



## Performance Evaluation of Some Neural Network Models Used in Forex Forecasting

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### Abstract

*This paper evaluates the performance of two neural network models used in Forex forecasting; neural network with wavelet de-noising based model and neural network with error back propagation algorithm to find out the model accuracy and the ability of reducing error rates to the minimum. Experiments have been conducted to obtain four important parameters necessary to design the neural networks, these parameters are; optimal number of neurons in the hidden layer, optimal number of both learning rates and momentum constant, activation function, and suitable data division. The neural networks were designed, trained, validated and tested for the parameters. The results shows that neural network with wavelet de-noising based model has the capacity to learn the data quickly and provides better accuracy than neural network with error back propagation algorithm. However, the results shows that neural networks are very sensitive, they easily respond to changes made to their architecture. Furthermore, the results reveal that, the performance of neural networks in Forex forecasting increase with the increase in the number of economic variables as inputs to the networks.*

**Keywords:** Neural Network; Forex; Forecasting; Error Back propagation Algorithm; Wavelet denoising model.

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### 1.0 INTRODUCTION

Along with the economic globalization, companies with multinational operations and/or investments are inevitably exposed to the risk that foreign exchange rates (Forex) will fluctuate in the future. Such fluctuations have the potential to either adversely or favourably affect the asset value of a company. A company's ability to compete internationally will, in some degrees, depend on its capability to appropriately and effectively manage the risks derived from multinational operations. Consequently, forecasting foreign exchange rates has significant meaning for multinational companies. Furthermore, as foreign exchange rates play an important role in international investment, the accuracy in forecasting the foreign exchange rate

is also a crucial factor for the success of fund managers. However, foreign exchange rates are affected by many highly correlated economic, political and even psychological factors. The interaction of these factors is in a very complex fashion Chong (2009). Therefore, to predict the movement of foreign exchange rates is a knotty business. As Alan Greenspan, the chairman of America's Federal Reserve, once remarked, forecasting exchange rates "has a success rate no better than that of forecasting the outcome of a coin toss" Greenspan (2004).

The foreign exchange rate time series usually contain the characteristics of high noise and non-stationary, which make classical statistical methods incompetent. It is thus necessary to adopt more advanced forecasting techniques.

Neural networks are a type of nonlinear model that have proved to be effective for time series prediction Chong (2009). Therefore, neural network is chosen as the forecasting tool.

The day to day development and spread of computer use in all fields of human science, particularly accounting and investment, has created a field of new technology, Artificial Neural Networks (ANNs) or Neural networks (NNs) are one of the latest achievements of this rapid process, Raei (2003). Decision makers use such networks to maximize efficiency and minimize the risk of investing in ambiguous conditions. Even though, ANNs are effective do to their ability to forecast the relationships among variables even when they are very complicated and non-linear, which are the shortcomings associated with the traditional statistical models. Previous researchers have earned the multiplicity of NNs models, and the relative ability of these models to forecast any Foreign Exchange Rates (Forex). However, the research question at the stake is the ability of these NNs to provide accuracy in forecasting the Forex or at least predicting the trend correctly, which have attracted so much concerns in the today's global economy and is of crucial importance for any future investment. With this problem at hand, this study want to compare the forecasting performance of two NNs models, that is, neural network with error backpropagation (BackProp) algorithm and neural network with wavelet de-noising to find out which model is more accurate and has the ability to reduce forecasting error rates to the minimum.

The main aim of this paper is to analyze some neural network models in forecasting Foreign Exchange Rates (Forex) and to figure out the best NN/ANN model with the ability to reduce error rates in forecasting Forex to the minimum.

## **2.0 LITERATURE REVIEW**

### **2.1 Introduction**

Atiya (1996), revealed that, due to the introduction of floating exchange rates and the rapid expansion of global trading markets over the last few decades, the foreign currency exchange market has experienced unprecedented growth. In fact, the exchange rates play an important role in controlling dynamics of the exchange market as well as the trading of goods in the import-export markets.

Exchange rates prediction is one of the challenging applications of modern time series forecasting. The rates are inherently noisy, non-stationary and chaotic, Atiya (1996). These characteristics suggest that there is no complete information that could be obtained from the past behavior of such markets to fully capture the dependency between the future exchange rates and that of the past. One general assumption made in such cases is that the historical data incorporate all those behavior, Bell and Ketell (1983).

### **2.2 Review of Related Work**

Yao and Tan (2000) revealed that, Artificial Neural Networks, the well-known function approximators in prediction and system modeling, has recently shown its great applicability in time-series analysis and forecasting. ANN assists multivariate analysis. Multivariate models can rely on greater information, where not only the lagged time series being forecast, but also other indicators (such as technical, fundamental, inter-marker etc. for financial market), are combined to act as predictors, Lean and Xuehuan (2013). In addition, ANN is more effective in describing the dynamics of non-stationary time series due to its unique non-parametric, non-assumable, noise-tolerant and adaptive properties. ANNs are universal function approximators that can map any nonlinear function without a priori assumptions about the data.

In several applications, Tang and Fishwich (1993), Jordar and Rahul (2004), and many other researchers have shown that ANNs perform better than ARIMA models, specifically, for more irregular series and for multiple-period-ahead forecasting. Kaastra and Boyd (1996) provided a general introduction of how a neural network model should be developed to model financial and economic time series. Many useful, practical considerations were presented in their article. Yao and Tan (2000) evaluated the capability of a backpropagation neural-network model as an option price forecasting tool. They also recognized the fact that neural-network models are context sensitive and when studies of this type are conducted, it should be as comprehensive as possible for different markets and different neural-network models.

In today global economy, accuracy in forecasting the Forex or at least predicting the trend correctly is the main concern. Two

research has been reported viz.; Mohammad and Mehdi (2012) revealed that neural network with error back propagation algorithm has less error in forecasting Forex, when compare with neural network train with genetic algorithm. Chong (2009), developed a neural network with wavelet de-noising based forecasting model, after comparing his model with other models (such as Linear Predictive Model, Auto Regressive Model, Cascade Correlation NN, 6th-order Polynomial, and ClusNet) in terms of their forecasting performance reported that his model outperform the other models in minimizing the error rates in forecasting Forex. However, despite the concerns on the accuracy of forecasting Forex, no study has been reported in the literature that compared these two works.

