# Currency Exchange Forecasting Using Sample Mean Estimator and Multiple Linear Regression Machine Learning Models

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**Abstract--** In recent time, there is an increasing growth in the amount of trading taking place in the currency exchange market. However, effective analysis and simulation tools for performing accurate prediction of these exchange rates are lacking. To alleviate this challenge, this work presents a hybrid machine learning and prediction model by suitably combining the Sample Mean Estimator (SME) simulation architecture with the multiple linear regression technique-based training of feed-forward parameters. The developed model has the capability to overcome prediction inaccuracy, inconsistent forecasting, slow response due to computational complexity and scalability problems. The SME method is used to overcome the problems of uncertainty and non-linearity nature of the predictive variable as it's always affected by economic and political factors. The implementation of the proposed currency exchange rate forecasting system is achieved through the use of a developed in-house Java program with Net Beans as the editor and compiler. Performance comparison between the present system and two baseline methods which are the Autoregressive Moving Average and the Deep Belief network techniques demonstrates that the present forecasting model out-performed the baseline methods studied. The experimental result shows that the precision rate of the present system is equal to or greater than 70%. Therefore, the present foreign exchange predictive system is capable of providing usable, consistent, efficient, faster and accurate prediction to the users consistently at any-time.

**Keywords:** currency exchange, feed-forward. Forecasting, Sample Mean Estimator, multiple linear regressions, prediction

## 1 INTRODUCTION

Expressing the price of one currency in term of another currency for the purpose of hedging against potential losses, arranging short and long term funds, performing investment analysis, and to assess earnings of a foreign subsidiary are critical task for the currency exchange market operators. Many entities such as a business owner, a trader, a currency exchange market operator (Bureau de Change) etc. are all having interest in being able to forecast the direction of exchange rates in order to guide their decision-making process so as to minimize risk and maximize returns on their investments.

However, the exchange rates among countries of the world are usually affected by a number of factors such as inflation rate, growth prospects, government policies, economic policies, etc. These factors are difficult to predict in advance, therefore makes future exchange rate prediction to become uncertain. Available published literature shows that numerous methods of forecasting exchange rate have been proposed by various scholars on exchange rate prediction but none of them have been shown to be superior to the other (Han and Kamber, 2006; Sewell and Shawe, 2012; Shen,Chao and Zhao, 2015; Olaniyan, Ojukwu and Ogude, 2019; Omolewa, *et.al.* 2021). The general problems confronted with in many existing exchange rate predictive systems includes: prediction inaccuracy, inconsistent forecasting, slow response due to computational complexity and scalability problems.

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**Section B-** ELECTRICAL/COMPUTER ENGINEERING & COMPUTING SCIENCES
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This work presents the design and realization of an automated currency exchange forecasting based on Sample Mean Estimator and Multiple Linear Regression Machine Learning (SME-MLRML) algorithms. This is aimed at presenting an accurate, consistent, fast and scalable exchange forecasting system to the users. This work is designed to cover a wide range of features; three of these are highlighted as follows.

First, this study presents the design and development of a new and novel foreign exchange prediction algorithm for exchange rate forecasting system. Specifically, effort was made to improve the performance of the exchange rate forecasting system through the introduction of multiple linear regression machine learning algorithm. This developed model can be used to perform currency exchange related operations in the future. The developed regression model is able to overcome computational inaccuracy problem, reduce response time and speed up execution. Second, the study showcases the development of a novel simulation method called Sample Mean Estimator (SME) simulation technique. This method was used at the preliminary stage of the forecasting system to simulate the values of the independent variables for the proposed predictive model for the forecasting system. The Sample Mean Estimator (SME) simulation method is capable of overcoming the problem of uncertainty and non-linearity nature of the predictive variables since it's always affected by political and economic factors which are probabilistic and always difficult to predict.

Finally, this work as well presents the implementation of the proposed currency exchange rate forecasting system using a developed in-house Java program with NetBeans as the editor and compiler. To demonstrate the superiority of the developed system over the existing currency exchange forecasting systems, performance comparison between the proposed system and two baseline methods which are the Autoregressive Moving

Average and the Deep Belief network techniques was carried out. The result demonstrates that the present forecasting model out-performed the baseline methods studied. A systematic presentation of the experimental result was carried out and the entire system will be implemented online and in real-time basis.

## 2 RELATED WORK

This section presents a review of related work considered relevant to Currency Exchange Forecasting and machine leaning techniques. In finance, an exchange rate between two currencies is the rate at which one currency will be exchanged for another. It is also viewed as the value of one country's currency in terms of another counter's currency. Foreign exchange market determines the exchange rate and open to different types of buyers and sellers, and the currency trading is continuous, 24 hours a day except weekends (Latife, 2014).

