418	0.50195	0.27065	5.48269	2.34152	2.31523	53.50931

4.4.4 Predictive accuracy (validation) of the models

To further ascertain the appropriate technique for predicting the exchange rate between the US Dollar and the Ghana Cedi, the predictive performance of the selected optimal network architectures for the various techniques are assessed. Figure 4.1, 4.2 and 4.3 show the graphical representation of the optimal architectures for the BPNN, RBFNN and the GRNN during the training stage, whiles Figure 4.4 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 to them (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 4.6. From Table 4.6, 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 4.1 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 4.6 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 Dollar Cedi (USD/GHS) exchange rate.

Table 4.6 Model Performance for Dollar and Cedi

Network	Arch.	spread	MAPE	PI	MAE	RMSE	R^2	Ranking
BPN	**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

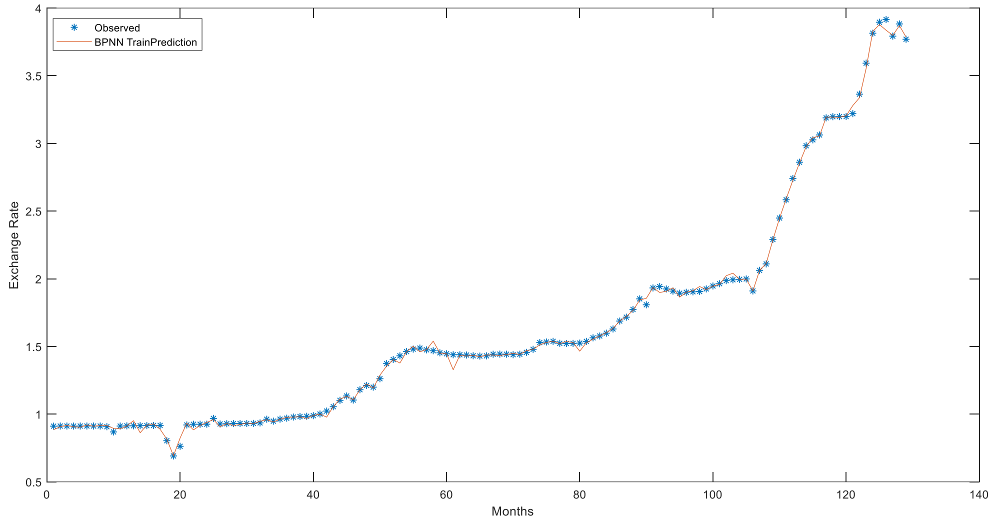

Figure 4.1 BPNN Graph Indicating Training Performance of Selected Architecture

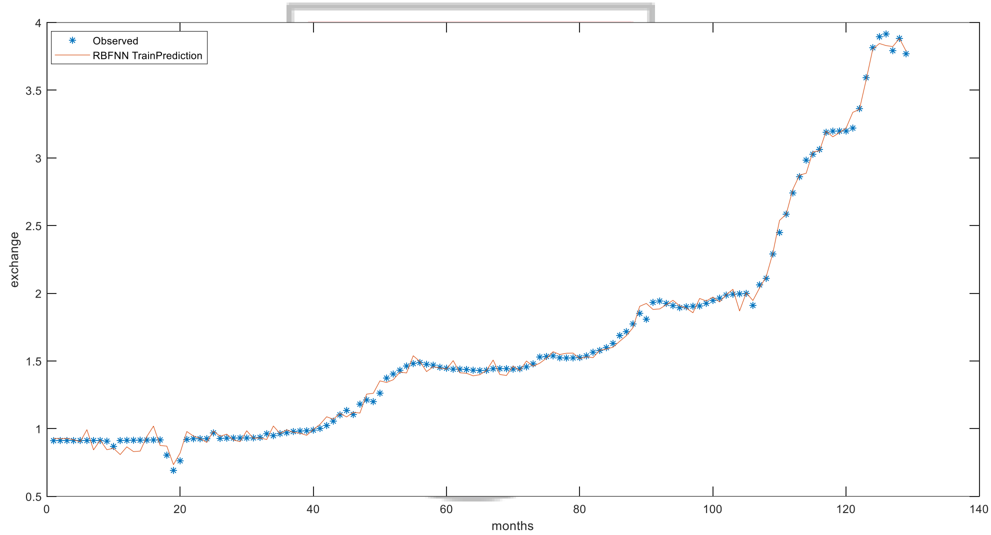

Figure 4.2 RBFNN Graph Indicating Training Performance of Selected Architecture

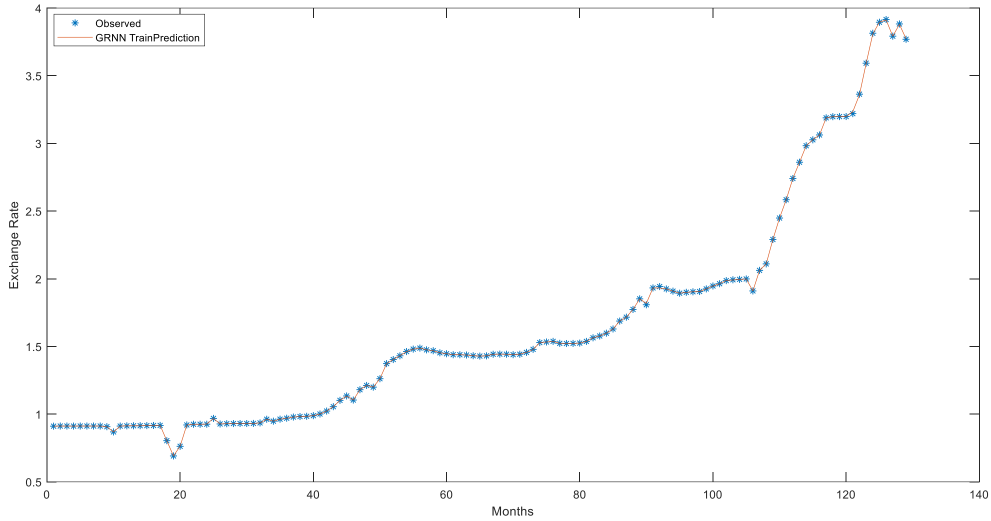

Figure 4.3 GRNN Graph Indicating Training Performance of Selected Spread

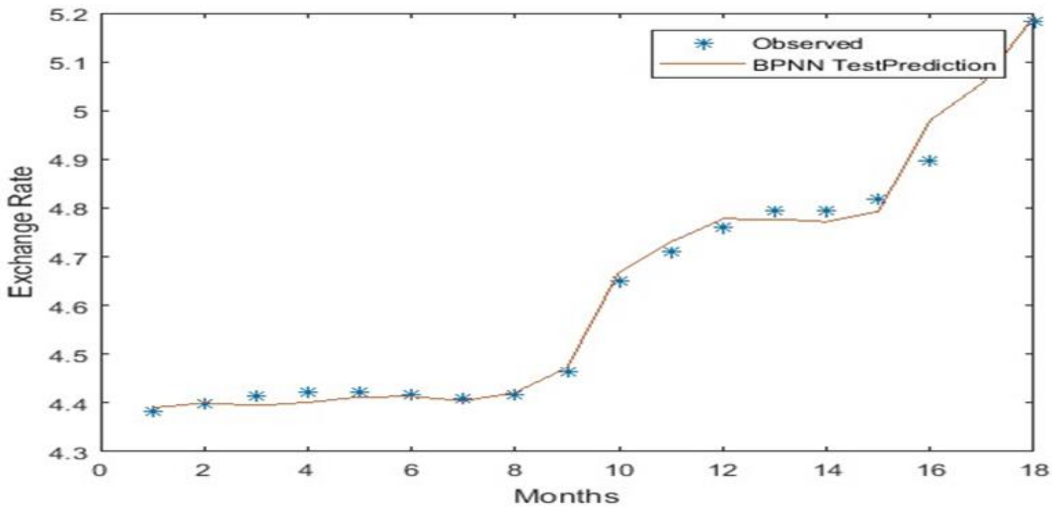

Figure 4.4 BPNN Graph Indicating Test Performance of Selected Architecture

4.5 Exchange Rate Between the Great Britain Pound (GBP) and the Ghana Cedi

This part of the research focuses on the result by the Back Propagation Neural Network (BPNN), Radial Basis Function Neural Network (RBFNN), and the Generalised Regression Neural Network (GRNN) technique employed in this study to predict the exchange rate between the Great Britain Pound and the Ghana Cedi

4.5.1 Back Propagation Neural Network (BPNN)

The results obtained by BPNN algorithm for the exchange rate between Great Britain Pound and Ghana (GBP/GHS) for thirty (30) architectures are shown in Table 4.7. It shows the

Performance Index (PI), MAE, RMSE, and the coefficient of determination for the trained neurons in the second part. In addition, the Table 4.7 also shows PI, MAE, RSME and the MAPE for the test neurons as indicated in the third part. considering different network architectures for the training and test set respectively.

