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Forecasting Inflation Rates Using Artificial Neural Networks

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Abstract Accuracy and reliability in forecasting the inflation rates or predicting it trend correctly is very importance for would be investors, academia, and policy makers. The use of intelligence based model have been found to be invaluable for forecasting financial and economic series like inflation rates exchange rates and stock bond so to mention the few. Researchers have used several parametric models in forecasting exchange rates and other financial and economics data. This paper therefore employs the use of non-parametric approach (artificial neural networks) in forecasting inflation rates. It is an indubitable fact that Artificial Neural networks (ANNs), emulates the information processing capabilities of neurons of the human brain. It uses a distributed representation of the information stored in the networks, and thus resulting in robustness against damage and corresponding fault tolerance. A major advantage of neural networks is their ability to provide flexible mapping between inputs and outputs. The arrangement of the simple units into a multi-layer frame works produces a map between inputs and outputs that is consistent with any underlying functional relationship irrespective of the true functional form. This paper therefore, used three artificial neural networks (Standard Backpropagation (SBP), Scaled Conjugate Gradient (SCG) and Backpropagation based forecasting model for Nigerian and American inflation rates. These models were evaluated using five performance series and a comparison was made with traditional ARIMA models. Inflation rates data of United States of America and Federal Republic of Nigeria were used for empirical illustration. The data were analyzed using both statistical programme for social science (SPSS) and Econometrics view (E-view). The results obtained show that all the ANN models outperformed ARIMA models. The implication of this is that ANN based model can be used to forecast the inflation rates market structure.

Keywords Artificial neural networks, ARIMA models, Economic and financial data, Backpropagation, Developed and developing economy

1. Introduction

An artificial neural network is an information processing device that is inspired by the way biological nervous systems, such as the brain, process information. The human brain learns by experience: It receives information and recognizes the pattern; the brain then generalizes and is able to predict based on the information received. It is this way of information processing by the brain that the ANN model tends to mimic. Although ANN models are too far from the way the human brain performs, by mimicking the basic features of the biological neural networks, they have succeeded in doing certain jobs very well [12], [5] and [11]. There have been dramatic improvements in forecasting the economic and financial time series data using non-parametric approach. These breakthroughs were largely fuelled by recent advances in neural network models, usually with multiple hidden layers, known as deep architectures [19], [20]; [16]; [10]; [13] this is made possible by the availability of large datasets [32] and very cheap computing power for model training. Exciting novel applications, such as conversational agents [30]; [25], have also emerged, as well as game-playing agents with human level performance [24]; [22].

In more than three decades of existence, ANN applications in economics and finance; for such tasks as pattern reorganization, recognition and time series forecasting, have dramatically increased. Many central banks use forecasting models based on ANN methodology

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for predicting various macroeconomic indicators, like inflation, gross domestic products Growth and currency in circulation and so on and so forth. In this paper, we have attempted to forecast monthly inflation rates of Nigeria and United States of America using ANN.

Modern day forecasting, has placed a lot of interest in studying the artificial neural network (ANN) forecasting in economics, financial, business and engineering applications including GDP growth, stock returns, currency in circulation, electricity demand, construction demand and exchange rates [14], [26]. Many central banks, for example: CZECH National Bank, [21], Bank of Canada, [28], are currently using their forecasting models based on ANN methodology for predicting various macroeconomic indicators. Using forecasts based on this methodology one may make correct classification and decisions such as stock selection, bond rating, credit assignment, property evaluation, and many others [12], [15] and [27]. Several studies have shown that artificial neural networks perform better than traditional ARIMA model among them are, [29], [17], [31], and many other researchers. For more irregular series and for multiple-period-ahead forecasting. [18] provided a general introduction of how a neural network model should be developed to model financial and economic time series. Many useful, practical considerations were presented in their article. [33] analysed backpropagation neural networks' ability to forecast an exchange rate.

Inflation forecast is used as guide in the formulation of the monetary policy by the monetary authorities in the world. Monetary policy decisions are based on inflation forecast extracted from the information from different models and other information suggested by relevant economic indicators of the economy. The central idea in this paper is to forecast monthly inflation rates of Nigeria and United States of America. We also compared the forecast performance of the ANN model with that of univariate AR(1) and ARIMA based models. It is observed that forecasts based on ANN are more precise than then those based upon AR(1) and ARIMA models.

