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Application of Artificial Neural Network (Ann) in Modeling Foreign Currency Exchange Rates
(A case of Kenyan Shilling against four world's major currency)

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Abstract
Investors, Policy makers, Governments etc. are all consumers of exchange rates data and thus exchange rate volatility is of great interest to them. Modeling foreign exchange (FOREX) rates is one of the most challenging research areas in modern time series prediction. Neural Network (NNs) are an alternative powerful data modeling tool that has ability to capture and represent complex input/output relationships.
This study describes application of neural networks in modeling of the Kenyan currency (KES) exchange rates volatility against four foreign currencies namely; USA dollar (USD), European currency (EUR), Great Britain Pound (GBP) and Japanese Yen (JPY) foreign currencies. The general objective of the proposed study is to model the Kenyan exchange rate volatility and confirm applicability of neural network model in the forecasting of foreign exchange rates volatility. In our case the Multilayer Perceptron (MLP) neural networks with back-propagation learning algorithm will be employed. The specific objectives of the study is to build the neural network for the Kenyan exchange rate volatility and examine the properties of the network, finally to forecast the volatility against four other major currencies. The proposed study will use secondary data of the mean daily exchange rates between the major currencies quoted against the Kenyan shilling. The data will be acquired from the central bank of Kenya's (CBK) website collected for ten years of trading period between the years 2005 to 2017. The data will be analyzed using both descriptive and inferential statistics, with the aid of R's neuralnet package. A number of performance metrics will be employed to evaluate the model. Conclusion and recommendations will be made at the end of the study.

Keywords: Neural Networks, Multi-layered perceptron, exchange rates, volatility, learning algorithm

1. Introduction

Background of the study

Foreign exchange rate is the price of one country's currency expressed in another country's currency. In other words, that it is the rate at which one currency can be exchanged for another. Exchange rate is a national and international political, social and economic indicator therefore, performance of securities market by large reflect the economic situation of a country. That being said in a globalized world, the narrative is a bit more complex as securities prices are affected by both the country's domestic economic situation and by foreign economic events majorly foreign exchange rates fluctuations. The volume of external trade has grown consistently over the last five years, the value of total trade increased by 12.5 per cent to KSh 2,155.6 billion in 2014. Similarly, the value of imports rose by 14.5 per cent in 2014 to KSh 1,618.3 billion while that of total exports grew by 6.9 per cent to KSh 537.2 billion during the same period. Domestic exports grew marginally from KSh 455.7 billion in 2013 to KSh 460.6 billion in 2014, while re-exports recorded a significant increase during the review period, [15]. According to the economic survey the Kenyan shilling weaken by 0.9 percent against major world currencies as reflected in the Trade Weighted Index which deteriorated from 107.06 to 107.98 in 2014. It is likely that the importance of the foreign events will continue fuelling the fluctuations in the financial sector especially foreign exchange market. Foreign exchange market developments and its trend have cost implications for the state, private firms down to households also [19], showed that exchange rate volatility have real economic costs that affect price stability, firm profitability and a country's economic stability. Exchange rate volatility has implications for the financial system of a country especially the stock market, [14]. The value of one currency versus another is determined by the international exchange rate and in most cases, it is subject to fluctuations based on open trading of currency in foreign exchange markets. A fixed exchange rate was maintained in the 1960s and 1970s, with the currency becoming over-valued, though not extremely so. Exchange controls were maintained from the early 1970s until a market-determined regime was adopted in the 1990s,[37]. Forecasting of Foreign Exchange Rate (FOREX) is one the challenging applications in modern time series forecasting [4], the rates are naturally noisy, disordered and non-stationary. These characteristics suggest that there is no absolute information that could be obtained from the past performance of such as markets to fully capture the dependency between the future exchange rates and that of the past. One assumption is made in such cases is that the historical data integrate all those behavior. As a result, the historical data plays a vital role in the process. The currency exchange rates play a significant role in the compulsive dynamics of the currency market. Proper prediction of currency exchange rate is a crucial factor for the success of the state, many business and investment _rms. Although the market is well known for its unpredictability, _fickleness and volatility, there are number of groups like banks, agencies and others predicting exchange rates using numerous techniques. There are many types of theoretical models including both time series and econometric approaches have been widely used to model and forecast exchange rates such as Autoregressive Conditional Heteroskedasticity (ARCH), General Autoregressive Conditional Heteroskedasticity (GARCH) models and other chaotic dynamics applied to financial forecasting. While these models may be better for a particular situation and they perform poorly in other essential applications. Artificial Neural Networks (ANNs) have of late received more attention as financial decision-making tools [4]. The Artificial Neural Networks are the well-known function approximates used in prediction and system modeling that has recently shown its great applicability in time series analysis and forecasting. Artificial Neural Network is more effective in describing the dynamics of non-stationary time series due to its unique nonparametric, noise tolerant and adaptive properties. ANNs are universal function approximates that can map any nonlinear function without a prior assumptions about the data. . Artificial neural network (ANN) is widely used by researchers as a prediction technique since it can provide the best prediction result [12]. The first step is to identify the underlying problem leading to this study.