It is deduced from the training data result in Table 4.7 that, architecture 9-7-1 has the minimum PI of 0.00476, MAE of 0.04479 and RMSE of 0.06899 with an appreciable estimated R^2 value of 99.72%. An R^2 value of 99.72% indicate that, the model can explain 99.72% of the model's performance. Nevertheless, the performance of architecture 9-2-1 in the test set outperformed network architecture 9-7-1 in the training set. This, suggests that architecture 9-2-1 has adequate accuracy for predicting the average monthly exchange rate between the Pound and the Cedi than network architecture 9-7-1. This claim is true, because Table 4.7 indicates that, architecture 9-7-1 was not adequate in predicting the Pound Cedi exchange rate than architecture 9-2-1 during the test stage. A critical analysis of their error estimates during the test stage as showed in Table 4.7 proves that, architecture 9-2-1 had the least errors with PI of 0.14855, MAE of 0.31016, RMSE of 0.38542 and MAPE of 5.62 as shown in Table 4.7.

Thus, the network architecture 9-2-1 is accepted as the adequate model for the BPNN and can be used to predict the Pound and the Cedi.

Table 4.7 Summary of Competing Network Architecture for GBP and Cedi using BPNN

	Train				Test			
Arch.	**PI**	**RMSE**	**MAE**	**R^2**	**PI**	**RMSE**	**MAE**	**MAPE**
1	0.05554	0.23568	0.18574	0.96669	0.27957	0.52875	0.41996	7.70872
2	0.03140	0.17720	0.12189	0.98117	**0.14855**	**0.38542**	**0.31016**	**5.62369**
3	0.02090	0.14456	0.09577	0.98747	0.27439	0.52382	0.45168	7.99476
4	0.07533	0.27446	0.08586	0.95482	6.98133	2.64222	2.33753	40.12168
5	0.01799	0.13413	0.06395	0.98921	0.24032	0.49023	0.40442	7.24316
6	0.01363	0.11675	0.06902	0.99183	2.88894	1.69969	1.50024	25.84435
7	**0.00476**	**0.06899**	**0.04479**	**0.99715**	4.10380	2.02578	1.69505	28.80628
8	0.00746	0.08639	0.03936	0.99552	0.92428	0.96139	0.73199	13.24729
9	0.00880	0.09383	0.04093	0.99472	7.34365	2.70992	2.34195	39.48621
10	0.14798	0.38469	0.08272	0.91124	9.82353	3.13425	2.86235	48.66403
11	0.02900	0.17029	0.05568	0.98261	4.68035	2.16341	1.94635	33.07744
12	0.03681	0.19186	0.04826	0.97792	1.68278	1.29722	0.97247	17.49180
13	0.04132	0.20328	0.03968	0.97522	2.50179	1.58170	1.34782	23.31029
14	0.01714	0.13090	0.03752	0.98972	3.54468	1.88273	1.64049	28.25146
15	0.01023	0.10113	0.02489	0.99387	8.53083	2.92076	2.55298	43.25697
16	0.06447	0.25390	0.06333	0.96133	5.29026	2.30006	2.25000	38.95706
17	0.09584	0.30958	0.06262	0.94252	3.39159	1.84163	1.49618	25.47189
18	0.10233	0.31990	0.06858	0.93862	1.15227	1.07344	0.84587	14.93634
19	0.01937	0.13917	0.03494	0.98838	1.54248	1.24197	1.03236	17.89927
20	0.00552	0.07427	0.02292	0.99669	10.04717	3.16973	2.67647	45.80852
21	0.00972	0.09859	0.03732	0.99417	4.97671	2.23085	1.90980	32.36024
22	0.00884	0.09402	0.02681	0.99470	1.13719	1.06639	0.87971	15.40258
23	0.01292	0.11368	0.03387	0.99225	6.35306	2.52053	2.19958	37.03724
24	0.00510	0.07139	0.03274	0.99694	5.23347	2.28768	1.89435	31.95175
25	0.04154	0.20381	0.05518	0.97509	3.46448	1.86131	1.41218	23.45997
26	0.02275	0.15083	0.04318	0.98636	9.59746	3.09798	2.74792	46.38844
27	0.02301	0.15170	0.06467	0.98620	0.42250	0.65000	0.55850	9.73396
28	0.13760	0.37095	0.07828	0.91747	1.41864	1.19107	0.97666	16.67228
29	0.01038	0.10189	0.03342	0.99377	7.18656	2.68078	2.36210	40.39136
30	0.01810	0.13452	0.03470	0.98915	0.83678	0.91476	0.77738	13.38865

4.5.2 Radial Basis Function Neural Network (RBFNN)

The result for the network approximation using RBFNN is captured in Table 4.8. For a better approximation, the spread and the maximum number of neurons were set to 1.0 and 30 respectively. The results of the training show that, architecture 9-3-1 has the least values of errors with PI of 0.01579, MAE of 0.07921 and RMSE of 0.12567, with a corresponding R^2 value of 99.05%

However, with the Test data, the same architecture 9-3-1 which was optimal in the training set emerged as the optimal model for the RBFNN with PI of 0.26893, MAE of 0.40857, RMSE of 0.51858 and MAPE of 7.02% in the test stage. Thus, 9-3-1 network architecture proved to be the adequate RBFNN model for both training and testing, hence, the most adequate architecture for predicting the Pound to Cedi exchange rate.

Table 4.8 Summary of Approximated Network Architecture for RBFNN

	Train				Test			
Arch.	**PI**	**RMSE**	**MAE**	**R^2**	**PI**	**RMSE**	**MAE**	**MAPE**
1	0.02063	0.14362	0.09414	0.98763	3.52342	1.87708	1.63806	27.58922
2	0.01686	0.12984	0.08315	0.98989	2.16818	1.47247	1.22921	20.51377
3	**0.01579**	**0.12567**	**0.07921**	**0.99053**	**0.26893**	**0.51858**	**0.40857**	**7.02492**
4	0.02035	0.14267	0.09475	0.98779	3.59296	1.89551	1.61272	27.78389
5	0.01729	0.13151	0.08655	0.98963	8.04314	2.83604	2.43990	41.79471
6	0.01891	0.13752	0.09485	0.98866	5.82859	2.41425	2.07455	35.49457
7	0.01950	0.13965	0.09738	0.98830	9.50833	3.08356	2.62735	44.61614
8	0.02158	0.14690	0.09768	0.98706	7.47226	2.73354	2.35236	39.86613
9	0.02166	0.14718	0.10172	0.98701	2.69545	1.64178	1.18741	20.35460
10	0.02265	0.15049	0.10184	0.98642	14.32146	3.78437	3.19242	53.95133
11	0.02360	0.15362	0.10445	0.98585	10.77221	3.28210	2.76637	47.05998
12	0.02831	0.16827	0.11632	0.98302	18.76304	4.33163	3.67914	62.16628
13	0.02821	0.16797	0.12316	0.98308	13.67734	3.69829	3.14066	52.92650
14	0.02342	0.15302	0.10528	0.98596	3.39435	1.84238	1.47818	25.40174
15	0.02343	0.15307	0.10539	0.98595	3.40990	1.84659	1.47761	25.38949
16	0.02532	0.15912	0.11164	0.98481	5.40520	2.32491	1.89601	32.55522
17	0.02367	0.15384	0.10356	0.98581	5.17460	2.27478	1.80094	31.13869
18	0.02368	0.15389	0.10362	0.98580	5.21108	2.28278	1.80690	31.24067
19	0.02369	0.15393	0.10367	0.98579	5.24211	2.28957	1.81194	31.32697
20	0.02370	0.15396	0.10371	0.98578	5.26871	2.29537	1.81625	31.40065
21	0.02526	0.15895	0.10324	0.98485	7.18104	2.67975	2.22258	37.99584
22	0.02527	0.15896	0.10327	0.98485	7.18598	2.68067	2.22351	38.01289
23	0.02551	0.15972	0.10746	0.98470	4.26488	2.06516	1.56086	26.80110
24	0.02471	0.15721	0.11296	0.98518	5.76619	2.40129	1.91493	32.96166
25	0.02472	0.15721	0.11296	0.98518	5.78062	2.40429	1.91628	32.98500
26	0.02472	0.15721	0.11296	0.98518	5.79348	2.40697	1.91757	33.00730
27	0.02472	0.15721	0.11297	0.98518	5.80498	2.40935	1.91873	33.02713
28	0.02472	0.15722	0.11297	0.98518	5.81531	2.41150	1.91976	33.04486
29	0.02472	0.15722	0.11297	0.98518	5.82462	2.41342	1.92068	33.06077
30	0.02472	0.15722	0.11297	0.98518	5.83303	2.41517	1.92151	33.07510

4.5.3 Generalised Regression Neural Network (GRNN)

Table 4.9 shows the results from the network approximation using GRNN technique. Similar to the RBFNN technique, the spread was varied from 0.1 to 3.0 so as to allow for a closer fit of the measured data. From Table 4.9, a spread of 0.1 at the Training stage produced the least values in terms of performance index with PI 0.00002, MAE 0.00156, and RMSE of 0.00463 and a corresponding high R^2 value of 100.00%.

