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Artificial Neural Network Model for Forecasting Foreign Exchange Rate

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Abstract— The present statistical models used for forecasting cannot effectively handle uncertainty and instability nature of foreign exchange data. In this work, 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 learn 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 datasets from oanda website were used as input in the back propagation for the evaluation and forecasting of foreign exchange rates. The design was implemented using matlab7.6 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.

Keywords- Artificial Neural Network; Back propagation Algorithm; Hidden Markov Model; Baum- Weld Algorithm; Sigmoid Activation Function and Foreign Exchange Rate.

I. INTRODUCTION

All standard paper components have been specified for three reasons: (1) ease of use when formatting individual papers, (2) automatic compliance to electronic requirements that facilitate the concurrent or later production of electronic products, and (3) conformity of style throughout conference proceedings. Margins, column widths, line spacing, and type styles are built-in; examples of the type styles are provided throughout this document and are identified in italic type, within parentheses, following the example. Some components, such as multi-leveled equations, graphics, and tables are not prescribed, although the various table text styles are provided. The formatter will need to create these components, incorporating the applicable criteria that follow.

Financial time series forecasting is regarded as one of the most challenging applications of modern time series forecasting. As explained by [16], financial time series are inherently noisy, non-stationary and deterministically chaotic. The noisy characteristic refers to the unavailability of complete information from the past behavior of financial markets to fully capture the dependency between future and past prices. One general assumption made in such cases is that the historical data incorporate all those behavior. As a result, the historical data is the major player in the prediction process. Because of the high volatility, complexity and noise market environments, neural networks techniques are prime candidates for prediction purpose.

The information that is not included in the model is considered as noise. The non-stationary characteristic implies that the distribution of financial time series is changing over time. By deterministically chaotic, one means that financial time series are short-term random but long-term deterministic. In recent years, neural networks have been successfully used for modeling financial time series. Neural networks are universal function approximators that can map any non-linear function without a priori assumptions about the properties of the data.

Neural networks are also more noise tolerant, having the ability to learn complex systems with incomplete and corrupted data. In addition, they are more flexible, having the capability to learn dynamic systems through a retraining process using new data patterns. The foreign exchange market is the largest and most liquid of the financial market with an estimated $3 trillion traded everyday as at 2008 [5]. Foreign exchange rates are amongst the most important economic indices in the international monetary markets. The forecasting of them poses many theoretical and experimental challenges given the abandonment of the field exchange rates, the implementation of the floating exchange rate system in the 1970s and 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. Therefore, to forecast the changes of foreign exchange rates is generally very difficult. Researchers and practitioners have been striving for an explanation of the movement of exchange rates. Thus, various kinds of forecasting methods have been developed by many researchers and experts. Technical and fundamental analyses are the basic and major forecasting methodologies which are in popular use in financial forecasting. Like many other economic time series, foreign exchange market has its own trend, cycle, season and irregularity. Thus to identify, model, extrapolate and recombine these patterns and to give foreign exchange market (forex) forecasting is the major challenge.

Well-trained ANNs can predict complex biological patterns, structures, or functions of newly discovered sequences. The foreign exchange market not only has known inputs and outputs but is also affected by external information causing uncertainty. The Hidden Markov Model (HMM) approach basically is used to predict the hidden relationship between inputs and outputs, and has been one of the most attractive research areas in the field of information systems. This approach can be used in simulating the foreign exchange market by taking a small subset of known information to reduce the effect of this uncertainty and noise.

A neural network is an alternative powerful data modeling tool that is able to capture and represent complex input/output relationships. This study describes the application of neural networks in foreign exchange rates forecasting among major currencies USA dollar, European Currency (EURO), Great Britain Pound (GB) and Japanese Currency (Yen) against Nigerian Money (Naira). Technological indicators and true series data are fed to neural networks to capture the movement in currency exchange rates.

One of the significant contributions of this paper is our ability to propose an Artificial Neural Networks model that outperformed Hidden Markov Model. Also, we have been able to substantiate weaknesses of the existing models. The remainders of this paper are organized as follows. Section 2 will discuss related works and section 3 will discuss the proposed method. Also, section 4 gives an overview of the datasets that we have used while section 5 gives experiments that we have performed and the descriptions of the results. Section 6 gives the conclusion and future research directions of the work.