Many economists proposed different theories to explain the movement of exchange rate in different foreign currencies. Among the first group was to explore the capacity of ARIMA (Auto-Regressive Integrated Moving Average), series to predict future exchange rate level, Bellgard and Goldschmidt (1999), investigated (AUD/USD) exchange rate using half hourly data during 1996. Their result show that statistical forecasting precision measures do not impact directly on profitability and foreign exchange time series show nonlinear patterns that are better explained by Neural Network models.

Andrew (2003) observed how exchange rate fluctuation plays a role in determining economic policy. Their result show that whenever there is short fall in the supply of foreign currency, the rate of import will drop and export will rise, thereby stabilizing the economy. The weakness of the proposed method is that they failed to explain the variables to be considered by the government in order to decide whether to increase or decrease the supply of foreign currency. Sewell and Shawe (2012) conducted a research to employ kernel methods to forecast exchange rate with the aim of beating the market existing standard methodology and any other existing state of the art method. Shen, Chao and Zhao (2015) proposed an improved Deep belief Network (DBN) solution for forecasting exchange rate. The result shows that DBN is a superior predictive accuracy with higher stability. The proposed DBN is only limited to weekly exchange rate data in their study. Our approach contrasts with both the DBN and the Kernel methods because their limitations are better addressed in our model.

Several authors have proposed a number of methods for simulating real life data using different methods (Akinyemi, et.al. 2019; Ayogu, Adetunmbi and Ayogu 2019; Jimoh, Ajayi and Ogundoyin 2020; Aliyu, et.al. 2020). Beltrametti *et al.* (1997) proposed a study on learning and forecasting on the foreign exchange market by means of an Artificial intelligence methodology which simulated learning and adaptation in complex and changing environment on two different exchange rates. The result obtained show that the system was able to classify the external states that evolved through time into patterns that when recognized triggered appropriate action. The researcher proposed system is limited to the nature of agents learning mechanism and how the agent can identify the phenomena that are relevant to the learning process. In this research work, the proposed system SME-MLRML, in addition to accurate and consistent prediction, overcomes the limitation of their model.

Machine learning is usually exploited as a tool for analysing data coming from experimental studies, but recently it has been applied to humans as if they were algorithms that learn from data. Madura and Fox (2007) proposed a random walk model that will be market-based forecasting technique of developing forecasts from market indicators. The result shows that anything that could happen in the future which influence exchange rates is only random or stochastic. The limitation of the proposed model is the neglect of the historical and the fundamental impact of the variables on the currency values which can as well ruin the prediction. Joseph (2011), experimented on exchange rate prediction and implementation of algorithm in the field of financial hedging. The author's experiment report includes standard exchange rate prediction task, and a real-data based simulation analysis of financial flow of internationally active real market data was performed. The limitation of their research is that the method cannot employ the use of semi-randomized selection strategy. This research work proposed sample mean estimator simulation method, in addition to overcoming the limitation, ensures prediction accuracy, consistent forecasting and quick response in spite of computational complexities.

Appiah and Adekunle (2011), observed a depreciating trend of the Ghana's cedi and the US dollar using Time series analysis. The result obtained shows that the predicted rates were consistent with the depreciating trends of the observed series and ARIMA was found to be the best model to such series. However, their proposed model does not reflect the actual economic reality for both countries. The author's proposed SME-MLRML model will outperform the ARIMA model and tackle other predicting challenges by the ARIMA model. Talebi, Hoang and Gavrilova. (2014), adopted a multi-scale feature extraction approach which was used for training multiple classifiers for each trend and Bayesian voting was used to find the ensemble of classifiers for each trend. The result obtained show superiority of ensemble classifiers over individual ones. The weakness of the system is that it cannot analyse the performance of other ensemble methods to combine the results of classifiers and can be improved upon to extract more features from foreign exchange rate. The author's present SME-MLRML model has the capability to overcome prediction inaccuracy, inconsistent forecasting, and slow response due to computational complexity and scalability problems.

Vahdat *et al.* (2015), conducted a research to explore the learning process of humans with the machine learning by using the cognitive science and machine learning methods. The outcome show that Human algorithmic Stability (HAS) can be measured without assumptions as



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Human Rademacher Complexity (HRC) and can be exploited for better understanding of human learning process. The short coming of the method is that it cannot be integrated into instructional design in classrooms to improve education which requires further research. The SME method learns from the simulated sample mean which is feed forward to forecast the next year's exchange rate forecast.

## 3 Methodology

This section described the detailed methodology for the realization of the currency exchange forecasting system and the application of the proposed Sample Mean Estimator (SME) Multiple linear regression models for the analysis of the predictive variables in order to arrive at a viable response variable forecast. In every research, the methods and procedures adopted are critical to achieving the desired objectives.