Some studies use economical meaningful variables to improve the forecasting performance of the model. For example, Joshi (2003) integrates a microeconomic variable and some macroeconomic variables including interest rate and crude oil price into a recurrent neural network forecasting model to predict the movements of Canada/US dollar exchange rate. The results demonstrate that both macroeconomic and microeconomic variables are useful for exchange rate forecasting.

Furthermore, previous research such as Joshi (2003), Herbrich and Keilbach (2009) and Yang (2000) has shown that using economically significant variables for inputs can improve the performance of the forecasting model. Therefore, I came up with an idea of feeding the neural network with four (4) economically meaningful variables namely, Inflation rates, Interest rates, Oil price, and All Share Index (ASI) to achieve accurate forecasting.

Based on the literatures reviewed that are concern with the accuracy of Forex, particularly, that of Chong (2009), Mohammad and Mehdi (2012) who both argued in their study that, their models performed well in providing accuracy in forecasting Forex. However, regardless of the concern on the accuracy of forecasting Forex, based on the literature reviewed I have found no study that has been reported to compare these two works. Consequently, it is pertinent to undertake this study, in order to discover the best model in providing accurate forecasting of Forex.

## **3.0 MATERIALS AND METHODS**

### **3.1 Introduction**

To successfully design and train the required NNs, certain development methodology needs to be selected. The choice of the number of hidden layers is an important issue because too many hidden layer can degrade the network's performance. Theoretically, neural networks with two hidden layers can approximate any nonlinear function to an arbitrary degree of accuracy, Chong (2009). Hence, there is no reason to use neural networks with more than two hidden layers. Furthermore, it has also been proved that for the vast majority of practical problems, there is no need to use more than one hidden layer. Therefore, in this study a 4x1x1 (four input nodes, one hidden layer, and one output layer) artificial neural networks is used to captured the movement of four currencies exchange rates.

Chong (2009) revealed that, another crucial issue is the choice of optimal number of hidden units in neural networks. If there are too few hidden nodes, the system will get high training error and high generalization error due to underfitting. On the contrary, if the number of hidden units is too large, then the model may get low training error but still have high generalization error due to overfitting Chong (2009), as a result several experiments would be carry out to determine the optimal number of hidden nodes in the neural network.

In this study, the data sets that were used are obtained from the official website of National Daily Trust News paper. Although the data sets obtained were daily data ranging from January 1<sup>st</sup>, 1999 to March, 21<sup>st</sup> 2015 with a total of 4,276 observations. However, this data has to be converted into a month-ahead horizon bringing the total instances to 242 instances. This has become necessary because all the four input variables obtained were month-ahead horizon. Furthermore, all the data obtained are normalized to the rage [-1, 1] before being fed into the neural networks.

After preparing the data, experiments were set up in the neuroph Studio environment in order to find the following variables:

- a. Optimal number of neurons in the hidden layer
- b. Optimal combination of both learning rates and momentum constant.
- c. Optimal activation function

d. Suitable data division  
 Thereafter, two optimal neural network models were design viz., wavelet neural network de-noising based model and neural network with error backpropagation algorithm, these networks are then train to check their performances. When the training is complete, it is often the case that, the networks memorize the training data well but, failed to generate current output for some of the new test data. Therefore, it is desirable to come up with some form of regularization. One form of regularization is to split the training set into a new training set and test set, which is termed suitable data division which will be obtained during the experiment. The network with best performance on the validation test is then used for actual testing. The validation error rate is analyzed periodically during the training and stop training when the validation error rate starts to go up. Though, the validation error is not a good estimate of the generalization error, one way to get a good estimate of the generalization error is to run the network on the

set of data that is not used at all during the training process. After testing all the networks, their error graphs are analyzed using the Mean Square Error (MSE), in order to find out the ANN with least error rates. Thereafter, the test result of the NN models is plotted with the actual exchange rates to help analyzes the matching performance of the two designed NN models.

**3.2 ANNs Architecture**

Based on the research conducted into the uses of ANNs in the field of forecasting, it has been shown that a three layer i.e. Multi Layer Perceptron (MLP) network is the most popular choice in forecast of time series analysis, Zhang and Flower (2000). As a result, it has been decided that the ANN architecture adopted for this study will be a three layer MLP having four inputs, one hidden and one output layers (i.e. 4x1x1). Figures 3.1 and Figure 3.2 present the proposed NNs architectures.

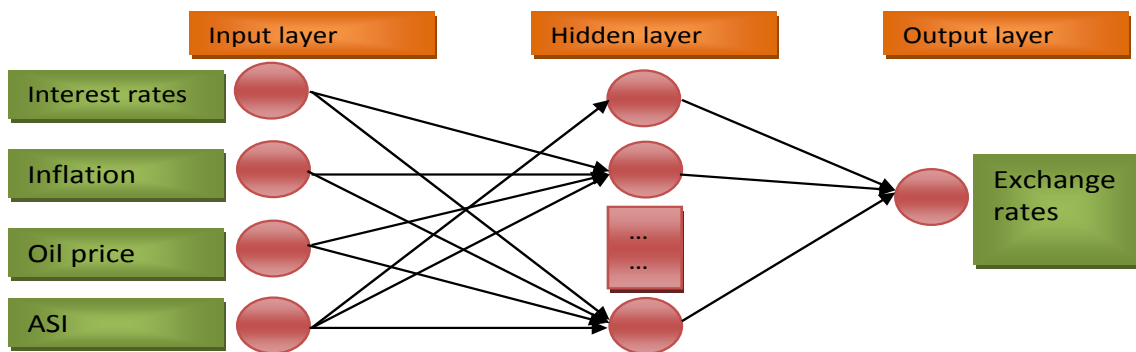


Figure 3.1: NN Model Architecture.