II. REVIEW OF RELATED WORKS

Different methods are used in Foreign Exchange Rates prediction. These methods are distinguishable from each other by what they hold to be constant into the future. For example, according to [3] hidden markov models are unstable to be taken in as a trading tool on foreign exchange data with too many factors influencing the results. The HMMs attempt to generate or predict an output signal given a model [4]. HMMs according to [3] does not improve results as one might have expected. The HMMs attempt to generate or predict an output signal given a model [4]. [17] investigated the stability of robustness of alternative novel Neural Network architectures when applied to the task of forecasting and trading the Euro/Dollar(EUR/USD) for exchange rate using the European Central Bank(ECB) fixing series with only auto regressive terms as inputs. Also, according to [6], Artificial neural networks (ANNs) are mathematical models simulating the learning and decision making processes of the human brain. The foreign exchange market, unlike the stock market is an over the counter market, that is built by a number of different banks. The participants of the foreign exchange market can be roughly divided into the central bank, commercial banks, non-bank financial entities, commercial companies and retail traders [3]. The central bank has a significant influence in the foreign exchange markets by virtue of their role in controlling the countries' money supply, inflation, and/or interest rates. ANNs were originally developed to model human brain function. ANNs are parameterized graphical models consisting of networks with three prime architectures: recurrent, feed-forward and layered [9]. [1] conducted a survey on the use of neural networks in business application that contains a list of works covering bankruptcy prediction. [21] focuses on portifolio optimization and short term equity forecasting. [15] mentioned the varying degree that ANN has the capability to forecast financial markets. [7] proposed a novel flexible model called neuron coefficient smooth transition auto regression (NCSTAR), an ANN to test for and model the nonlinearities in monthly exchange rates. Traditionally, statistical models such as Box-Jenkins models dominate the time series forecasting [11]. [29] suggested that the relationship between neural networks and conventional statistical approaches for time series forecasting are complementary. [24] also indicated that traditional statistical techniques for forecasting have reached their limitation in applications with nonlinearities in the data set such as stock indices. Neural Network technology has seen many application areas in business especially when the problem domain involves classification, recognition and predictions. According to a survey research conducted by [8] more than 127 neural network business applications had been published in international journals up to September, 1994. The number rose to 213 after a year. [10] said that the multilayer feed forwards are one of the most important and most popular classes of ANNs in real world applications. According to him, a multilayer perceptron has three distinctive characteristics:

- The model of each neuron in the network includes usually a non-linear activation function, sigmoids or hyperbolic.
- The network contains one or more layers of hidden neurons that are not part of the input or output of the network to learn complex and highly nonlinear tasks by extracting progressively more meaningful features from the input patterns.

The network exhibits a high degree or connectivity from one layer to the next one.

III. METHODOLOGY

The proposed forecasting of Foreign exchange rate used AFERFM with the considerations of the existing HFERFM.

A. Hidden Markov Model

The Hidden Markov Model (HMM) is a variant of a finite state machine having a set of hidden states Q, an output alphabet (observations), O, transition probabilities, A, output (emission) probabilities, B, and initial state probabilities, Π. The current state is not observable instead, each state produces an output with a certain probability (B). Usually the states, Q, and outputs, O, are understood, so an HMM is said to be a triple, (A, B, Π).

Hidden states Q = { qi; i = 1, . . . , N }.

Transition probabilities A = {aij = P(qj at t +1 | qi at t)}, where P(a | b) is the conditional probability of a given b, t = 1, . . . , T is time, and qi in Q. Informally, A is the probability that the next state is qj given that the current state is qi.

Observations (symbols) O = { ok }, k = 1, . . . , M .

Emission probabilities B = { bik = bi(ok) = P(ok | qi) }, where ok in O. Informally, B is the probability that the output is ok given that the current state is qi.

Initial state probabilities Π = {pi = P(qi at t = 1)}.

The model is characterized by the complete set of parameters: Λ = {A, B, Π}

There are 3 canonical problems to solve with HMMs:

- Given the model parameters, compute the probability of a particular output sequence. This problem is solved by the Forward and Backward algorithms.
- Given the model parameters, find the most likely sequence of (hidden) states which could have generated a given output sequence.This is solved by the Viterbi algorithm and Posterior decoding.
- Given an output sequence, find the most likely set of state transition and output probabilities solved by the Baum-Welch algorithm In this work, Baum-Welch algorithm was used.