### 3.1 The Overall Architecture of the Entire Forecasting System

The present forecasting system implementation consists of several layers. On top of these layers is the **browser** running on the desktops and mobile devices which a user uses to access the forecasting application hosted on the internet. The extracted/collected data about exchange rates and economic indices data, from the source are cleansed and formatted into a computer readable form (pre-processing) then stores into the forecasting database. The end-user/client makes request for foreign exchange forecast through the internet. The system retrieves the predictor variables from the forecasting database, then performs simulation of the current year's predictive variables using the Sample Mean Estimator (SME) algorithm and send information to the model building layer.

Then a model is built for the currency forecasting system using SME-MLRML technique, exchange rate prediction is performed and forecasting is done online and on real time bases. The system also carries out system testing and evaluation. If the solution or the forecasting procedure is verified as accurate, the system performs memory update by adding the new sets of simulated variables to the database for reuse, that is, feed forward the variables, otherwise, it discards the new sets solution. The overall architecture of the entire system is shown in Figure 1.

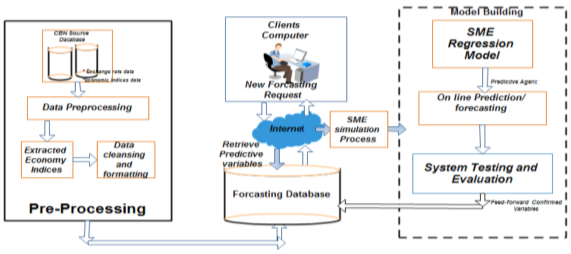


Fig. 1: The overall architecture of the entire forecasting system

### 3.2 Data Collection

The data used herein were collected from the Central Bank of Nigeria (CBN) for a period of 33 years; from 1981 through 2013 (CBN, 2015). The data consists of economic indices such as interest rate, inflation rate, Gross Domestic Product GDP, etc.

### 3.3. Simulation Of Predictive Variable for the Currency Exchange Forecasting Using Sample Mean Estimator Technique

The simulation techniques are widely used in statistics and methodological research work across the globe. This present work adopts the sample mean estimator techniques.

#### 3.3.1 The Sample Mean Estimator Simulation Technique

The sample mean estimator techniques calculates the mean of the sample statistics using the expression:

$$X_i = \begin{cases} 0 & if\ K_{ij} = 0 \\ \frac{\sum_{i=1}^{k} x_{ij}}{k} & if K_{ij} > 0 \end{cases} \quad (1)$$

Where K is the sample size, that is k=1,2,..., n, I = 1,2, …………..m, j= 1,2, ………………

$X_i$ is the mean estimate of the given population that is, the arithmetic average of the given predictive variable.

Algorithm Listing 1: The Algorithm for the Sample Mean Estimator Simulation Model for Predictive Variables.

1. Let $k$ be the sample size of each of the given predictive variables
2. Let $m$ be the number of predictive variable ($x_1$,$x_2$, ………….., $x_m$)
3. Let $k_{1j}$ be the value of variable $x_1$as it occurs in sample $x_j$
4. Begin
5. Input $k$ of unknown sample
6. input $m$ of unknown variable
7. Let $i = 1$:  $Let\ J = 1$
8. Do while not (end of length of sample($k$))
9. For $J = 1\ to\ m$
10. For $i = 1\ to\ 5$
11. If($k_{ij} = 0$) Then
12. $X_i = 0$
13. Else
14. $Sum_{i,j} = Sum_{i,j} + x_{ij}$
15. $End\ if$
16. $i = i + 1$
17. $X_i = Sum_{i,j}/k$
18. End for $i$
19. $J = J + 1$
20. End for $J$; End do; End

#### 3.3.2 Application of the Sample Mean Estimator Simulation Model

In this experiment, given a set of predictive variables for inflation rate % ($x_1$), interest rate % ($x_2$), GDP ($x_3$), Speculation ($x_4$) and change in competitiveness as ($x_5$) with data sets between the year 2000 and 2013 as presented in figure 2 using the proposed sample mean estimate simulation technique. At this point values of these variables for the year 2014 will be simulated using values of sample from previous years data, that is, 2000 to 2013 using equation 1.