2. Methodology

2.1 Introduction

This chapter outlines the methods that were used to conduct the study. This includes the research model, target population, multi-layered perceptron, data processing and analysis methods that were used.

2.2 Target population

In this research, it will be important to use FOREX rates collected for over ten years. The data was obtained from CBK's website; www.centralbank.go.ke. This will help in getting the trend in financial daily FOREX market history. The variable modeled is the normalize time series data.

2.3 Research model

The research model is a time series of exchange rates over a time period of over ten years. This shows the relationship between the current exchange rates and the previous trading rates. This time series is represented by the following model;

$$Y=f(\sum_{j=1}^{n} w_{i,j}x_j) \qquad (1)$$

Where y is the output, f(x) is a non linear transfer function and n is three number of input lines of the neuron i. Thus the ANN is the same as the nonlinear autoregressive model along the series

2.4 multi-layered perceptron (mlp)

A multi-layered perceptron or feed-forward neural network (NN) is a non-parametric statistical model for extracting nonlinear relations in the data. An ANN characterized by its architecture, training and learning procedures and the activation functions.

2.5 Architecture

The perception chosen for this study contains three layers with a structure 6-n-1; Six processing elements in the input layer, arbitrary number n in the hidden layer and one output or the predicted value. Normalized time series data is fed into a multi-layered feed forward network with d input nodes, H hidden nodes, and one output node. Normalization of data was done as sigmoid transfer function was selected as the activation function to generate relationship between input and output nodes producing a binary output. The input at hidden layer nodes are connected by weight parameters W_{hj} for $h \in (1,\ldots,H)$), $j \in (0,\ldots,d)$ and w_{ho} is the bias parameter for the i^{th} hidden node. The bias parameters are regarded as the weights for constant inputs of value 1. The hidden and output layers are connected by weights α_h for $h \in (1,\ldots,H)$. The input $v_h(x)$ to the h^{th} hidden node is the value

$$v_h(x)= w_{ho+} \sum_{j=1}^{6} w_{hj}x_j \qquad (2)$$

The output $\varnothing_h(x)$ to the h^{th} hidden node is the value

$$\varnothing_h(x)= \mu(v_h(x)) \qquad (3)$$

The net input value to output node is the value

$$z(x)= \alpha_o\sum_{j=1}^{6} \alpha_o \varnothing_0(x) \qquad (4)$$

The output of the network is

$$Z(x) = (z(x)) \qquad (5)$$

2.5.1 Back propagation(BP) learning algorithm

In this study we used the standard back-propagation (SBP) learning algorithm. Training algorithm is used to attain a set of weights that minimizes the difference between the target and actual output produced by the network. The weights were adjusted through supervised training, for the feed-forward ANN, a sigmoid activation function is selected to generate relationship between input and output nodes. Algorithm that implements that idea is called error back propagation algorithm and can be described as follows:

a) Initialization

The first step is selecting the network architecture and setting its initial weights. The most common method of the weights initialization is choosing small random numbers with the zero mean value and uniform distribution. For every training sample, there are two steps that are taking place; forward computation and backward computation .

b) Feed-forward computation

For a training data set T, consisting of N pairs (xi,di)

$$T = (x_i, d_i)\ i = 1,\ldots\ldots,N,\ x_i \in R^n,\ d_i \in R^m \qquad (5)$$

x_i is the input vector and d_i is the desired output vector.