However, as shown in Table 4.9, the same spread of 0.1 proved to be adequate during the testing stage with a PI of 0.53653, MAE of 0.50627, RMSE of 0.73248 and MAPE of 8.48%.

Therefore, the GRNN network architecture with spread of 0.1 was accepted as the optimal model for GRNN architecture and can be used for predicting exchange rate between the GBP and Ghana Cedi.

Table 4.9 Summary of Approximated GRNN Network Architecture for GBP and Cedi

Spread (Architecture)	Train				Test			
	PI	RMSE	MAE	R^2	PI	RMSE	MAE	MAPE
0.1	**0.00002**	**0.00463**	**0.00156**	**0.99999**	**0.53653**	**0.73248**	**0.50627**	**8.47685**
0.2	0.00429	0.06549	0.02409	0.99743	0.53274	0.72989	0.51648	8.64218
0.3	0.01101	0.10494	0.04985	0.99339	0.52315	0.72329	0.52568	8.79771
0.4	0.01681	0.12966	0.07192	0.98992	0.56576	0.75217	0.55939	9.34833
0.5	0.02219	0.14897	0.09266	0.98669	0.69409	0.83312	0.63722	10.61873
0.6	0.02841	0.16855	0.11151	0.98296	0.86085	0.92782	0.72848	12.11479
0.7	0.03718	0.19281	0.13143	0.97770	1.03432	1.01701	0.81647	13.56416
0.8	0.05195	0.22793	0.15422	0.96884	1.22365	1.10619	0.90208	14.98186
0.9	0.07825	0.27974	0.18983	0.95307	1.44042	1.20018	1.00247	16.68922
1.0	0.12043	0.34702	0.23373	0.92777	1.68653	1.29867	1.10999	18.53738
1.1	0.17877	0.42281	0.28386	0.89278	1.95669	1.39882	1.22407	20.52373
1.2	0.25010	0.50010	0.33567	0.85000	2.24389	1.49796	1.34179	22.59529
1.3	0.32978	0.57427	0.38841	0.80221	2.54290	1.59465	1.45618	24.61413
1.4	0.41333	0.64291	0.43732	0.75210	2.85046	1.68833	1.56632	26.56347
1.5	0.49710	0.70505	0.48213	0.70186	3.16388	1.77873	1.67144	28.42781
1.6	0.57852	0.76060	0.52264	0.65303	3.47999	1.86547	1.77087	30.19327
1.7	0.65594	0.80990	0.55955	0.60659	3.79493	1.94806	1.86407	31.84882
1.8	0.72846	0.85350	0.59341	0.56310	4.10461	2.02598	1.95069	33.38732
1.9	0.79568	0.89201	0.62490	0.52278	4.40521	2.09886	2.03062	34.80590
2.0	0.85758	0.92606	0.65416	0.48565	4.69361	2.16647	2.10390	36.10559
2.1	0.91434	0.95621	0.68043	0.45161	4.96753	2.22879	2.17079	37.29059
2.2	0.96624	0.98298	0.70423	0.42048	5.22556	2.28595	2.23162	38.36725
2.3	1.01365	1.00680	0.72568	0.39205	5.46704	2.33817	2.28682	39.34326
2.4	1.05694	1.02808	0.74512	0.36609	5.69189	2.38577	2.33684	40.22693
2.5	1.09648	1.04713	0.76266	0.34237	5.90048	2.42909	2.38215	41.02664
2.6	1.13262	1.06425	0.77855	0.32069	6.09348	2.46850	2.42320	41.75055
2.7	1.16570	1.07967	0.79296	0.30086	6.27173	2.50434	2.46041	42.40631
2.8	1.19600	1.09362	0.80605	0.28268	6.43620	2.53697	2.49418	43.00101
2.9	1.22380	1.10625	0.81807	0.26601	6.58788	2.56669	2.52486	43.54109
3.0	1.24935	1.11774	0.82904	0.25069	6.72775	2.59379	2.55279	44.03236

4.5.4 Predictive accuracy (validation) of the GBP/GHS model

To further ascertain the appropriate technique for predicting the exchange rate between the US Dollar and the Ghana Cedi, the predictive performance of the selected optimal network architectures for the various techniques are assessed. Figure 4.5, 4.6 and 4.7 show the graphical representation of the optimal architectures for the BPNN, RBFNN and the GRNN during the training stage, whiles Figure 4.9 shows the graphs of the adequate (BPNN) model that was able to predict better when new data sets were introduced to it at the test stage. The asterisks (***) on the graphs indicate the observed values, whiles the continuous line indicates the graph of the prediction trend.

The variance accounted for by the trained models are also shown in Table 4.10. GRNN of architecture (spread) of 0.1 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 4.10 shows the predictions between the neural network 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 4.10 indicates that, the BPNN architecture (9-2-1) produced the least error estimate values with PI of 0.0.14855, MAE of 0.31016, RMSE of 0.38542 and MAPE of 5.62%.

Therefore, the BPNN architecture (9-2-1) is selected as the adequate network architecture with adequate accuracy for predicting exchange rate between Pound and the Cedi, hence ranked 1.

Therefore, the back propagation neural network with architecture 9-1-1 is the best model for predicting the Dollar Cedi (USD/GHS) exchange rate.

Table 4.10 Model performance for GBP-GHS

Network	Arch.	spread	MAPE	PI	MAE	RMSE	Test R^2	Ranking
BPN	**9-2-1**	**---**	**5.62**	**0.14855**	**0.31016**	**0.38542**	**0.7912**	**1**
RBNN	9-3-1	1.0	7.02	0.26893	0.40857	0.51858	0.3705	2
GRNN	---	0.1	8.48	0.53653	0.50627	0.73248	0.2189	3