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Table 1. Sample Data from Inflation Values between Year 2000 and 2013

| Year | 2000 | 2001 | 2002 | 2003 | 2004 | 2005 | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Inflation Rate % | 10.2 | 10.5 | 10.8 | 12.3 | 15 | 14 | 17.9 | 8 | 5.5 | 12 | 12.6 | 13.5 | 10.9 | 11.9 |

Using sample data from inflation rate values between year 2000 and 2013 as shown in the Table 1; because, the data is time dependent, we can build a time series representation for each variable using time as the proposed sample mean estimation techniques and use same for prediction using the Regression analysis model by adopting equation 1, we have:

$X_1$ (Inflation rate for 2014) =

$$= \frac{10.2 + 10.5 + 10.8 + 12.3 + 15.0 + 14.0 + 17.9 + 8.0 + 5.5 + 12.0 + 12.6 + 13.5 + 10.9 + 11.9}{14}$$

$$= \frac{165.1}{14} \;;\; x_1 = 11.79$$

Repeating the same process for other predictive variables, that is $x_2$ (interest rate), $x_3$, (GDP), $x_4$ (speculation) and $x_5$ (change in competitiveness). So we have $x_1 = 11.79$, $x_2 = 18.85$, $x_3 = 21427.7$, $x_4 = 1591.64$, $x_5 = 3074.19$ for 2014. We can now apply these values to predict the Naira/Dollar exchange rate for the year 2014.

### 3.4. The Working of the Multiple Linear Regression Technique

A simple or straight-line regression analysis involves a response variable, Y and a single predictor variable, x where Y is a linear function of x.

$$Y = b + \beta x + \in_i \qquad (2)$$

The error term ei≅ N(o,6²), that is, the error term in the regression equation which may be simple or multiple is distributed normally with mean zero (o) and variance 6², where b is the intercept or constant in the regression equation, and $\beta$is the slope parameter which gives weight to the predictor variable.

$$Y = b + \beta x, \qquad (3)$$

Equation (3) can be written as:

$$Y = \alpha + \beta x, \text{ where } \alpha \text{ is the intercept} \qquad (4)$$

The regression coefficient in equation (4) can be estimated using the least square method.

$$\beta_i = \frac{\sum_{i=1}^{|D|}(x_i - \bar{x})(Y_i - \bar{Y})}{\sum_{i=1}^{|D|}(x_i - \bar{x})^2} \qquad (5)$$

Where: $x_i$, $Y_i$) is the training tuple I with associated Class label $Y_i$, X is a variable vector

D is a training set consisting of values of predictor variable, x for some population and their associated value for response variable Y

|D|: is the training set containing data point of the form ($x_1$, $y_1$), ($x_2$, $y_2$) - - - $x_{(D)}$, $y_{(D)}$). and:

$$\alpha = Y - \beta_1 x \qquad (6)$$

Where $\bar{x}$: is the mean value of $x_1$, $x_2$, $x_3$, - - - - $x_{(D)}$, and

$\bar{Y}$: is the mean value of $y_1$, $y_2$ - - - $y_{(D)}$

Multiple linear regression is an extension of straight-line regression that allows us to use more than one predictor variable. It allows response variable Y to be modelled as a linear function of n predictor variables, such as $A_1$, $A_2$, $A_n$ describing an attribute x, where x = ($x_1$, $x_2$ - - - - $x_n$), so the training data set D, contains data of the form ($x_1$, $y_1$), ($x_2$, $y_2$) - - - - ($x_{(D)}$,$y_{(D)}$), where $x_i$ are the n – dimensional training tuples with associate class labels $Y_i$.

For instance, a multiple linear regression model with n predictor variables $A_1$, $A_2$, $A_3$, $A_4$, - $A_n$ can be represented with equation 7:

$$Y = \alpha + \beta_1 x_1 + \beta_2 x_2 + - - - + \beta_n x_n \qquad (7)$$

Where $x_1$, $x_2$ - - - - $x_n$ are the values of attribute $A_1$, $A_2$, $A_3$, $A_4$, - $A_n$, respectively, in X

The least square method shown in equation 5 and 6 can be extended to solve for $\alpha$,$\beta_1$, $\beta_2$, - - - - $\beta_n$. The process of building multiple regression models with some predictors was employed for this particular study. Hence, from equation 7 the population regression model is applied as follows:

$$Y_i = \alpha + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i}$$

Where:

$Y_i$ =Exchange Rate, $\alpha$ =Population regression constant
$\beta_1$ = Population regression coefficient for inflation rate,
$\beta_2$ = Population regression coefficient for interest rate
$\beta_3$ = Population regression coefficient for economic growth (GDP), $\beta_4$ = Population regression coefficient for speculations, $\beta_5$ = Population regression coefficient for change of competitiveness

The parameters are obtained through the solutions of the systems of equations called the normal equations. Alternatively, the matrix approach could be used to obtain the parameters in a more simplified way, hence, the coefficient matrix and the vector of constants can be obtained respectively.

However, the equation 7 can become unreasonably long with more predictor variable, so the computation becomes tedious to solve by hand and consequently becomes error prone. Instead, statistical software packages such as SPSS, S-plus, SAS are always used to solve multiple regression problems. Automated solution will be employed herein and the bulk of the calculations will be done using the proposed Java program. Below is the algorithm for the Regression Machine Learning model. (Han and Kamber, 2006).