The network passes the input vector from layer to layer and sequentially computes the outputs for all the layer's neurons. Those outputs form an input vector for the next layer. For every neuron j in the layer hidden layer l (with the exception of input neurons) the output y_j^I signals are computed from the previous layer output signals y_i^{l-1} as follows

$$S_j=\sum_{i=1}^{mi} w_{ij}{}^{l} y_i{}^{l-1} \qquad (6)$$

$$Y_j^l=F(S_j) \qquad (7)$$

Here m_l is the number of weights for all the neurons of the layer l. That number is determined by the number of neurons of the previous layer and is the same for every layer's neuron. At the first step the neuron calculates the linear combination of outputs of the neurons of the previous layer (7). The output value is calculated by applying neuron's activation function to the value computed in the first step (8). For input layer - layer 0 - the formula is simply

$$Y_i^0 = X_{ij} \qquad (8)$$

where x_{ij} is the J^{th} element of the input vector x_i.

After the input vector x_i passes all the layers, the network produces the output vector $o_i = [y_1^{out},\ldots\ldots\ldots.,y_m^{out}]$, that is used for the error signal computation

$$e_i = d_i - o_i \qquad (9)$$

c) Backward computation.

During that step synaptic weights are adjusted in order to produce smaller error value. Those adjustments are derived from the error signal. For each output unit j calculates $\delta^{out}{}_j$

$$\delta^{out}{}_j=e_{ij}F'(S_j) \qquad (10)$$

where e_{ij} is the j^{th} element of the error vector e_i and F is the derivative function for the function F. For hidden neuron j of the layer l calculates $\delta^{hid}{}_j$

$$\delta^{out}{}_j=e_{ij}F'(S_j) \qquad (11)$$

where summarization is done over all neurons k of the following layer, and w is the weight that connects neurons j and k. When all δ are calculated. Weights are adjusted using the formulas below

$$W_{jk}{}^{t+1} = W_{jk}{}^{t} + \Delta W_{jk}{}^{t} \qquad (12)$$

$$\Delta W_{jk}{}^{t}=\eta\, \delta_j\, y_j{}^{l-1} - \mu(W_{jk}{}^{t} + W_{jk}{}^{t-1}) \qquad (13)$$

where η is called learning rate, y_i^{l-1} is the output of the neuron j of the previous layer and μ is momentum. Learning rate and momentum are numbers between 0 and 1.

Learning rate.

Learning rate is a number between 0 and 1 that determines how fast the neural network adjusts itself to the patterns in the training data. It does not have to be a constant and can also dynamically decrease or increase with time

Momentum.

The Momentum indicator is a speed of movement (or rate of change) indicator, that is designed to identify the speed (or strength) of a price movement . Usually, the momentum indicator compares the most recent closing price to a previous closing price. Momentum term influences the way of how previous weights affect the current one. It helps the algorithm in preventing being stuck in a local minimum. That value must also be chosen carefully and should be determined experimentally. The use of momentum can be omitted. However it may improve neural network's performance greatly and therefore it is commonly used.

2.5.2 Transfer functions

Other important criteria for neural network design are selecting of transfer function for each layer. Here, we selected sigmoid transfer function for second and Linear transfer functions for third layer. sigmoid transfer function, is used to transform the input into a standard range [0, 1] .

$$\varphi = \frac{1}{1+exp^{\gamma \sum_{j=0}^{n} Wi,jXj}} \qquad (14)$$

where n represents the number of inputs, $W_{i,j}$ the weight associated with hidden neuron i and input j, and x_j represents j^{th} input. The given sigmoid gives value between 0 and 1 hence forcing normalization of data.

2.6 Network parameters

There are three types of neural networks that are commonly used by economists and researchers in market prediction. After the model is selected, it should be instanced using particular parameters; Number of inputs, outputs and number of hidden layers.

2.6.1 Number of input neurons

This number is determined easily when the previously defined steps have been done. As every input variable is treated by a single input neuron, input neurons' count is determined by the size of the input vector (which, as we seen before, can be found using Takens theorem with the following input compression, or selecting a set of input indicators).

2.6.2 Number of hidden layers

Number of hidden layers cannot be clearly defined because the optimal number strongly depends on the data and may differ from case to case. However, researches [32] and [27] approached that problem and developed common advices; In most cases, one or two hidden layers proved to be enough, and increasing the number of those layers also increases the danger of over-fitting [33]. Due to the nature of the quote or FOREX movements, number of hidden layers can't be predicted easily and training of networks with the different number of hidden layers for comparison is required.