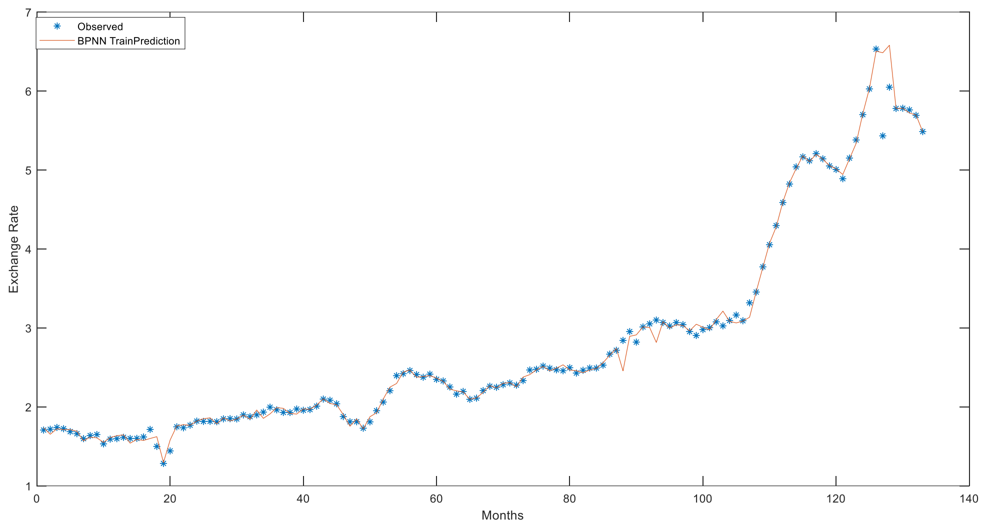

Figure 4.5 BPNN Graph Indicating Training Performance of Selected Architecture

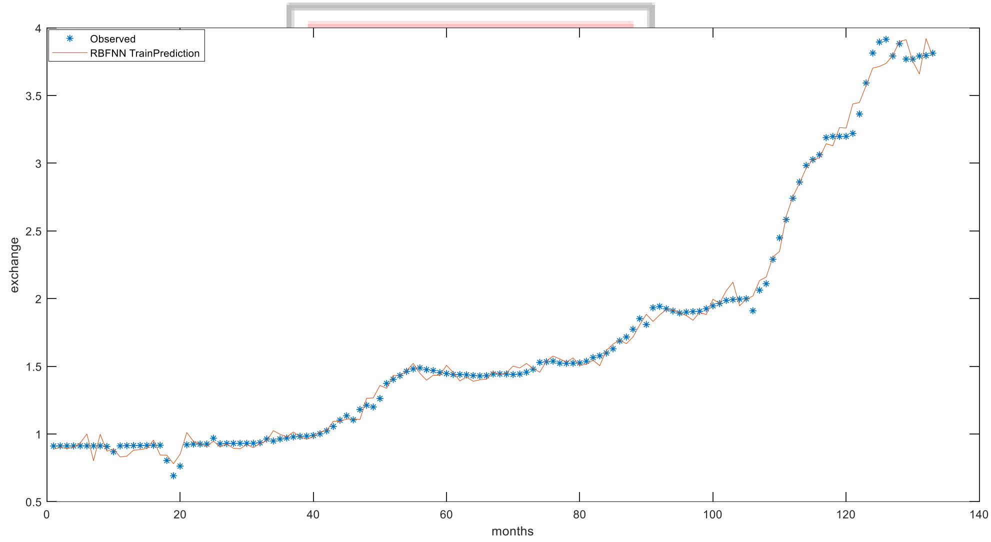

Figure 4.6 RBFNN Graph Indicating Training Performance of Selected Architecture

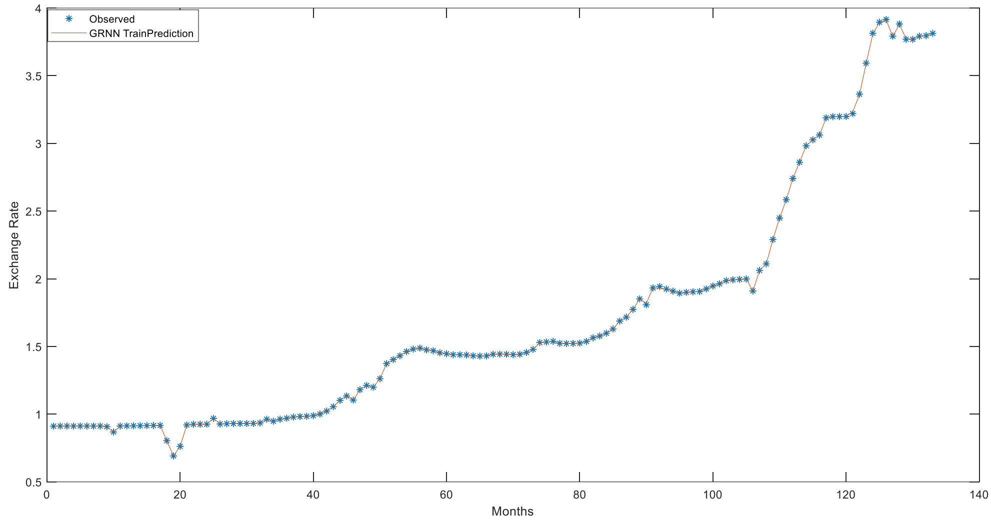

Figure 4.7 GRNN Graph Indicating Training Performance of Selected Architecture

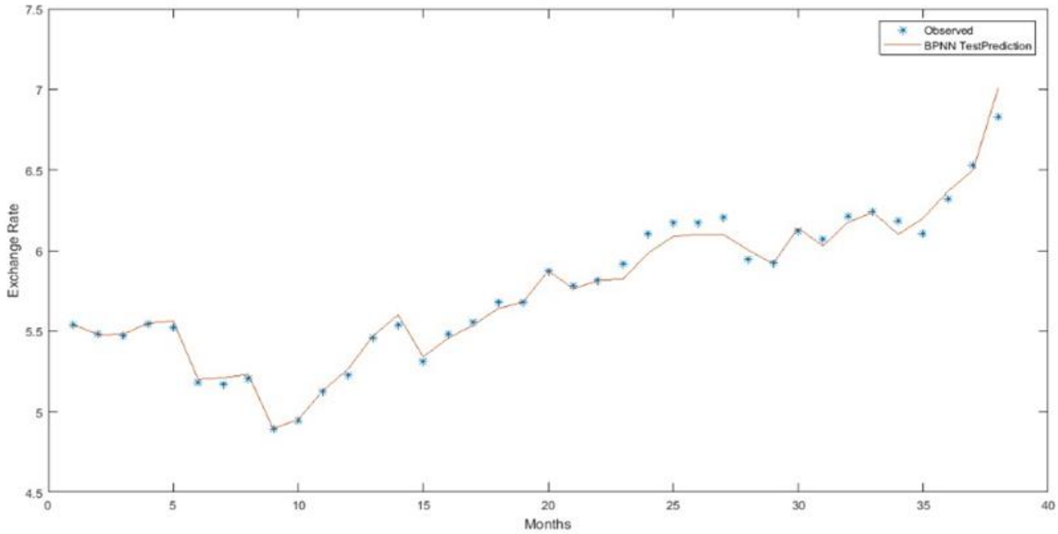

Figure 4.8 BPNN Graph Indicating Test Performance of Selected Architecture

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

5.1 Conclusion

This study 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 of Ghana's currency.

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 4.1 and 4.2. 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% alpha level except for trade balance and inflation rate which are significant at the 5% and 10% alpha levels respectively.
Also, an overall F-Statistics of 483.97 and 435.01 for the Dollar Cedi and the Pound Cedi respectively obtained the same 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.

Respective models for predicting the exchange rates of the Dollar Cedi (USD-GHS) and the Pound Cedi (GBP-GHS) were obtained. The optimal performance model for the USD-GHS was obtained at architecture 9-1-1, whiles that of the Pound Cedi was obtained at architecture 9-2-1. 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 Tables 4.6 and 4.10.

5.2 Recommendations

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 US Dollar and Ghana Cedi, the backpropagation neural network model at architecture 9-1-1 should be used, whiles in predicting the exchange rate between the Great Britain Pound and the Ghana Cedi, back propagation neural network model with architecture 9-2-1 should be considered.

Moreover, it was evident from the study that, subsequent research work must consider a large range of data points for the development of the ANN model during the training and testing stages to enable it enhance the accuracies of the models.