A. Theoretical aspect of Baum-Welch Algorithm Let us define

$\xi_t(i, j)$, the joint probability of being in state q_i at time t and state q_j at time t +1 , given the model and the observed sequence:

$$\xi(i,j) = P(q(t) \\ = q, q(t+1) \\ = q_j \ |\mathrm{O}, \lambda) \tag{1}$$

Therefore we get

$$\zeta_t(i,j) = \frac{\alpha_i(i) a_{ij} b_j(o(t+1))\beta_{i+1}(j)}{P(O|\Lambda)} \tag{2}$$

The probability of output sequence can be expressed as

$$P(\mathrm{O}|\lambda) = \sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_t(\tau)a_{ij}b_j(o(t+1))\beta_{t+1}(j)$$

$$= \sum_{i=1}^{N}\alpha_t(\tau)\beta_t(\tau) \tag{3}$$

The probability of being in state q_i at time t:

$$\lambda_t(i) = \sum_{j=1}^{N}\xi_t(i,j)\frac{\alpha_t(\tau)\beta_t(\tau)}{P(\mathrm{O}|\lambda)} \tag{4}$$

Estimate

$$initial\ \ probabilities = p\gamma_i(\tau) \tag{5}$$

$$transition$$

$$probability\ \bar{a}_{ij} = \frac{\sum_{i=1}^{r-1}\zeta_t(i,j)}{\sum_{i=1}^{r-1}\gamma_t(i)} \tag{6}$$

$$emission\ probability\ \bar{b}_{jk} = \frac{\sum_{t=1}^{*} \gamma_t(j)}{\sum_{t=1}^{r} \gamma_t(j)} \quad (7)$$

Baum-Welch Algorithm

Baum-Welch Algorithm will learn the

Input: A set of observed sequence $O^1, O^2, O^3, O^4, \ldots$

Initialization: select arbitrary model parameters

$$\lambda' = a_{ij}, e_i() \ ; \ data = \sum_d P(O^d \setminus \lambda')$$

repeat

{ $\lambda = \lambda'$, $S = S'$

for each sequence, O^d

{

calculate $\alpha(t,i)$ for O^d using forward algorithm

calculate $\beta(t,i)$ for O^d using backward algorithm

calculate the contribution of O^d to A using

$$A_{ij} = \sum_d \frac{1}{p(O^d)} \sum_t \alpha(t,i) a_{ij} \ e_i(O^d_{t+1}) \beta(t+1,i)$$

calculate the contribution of σ^d to E using

$$E_i(\sigma) = \sum_d \frac{1}{P(\sigma^d)} \sum_{\{t \setminus O^d_t = \sigma\}} \sigma(t,i) \beta(t,i)$$

}

$$a_{ij} = \frac{A_{ij}}{\sum_i A_{ij}} \ ; \quad e_i(\sigma) = \frac{E_i(\sigma)}{\sum_r E_i(r)}$$

$$data = \sum_d P(O^d / d_{ij}, e_i())$$

}

until the change in data is less than some predefined threshold

Figure 1: Baum-Welch Algorithm

parameters from the data and implicitly discovers the motif. We use Viterbi algorithm to determine the motif for the states of each input data. The algorithm is depicted in fig. 1. While this method may require significantly more effort due to the amount of data needed, it may result in a more accurate projection if the data is accurate, hence the use of AFERFM

IV. BACK PROPAGATION ALGORITHM OF ARTIFICIAL NEURAL NETWORK

Training basically involves feeding training samples as input vectors through a neural network, calculating the error of the output layer, and then adjusting the weights of the network to minimize the error. Each "training epoch" involves one exposure of the network to a training sample from the training set, and adjustment of each of the weights of the network one layer by layer.

The back propagation algorithm has emerged as one of the most used learning procedures for multilayer networks as shown in fig. 2. They have been shown to have great potentials for financial forecasting. The process of determining the magnitude of the weight factors that result in accurate output is called training. Several methods are available to accomplish this but the back propagation algorithm method is the most commonly used. The method according to [14] is based on the determining the error between the predicted output variables and the known values of the training data set. The error parameter is commonly defined as the root mean square of the errors for all the processes take the form of determining the partial derivatives of the errors with respect to each of the weights. The algorithm used to propagate the error correction back into the network according to [14] is generally of the form:

$$w_{ij}new - w_{ij}old = \frac{\partial E}{-\Delta \partial w_{ij}} \quad (8)$$

Where E is the error parameter, Δ is the proportional factor called the learning rate.