2.6.3 Number of hidden neurons

There are no clear rules of how to select the right number of hidden neurons. The most common technique is to determine appropriate number during the experimentation phase. But it was also necessary to keep in mind that too big number is demanding on resources, and too small number may not reflect all the variety of the input data. [17] suggest always prefer the network that performs well on the testing set and has the least number of hidden neurons.

2.6.4 Number of output neurons

Most neural networks use only one output neuron for the next value forecasting or one step ahead forecast.

2.7 Data processing

2.7.1 Selection of input and output variables

Good selection of the input and output variables is fundamental for the accurate forecast. Often it requires a deep understanding of the economical background. The distinct feature of input variables of neural networks is that the input variables should not be much correlated, since the correlated input variables may worsen the prediction performance by interacting with each other and generating a biased effect. In order to let the input variables correlated to the output variable be used in the model, we should choose the input variable with less lags such as y_{t-2},y_{t-2}, y_{t-3},……,y_{t-n} where, y_t the value at time t and since NN is a nonparametric method choosing the number of input variables is very vital since with less of lags between each input variable may result to over-fitting whereas increase in the lag between input variable may result to under-fitting. To handle this issue of under-fitting or over-fitting, we selected few number of lags and test the performance of the neural network on a trial and error basis to get the optimum lag combination by checking goodness of fit for each model.

2.7.2 Data set construction

There are several approaches that are commonly used sliding window below was used in this study.

Sliding window. Financial time series can be represented as a series of vectors:

$$X_d^t = (x_{t-1}, \ldots\ldots, x_{t-d}) \quad (15)$$

where X_d^t contains d values that preceded t^{th} value of the series. Then the fore-casting method can be formally stated as finding a function f : R^d > R such as next value xt+1 is determined by the previous d values of X_d^t

$$x_{t+1} = f(x_t^d) \quad (16)$$

Neural networks perform that task by using feedforward network architecture, of which the MLP in our case . The input value is a d-dimensional vector and output is the single number that represents next value. Multiple next values are also possible, but rare. That method is also called sliding window as vector X_t^d "slides" over the full training set.

2.7.3 Data segmentation

Historical data in this study were divided into two portions; training and testing sets. According to [25] based on the rule of the thumb derived from their experience, made their tests using the same segmentation namely, 70% of the data for training and 30% for testing. This segmentation was used for all data sets in this study to produce results. This is generally considered a good segmentation because it allows enough data for training phase while keeping enough for testing phase so that the network usually generalizes best out of sample data. A model is considered good if the error out-of-sample testing is lowest compared to other models. The data sets of four currencies studied in this paper comprise of 3204 daily rates for sampling periods of between 1st January 2005 and 1st October 2017. The data are chosen and segregated in time order where earlier period 2005 and 2014 with 1920 daily rates representing 70% were used as training sets while the remaining 30% between 2014 and 2017 as testing set.

2.7.4 Data normalization and de-normalization

since the sigmoid was chosen as the activation function gives output of interval (0,1) It was necessary to normalize data into this interval. The data was de-normalized to display the results. Normalization was done using the formula below,

$$Y = \frac{x-Min}{Max-Min}(\omega - \alpha) + \alpha \quad (16)$$

where x is the input data to normalize, y the normalized result min and max represents the minimum and maximum data over the whole data set respectively, and are the lowest and upper bound of the interval respectively. In our case 0.1 and 0.9 were used, to avoid working near asymptote of the sigmoid. De-normalization was done using the inverse of the normalization formula;

$$Y = \frac{x-\alpha}{\omega-\alpha}(Max - Min) + Min \quad (17)$$

2.8 Model parameters

All the experiments were conducted under the following parameters number of iterations depended on the MSE values and stopped on minimum MSE values.

momentum(α) =0.9 learning rate =0.05

Hidden layer =Half the input layer nodes

2.9 Performance metrics

According to [4] forecasting performance of the proposed system is evaluated against a number of widely used three statistical metrics, namely, Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE).