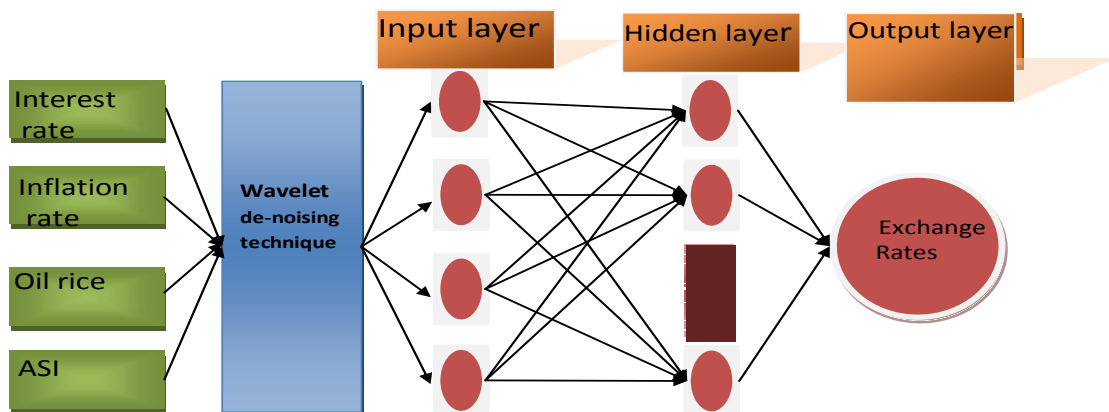


Figure 3.2: Wavelet NN De-noising Based Model Architecture.

### 3.3 Performance Measures

An accuracy measure is often defined in terms of the forecasting error which is the difference between the actual (desired) and the predicted value. There are a number of measures of accuracy in the forecasting literature. In this study, Mean Square Error (MSE) statistical measure is employed to evaluate the performance of the two different forecasting models.

### 3.4 Programming Language

In this study Neuroph is employed to create and train the neural network models to be analyzed. Neuroph is an object-oriented neural network framework written in Java. It can be used to create and train neural networks in Java programs. Neuroph provides Java class library as well as GUI tool easyNeurons for creating and training neural networks.

### 3.5 ANN design experiments

To design the proposed ANN system, various constant and variable factors need to be known. These factors all affect the accuracy of the ANN. The constant factors are:

- a. Number of input layer neurons (4)

- b. Number of output layer neurons (1)
- c. Training algorithm (EBTP, RBP)
- d. The number of epoch= 10000
- e. Performance goal= 1e-2

The variable factors are:

- a. Number of neurons in the hidden layer
- b. The value of learning rate
- c. The value of momentum constant
- d. Activation function

To find the optimal values for the variable factors, several experiments will be carried out. The experimentation will begin with first initialising the constant factors and also setting default values for some of the variable factors. Each experiment will be conducted for the purpose of finding the relationship between the variable factor and the ANN accuracy. However, due to random initialisation of weights by MLP network, each experiment will be conducted five times and average of these experiments will be recorded as the accuracy of the ANN.

The proposed full plan design experimentation settings can be found on the Table 3.1:

Table 3.1 ANN experimental settings.

Test number	Description	Constant variables	Variable values to be tested	Result
1.	To find the optimal number of neuron in the hidden layer	Epoch=10000, Momemtum constant=0.9, Learning rate=0.02, Input layer neurons=4, Hidden layer neurons=x, Performance goal=0.02	Hidden layer neuron to be tested=2, 3, 4, 6, 7, 8, 10	Optimal number of neurons found = x
2.	To find the best combination for both learning rate and momentum constant	Epoch=10000, ,Input layer neurons=4, Hidden layer neurons=x, Performance goal=0.02,	Learning rate values to be tested= 0.2, 0.4, 0.6, 0.8, 0.9. Momentum constant values= 0.2, 0.3, 0.4, 0.5, 0.6, 0.7	Optimal value of learning rate = y Optimal momentum constant = z
3.	To find the best activation function	Epoch=10000, ,Input layer neurons=4, Hidden layer neurons=x, Performance goal=0.02, Momemtum constant=z, Learning rate=y	Activation function Sigmoid, Hyperbolic Tangent	Optimal activation function = a
4.	Effect of data division	Epoch=10000, Momemtum constant=0.7, Input layer neurons=4, Hidden layer neurons=x, Performance goal=0.02, Learning	Data division (50/50 or 80/20)	Suitable data division

		rate=0.2,activation function=a		
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Each of the experiments in Table 3.1 with the exception of experiment 2 will be conducted five times and the accuracy recorded. Then, the average of the five runs will be taking as the final accuracy. This is due to random initialisation of weights by MLP network. The reason for not running experiment 2 five times is because I have decided to combine both learning rate and momentum constant in one experiment and it will be time consuming to run each combination five times.

#### 4.0 IMPLIMENTATION, RESULTS AND DISCUSSION

This section reveals the implementation, results and discussion of the study.

##### 4.1. Experimentations

##### 4.2.1 Experiment 1- Neurons in hidden layer

The aim of this experiment is to find the best value that will not result in over fitting or under fitting of the network.

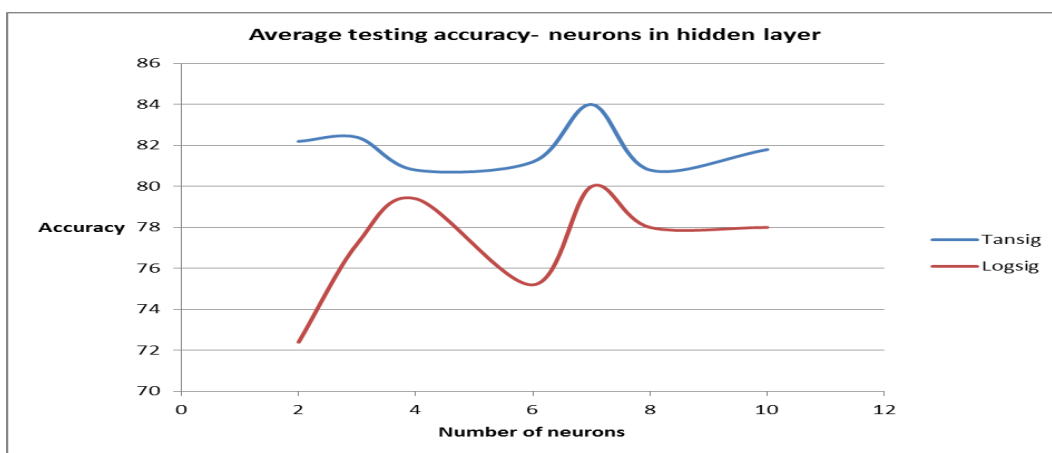


Figure 4.1: Number of neurons in the hidden layer.

By looking at the graph above, it is obvious that for both sigmoid and hyperbolic tangent activation function, seven neurons resulted in the best accuracy. Therefore seven neurons will be used in the hidden layer of the two networks.

The aim of this experiment is to find the best combination of both learning rate and momentum constant values that will increase both the network's training time and performance.