Algorithm Listing 2: Algorithm for the Regression Machine Learning Model (Han and Kamber, 2006)

1. Let $X_i$ be an input predictive variable with values ($x_{i1}$, $x_{i2}$, … ………, $x_{in}$)
2. Let $Y_i$ be the observed values of the forecast variable ($Y_i$ depends on fixed predictive variable values ($x_{i1}$, $x_{i2}$, $x_{i3}$, ………, $x_{in}$))
3. Let K= 1≤K≤ n
4. Let $Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + - - - + \beta_n x_n$, i= 1, 2, 3…., n (n is the number of observations)
5. Let $\beta_0$, $\beta_1,\beta_2$ , - - - , $\beta_n$ be the unknown model parameters. Using the least square method to provide estimates of the unknown model parameters $\beta_0$, $\beta_1,\beta_2$ , - - - , $\beta_n$ which minimizes Q
6. Min Q=SSE= $\sum_{i=1}^{n} e_i{}^2$
7. Total sum of square (SST) = $\sum(Yi - \bar{Y})^2$
8. Regression sum of Square (SSR) = SST-SSE
9. Transform the Y= $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + - - - + \beta_n x_n$, to matrix notation $Y = \begin{pmatrix} Y1 \\ Y2 \\ . \\ . \\ Yn \end{pmatrix}, y = \begin{pmatrix} y1 \\ y2 \\ . \\ . \\ Yn \end{pmatrix}, E = \begin{pmatrix} E1 \\ E2 \\ . \\ . \\ En \end{pmatrix}$

Let $Y_i$= $\begin{bmatrix} \beta_0 & x_{i1} & x_{i2} \cdots x_{in} \\ \beta_1 & x_{2i} & x_{22} \cdots x_{2n} \\ \vdots & \vdots & \vdots \; \vdots \; \vdots \\ \beta_n & x_{k1} & x_{k2} \cdots x_{kn} \end{bmatrix}$

Let $\hat{\boldsymbol{\beta}} = \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_o \\ \hat{\beta} \\ \hat{\beta}_n \end{pmatrix}$

10. $\beta$ → the (n+1)x1 vector of unknown parameters
11. Least square estimates
12. Let the formula $Y_i$= $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + - - - + \beta_n x_n$ becomes Y= $X\beta$ + e
13. Solve the equation with respect to $\beta$, we have $\hat{\beta}$= $(X'X)^{-1}\langle X'Y\rangle$
14. If the inverse of $(X'X)(X'Y)$ exist then,
15. Get the value of $\beta$
16. End If
17. Do until (end of forecast)
18. Simulate the values of predictive variables $x_1$, $x_2$, $x_3$, …, $x_n$ for the subsequent year using steps in the algorithm in sample mean estimator.
19. Forecast the exchange rate for subsequent year using the equation $Y_i$= $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + - - - + \beta_n x_n$
20. To forecast the exchange rate for next fiscal year, feed forward the output of the previous year as part of sets of data for the forecast
21. End do Until;
22. End.

The algorithm listing 2, is used to derive the forecasting equation $Y_i$= $\beta_0 + \beta_1 x_1 + \beta_2 x_2 + - - - + \beta_n x_n$ which is applied in section 3.5 to forecast Naira to dollars exchange rate after generating the predictive variables $X_1$,$X_2$,$X_3$..$X_5$ using SME technique.

### 3.5 Application of the Currency Forecasting Using Sample Mean Estimator Multiple Linear Regression Model To Forecast Naira/Dollars Exchange Rate Using our Sample Data

In this experiment, the data tuples are restricted to thirty-three (33) years period between 1981 and 2013 and are described by the five (5) predictor variables.

- Inflation rate % ($x_1$), - Interest rate % ($x_2$)
- GDP (₦) % ($x_3$), - Speculation % ($x_4$) and
- Change in Competitiveness ($x_5$)

The response variable given as "Naira/Dollars" exchange rate (Y). Assuming the exchange rate for year 2014 is unknown. To determine or forecast the exchange rate for year 2014, we have to compute $\partial,\beta_1$, $\beta_2$, $\beta_3$, $\beta_4$ and$\beta_5$, using equations 5 and 6 then the value of Y using equation 7.