3. Results and Discussion

3.1 Introduction

This chapter presents results arising from the analysis of the daily average foreign ex-change rates of Kenyan shilling against four world major currencies, namely; The US dollar (KES/USD), The Great Britain pound (KES/GBP), The European currency (KES/EUR) and The Japanese Yen (KES/JPY), between January 2005 to October 2017 consisting of 3204 observations each. Data was obtained from the Central Bank of Kenya's website. The arising results were obtained with the aid of R-statistical software(Neuralnet package)

3.2 Exploratory data analysis

In order to explore the data the histogram and time plots were used to visualize the data set distribution

3.2.1 Exchange rates data

The time plot of the exchange rates volatility are as shown in figures below. The KES/JPY graph shows it is the most volatile compared to the other three currencies

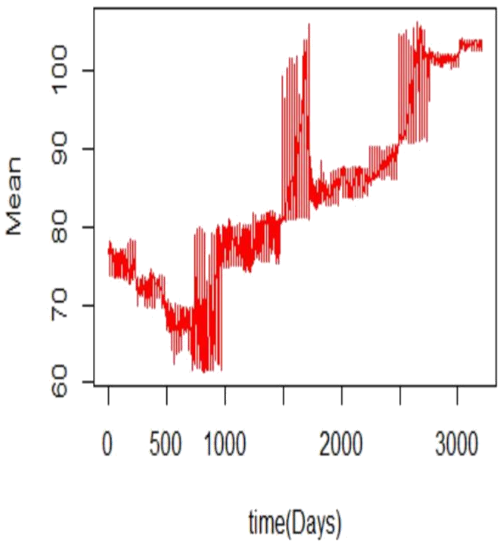

Figure 1: KES/USD exchange rates series

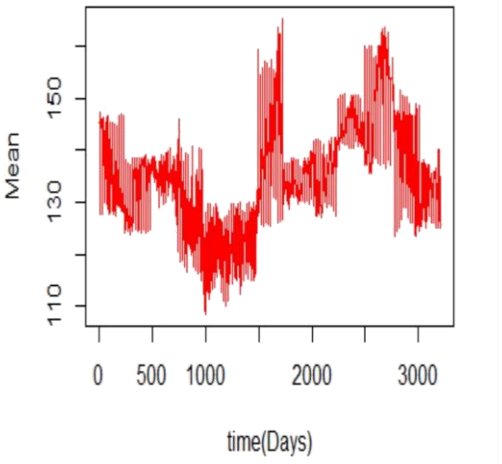

Figure 2: KES/GBP exchange rates series

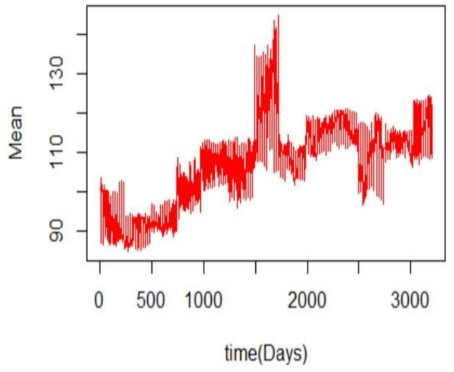

Figure 3: KES/EUR exchange rates series

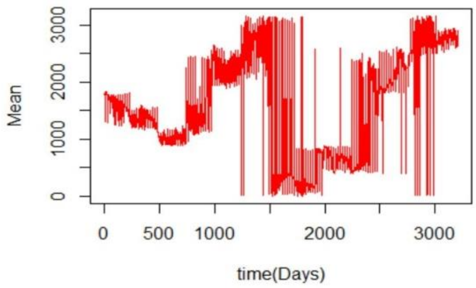

Figure 4:KES/JPY exchange rates series

Histogram of exchange rates

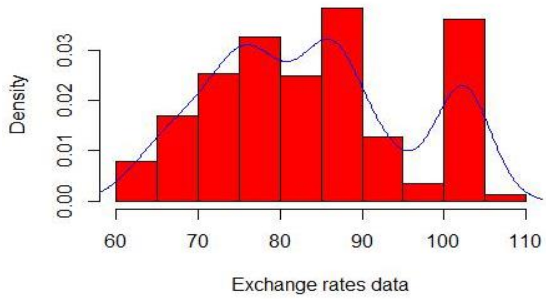

Figure 5: Histogram of KES/USD exchange rates

Further tests were also carried out i.e. plots of the histograms of the exchange rates time series data show that the data is not normal but is heavy tailed.