##### 4.2.2 Experiment 2- Best Combination of learning rate and momentum constant

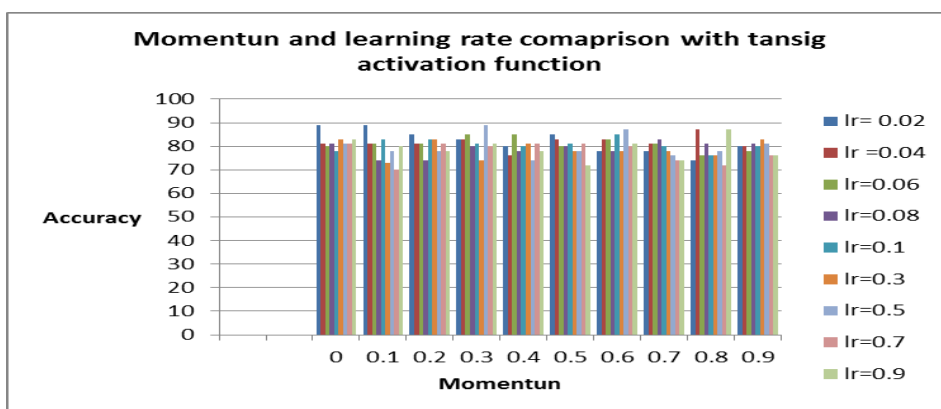


Figure 4.2: Learning rate versus momentum constant using Tansig activation function.

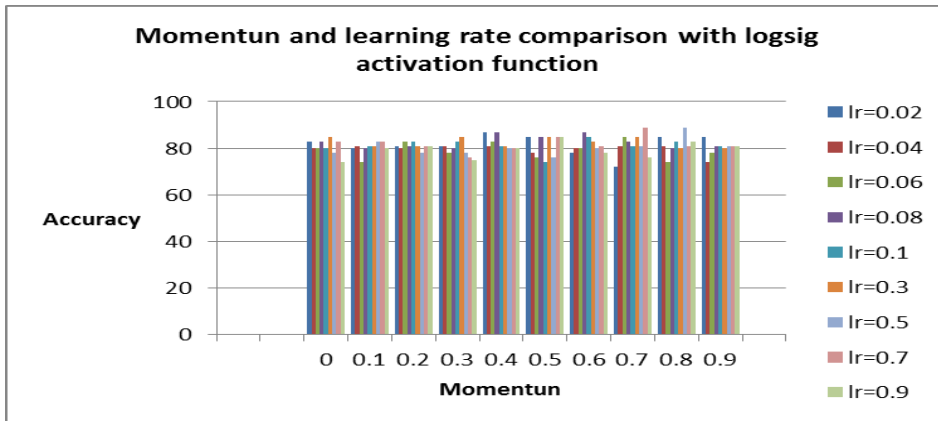


Figure 4.3: Learning rate versus momentum constant using logsig activation function.

Figure 4.2 and Figure 4.3 are graphical representations of the comparison between learning rate and momentum constant for both sigmoid and hyperbolic tangent activation functions. For hyperbolic tangent, it's clear that the highest accuracy was produced when the learning rate was 0.02 and momentum constant was 0.1. However, similar result was produced when the momentum was 0.1 and 0.3, nevertheless; the graph appears to be different for sigmoid activation function with highest accuracy achieved at learning rate 0.7 and momentum constant 0.7. Similarly, same result

was produced with learning rate 0.5 and momentum constant 0.8. Due to this inconsistency, the value of the momentum and learning rate will be determined after finding the optimal activation function for the ANNs.

**4.2.3 Experiment 3- Activation function**

The following experiment was carried out to find the activation function that gives the best accuracy for both testing and training of the ANNs. This will be used to determine the best activation function for the ANNs. Each activation function will be tested with it best momentum and learning rate values found on the previous experiments.

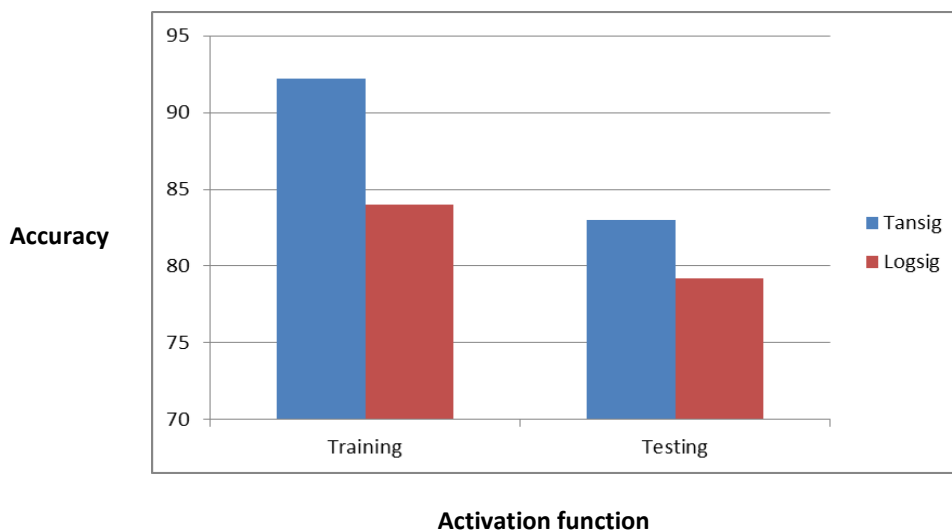


Figure 4.4: Experimentation on activation function.

From the Figure 4.4, the hyperbolic tangent produced the highest accuracy of 92.2 in training and 83 in testing. Therefore, the ANN will be implemented with hyperbolic tangent.

**4.2.4 Experiment 4- Data division**

The experiment was carried out to analyse the relationship between data division and accuracy

of the network. This will be used to determine

the suitable data division for the ANNs.