2. Methodology

2.1. The Human Neuron

The human brain or the central nervous system is made up of interconnected units called neurons. This system or group of interconnected neurons working together to perform the functions of the brain (i.e., learning) is the neural network. By definition, "Neurons are basic signaling units of the nervous system of a living being in which each neuron is a discrete cell whose several processes are from its cell body." Figure 1 shows the biological structure of the human neuron.

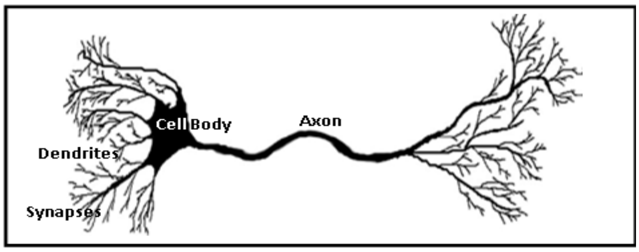

Figure 1. Biological model of human neureon's (*Source: Hadrat, et.al Int. Journal of Economics & Management Sciences (2015)*)

The biological neuron has four main regions to its structure: The cell body, the dendrites or membrane, the axon and the synapses. The cell body is the heart of the neuron. The human neuron receives signals through synapses located on the dendrites or membrane. When the signals received is strong enough (i.e., surpasses a certain threshold), the cell body is activated and emits another signal through the axon. The emitted signal (or action potentials) is sent to activate other neurons within the system. As similar signals continue to cross the threshold, the network recognises the path of the signals, assumes a pattern, and as a result generalises that if the signal is like this then, the output should be that. That is, the network is able to predict based on the pattern of the signals received.

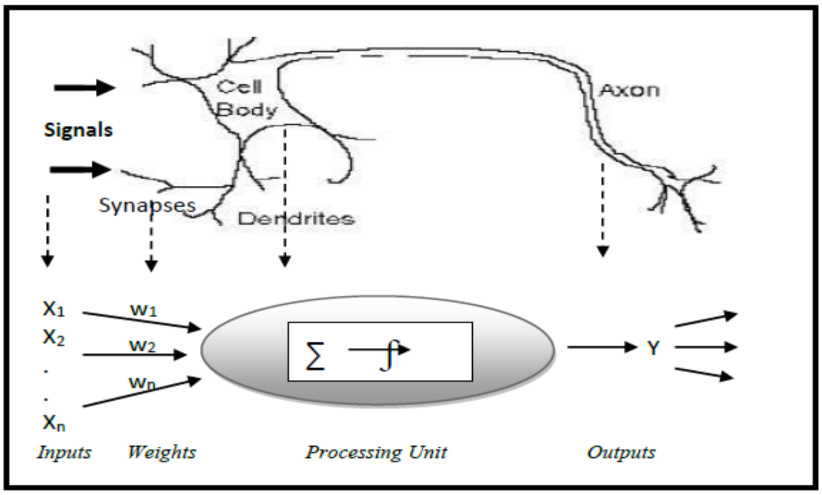

Figure 2. Natural and artificial neureon's (*Source: Hadrat, et.al Int. Journal of Economics & Management Sciences (2015)*)

2.2. The Artificial Neuron

The artificial neuron is a mimic of the natural human neuron. The human brain, for example, contains approximately ten billion (10^{10}) neurons, each connected on average to ten thousand (10^4) other neurons, making a total of (10^{15}) synaptic connections [1], [23] and [4]. A mimic of the way biological networks perform may appear more than complex. Artificial neural networks represent an attempt at a very basic level to imitate the type of nonlinear learning that occurs in the networks of neurons found in nature. As shown in Figure 2, a natural neuron uses the synapses located on the dendrite to gather inputs (signals) from other neurons and combines the input information, generate a nonlinear response ("firing") when some threshold is reached, which it sends to other neurons using the axon. Similarly, the artificial neuron collects inputs (x_i) from input neurons, attaches weights and combines them through a combination function such as summation ($\sum$). It is then activated by a function (usually nonlinear) to produce an output response (y), which is again sent to other neurons [2], Allen P.G., and [10], [7], [8], [6] and [9].