Before computing the exchange rate for the year 2014, the values of the predictive variables $x_1$, $x_2$,$x_3$,$x_4$,$x_5$ for the year 2014 have to be simulated using equation 1, in the developed Sample Mean Estimate Simulation Model discussed in Section 3.3. The exchange rate data collected for a ten (10) years period between the years 2004 to 2013 will be applied. Therefore, we have:

$$\frac{\sum_{i=1}^{k} X_{ij}}{k} = \frac{121.3}{10} = 12.13$$

Repeating the same process for $X_2$,$X_3$, $X_4$,$X_5$, gives

$X_2$ = 18.11, $X_3$= 26867.0, $X_4$ = 2223.47, ,$X_5$ = 3608.54,

Therefore: Exchange rate ($\hat{Y}$) for 2014

=418.335+(3.224*12.131) + (-13.853*18.11) + (0.003*26867) + (-0.004*2223.47) + (-0.029*3608.54)= 173.627 *(Naira to 1 US Dollar)*

The model is capable of predicting the annual average exchange rate for any given period. To predict the exchange rate for subsequent year, the system will adapt the output from the previous forecast to serve as input to the process of prediction for subsequent year. The inputs are combined in exactly the same way. This process shall be repeated for predicting exchange rate for a period of ten (10) years between the years 2014 to 2023.

**Notes:** (1) The predictive variables $X_1$ to $X_5$ for the forecast period is generated using the proposed Sample Mean Estimate Simulation Model described in section 3.3.
(2) The same technique described above can be applied to any other world currency against US Dollars such as Chinese yuan, European Euros, Japanese Yan, etc., provided we have the economic indices for the country.

## 4. System Implementation

This section presents the process of implementing a system to satisfy the specific requirement of the user or client. It presents the application of a system theory to product development. The section as well described the programming technique required in the design and realization of the proposed currency exchange forecasting system. The present forecasting model is trained on the naira to dollars exchange rate data extracted from the




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Central Bank of Nigeria (CBN) for a period of thirty-three (33) years from 1981 to 2013 (CBN, 2015). The study data consists of Nigerian economic indices and exchange rates. The records were studied and the economic indices that serves as major factors responsible for the exchange rate were identified as inflation rate, interest rate, GDP, speculations and change in competitiveness and are referred to as predictive variables. The proposed sample mean estimator technique was used to simulate subsequent predictive variable for the years 2014 and beyond, these values were used in forecasting the exchange rate for the subsequent years.

### 4.1 Implementation of the Forecasting System Using Java Programming Language

This section presents the design and implementation of a user-friendly software system for the processing of currency exchange rate forecasting. To this effect the java programming language was adopted with MYSQL used for database creation and management. A user can personally interact with the system by entering the values for variables that were considered to have a significant impact on the currency exchange rate in order to obtain estimates of currency exchange rate forecast for the given period of time. The proposed algorithm performs memory updating if the solution or the forecasting procedure is verified as accurate, the new sets of simulated variables will be added to the database for reuse, otherwise, it will be discarded. Figure 2 is the screen shot of the exchange rate forecasting window. On this form the user can click different options of interest such as Naira to US dollars, Naira to Chinese Yuan, Naira to Euros, Naira to pound etc.

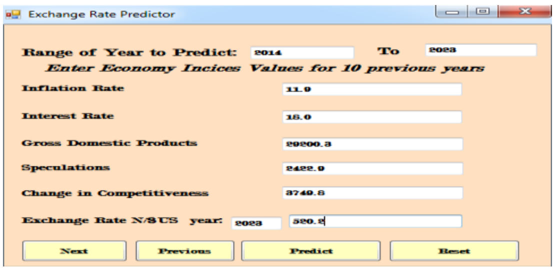


Fig. 2: Exchange rate forecasting window

### 4.2 Evaluation of the Developed Currency Forecasting Using SME-MLRML

Evaluation is a measure used to obtain a reliability estimate of accuracy of an entity in terms of errors. There exist different criteria used in measuring the performance of a forecasting system. These are: Accuracy, True Positive Rate (TPR), False Positive Rate (FPR), False Negative Rate (FNR), True Negative Rate (TNR) etc.

#### 4.2.1 Evaluation Metric

To evaluate the performance of the present currency forecasting using SME-MLRML forecasting application, the offline evaluation method is adopted. The performance of the proposed currency forecasting using SME-MLRML model is evaluated by comparing it with the baseline methods offline. The result from the proposed system is also compared with the actual forecasting values from the exchange rate forecast data collected from the Central Bank of Nigeria. The criteria used in evaluating the proposed system includes: Accuracy, True positive rate and False positive rate.

Let: TPR = The ratio of correctly forecasted instances to the total forecasted; FPR = The proportion of negative or incorrectly forecasted, FN (False negative) = Actually positive but forecasted negative, TP (True positive) = Actually positive and forecasted positive, FP (False positive) = Actually negative but forecasted as positive, TN (True negative) = Actually negative and forecasted as negative.