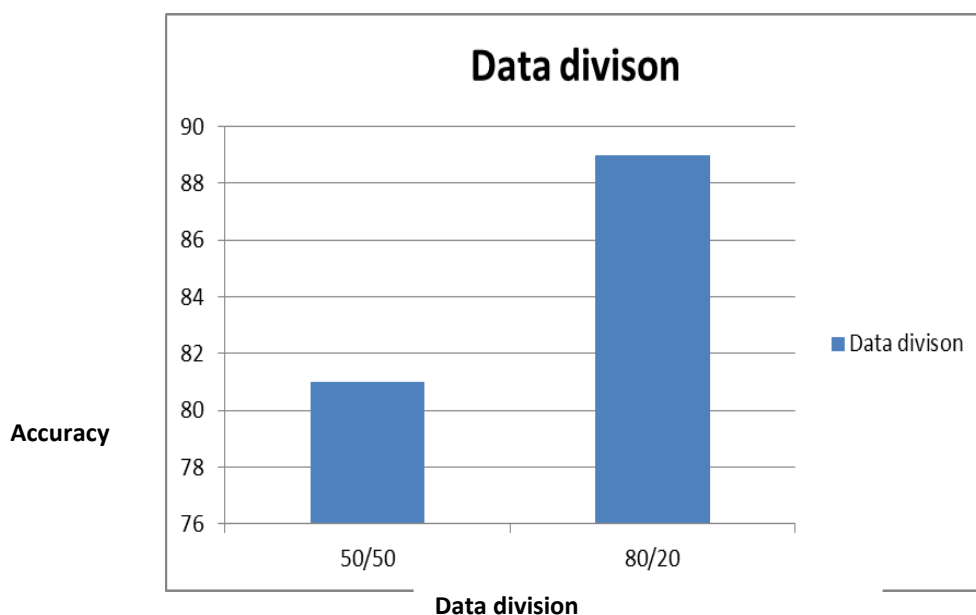


Figure 4.5: Experimentation on data division.

Key points about the graph

50/50- 50% used for training and 50% used for testing

80/20- 80% used for training and 20% used for testing.

From Figure 4.5, it is evident that 80/20 produced the best accuracy, saying that the higher the percentage of data used in training the better the testing accuracy. As a result the most suitable ANNs is as follows:

- a. 7 neurons in the hidden layer
- b. 0.02 as the learning rate
- c. 0.7 as the momentum constant
- d. Hyperbolic tangent as the activation function
- e. 80/20 as the data division.

### 4.3 Error graphs

The following graphs are generated by Mean Square Error (MSE) during the validation process of the

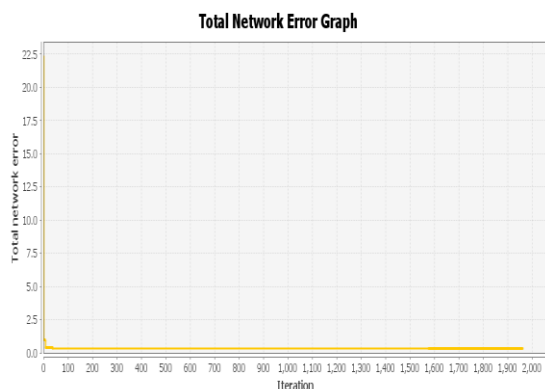


Table 4.1: Total MSE of USD/NGN using wavelet de-noising.

PERIOD	TOTAL MSE
1 – 72 (months) 1995 – 2001 (years)	0.7497
73 – 140 (months) 2002 - 2008 (years)	0.0809
141 – 240 (months) 2009 – 2015 (years)	0.0759

Figure 4.6: Error graph of USD using NN with Wavelet.

Figure 4.6 and table 4.1 depict the total MSE generated by the wavelet denoising NN model during the training process of USD/NGN Forex, both the figure and the table showed a quicker decline of the total

MSE due to the removal of noise in the data by the denoising techniques present in the wavelet denoising model prior to the training process.

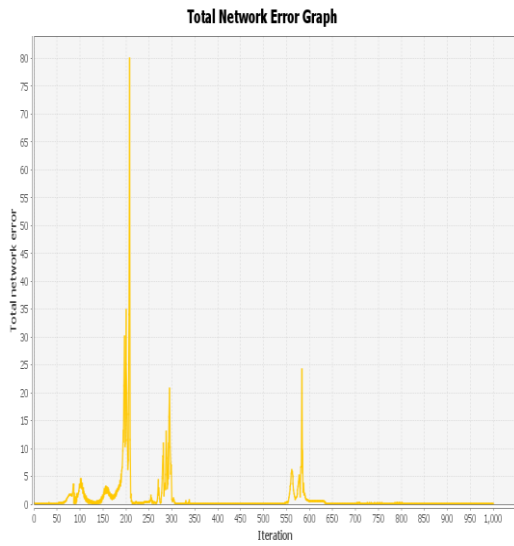


Figure 4.7: Error graph of USD using NN with ErrorProp.

Table 4.2: Total MSE of USD/NGN using ErrorProp

PERIOD	TOTAL MSE
1 – 72 (months) 1995 – 2001 (years)	2.5183
73 – 140 (months) 2002 - 2008 (years)	0.8051
141 – 240 (months) 2009 – 2015 (years)	0.0798

Figure 4.7 and table 4.2 showed that NN with error backpropagation algorithm experience much error during the training process caused by the disturbance of noise in the data that takes the network long time to learn the data.

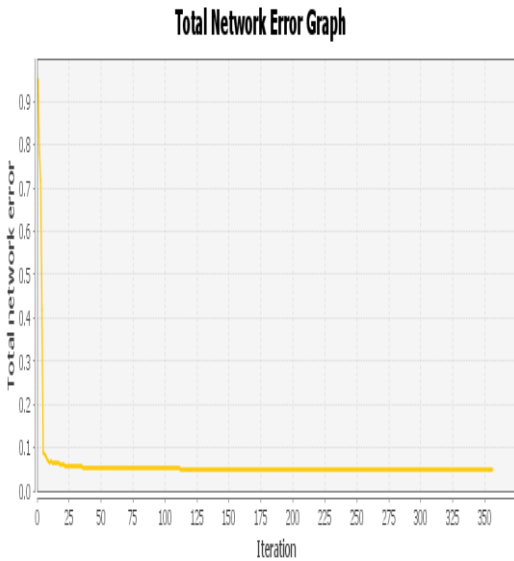


Figure 4.8: Error graph of CND using wavelet de-noising.

Table 4.3: Total MSE of NGN/CND using wavelet.

PERIOD	TOTAL MSE
1 – 72 (months) 1995 – 2001 (years)	0.7518
73 – 140 (months) 2002 - 2008 (years)	0.0868
141 – 240 (months) 2009 – 2015 (years)	0.0747

Figure 4.8 and table 4.3 showed the total MSE generated by the wavelet denoising NN model during the training process of NGN/CND Forex, both the figure and the table showed that the network was able to learn the data in time due to the removal of noise by the denoising techniques.