3. Mathematical Specification

There are three distinct functional operations that take place in a neuron. These are: the weight function, the net input function and the transfer function as shown in Figure 3.

3.1. The Weight Function

The inputs, $(x : x_1, x_2, \cdots x_n)$ are fed into the neuron. Each input is multiplied by a random weight (w_i) to form the product and summed $\left(\sum w_i x_i\right)$. The inputs and weights are the same as the variables and parameters, respectively, in linear regression models. For many types of neural networks, the weight function is a product of a weight times the input, but other weight functions (e.g., the distance between the weight and the input, $|w-x|$ are sometimes used.

3.2. The Net Input Function

Next, the weighted input $\left(\sum w_i x_i\right)$ is added to a bias (b) to form the net input (n). That is, the net input becomes: $n = b + \sum w_i x_i$. The bias is similar to the constant in linear models. Themost common net input function is the summation of the weightedinputs with the bias, but other operations, such as multiplication, can be used.

3.3. The Transfer or Activation Function

Then, the net input is passedthrough the transfer function (f), (Figure 4) which produces the output (f).

The three processes can be shown as follows:

$$y = f\left(b + \sum w_i x_i\right) \tag{1}$$

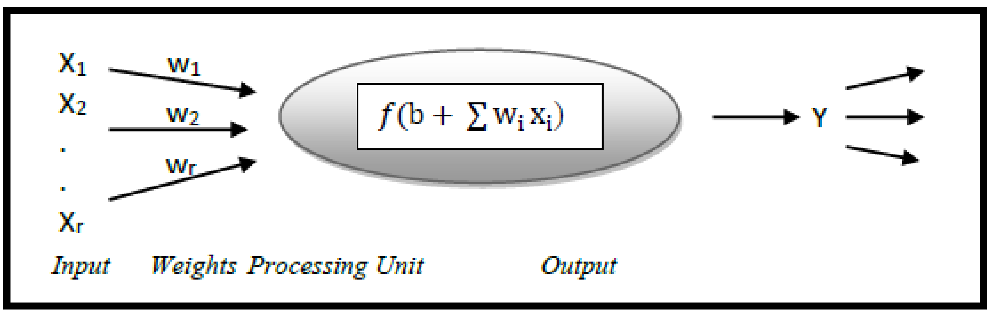

Figure 3. Basic structure of artificial neural networks (*Source: Hadrat, et.al Int. Journal of Economics & Management Sciences (2015)*)

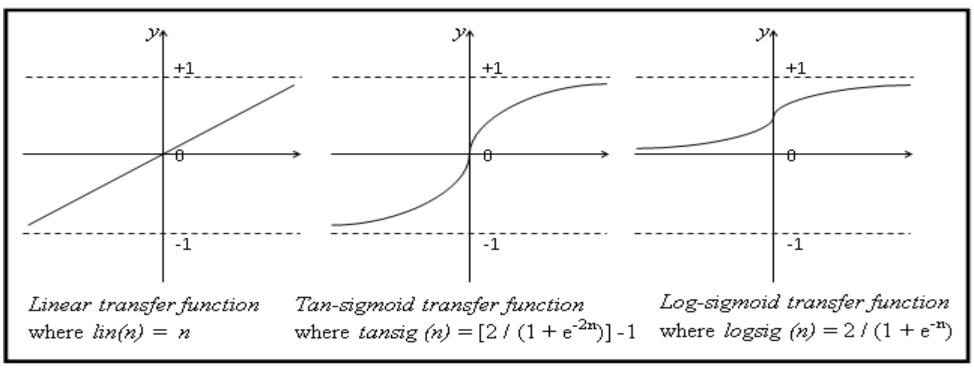

Figure 4. Three commonly used artificial neural networks (*Source: Hadrat, et.al Int. Journal of Economics & Management Sciences (2015)*)