The process of adjusting weights is continued until the error is less than some desired limit after which the network is considered trained. Once the network is trained, it can receive new input data that were not used for training and apply the weight factors obtained during training [23]. Input vectors are applied to the network and calculated gradients at each training sample are added to determine the change in weights and biases. Traingdx function is used for the training of the network. The network is created using newff. The newff creates feed-forward back-propagation network. The connection of the input to hidden layer, then the first hidden layer to output layer is automatically achieved when newff function is called. And as each layer has its own transfer function, the newff provides a means of specifying the transfer function of the layers in its syntax. Selection of training samples from the training set involved going through each training sample in order. The network performance was assessed using “outside" samples which make up the "validation" set. Test was done using samples outside the training set which enable us to confirm that the network is also capable of classifying.

V. DATA COLLECTION

A currency exchange rate usually consists of two numbers, the bid and the ask price. For simplicity, exchange rate was considered as a single number. The data used is constituted of the daily averages and was downloaded from http://www.oanada.com website. The size of data set amounts to approximately 800 daily price quotes from the years 2003-2005 for each currency in which 500 daily data for training, 200 daily data for validation and 100 daily data for testing as shown in table 1. The first 500 daily data are used as inputs to the neural network. The first 500 daily data are fed to the neural networks to predict the following 100 daily's rate after training and validation. Sigmoid Activation Function (SAF) was used to transform the input into a standard range [0, 1]. The equation and the graph are depicted in fig. 3.

TABLE I. DISTRIBUTION OF SAMPLE DATA

Types of data sets	Size of data sets
Train data	500
Validation data	200
Test data	100
Total	800

1. Create a feed-forward network ni inputs, nh hidden units, and no output units.
2. Initialize all weights to small random values (e.g. between -0.1 and 0.1)
3. Until termination condition is met, do
4. For each training sample vector(x, t) do
5. Compute the output ou for every unit of x
6. For each output unit k, calculate
   δk=0k(1-0k)(tk-0k)
7. For each hidden unit h,calculate
   δh=0h(1-0h)∑ δkwkh where
   k∈ downstream(h)
8. Update each network weight wji as follows:
   wji←wji+Δwji where Δwji =ηδjxji

Figure 2: Back propagation algorithm

$$P(t) = \frac{1}{1+e^{-t}}.$$

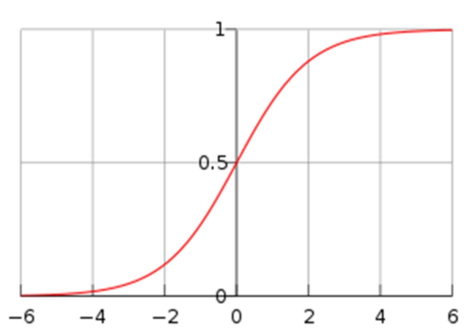

Figure 3: Sigmoid Activation Function (SAF)

VI. IMPLEMENTATION AND RESULTS

The algorithm of back propagation for AFERFM described in figure 2 and Baum-Welch Algorithm in figure 1 were developed on visual studio and MATLAB 7.6. Each training sample is of the form (x, t) where x is the input vector and t is the target vector and η is the learning rate. The parameters of ni, nh and no are the number of input, hidden and output nodes respectively. The input i to unit j is denoted xij and its weight by wij. Data collected from oanda website served as input to both models. The results of the training of both models in Nigerian Money (Naira) as against USA dollars, Europeans Money (EURO), Great Britain Pound (GBP) and Japanese money (Yen) are illustrated in table 2 to 5. Looking at table 2 to 5, the values of both AFERFM and HFERFM for USA dollar, EURO, GBP and Japanese Yen are very close as against Nigerian currency (Naira). From the results of table 2 to 5, AFERFM and HFERFM accuracy forecast were computed together with mean square error (MSE) and standard deviation (SDEV) as follows:

AFERFM accuracy

$$forecast = \frac{\sigma(pv)-\sigma(av)}{\sigma(av)}*100 \qquad (9)$$

HFERFM accuracy

$$forecast = \frac{\sigma(pv)-\sigma(av)}{\sigma(av)}*100 \qquad (10)$$

Where standard deviation is

$$\sigma = \sqrt{E(X-\mu)^2}$$

and Mean square error is

$$MSE = \frac{(\sum FE)}{N-1}$$

and FE is forecast error and was calculated as different between actual value and predicted value. The task is to have minimal value of MSE. The results of MSE , SDEV and percentage accuracy of both models for one day, one year, five years and 10 years are depicted in table 6 to 9. Looking at the table 6 to 9, The MSE and SDEV of HFERFM for USA dollar, EURO, GBP and Yen as against Naira are close to 1 compared with the values of AFERFM. This indicates the weakness of HFERFM values for prediction. For all the tests 1 to 4, the values of percentage accuracies of AFERFM are higher than HFERFM. This is evidence that AFERFM is better than HFERFM for prediction.

The forecasting of foreign exchange rate into distance future using both models is illustrated in fig. 4 to 7. Looking at these fig. 4, 5 and 6 except fig. 7, they produced various magnitudes of foreign exchange rates forecasting where each of them could be compared together with actual values. They also showed the highest magnitudes levels of uncertainty and non-statonary nature of currencies to AFERFM and HFERFM. As indicated in the figures, the rate of magnitude level of AFERFM is certain and stationary compared with the HFERFM.

VII. CONCLUSION AND FUTURE WORK

From the various tests performed on the results of the train and validation, it was confirmed that AFERFM performs better in estimating the foreign exchange rates. The percentage accuracies are good evidences of the fact that given enough data at its disposal, the AFERFM can ensure foreign exchange rate. It can also be observed that when the performance of AFERFM is compared with the HFERFM of Foreign Exchange Rates projection, the formal performs better than the latter. The best known related work, Hidden Markov Model, HFERFM showed an accuracy of 69.9%. The evaluation results showed that AFERFM had an accuracy of 81.2%. This shows that the new approach provides an improved technique for carrying out foreign exchange rates forecasting. The scope of the work had been on the Nigerian foreign Exchange Rates as against four currencies, an improvement of the work can be made by extending the work to other country foreign exchange rates.. The research work can also be improved by developing an analytical model using artificial neural network with other model or any suitable analytical method.

TABLE II. NAIRA AS AGAINST USA DOLLARS

S/n	Actual	AFERFM	HFERFM
1	129.63	129.61	130.06
2	129.63	129.61	130.06
3	133.17	133.20	132.74
4	133.62	133.65	133.07
5	133.89	133.92	133.28
.	.	.	.
.	.	.	.
.	.	.	.
65	129.63	129.61	130.06
66	129.63	129.61	130.06
67	134.04	134.11	133.45
68	133.83	133.86	133.23
69	129.63	129.61	130.06
70	133.83	133.86	133.23
.	.	.	.
.	.	.	.
97	129.63	129.61	130.06
98	129.63	129.61	130.06
99	134.90	134.93	134.25
100	134.93	134.96	134.29

TABLE III. NAIRA AS AGAINST EURO

S/n	Actual	AFERFM	HFERFM
1	154.37	154.38	154.37
2	152.74	152.76	152.74
3	152.65	152.67	152.65
4	151.90	151.92	151.90
5	156.51	156.53	156.54
.	.	.	.
.	.	.	.
.	.	.	.
65	156.81	156.81	156.81
66	155.64	155.64	155.64
67	158.51	158.49	158.51
68	151.68	151.73	151.69
69	151.68	151.73	151.68
70	151.70	151.73	151.70
.	.	.	.
.	.	.	.
97	151.86	151.89	151.86
98	156.53	156.53	156.53
99	157.35	157.34	157.35
100	158.14	158.11	158.14

TABLE IV. NAIRA AS AGAINST GBP

S/n	Actual	AFERFM	HFERFM
1	206.78	206.76	206.78
2	206.78	206.76	206.78
3	213.15	206.75	206.78
4	213.21	212.33	212.43
5	213.58	213.13	213.15
.	.	.	.
.	.	.	.
.	.	.	.
65	206.78	205.21	213,21
66	206.78	205.58	213.21
67	206.78	205.78	213.58
68	213.85	206.78	206.78
69	213.48	206.68	206.78
70	214.23	206.68	206.78
.	.	.	.
.	.	.	.
97	214.54	206.69	206.74
98	206.78	213.46	213.49
99	206.78	214.13	214.25
100	206.78	206.76	206.78