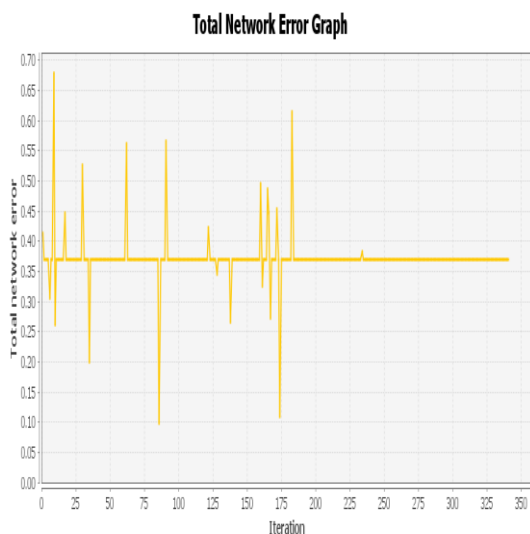


Table 4.4: Total MSE of NGN/CND using ErrorProp.

PERIOD	TOTAL MSE
1 – 72 (months) 1995 – 2001 (years)	2.0164
73 – 140 (months) 2002 - 2008 (years)	0.8123
141 – 240 (months) 2009 – 2015 (years)	0.0812

Figure 4.9: Error graph of CND using NN with Error BackProp.

Figure 4.9 and table 4.4 showed that the error backpropagation NN model experienced slower learning process and higher errors during the training process of NGN/CND.

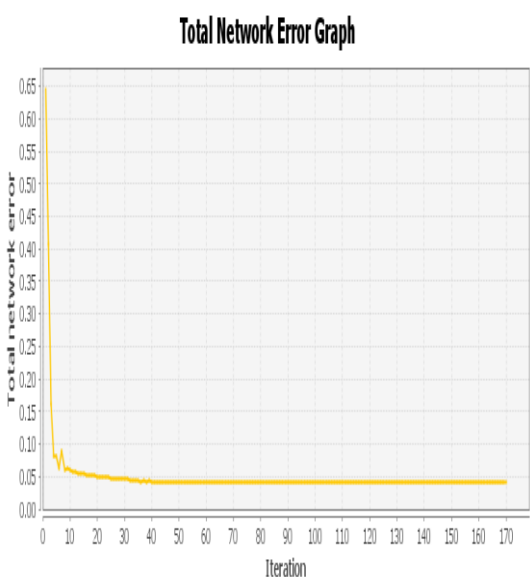


Table 4.5: Total MSE of NGN/MLY using wavelet de-noising .

PERIOD	TOTAL MSE
1 – 72 (months) 1995 – 2001 (years)	0.9486
73 – 140 (months) 2002 - 2008 (years)	0.0822
141 – 240 (months) 2009 – 2015 (years)	0.0813

Figure 4.10: Error graph of CND using wavelet denoising NN.

Figure 4.10 showed that the network achieved the specified minimum error during the training process of NGN/MLY forex by the wavelet denoising neural network model, and also the network was able to generate less errors by the MSE as shown in table 4.5.

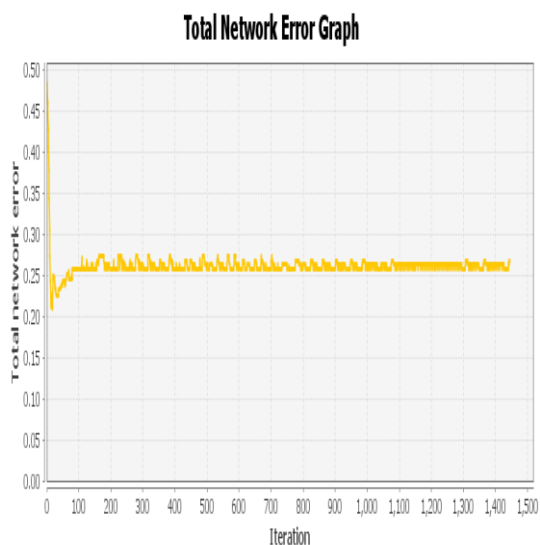


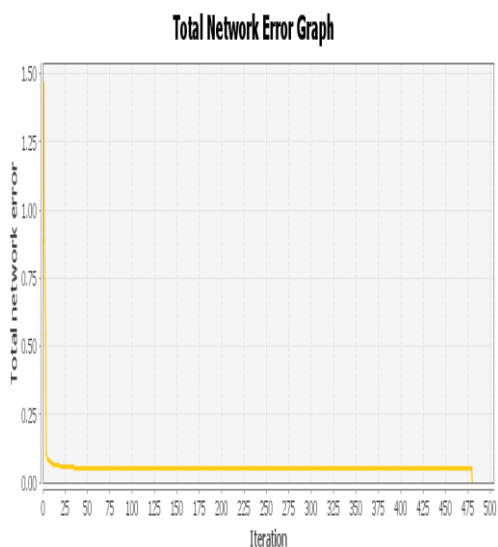
Table 4.6: Total MSE of NGN/MLY using Error Backprop

PERIOD	TOTAL MSE
1 – 72 (months)	2.0125
1995 – 2001 (years)	
73 – 140 (months)	0.8223
2002 - 2008 (years)	
141 – 240 (months)	0.0774
2009 – 2015 (years)	

Figure 4.11: Error graph of MLY using NN with Error BackProp

Figure 4.11 showed that the network experienced a disturbance caused by noise in the data during the training process of NGN/MLY Forex by the error Backpro which resulted in the generation of higher errors by the MSE as shown in table 4.6.

Table 4.7: Total MSE of NGN/JPY using wavelet de-noising



PERIOD	TOTAL MSE
1 – 72 (months)	0.7955
1995 – 2001 (years)	
73 – 140 (months)	0.0860
2002 - 2008 (years)	
141 – 240 (months)	0.0624
2009 – 2015 (years)	

Figure 4.12: Error graph of JPY using Wavelet NN.

Figure 4.12 is the error graph of NGN/JPY using NN with wavelet denoising model in which the model was able to learned the data quickly due to the removal of noise from the data before being to the network. Table 4.7 shows the error generated during the training process.