There exist many types of activation functions. If the function is linear, it only transfers the net " n " value to the output unit that is, $f(n)=n$. This is similar to the linear regression model in econometrics:

$$y = b + \sum w_i x_i \quad (2)$$

The activation function in most applications however, takes the form of the "log-sigmoid or hyperbolic tangent sigmoid function" which is continuous and nonlinear function and generates the values between 0 and 1, and-1 and +1 respectively. One of the reasons for the popularity of the sigmoid function is that calculating its first derivative, which is needed for weight adjustment in back-propagation, is relatively simple. The sigmoid function is similar to the logit model, where the dependent variable has the logistic functional form. They have the following forms:

$$y = \tan sigb + \sum w_i x_i \quad (3)$$

$$y = \log sigb + \sum w_i x_i \quad (4)$$

3.4. Performance Measure Indices

The following forecast performances were used to analyze the forecast efficacy of artificial neural network (ANN). The indices used are Normalized Mean Square Error (NMSE), Mean Absolute Error (MAE), Directional Symmetry (DS), Correct Up trend (CU) and Correct Down trend (CD).

$$i \quad NMSE \quad \frac{\sum_k^n (x_k - \hat{x}_k)^2}{\sum_k^n (x_k - \bar{x}_k)^2} = \frac{1}{\sigma^2}\sum_k^n (x_k - \hat{x}_k)^2$$

$$ii. \quad MAE \quad \frac{1}{N}|x_k - \hat{x}_k|$$

$$iii. \quad DS \quad \frac{100}{N}\sum_k^n d_k$$

$$d_k = \begin{cases} 1 & if \quad (x_k - x_{k-1})(\hat{x}_k - \hat{x}_{k-1}) \geq 0 \\ 0 & otherwise \end{cases}$$

$$iv. \quad CU = \frac{100\sum_k^n d_k}{\sum_k^n t_k}$$

$$d_k = \begin{cases} 1 & if \quad (\hat{x}_k - \hat{x}_{k-1}) > 0(\hat{x}_k - \hat{x}_{k-1})(x_k - x_{k-1}) > 0 \\ 0 & otherwise \end{cases}$$

$$t_k = \begin{cases} 1 & if \quad (x_k - x_{k-1}) > 0 \\ 0 & otherwise \end{cases}$$

$$v. \quad CD = \frac{100\sum_k^n d_k}{\sum_k^n t_k}$$

$$d_k = \begin{cases} 1 & if \quad (\hat{x}_k - \hat{x}_{k-1}) < 0(\hat{x}_k - \hat{x}_{k-1})(x_k - x_{k-1}) \geq 0 \\ 0 & otherwise \end{cases}$$

$$t_k = \begin{cases} 1 & if \quad (x_k - x_{k-1}) < 0 \\ 0 & otherwise \end{cases}$$

4. Data and Model Specifications

The main objective of this study is to forecast monthly inflation rates data of United States of America and Federal Republic of Nigeria using the three ANN earlier mentioned (using Standard Backpropagation (SBP), Scaled Conjugate Gradient (SCG) and Backpropagation with ARIMA model as a model for comparison. We used data on monthly basis since from January 1991 to December 2016, representing 300 months for the two countries. The data was analyzed using both SPSS and E-view. From the analysis the following information were extracted.

4.1. Data Analysis

Table 1. Descriptive statistics of the series used for the study

Descriptive Statistics

	N	Range	Minimum	Maximum	Mean		Std. Deviation	Variance
	Statistic	Statistic	Statistic	Statistic	Statistic	Std. Error	Statistic	Statistic
nigeriainflation	312	77.60	.90	78.50	19.0776	1.00293	17.71531	313.832
americaninflation	312	7.80	-2.10	5.70	2.3763	.06870	1.21349	1.473
Valid N (listwise)	312							

From the analysis the following model summary were extracted

Table 2. Model Summary

Model Summary

Training	Sum of Squares Error	85.170
	Relative Error	.803
	Stopping Rule Used	1 consecutive step(s) with no decrease in error[a]
	Training Time	0:00:00.30
Testing	Sum of Squares Error	41.405
	Relative Error	.735

Dependent Variable: nigeriainflation
a. Error computations are based on the testing sample.