Therefore;

$$AC = \frac{TN+TP}{TP+TN+FP+FN} \quad (8)$$

$$TPR = \frac{TP}{TP+FN} \quad (9)$$

$$FPR = \frac{FP}{FN+TN} \quad (10)$$

The degree of accuracy is computed as the ratio of correctly forecast instance to the total forecasted multiplied by 100.

$$\% \, AC = TP/TP + FP \times \frac{100}{1} \quad (11)$$

Figure 3 shows the accuracy of each prediction in percentage (%) at different length of forecast using the Central Bank of Nigeria (CBN) exchange rate and economic indices data sets collected.

#### 4.2.2 Dataset for Evaluation

Evaluating a forecasting system is usually based on relevant data set in the context in which the system is developed. The external data set is adopted in this work. The exchange rate data collected from the Central Bank of Nigeria (CBN) was applied. The data is made up of the economic indices and exchange rate of naira to US dollars for a period of thirty-three (33) years from 1981 through 2013.

### 4.3 Presentation and Analysis of the Result

The method adopted in the previous example is applied to the given data between 2001 to 2013 in order to predict the exchange rate of Naira to US dollar for a subsequent period of ten (10) years between year 2014 to year 2023. The proposed SME-MLRML algorithm is executed in order to arrive at exchange rate forecast of Naira to US dollars for the ten years period, that is, year 2014 to 2023 based on the Nigeria Central Bank Economic indices data sets.

#### 4.3.1 Analysis of the Result

In order to model the currency exchange rate of Nigeria Naira to US dollars or any foreign currency, the proposed Sample Mean Estimator Regression Machine learning techniques was applied to the Nigerian Central Bank exchange rate and economy indices data. The forecasting data sets were produced by first simulating the economic indices values, then the exchange rate, the data of which are feed forwarded to generate the exchange rate for the subsequent years repeatedly as shown in example 1.

Figure 3, and figure 4 presents the graphical analysis of performance comparisons in terms of accuracy and speed of execution of the proposed SME-MLRML Model and the baseline methods.



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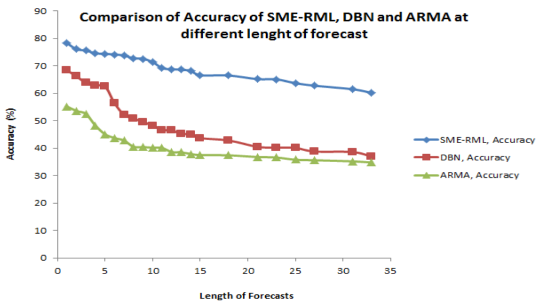


Fig. 3: Comparison of Accuracy of SME-MLRML, DBN and ARMA models at different length of forecast.

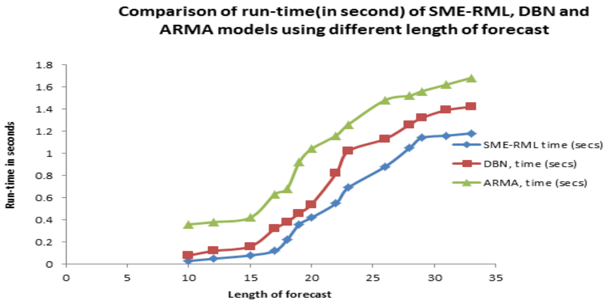


Fig. 4: Comparison of run-time (in seconds) of SME-MLRML, DBN and ARMA models at different length of forecast.

### 4.3.2 Discussion

The experimental result shows a great improvement in the proposed currency forecasting using Sample Mean Estimator Regression Machine Learning (SME-RML) model over the baseline methods studied. A comparative study among the currency forecasting using Sample Mean Estimator Regression Machine Learning (SME-RML) and two other methods, that is, Autoregressive Moving Average (ARMA) and Deep Belief Network (DBN) was conducted on exchange rate forecasting by using the same data sets.

The results shows that though there are significant differences between the performance of the different algorithms studied but generally, the degree of all the algorithm was high at lower length of forecast and later decreases steadily with higher length of forecast, but in all the cases the proposed currency forecasting using Sample Mean Estimator Regression Machine Learning (SME-RML) model recorded the highest degree of accuracy. Performance comparison between the proposed currency forecasting using Sample Mean Estimator Regression Machine Learning (SME-RML) model, the Autoregressive Moving Average (ARMA) and the Deep Belief Network (DBN) models used as baseline as shown in figure 3 and Figure 4, indicates a fantastic effect of the proposed currency forecasting using SME-MLRML algorithm over baseline methods. Lowest accuracies are detected from the ARMA when used on the experimental data set as shown in Figure 3. The Autoregressive Moving Average (ARMA) performed poorly compared to other methods.