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APPENDICES

APPENDIX A MACROECONOMIC INDICATORS

Table A1 Monthly Macroeconomic indicators

Year	USD-GHS	GBP-GHS	Inflation	Nominal Growth	Monetary Policy	Interest Rate	Trade Balance	USA Inflation	Gross International Reserve	Foreign Currency Deposit
2005	0.9113	1.7066	16.83	22.13	18.50	17.08	-161.41	2.97	1672.24	585.68
	0.9122	1.7167	16.96	19.35	18.50	17.17	-215.15	3.01	1620.13	584.24
	0.9122	1.7392	17.79	17.41	18.50	17.23	-134.66	3.15	1542.98	592.86
	0.9119	1.7238	17.14	17.55	18.50	17.25	-179.29	3.51	1532.88	635.30
	0.9123	1.6866	14.51	18.38	16.50	17.29	-206.67	2.80	1453.29	644.24
	0.9123	1.6604	14.05	14	16.50	16.50	-212.35	2.53	1463.13	616.06
	0.9123	1.598	20.50	11.5	16.50	15.79	-225.32	3.17	1478.76	648.58
	0.9124	1.6367	13.33	19.39	16.50	15.27	-307.16	3.64	1488.45	604.53
	0.9075	1.6499	14.34	17.51	15.50	13.90	-224.54	4.69	1641.51	586.41
	0.9122	1.5318	14.92	13.34	15.50	13.32	-280.74	4.35	1631.91	627.33
	0.9121	1.5913	14.65	19.46	15.50	12.58	-241.61	3.46	1641.51	614.18
	0.9137	1.5975	13.91	18.27	15.50	11.77	-203.82	3.42	1888.92	659.81
2006	0.9021	1.6148	12.76	22.39	14.50	11.38	-155.95	3.99	1286.35	660.12
	0.9148	1.5998	12.27	20.35	14.50	10.28	-272.74	3.60	1272.29	693.20
	0.9157	1.6011	11.28	18.15	14.50	9.80	-158.68	3.36	1597.34	689.33
	0.9163	1.6194	11.21	13.29	14.50	9.63	-138.41	3.55	1623.97	733.38
	0.9168	1.7145	11.75	22.07	14.50	9.68	-196.41	4.17	1579.30	719.57
	0	0	11.39	25.49	14.50	9.68	-292.44	4.32	1649.31	713.65
	0.9218	1.284	20.50	11.5	14.50	9.68	-188.28	4.15	1598.02	698.45
	0.923	1.4426	12.56	23.86	14.50	10.28	-317.56	3.82	1514.68	731.38
	0.9202	1.7479	11.67	15.55	14.50	10.35	-224.24	2.06	1366.33	762.26
	0.9254	1.735	10.87	24.48	14.50	10.35	-303.90	1.31	1561.02	821.72
	0.9254	1.7677	10.70	27.35	14.50	10.34	-234.21	1.97	1560.52	872.94
	0.9258	1.8198	10.92	26.22	12.50	10.19	-305.69	2.54	1828.20	902.44
2007	0.9686	1.8155	10.89	19.46	12.50	9.91	-243.66	2.08	2085.56	892.79
	0.9277	1.8169	10.42	25.71	12.50	9.74	-194.57	2.42	2039.83	880.41
	0.9297	1.8122	10.19	23.96	12.50	9.61	-191.85	2.78	1908.21	862.21
	0.9304	1.8484	10.50	29.76	12.50	9.60	-385.25	2.57	2064.81	945.98
	0.931	1.8507	11.02	26.85	12.50	9.63	-328.80	2.69	2037.62	956.34
	0.9309	1.8471	10.69	22.48	12.50	9.63	-105.03	2.69	2132.75	923.61
	0.9317	1.8983	20.50	11.5	12.50	9.68	-413.85	2.36	2094.23	973.41
	0.9355	1.8764	10.41	29.06	12.50	9.78	-456.48	1.97	1830.49	1050.63
	0.9624	1.8992	10.19	34.89	12.50	9.82	-412.02	2.76	1790.33	980.42

	0.9482	1.9336	10.14	29.87	12.50	10.25	-575.06	3.54	2409.47	1019.88
	0.963	1.996	11.40	29.22	13.50	10.57	-316.22	4.31	2198.55	1025.09
	0.9701	1.9624	12.75	28.22	13.50	10.61	-227.80	4.08	2827.89	992.91
2008	0.9787	1.9296	12.81	36.85	13.50	10.71	-417.88	4.28	2150.11	1127.98
	0.9825	1.9288	13.21	33.54	13.50	10.78	-386.65	4.03	2440.90	1178.34
	0.9843	1.9728	13.79	31.68	14.25	10.88	-288.00	3.96	2247.93	1212.62
	0.9889	1.9574	15.29	36.55	14.25	11.44	-340.07	3.94	2189.85	1254.49
	1.0011	1.9662	16.88	32.84	16.00	13.19	-238.00	4.19	2032.47	1273.95
	1.0229	2.0091	18.41	32.52	16.00	16.30	-287.12	5.02	2320.65	1353.90
	1.0553	2.0987	20.50	11.5	17.00	18.76	-490.33	5.60	2032.07	1458.12
	1.1019	2.0836	18.10	26.7	17.00	22.90	-516.62	5.37	2492.70	1708.76
	1.1344	2.0394	17.89	27.41	17.00	24.64	-439.90	4.94	2265.70	1717.16
	1.1044	1.8768	17.30	33.5	17.00	24.63	-409.74	3.66	2048.68	1689.48
	1.1808	1.8116	17.44	26.02	17.00	24.68	-404.04	1.07	1738.35	1590.71
	1.2121	18120	18.13	21.54	17.00	24.67	-246.29	0.09	2036.22	1816.81
2009	1.1996	1.7299	19.86	23.56	17.00	24.69	-198.16	0.03	1940.30	1742.56
	1.262	1.8105	20.34	18.05	18.50	24.70	-190.49	0.24	1814.16	1942.89
	1.3734	1.9517	20.53	21.42	18.50	25.29	-273.44	-0.38	1750.30	2190.66
	1.4035	2.0611	20.56	18.02	18.50	25.68	-40.17	-0.74	1631.05	2118.84
	1.4312	2.205	20.06	15.1	18.50	25.72	-157.53	-1.28	1570.69	2192.66
	1.4624	2.3952	20.74	18.26	18.50	25.82	-127.42	-1.43	1705.22	2363.94
	1.4805	2.4204	20.50	11.5	18.50	25.90	-284.73	-2.10	1895.14	2490.17
	1.488	2.4596	19.65	10.25	18.50	25.89	-226.87	-1.48	1772.14	2455.83
	1.4752	2.4092	18.37	13.75	18.50	25.89	-262.62	-1.29	2317.04	2356.06
	1.4688	2.3754	18.04	10.78	18.50	25.83	-297.96	-0.18	2612.76	2347.86
	1.4534	2.4142	16.92	9.03	18.00	25.47	-136.31	1.84	2999.05	2307.56
	1.4463	2.3487	15.98	21.09	18.00	23.70	-10.85	2.72	3164.81	2661.34
2010	1.4392	2.3287	14.80	13.72	18.00	20.13	-166.47	2.63	3185.51	2449.20
	1.4391	2.2523	14.20	12.31	16.00	17.78	-154.69	2.14	3076.91	2341.05
	1.437	2.1612	13.30	13.56	16.00	16.16	-290.46	2.31	3304.21	2426.06
	1.4316	2.1958	11.70	11.4	15.00	13.71	-237.00	2.24	3205.52	2380.73
	1.4291	2.0957	10.70	14.08	15.00	13.14	-218.56	2.02	3149.80	2317.78
	1.4308	2.1108	9.50	15.87	15.00	12.89	-161.65	1.05	3451.15	2405.35
	1.4425	2.2065	9.50	9.2	13.50	12.83	-98.35	1.24	3311.03	2465.11
	1.4435	2.2614	9.40	20.82	13.50	12.74	-415.02	1.15	3300.24	2525.20
	1.4428	2.2482	9.40	18.97	13.50	12.57	-233.30	1.14	3306.23	2508.92
	1.4395	2.2811	9.40	16.38	13.50	12.41	-467.35	1.17	4006.01	2676.47
	1.4426	2.3033	9.10	20.64	13.50	12.34	-149.34	1.14	4410.94	2623.35
	1.4563	2.2756	8.60	15.77	13.50	12.28	-200.31	1.50	4644.85	2727.91
2011	1.4787	2.3329	9.08	19.6	13.50	12.16	-186.92	1.63	4767.82	2978.11
	1.5289	2.4673	9.16	19.15	13.50	12.12	-70.93	2.11	4825.52	3160.86
	1.5331	2.4761	9.13	26.22	13.50	12.11	18.94	2.66	4503.64	3268.96
	1.5377	2.5164	9.02	26.37	13.50	12.08	-136.15	3.16	4882.99	3378.23
	1.5232	2.4894	8.90	23.99	13.00	11.17	-215.03	3.67	4704.49	3387.53
	1.5219	2.4694	8.59	25.44	13.00	10.58	-300.86	3.56	4764.93	3669.64