TABLE V. NAIRA AS AGAINST JAPANESE YEN

S/n	Actual	AFERFM	HFERFM
1	1.099	1.099	1.099
2	1.086	1.086	1.086
3	1.086	1.086	1.086
4	1.084	1.083	1.084
5	1.123	1.123	1.123
.	.	.	.
.	.	.	.
.	.	.	.
65	1.124	1.125	1.124
66	1.121	1.121	1.121
67	1.137	1.137	1.137
68	1.092	1.092	1.092
69	1.092	1.092	1.092
70	1.092	1.091	1.091
.	.	.	.
.	.	.	.
97	1.092	1.096	1.096
98	1.138	1.138	1.138
99	1.136	1.136	1.136
100	1.141	1.141	1.141

TABLE VI. PERCENTAGE ACCURACY OF THE AFERFM AND HFERFM FOR USA DOLLARS AGAINST NIGERIAN CURRENCY (NAIRA)

M	T	days	ME	S	%
H	1	1	0.99	0.99	68
A	1	1	0.25	0.26	80
H	2	365	0.97	0.97	69
A	2	365	0.25	0.24	81
H	3	1825	0.98	0.98	68
A	3	1825	0.25	0.25	80
H	4	3650	0.99	0.99	67
A	4	3650	0.25	0.25	79

Where H = HFERFM, A=AFERFM, T= Test, ME= MSE, S= SDEV, M=Model , % = percentage accuracy

TABLE VII. PERCENTAGE ACCURACY OF THE AFERFM AND HFERFM FOR EURO AGAINST NIGERIAN CURRENCY (NAIRA)

M	T	Days	ME	S	%
H	1	1	0.99	0.99	67
A	1	1	0.25	0.25	80
H	2	365	0.99	0.99	68
A	2	365	0.25	0.25	80
H	3	1825	0.99	0.99	68
A	3	1825	0.25	0.25	80
H	4	3650	0.99	0.99	65
A	4	3650	0.25	0.25	79

where H = HFERFM, A=AFERFM, T= Test, ME= MSE, S= SDEV, M=Model, % = percentage accuracy

TABLE VIII. TABLE 8: PERCENTAGE ACCURACY OF THE AFERFM AND HFERFM FOR GREAT BRITIAN POUNDS AGAINST NIGERIAN CURRENCY (NAIRA)

M	T	Days	ME	S	%
H	1	1	0.99	0.99	68
A	1	1	0.25	0.26	80
H	2	365	0.99	0.99	68
A	2	365	0.25	0.26	80
H	3	1825	0.99	0.99	68
A	3	1825	0.25	0.26	80
H	4	3650	0.99	0.99	66
A	4	3650	0.25	0.26	80

where H = HFERFM, A=AFERFM, T= Test, ME= MSE, S= SDEV, M=Model, % = percentage accuracy

TABLE IX. PERCENTAGE ACCURACY OF THE AFERFM AND HFERFM FOR JAPANESE YEN AGAINST NIGERIAN CURRENCY (NAIRA)

M	T	Days	ME	S	%
H	1	1	0.99	0.99	66
A	1	1	0.25	0.26	80
H	2	365	0.99	0.99	68
A	2	365	0.25	0.26	80
H	3	1825	0.99	0.99	66
A	3	1825	0.25	0.26	80
H	4	3650	0.99	0.99	66
A	4	3650	0.25	0.26	80

where H = HFERFM, A=AFERFM, T= Test, ME= MSE, S= SDEV, M=Model, % = percentage accuracy

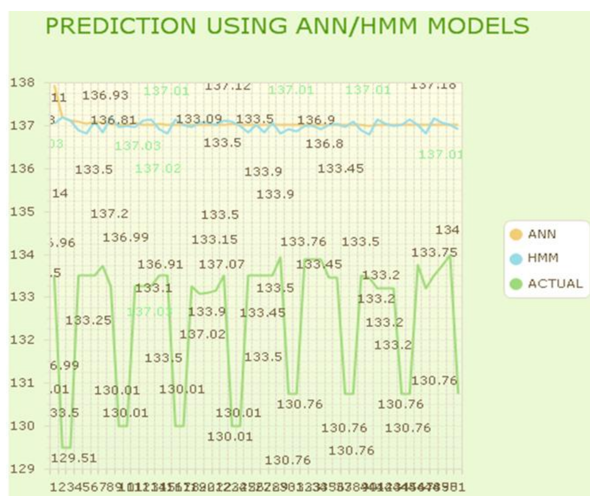

Figure 4: Forecasting Exchange Rate for USA dollars against Nigerian Currency (Naira)