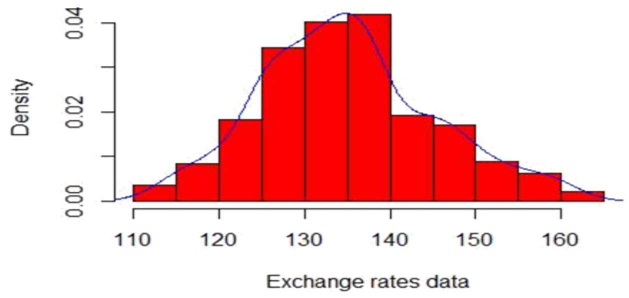

Figure 6: Histogram of KES/GBP exchange rates

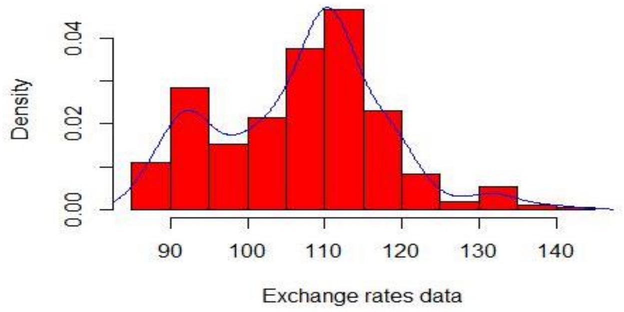

Figure 7: Histogram of KES/EUR exchange rates

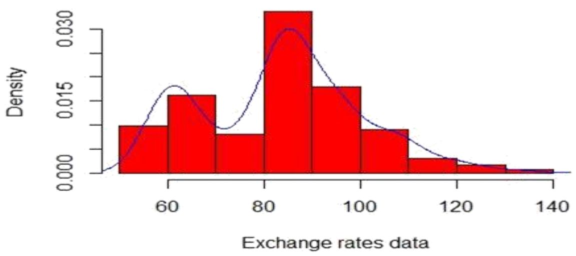

Figure 8: Histogram of KES/JPY exchange rates

Simulations

KES/USD

The results for KES/USD were computed using the below model

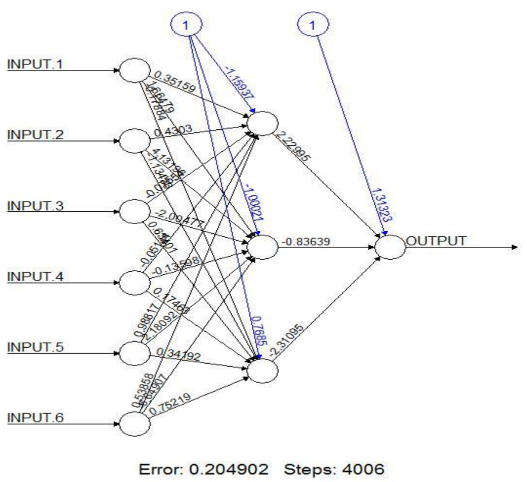

Figure 9: KES/USD exchange rates NN model plot

where steps is the number of iterations and the "blue" lines are the bias nodes with weight values of 1

summary of the network is given by the table below

Table 1

Model	MSE	MAE	MAPE	Predicted Value
6-3-1	0.001889	0.0045	0.45	104.62

Goodness-of-fit of the model

plot of the real vs predicted values is given below

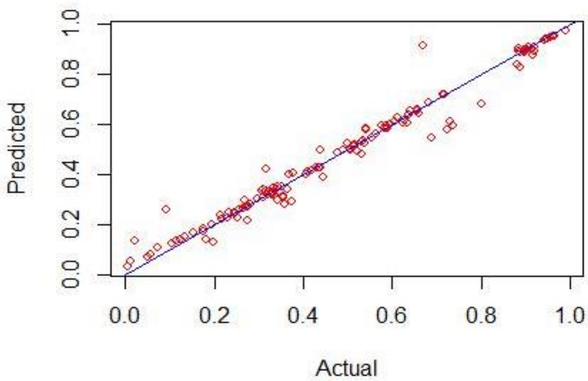

Figure 10: Real Vs Predicted values plot

The step above was done to access the performance of the network. We put the entire data set through the network (training and test) and performed a linear regression between the network output and corresponding targets. The output seems to track the targets reasonably well.