The currency forecasting using SME-MLRML method has a high degree of accuracy on the experimental data set than the DBN method. The researcher experimented with over 30 years exchange rate data with different economic indices from the Central Bank of Nigeria (CBN) at different length of forecasts and found out that the ARMA performed well at shorter length of forecasts, but the performance declines rapidly at longer lengths of forecasts as shown in Figure 3, thereby resulting to a limited number of useful predictions. In the case of the currency forecasting using SME-MLRML model, the same experimental setting similar to that used earlier for ARMA model was used. The results show that for all sample length of predictions between 1 and 10, the currency forecasting using Sample Mean Estimator Regression Machine Learning (SME-RML predictor has above 70% degree of accuracy and thereafter maintain about 61% to 69% degree of accuracy at longer length of forecasts as shown in figure 3.

Therefore, the currency forecasting using SME-MLRML remain the most appropriate technique for this study as it manifests a great improvement over other methods studied. In the case of DBN method, similar experimental setting to the ARMA and the currency forecasting using SME-MLRML models was adopted. The result as shown in figure 3, shows that the DBN performance is close to the proposed currency forecasting using SME-MLRML model but with lesser degree of accuracy. Thus, the currency forecasting using SME-MLRML method became the clear winner in this experiment as it manifests an excellent performance over the baseline methods studied. It can be seen that currency forecasting using SME-MLRML model gives a better predictive accuracy than baseline methods in all cases. This improvement in the proposed method is a result of the adoption of multiple techniques in arriving at a forecast; the use of sample mean estimator technique to simulate values of the dependent variables for the predictive model, technique of feed-forwarding parameters and the adoption of multiple linear regression machine learning method of forecasting. Thus, the currency forecasting using SME-MLRML predictive model remains the most appropriate technique for this study being a model-based algorithm.

Furthermore, in order to determine the speed of execution of each algorithm, the run – time of each algorithm i.e. the DBN the ARMA and the proposed currency forecasting using SME-MLRML was recorded at different length of forecast for each algorithm, under the same experimental setting for all the algorithms. The comparison of run-time for currency forecasting using SME-MLRML. ARMA and the DBN predictors indicates that the currency forecasting using SME-MLRML executes faster than the baseline methods, as shown in figure 4. It was shown that the runtime of DBN and ARMA methods rapidly increases as the length of forecast increases, while the currency forecasting using SME-MLRML runtime initially stables at lower length of forecast, then increases a bit at length greater than 15, then decreasing and became stable as the length of forecast increases. This is probably due to the fact that the currency forecasting using SME-MLRML technique drastically reduces computing load and scalability problems. These therefore, make the proposed method achieve better result when handling a very large data set.



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In summary, the currency forecasting using SME-MLRML model is capable of overcoming predictive inaccuracy, inconsistent forecasting, slow response and scalability problems. Finally, the currency forecasting using SME-MLRML model can outperform the DBN and the ARMA predictors when it comes to a very difficult prediction that involves uncertainty and non-linearity prediction variables and large data sets.

## 6 Conclusion and Recommendations

This work provides a basis for the design and realization of an automated currency exchange forecasting system. The system is capable of accepting historical exchange rate data for a given period of time and predict the exchange rate values for subsequent years through the application of the proposed currency forecasting using SME-MLRML algorithm. Many proposed approaches to creating an automated currency exchange forecasting systems are marred with the problems of prediction inaccuracy, inconsistent forecasting, slow response due to computational complexity and scalability problems.

Likewise, some perform poorly when dealing with large data set and difficult predictive cases. The present approach seeks to overcome some of these problems. The adoption of the Sample Mean Estimator (SME) simulation technique at the preliminary stage of the forecasting system to simulate the values of the independent variable for the predictive model has helped to overcome the problem of uncertainty and non-linearly nature of the predictive variables and thereby improve the accuracy of the proposed currency forecasting using SME-MLRML predictive algorithm. The proposed forecasting system is capable of generating a set of foreign exchange rate forecast to the client at a faster rate and at a very high degree of accuracy. The present system has also been proved to have the capability to overcome the problems of poor run time performance, computational complexity and scalability problems common to many existing predictive models when dealing with larger training sets.

Performance comparison between the proposed system, the Deep Belief Network (DBN) and the Autoregressive Moving Average (ARMA) models, as shown in figure 3 shows that the currency forecasting using Sample Mean Estimator Regression Machine Learning (SME-RML) predictor can provide a more accurate forecasting that outperformed the baseline models. In most cases, the degree of accuracy or quality of forecast is equal to or greater than 70%. This means that over 70% of the exchange rate forecast to the client is correct and useful. Thus, the proposed system is capable of providing a useful, accurate, faster and efficient foreign currency exchange forecast to the client consistently.

The researcher is of the opinion that this study could be taken much further by collecting more historical data on other countries exchange rate data against Nigeria Naira, which might include the European Euro's, Chinese Yen, Ghana Cedi etc, on a continuous basis. In addition, more research also needs to be carried out on other predictive methods and the result should be compared with this model in order to determine the most effective ways of solving a problem of this nature in the near future.

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