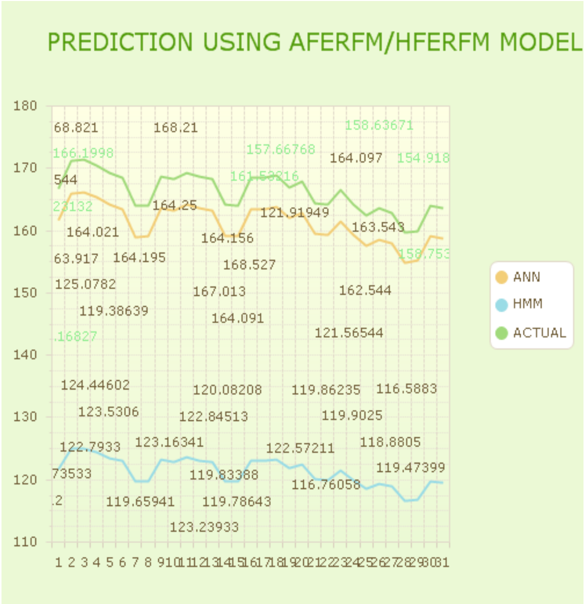

Figure 5: Forecasting Exchange Rate for EURO against Nigeria Currency (Naira)

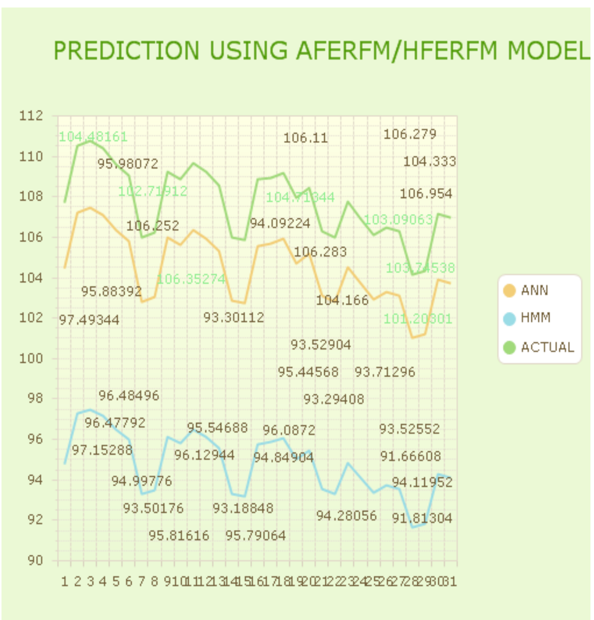

Figure 6: Forecasting Exchange Rate for Great Britain Pound against Nigeria Currency (Naira)

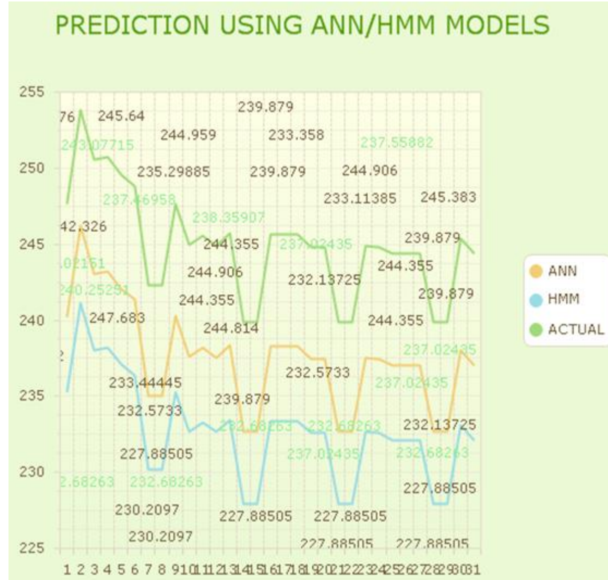

Figure 7: Forecasting Exchange Rate for Japanese Yen against Nigeria Currency (Naira)

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