4.4.2 KES/GBP

The results for KES/GBP were computed using the below model

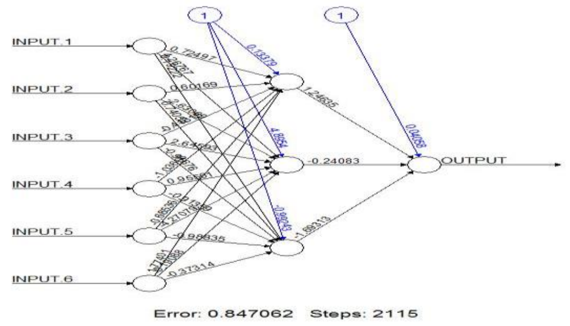

Figure 11: KES/GBP Exchange rates NN model

where steps is the number of iterations and the "blue" lines are the bias nodes with weight values of 1

summary of the network is given by the table below

Table 2

Model	MSE	MAE	MAPE	Predicted Value
6-3-1	0.001889	0.0041	0.41	133.43

Goodness-of-fit of the model
plot of the real vs predicted values is given below

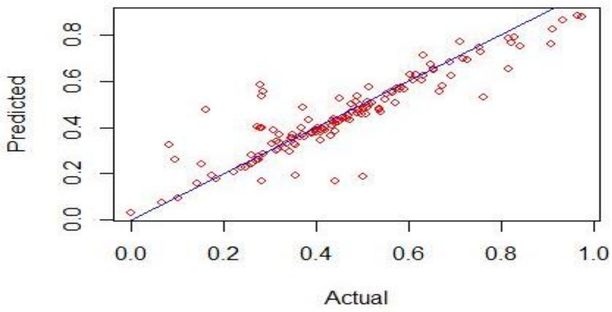

Figure 12: Real Vs Predicted values plot

The step above was done to access the performance of the network. We put the entire data set through the network (training and test) and performed a linear regression between the network output and corresponding targets. The output seems to track the targets reasonably well.

KES/EUR

The results for KES/EUR were computed using

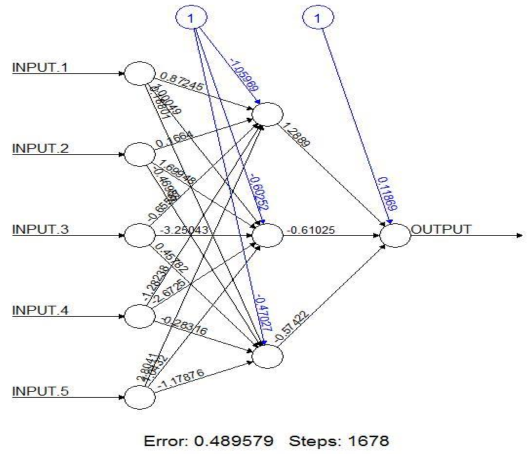

Figure 13: KES/EUR Exchange rates NN model

where steps is the number of iterations and the "blue" lines are the bias nodes

summary of the network is given by the table below

Table 3

Model	MSE	MAE	MAPE	Predicted Value
6-3-1	0.001889	0.00563	0.563	93.84

Goodness-of-fit of the model
plot of the real vs predicted values is given below

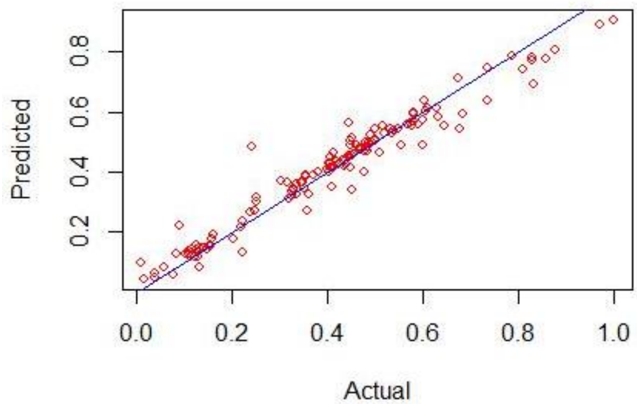

Figure 14: Real Vs Predicted values plot

The step above was done to access the performance of the network. We put the entire data set through the network (training and test) and performed a linear regression between the network output and corresponding targets. The output seems to track the targets reasonably well.