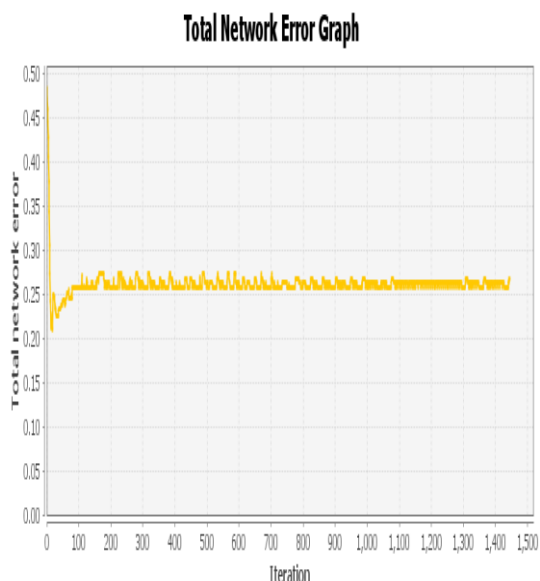


Figure 4.13: Error graph of JPY using Error BackProp.

Figure 4.13 is the error graph of NGN/JPN Forex using NN with error backpropagation algorithm were the network experience a lot of oscillations during the training process as a results of noise contained in the data, table 4.8 shows the errors generated by the MSE during the training process.

It's obvious from the above graphs that all the networks were able to learned all the data, even though some oscillations are experienced in some graphs associated with neural network with error Backprop, this occur as a result of noise in the data that takes the network time to converge. However, graph associated with wavelet de-noising neural network do not experience oscillation as a result of the de-noising mechanisms in the wavelet neural network model, which removed all the noise in the data before being fed into the neural network, this cause the networks to learn the data quickly and converge in time

Table 4.8: Total MSE of NGN/JPY using Error Backprop.

PERIOD	TOTAL MSE
1 – 72 (months) 1995 – 2001 (years)	2.0125
73 – 140 (months) 2002 - 2008 (years)	0.8223
141 – 240 (months) 2009 – 2015 (years)	0.0774

#### 4.4 Testing

After the networks have learned all the data through the training process, the networks were tested with new unseen data, this will help to determine whether the networks have learned the data or not. Thereafter, the testing results were plotted along with the existing or historical foreign exchange rates to show case matching performance.

Figure 4.14 and figure 4.16 showed forecast matching performance of USD/NGN and that of NGN/CND Forex respectively, both the figures showed that wavelet denoising NN does not experience disturbance of noise in the data and achieved closer forecasting at the early stage of the training process. However, figure 4.15 and figure 4.17 of error backprop model showed different results, the network under this model was able to achieved closer forecast at the end of the training process.

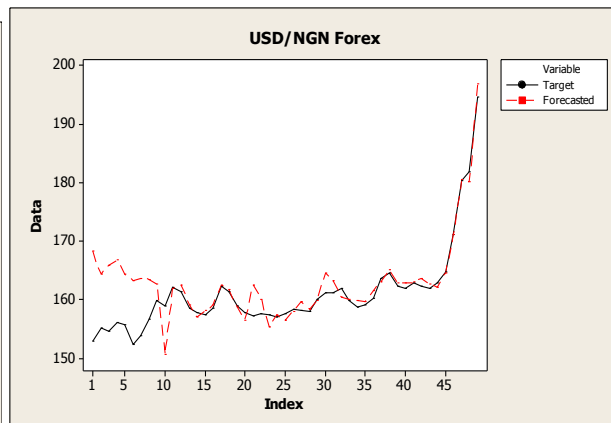
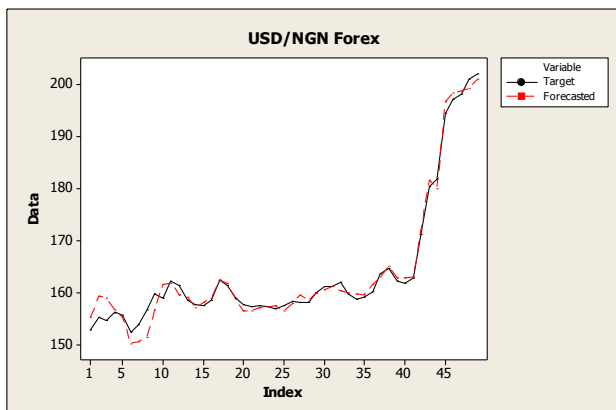


Figure 4.14: USD/NGN Forex using Wavelet NN. Figure 4.15: USD/NGN Forex using ErrorProp.

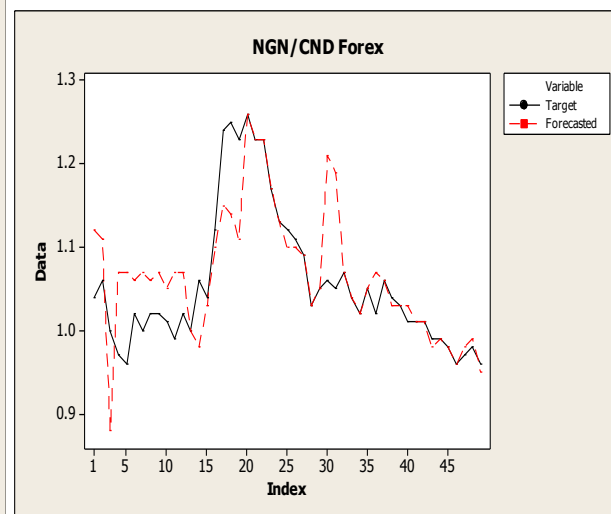
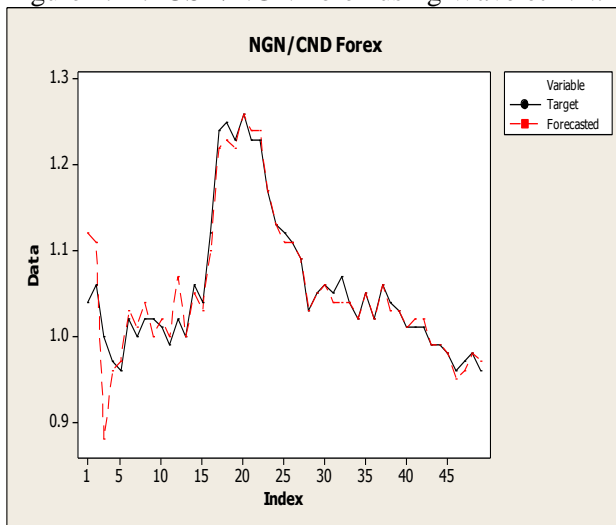


Figure 4.16: NGN/CND Forex using Wavelet NN. Figure 4.17: NGN/CND Forex using ErrorProp.