	1.5226	2.4581	8.39	27.44	12.50	10.39	-301.71	3.63	4629.23	3754.24
	1.525	2.4961	8.41	24.27	12.50	9.40	-68.55	3.77	4502.04	3712.79
	1.5375	2.4282	8.40	27.27	12.50	9.39	-390.28	3.87	4594.66	3791.39
	1.5642	2.4639	8.56	22.82	12.50	9.26	-215.56	3.53	4977.64	3811.27
	1.5775	2.4919	8.55	21.86	12.50	9.25	-707.00	3.39	4845.83	4084.12
	1.5982	2.4921	8.58	20.66	12.50	10.30	-490.96	2.96	5452.12	3954.15
2012	1.6293	2.5283	8.73	21.79	12.50	10.85	51.40	2.93	4557.96	4266.47
	1.6877	2.6675	8.64	31.73	13.50	11.34	8.30	2.87	4708.04	4500.71
	1.7165	2.717	8.78	21.99	13.50	12.30	-59.66	2.66	4640.96	4827.68
	1.7736	2.8415	9.11	13.23	14.50	13.97	-367.39	2.30	4401.27	4967.54
	1.8518	2.9536	9.34	23.27	14.50	16.92	-486.17	1.70	4166.21	5212.46
	1.8082	2.8201	9.44	17.46	15.00	21.70	-478.77	1.66	4340.94	5404.53
	1.9326	3.0124	9.54	19.94	15.00	22.85	-695.06	1.41	4289.11	5045.24
	1.9426	3.052	9.46	17.43	15.00	22.85	-522.53	1.69	4492.85	5188.41
	1.925	3.0996	9.43	12.43	15.00	23.03	-420.47	1.99	4446.31	5352.42
	1.9088	3.0679	9.24	21.73	15.00	23.09	-460.01	2.16	5518.07	5096.96
	1.8936	3.0247	9.31	19.77	15.00	22.34	-384.92	1.76	5600.31	4990.43
	1.9001	3.0675	8.84	14.82	15.00	22.90	-384.83	1.74	5442.29	5116.80
2013	1.904	3.0416	10.09	15.28	15.00	22.90	-32.37	1.59	5349.95	5148.03
	1.9061	2.9539	10.40	5.12	15.00	23.00	-200.27	1.98	5178.38	5355.07
	1.9254	2.9042	10.78	7.88	15.00	22.86	-86.83	1.47	5049.31	5509.50
	1.9469	2.9787	10.87	21.34	15.00	22.96	-428.85	1.06	5015.78	5266.57
	1.9636	3.0033	11.02	13.84	16.00	22.95	-243.20	1.36	4785.33	5414.05
	1.9865	3.0771	11.63	10.74	16.00	23.06	-338.60	1.75	4602.52	5503.79
	1.9927	3.0261	11.79	12.22	16.00	23.07	-344.34	1.96	4472.48	5357.98
	3.8354	5.404	11.45	11.61	16.00	22.86	-556.27	1.52	5113.28	5404.80
	1.9989	3.1629	11.95	16.3	16.00	21.59	-485.69	1.18	5017.13	5588.25
	1.9104	3.0908	13.09	12.07	16.00	20.29	-733.06	0.96	4810.32	5555.53
	2.0622	3.3182	13.22	11.1	16.00	19.23	-254.26	1.24	5118.18	5653.38
	2.1101	3.4542	13.50	13.64	16.00	18.80	-144.69	1.50	5632.15	6245.03
2014	2.2904	3.7734	13.80	15	16.00	19.46	-231.90	1.58	5306.18	6742.75
	2.4488	4.0538	14.03	20.6	18.00	20.38	-126.43	1.13	4877.13	6923.27
	2.5841	4.2957	14.52	20.49	18.00	22.89	143.12	1.51	4721.94	7290.78
	2.7412	4.5875	14.69	15.63	18.00	24.04	-95.52	1.95	4821.37	7486.86
	2.861	4.8217	14.84	21.08	18.00	24.07	-0.97	2.13	5201.41	7603.51
	2.9832	5.0396	14.99	23.4	18.00	24.07	59.63	2.07	4489.39	8098.73
	3.0267	5.1666	15.32	24.26	19.00	24.65	-88.09	1.99	4324.85	8246.11
	3.0625	5.117	15.90	19.36	19.00	25.01	-203.64	1.70	4188.04	8777.40
	3.1892	5.2065	16.47	18.4	19.00	25.34	-167.73	1.66	5679.19	9049.98
	3.1977	5.1414	16.90	16.7	19.00	25.68	-410.51	1.66	5833.18	8955.40
	3.1983	5.0515	17.05	19.8	21.00	25.73	-108.86	1.32	5896.15	8585.47
	3.1987	5.0062	16.99	20.74	21.00	25.79	-152.53	0.76	5461.01	9313.00
2015	3.2212	4.8896	16.44	14.92	21.00	25.83	-125.70	-0.09	4910.72	34.25
	3.3639	5.1505	16.50	14.85	21.00	25.62	-39.95	-0.03	4674.72	35.31
	3.5927	5.3802	16.64	16.44	21.00	25.55	-218.96	-0.07	4964.53	34.54

	3.8141	5.7011	16.76	19.13	21.00	25.18	-158.08	-0.20	4834.92	34.79
	3.8952	6.0272	16.91	11.54	22.00	25.09	-232.19	-0.04	4521.06	35.02
	4.1954	6.5309	17.08	14.13	22.00	25.17	-166.92	0.12	4539.70	34.22
	3.4924	5.4325	17.94	8.37	22.00	25.20	-431.58	0.17	4395.60	32.65
	3.8826	6.0481	17.30	15.3	24.00	25.22	-404.82	0.20	4593.98	35.26
	3.7695	5.7789	17.36	13.24	25.00	25.28	-389.55	-0.04	4520.53	35.29
	3.7688	5.7819	17.38	17.84	25.00	25.33	-665.00	0.17	5688.01	34.60
	3.7922	5.761	17.58	14.81	26.00	24.50	-122.22	0.50	6028.80	34.52
	3.796	5.6919	17.70	14.82	26.00	23.12	-188.85	0.73	5884.73	34.23
2016	3.8129	5.4861	19.00	16.51	26.00	22.73	-247.86	1.37	5838.63	11297.14
	3.8759	5.5391	18.50	19.62	26.00	22.67	-149.42	1.02	5531.27	11769.84
	3.8499	5.4819	19.20	11.98	26.00	22.62	-278.74	0.85	5696.33	12084.11
	3.8196	5.468	18.70	7.73	26.00	22.77	-259.65	1.13	5950.99	11752.85
	3.8172	5.5439	18.90	14.62	26.00	22.79	-299.72	1.02	5498.04	11931.59
	3.8882	5.522	18.40	13	26.00	22.80	-164.81	1.00	5199.44	12017.70
	3.9414	5.1818	16.70	16.14	26.00	22.77	-278.29	0.83	5049.71	12304.59
	3.9471	5.1713	16.90	13.74	26.00	22.77	-165.10	1.06	4903.32	12272.12
	3.9597	5.2057	17.20	11.79	26.00	22.87	26.88	1.46	4788.11	12236.26
	3.9692	4.8943	15.80	3.48	26.00	22.76	-191.48	1.64	5917.44	12466.86
	3.9765	4.9436	15.50	7.06	25.50	20.87	4.37	1.69	6098.95	12404.29
	4.1035	5.1249	15.40	9.12	25.50	16.81	222.05	2.07	6161.80	13239.62
2017	4.2359	5.2253	13.30	13.29	25.50	16.16	246.42	2.50	6401.56	13847.84
	4.3751	5.4614	13.20	9.02	25.50	15.89	252.36	2.74	6248.30	14659.85
	4.4864	5.5385	12.80	12.14	23.50	16.89	413.84	2.38	6396.78	14090.59
	4.1986	5.3111	13.00	14.92	23.50	16.47	251.34	2.20	8289.71	13301.82
	4.2397	5.4809	12.60	9.98	22.50	13.69	107.13	1.87	8095.95	13804.90
	4.3343	5.5549	12.10	9.08	22.50	12.08	-142.34	1.63	7842.05	14110.56
	4.3691	5.6775	11.90	8.87	21.00	12.33	-84.80	1.73	7505.79	14225.17
	4.3874	5.6824	12.30	10.32	21.00	12.80	-178.24	1.94	7082.58	14225.98
	4.4059	5.8741	12.20	8.8	21.00	13.19	-87.88	2.23	6850.69	14208.51
	4.3835	5.7845	11.60	11.77	21.00	13.26	-47.01	2.04	6938.50	14473.80
	4.3982	5.8139	11.70	15.1	20.00	13.28	231.74	2.20	7308.55	14308.33
	4.4145	5.9162	11.80	13.43	20.00	13.33	225.11	2.11	7554.84	14105.58
2018	4.4229	6.1053	10.35	9.69	20.00	13.34	253.45	2.07	7106.02	14087.84
	4.4217	6.173	10.58	9.26	20.00	13.34	259.87	2.21	6941.95	14371.81
	4.4158	6.1723	10.36	8.46	18.00	13.36	212.79	2.36	7040.94	14383.01
	4.4076	6.2083	9.55	8.5	18.00	13.34	301.78	2.46	6901.10	14445.75
	4.4161	5.9449	9.81	7.28	18.00	13.35	239.70	2.80	7835.13	14666.11
	4.4647	5.9242	9.97	8.2	17.00	13.30	-10.13	2.87	7294.10	15012.17
	4.6499	6.1243	9.63	9.94	17.00	13.32	-3.78	2.95	7035.11	16421.73
	4.7106	6.068	9.86	8.41	17.00	13.31	141.45	2.70	6693.15	16834.95
	4.7596	6.214	9.79	11.83	17.00	13.37	162.18	2.28	6756.43	17088.52
	4.7946	6.2405	9.52	12.65	17.00	13.59	52.74	2.52	6352.37	16333.20
	4.7935	6.1858	9.34	9.26	17.00	14.37	200.39	2.18	6854.14	16123.36
	4.8171	6.1049	9.43	7.84	17.00	14.56	-1.80	1.91	7024.78	16125.56