KES/JPY

The results for KES/JPY were computed using the below model

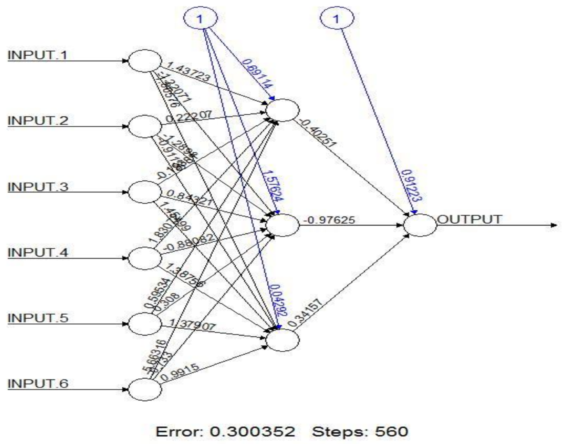

Figure 15: KES/JPY Exchange rates NN model

where steps is the number of iterations and the "blue" lines are the bias nodes

summary of the network is given by the table below

Table 4

Model	MSE	MAE	MAPE	Predicted Value
6-3-1	0.001889	0.022	2.2	55

Goodness-of-fit of the model

plot of the real vs predicted values is given below

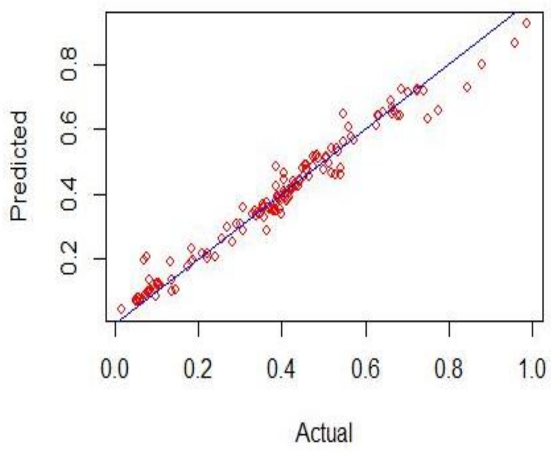

Figure 16: Real Vs Predicted values plot

The step above was done to access the performance of the network. We put the entire data set through the network (training and test) and performed a linear regression between the network output and corresponding targets. The output seems to track the targets reasonably well.

4. Summary, conclusion and recommendations

4.1 Summary and conclusion

This paper is the implementation of back-propagation neural networks on foreign currency exchange rates. We attempted to prove that by using a back-propagation neural network, FOREX rates can be predicted correctly. This paper describes how to build an artificial neural network model to predict trends in foreign currency ex-change rates. Knowledge discovered in the databases were used for construction of the model for forecasting.

The back-propagation neural network was chosen for this research because it is capable of solving a wide variety of problems and it commonly is used in time series fore-casting. We used feed-forward topologies, supervised learning and back-propagation learning algorithms on the networks based on the daily mean data of the currency pairs. This paper uses R-neuralnet package software as a tool to test and try to correctly predict FOREX rates; thereby, decreasing the risk of making unreasonable decisions. There are, however, still limitations and cautions that must be considered when using neural networks as predictive models. Although a multi-layer back-propagation network with enough neurons can implement just about any function, back-propagation will not always find the correct weights for the optimal solution. While a network being trained may be theoretically capable of performing correctly, back-propagation and its variations may not always find a solution. Picking the learning rate for a nonlinear network is a challenge. Unlike linear networks, there are no easy methods for picking a good learning rate for nonlinear multi- layer networks. Networks are also sensitive to the number of neurons in their hidden layers. Too few neurons can lead to under-fitting, too many can contribute to over-fitting. One may want to reinitialize the network and retrain several times to guarantee that one has the best solution. Overall, using the right analytical tools and methods can decrease the chance of making incorrect decisions and increase the possibility of profitability in the area of foreign currency exchange rate

4.2 Recommendations

The study revealed a high potential of ANN in forecasting the daily foreign exchange rates in Kenya. After testing the model showed that the average value of NN have low error, that can be taken for predictive indicator. Technical analysis can predict the trends of any kind of price but the model or technique of this analysis adapts to the instrument which is the subject of this analysis (For example securities or FOREX). Bearing that in mind the neural network model would be certainly adequate for forecasting. Information on volatility of exchange rates is crucial to various groups such as importers, investors, exporters, policy makers government and many more. There is thus need to build models that can then be used for simulation and possibly forecasting. This study points on the future research to lay emphasis on how the goodness-of- fit of this model can be achieved.

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