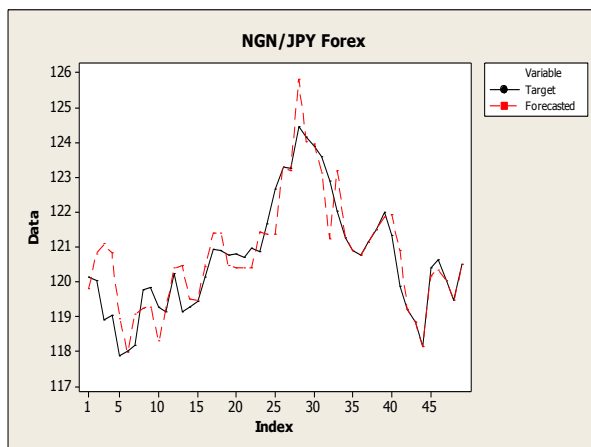
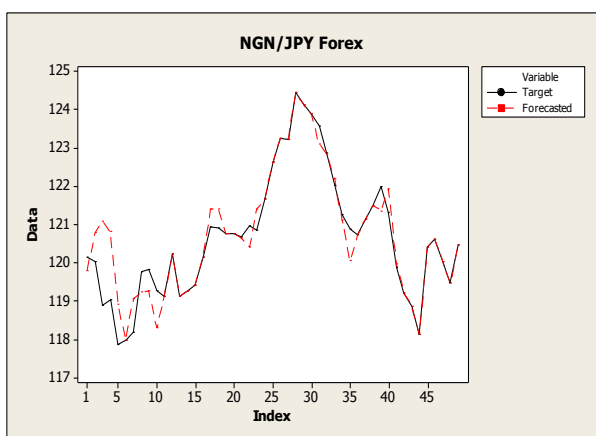


Figure 4.18: NGN/JPY Forex using Wavelet NN. Figure 4.19: NGN/JPY Forex using ErrorProp.

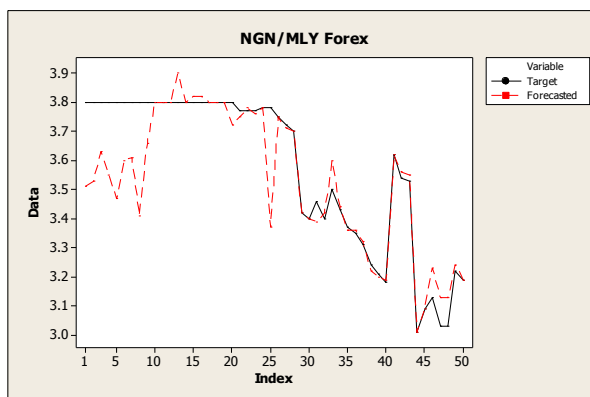
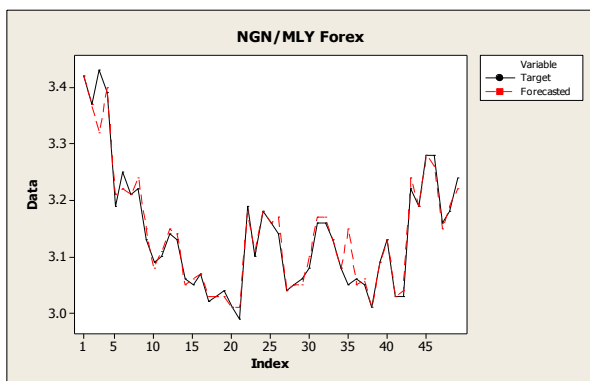


Figure 4.20: NGN/MLY Forex using Wavelet NN.

Figure 4.21: NGN/MLY Forex using ErrorProp.

The graphs above showed the forecast matching performance when compared with the previously occurred exchange rates. It's obvious from the graphs that the networks were able to forecast the foreign exchange rates with a minimum of errors. Graphs in figure 4.14 to figure 4.20 associated with wavelet neural network showed better performance over the neural network with error BackProp, because of the de-noising mechanisms in the wavelet neural network model.

### 4.5 Effect of some Economic variables on Foreign Exchange Rate Forecasting

Based on the experiments conducted in this study showed that significant economic variables as inputs to the neural networks affect the forecasting performance of neural networks, the performance of the networks increase with the increase in the number of economic variables. Table 4.9 shows the result of the experiment.

Table 4.9: Effect of significant economic variables on Forex forecasting

No. of input variables	MSE Wavelet de-noising	MSE Error Backprop
0 Economic variables	15. 79552564861551256	18. 2239654826159
2 Economic variables	8. 06248331222575462	11. 2270188846877
3 Economic variables	3. 82239654826159546	5. 95525648615512
4 Economic variables	0.06248331222575462	0.07745689819388661

Table 4.9 shows how significant economic variables affect the performance of NN models during the forecasting process of exchange rates, the table depicts that the more the economic variables, the higher the accuracy of the forecast.

## 5.0 FINDINGS AND CONCLUSION

### 5.1 Summary

This study analyses two different neural network models to determine their capability in forecasting foreign exchange rates using four significant economic variables to feed the networks.

However, in the course of the research, the effect of network architecture on performance metrics has been investigated, the performance varies

slightly with the number of nodes in hidden layer. The optimum number of hidden units has been determined by trial and error through experimentations. This chapter presents the research findings, recommendations and future works.

### 5.2 Findings

The findings from this research revealed the following:

- a. Neural network is very sensitive, it easily responds to changes made to its architecture.
- b. Using significant economic variables aid the forecasting performance of neural network, the forecasting performance increasing with the increase of number of economic variables.
- c. Neural network with error Back Propagation shows its potential ability in forecasting non-linear time series data, but a hybrid model, wavelet de-noising based neural network model shows better performance over the pure neural network model.

### 5.3 Conclusion

The following are the recommendations drawn from the research findings

- a. When designing neural network model, parameters that determine its architecture such as learning rates, momentum constants and activation function should be carefully selected through experimentations.
- b. Significant economic variables should be integrated in the forecast of non-linear time series data, in order to achieve accurate forecasting.
- c. Neural networks can forecast non-linear time series data with minimum errors, but a hybrid model seems more promising and should be adopted.

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