2019	4.8972	6.3194	9.01	8.38	16.00	14.65	85.45	1.55	6584.96	24390.00
	5.0787	6.5279	9.17	11.18	16.00	14.71	292.75	1.52	6309.97	18000.43
	5.1823	6.8281	9.28	9.99	16.00	14.71	264.17	1.86	9959.61	18772.59

APPENDIX B CODES

Back Propagation Neural Network

```
%%READING THE EXCEL FILE

Output=zeros(30,9);

Training_Data = xlsread('TrainF.xlsx');

Testing_Data = xlsread('TestF.xlsx');

%%Training Data

Xtrain = transpose(Training_Data(:,4:12));% specify training input data

Ytrain = transpose(Training_Data(:,3));% specifitarget (Au)

%%Testing data

Xtest = transpose(Testing_Data(:,4:12));%specify testing input data

Ytest = transpose(Testing_Data(:,3));%specify testing target data

%Data normalization of Training, Validation and Testing set into[-1,1]

%%Normalizing Training Set

[train_X1, ps] = mapminmax(Xtrain);% train_X1 contains the normalized values of Training(input);

% ps contains the max and min values of the original training set

[train_X2, pn] = mapminmax(Ytrain);% train_X2 contains the normalized values of Validation set;

% pn contains the max and min values of the original training set

%%Normalizing Testing Input Set

test_X1 = mapminmax('apply',Xtest,ps);% tn contains the normalized values of Target(output);

%Ytrain= smoothdata(Ytrain);

%% Setting the random seed number to stabilise the BPNN system

setdemorandstream(491218382);

%%Creating a BPANN %%OPTIMAL NEURONS=11

for Nb_Neuron=1:30
```

```
MyNetwork = newff(train_X1,train_X2,[Nb_Neuron],{'tansig' 'purelin'},'trainbr');%%Optimum hidden neuron is 8 after several trials

MyNetwork.trainparam.min_grad = 0.0000001;%%denotes the minimum performance gradient

MyNetwork.trainParam.epochs = 5000;%%denotes the maximum number of epochs to train

MyNetwork.trainParam.goal = 0;

%MyNetwork.trainParam.lr = 0.03;%%denotes the learning rate

%MyNetwork.trainParam.mc = 0.7;%%default momentum value is 0.9

%MyNetwork.trainParam.max_fail = 6;%%denotes the maximum validation failures

MyNetwork.performFcn = 'mse';  % Mean squared error

%%TRAINING THE NETWORK

MyNetwork = train(MyNetwork,train_X1,train_X2);

disp('Nb_Neuron TRAINING_MSE TRAINING_RMSE TESTING_MSE TESTING_RMSE');

%% %% SUMMARY OF NETWORK PERFOMANCE

%%Training data Performance

y = MyNetwork(train_X1);%%New training out values from the trained network

Training_prediction = mapminmax('reverse',y,pn); %denormalizing the BPANN prediction

Training_error = gsubtract(Ytrain,Training_prediction);%%calculates the error between training input and new estimated trained output

trainingPerformance = perform(MyNetwork,Ytrain,Training_prediction);%%MSE training value

TRAINING_RMSE = sqrt(trainingPerformance);

Train_MAE = mae(Ytrain,Training_prediction);

Train_R2= 1- (sum((Ytrain-Training_prediction).^2)/sum((Ytrain-mean(Ytrain)).^2));

Train_MAPE= mean((abs(Ytrain-Training_prediction)./Ytrain))*100;

TRAINING_MAPE = (mean(abs(Ytrain-Training_prediction)./Ytrain))*100;

%% Test data Performance

t = sim(MyNetwork,test_X1);%%Simulating the network with Testing data
```

```
Testing_prediction = mapminmax('reverse',t,pn);%denormalizing the BPANN prediction

testing_error = gsubtract(Ytest,Testing_prediction);%calculates the error Ytest and predicted test target (T)

testPerformance = perform(MyNetwork,Ytest,Testing_prediction);%%MSE test value

TESTING_RMSE = sqrt(testPerformance);

Test_MAE = mae(Ytest,Testing_prediction);

Test_R2= 1- (sum((Ytest-Testing_prediction).^2)/sum((Ytest-mean(Ytest)).^2));

Test_MAPE= mean((abs(Ytest-Testing_prediction)./Ytest))*100;

TESTING_MAPE = mean(abs(testing_error)./Ytest)*100;

t1=1:length(Ytrain);

t2=1:length(Ytest);

figure(1)

plot(t1,Ytrain,t1,Training_prediction)

plot(t1,Ytrain,"*", t1,Training_prediction,"-")

xlabel('Months')

ylabel('Exchange Rate')

%residual_norm=norm(Ytrain-Training_prediction)

legend("Observed","BPNN TrainPrediction")

figure(2)

plot(t2,Ytest,t2,Testing_prediction)

plot(t2,Ytest,"*", t2,Testing_prediction,"-")

xlabel('Months')

ylabel('Exchange Rate')

%residual_norm=norm(Ytest-Testing_prediction)

legend("Observed","BPNN TestPrediction")

%subplot(2,1,1),plot(t1,Ytrain,t1,Training_prediction)

%subplot(2,1,2),plot(t2,Ytest,t2,Testing_prediction)
```

```
Output(Nb_Neuron,1)=Nb_Neuron;

Output(Nb_Neuron,2)=trainingPerformance;

Output(Nb_Neuron,3)=TRAINING_RMSE;

Output(Nb_Neuron,4)=Train_MAE;

Output(Nb_Neuron,5)=Train_R2;

Output(Nb_Neuron,6)=Train_MAPE;

Output(Nb_Neuron,7)=testPerformance;

Output(Nb_Neuron,8)=TESTING_RMSE;

Output(Nb_Neuron,9)=Test_MAE;

Output(Nb_Neuron,10) =Test_MAPE

Output(Nb_Neuron,11)=Test_R2;

% View the Network

%view(MyNetwork)

% Plots

% Uncomment these lines to enable various plots.

%figure, plotregression(Ytrain,Training_prediction,'Training')

%figure, plotregression(Ytest,Testing_prediction,'Test')

%fprintf('%d    %f    %f    %f     %f    %f     %f\n', Nb_Neuron, trainingPerformance,
TRAINING_RMSE,  testPerformance, TESTING_RMSE);

end

save('BPNN')
```

Radial Basis Function Neural Network

```
 %%READING THE EXCEL FILE

Output=zeros(30,9);

Training_Data = xlsread('TrainF.xlsx');

Testing_Data = xlsread('TestF.xlsx');
```

```
%%Training Data

Xtrain = transpose(Training_Data(:,4:12));% specify training input data

Ytrain = transpose(Training_Data(:,3));% specifitarget (Au)

%%Testing data

Xtest = transpose(Testing_Data(:,4:12));%specify testing input data

Ytest = transpose(Testing_Data(:,3));%specify testing target data

%Data normalization of Training, Validation and Testing set into[-1,1]

%%Normalizing Training Set

[train_X1, ps] = mapminmax(Xtrain);% train_X1 contains the normalized values of Training(input);

% ps contains the max and min values of the original training set

[train_X2, pn] = mapminmax(Ytrain);% train_X2 contains the normalized values of Validation set;

% pn contains the max and min values of the original training set

%%Normalizing Testing Input Set

test_X1 = mapminmax('apply',Xtest,ps);% tn contains the normalized values of Target(output

for spread = 1:30
%%Creating a RBFNN

%% denotes the mean square error

goal = 0;

%% denote the spread constants

%spread = 13;%%OPTIMAL SPREAD CONSTANT

%% the maximum number of neurons

mn = 30;

%% number of neurons to add between displays

df = 1;

%%Creating the network

MyNetwork = newrb(train_X1,train_X2,goal,spread,mn,df);
```

```
disp('spread  training_RMSE   test_RMSE')

%% %% SUMMARY OF NETWORK PERFOMANCE

%%Training data Performance

y = MyNetwork(train_X1);%%New training out values from the trained network

Training_Prediction = mapminmax('reverse',y,pn); %denormalizing the RBFNN prediction

training_error = gsubtract(Ytrain,Training_Prediction);%%calculates the error between training input and new estimated trained output

trainingperformance = perform(MyNetwork,Ytrain,Training_Prediction);%%MSE training value

training_RMSE = sqrt(trainingperformance);

Train_MAE = mae(Ytrain,Training_Prediction);

Train_R2= 1- (sum((Ytrain-Training_Prediction).^2)/sum((Ytrain-mean(Ytrain)).^2));

Train_MAPE= mean((abs(Ytrain-Training_Prediction)./Ytrain))*100;

%% Test data Performance

t = sim(MyNetwork,test_X1);%%Simulating the network with Testing data

Testing_Prediction = mapminmax('reverse',t,pn);%denormalizing the RBFNN prediction

testing_error = gsubtract(Ytest,Testing_Prediction);%calculates the error Ytest and predicted test target (T)

testPerformance = perform(MyNetwork,Ytest,Testing_Prediction);%%MSE test value

test_RMSE = sqrt(testPerformance);

Test_MAE = mae(Ytest,Testing_Prediction);

Test_R2= 1- (sum((Ytest-Testing_Prediction).^2)/sum((Ytest-mean(Ytest)).^2));

Test_MAPE= mean((abs(Ytest-Testing_Prediction)./Ytest))*100;
% View the Network

%view(MyNetwork)

t1=1:length(Ytrain);

t2=1:length(Ytest);

figure(1)

plot(t1,Ytrain,t1,Training_Prediction)
```

```
plot(t1,Ytrain,"*", t1,Training_Prediction,"-")
xlabel('months')
ylabel('exchange')
%residual_norm=norm(Ytrain-Training_Prediction)
legend("Observed","RBFNN TrainPrediction")
figure(2)
plot(t2,Ytest,t2,Testing_Prediction)
plot(t2,Ytest,"*", t2,Testing_Prediction,"-")
xlabel('months')
ylabel('exchange')
%residual_norm=norm(Ytest-Testing_Prediction)
legend("Observed","RBFNN TestPrediction")
%figure()
%subplot(2,1,1),plot(t1,Ytrain,t1,Training_Prediction)
%subplot(2,1,2),plot(t2,Ytest,t2,Testing_Prediction)
Output(spread,1)=spread;
Output(spread,2)=trainingperformance;
Output(spread,3)=training_RMSE;
Output(spread,4)=Train_MAE;
Output(spread,5)=Train_R2;
Output(spread,6)=Train_MAPE
Output(spread,7)=testPerformance;
Output(spread,8)=test_RMSE;
Output(spread,9)=Test_MAE;
Output(spread,10) =Test_MAPE
Output(spread,11)=Test_R2;
% Plots
```

```
% Uncomment these lines to enable various plots.

%figure, plotregression(Ytrain,Y,'Training')

%figure, plotregression(Yval,X,'Validation')

%figure, plotregression(Ytest,T,'Testing')

fprintf('%d    %f    %f     %f     %f\n', spread,   training_RMSE,   test_RMSE)
end

save('RBFNN')
```

Generalized Regression Neural Network

```
%%READING THE EXCEL FILE

Output=zeros(30,9);

Training_Data = xlsread('TrainF.xlsx');

Testing_Data = xlsread('TestF.xlsx');

%%Training Data

Xtrain = transpose(Training_Data(:,4:12));% specify training input data

Ytrain = transpose(Training_Data(:,3));% specifitarget (Au)

%%Testing data

Xtest = transpose(Testing_Data(:,4:12));%specify testing input data

Ytest = transpose(Testing_Data(:,3));%specify testing target data

%Data normalization of Training, Validation and Testing set into[-1,1]

%%Normalizing Training Set

[train_X1, ps] = mapminmax(Xtrain);%train_X1 contains the normalized values of Training(input);

% ps contains the max and min values of the original training set

[train_X2, pn] = mapminmax(Ytrain);%train_X2 contains the normalized values of Validation set;

% pn contains the max and min values of the original training set

%%Normalizing Testing Input Set

test_X1 = mapminmax('apply',Xtest,ps);% tn contains the normalized values of Target(output);
```

```
p1=0;

%%Creating a GRNN

%% denotes the mean square error

for spread = 0.1:0.1:3

%spread = 0.10;

%%Creating the network

MyNetwork = newgrnn(train_X1,train_X2,spread);

disp('spread  training_RMSE    testing_RMSE')

%% %% SUMMARY OF NETWORK PERFOMANCE

%%Training data Performance

y = MyNetwork(train_X1);%%New training out values from the trained network

training_prediction = mapminmax('reverse',y,pn); %denormalizing the RBFNN prediction
training_error = gsubtract(Ytrain,training_prediction);%%calculates the error between training input and new estimated trained output

trainingperformance = perform(MyNetwork,Ytrain,training_prediction);%%MSE training value

training_RMSE = sqrt(trainingperformance);

Train_MAE = mae(Ytrain,training_prediction);

Train_R2= 1- (sum((Ytrain-training_prediction).^2)/sum((Ytrain-mean(Ytrain)).^2));

Train_MAPE= mean((abs(Ytrain-training_prediction)./Ytrain))*100;

%% Test data Performance

t = sim(MyNetwork,test_X1);%%Simulating the network with Testing data

testing_prediction = mapminmax('reverse',t,pn);%denormalizing the RBFNN prediction

testing_error = gsubtract(Ytest,testing_prediction);%calculates the error Ytest and predicted test target (T)

testPerformance = perform(MyNetwork,Ytest,testing_prediction);%%MSE test value

testing_RMSE = sqrt(testPerformance);

Test_MAE = mae(Ytest,testing_prediction);

Test_R2= 1- (sum((Ytest-testing_prediction).^2)/sum((Ytest-mean(Ytest)).^2));
```

```
Test_MAPE= mean((abs(Ytest-testing_prediction)./Ytest))*100;
% View the Network
%view(MyNetwork)
t1=1:length(Ytrain);
t2=1:length(Ytest);
figure(1)
plot(t1,Ytrain,t1,training_prediction)
plot(t1,Ytrain,"*", t1,training_prediction,"-")
xlabel('Months')
ylabel('Exchange Rate')
residual_norm=norm(Ytrain-training_prediction)
legend("Observed","GRNN TrainPrediction")
figure(2)
plot(t2,Ytest,t2,testing_prediction)
plot(t2,Ytest,t2,testing_prediction)
plot(t2,Ytest,"*", t2,testing_prediction,"-")
xlabel('Months')
ylabel('Exchange Rate')
residual_norm=norm(Ytest-testing_prediction)
legend("Observed","GRNN TestPrediction")
%figure()
%subplot(2,1,1),plot(t1,Ytrain,t1,training_prediction)
%subplot(2,1,2),plot(t2,Ytest,t2,testing_prediction)
p1=p1+1;
Output(p1,1)=spread;
Output(p1,2)=trainingperformance;
Output(p1,3)=training_RMSE;
```

```
Output(p1,4)=Train_MAE;
Output(p1,5)=Train_R2;
Output(p1,6)=Train_MAPE
Output(p1,7)=testPerformance;
Output(p1,8)=testing_RMSE;
Output(p1,9)=Test_MAE;
Output(p1,10)=Test_MAPE;
Output(p1,11)=Test_R2;
% View the Network
%view(MyNetwork)
% Plots
% Uncomment these lines to enable various plots.
%figure, plotregression(Ytrain,Y,'Training')
%figure, plotregression(Yval,X,'Validation')
%figure, plotregression(Ytest,T,'Testing')
%fprintf('%d     %f     %f      %f      %f\n',spread, training_RMSE, testing_RMSE)
%end
%figure
%plot(t1,Ytrain,t1,Training_prediction)
%figure
%plot(t2,Ytest,t2,Testing_prediction)
end
save('GRNN')
```