4.2. Network Information

Table 3. Network Information

Network Information

Input Layer	Covariates	1	americaninflation
	Number of Units[a]		1
	Rescaling Method for Covariates		Normalized
Hidden Layer(s)	Number of Hidden Layers		1
	Number of Units in Hidden Layer 1[a]		6
	Activation Function		Hyperbolic tangent
Output Layer	Dependent Variables	1	nigeriainflation
	Number of Units		1
	Rescaling Method for Scale Dependents		Standardized
	Activation Function		Identity
	Error Function		Sum of Squares

a. Excluding the bias unit

4.3. Network Architecture for the Data Used

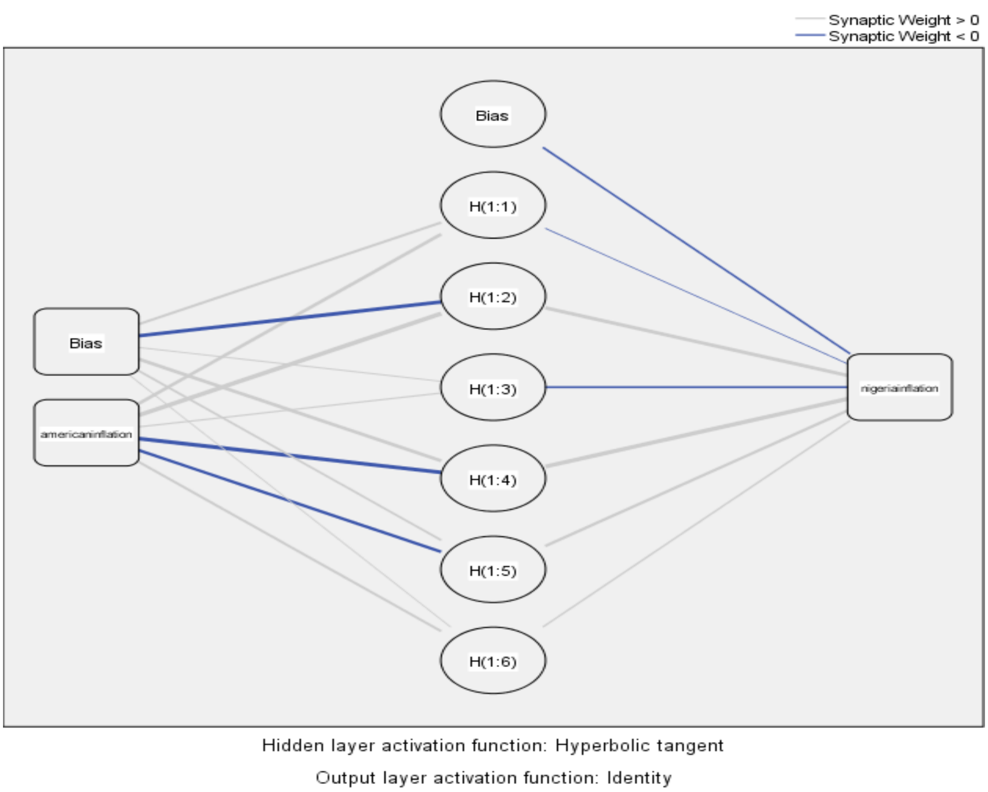

Figure 5. Architecture of the data

4.4. Forecast Results for United States of America Inflation Rates Based on Neural Networks and Arima Models

Table 4. Forecast results for US inflation rates

CRITERIA	SBP	SCG	BPR	ARIMA (1,1,1)
NMSE	0.2112	0.0423	0.0501	0.9231
MAE	0.0037	0.0015	0.0017	0.0091
DS	62.1121	71.2312	74.0012	33.2210
CU	64.2123	73.1321	76.2314	21.1201
CD	59.9712	74.2113	80.0012	98.1217

The table 4 above shows the forecast performance of United states of American inflation rates, it clearly shown that SBP, SCG and BPR out performed ARIMA model. In the same way, the best model here is BPR follows by SCG and SBP in that order.

4.5. Forecast Results for Nigerian Naira Based on Neural Networks and Arima Models

Table 5. Forecast results for Nigerian inflation rates

CRITERIA	SBP	SCG	BPR	ARIMA
NMSE	0.0215	0.0123	0,0019	0.6451
MAE	0.0015	0.0119	0.0128	0.0494
DS	62.1111	67.1123	69.2117	39.1175
CU	71.2142	78.2213	82.7889	10.2213
CD	61.0115	87.2116	79.9916	89.1132

In the same way Nigerian inflation rates data follows identical parts as obtained for United States of American data.

5. Conclusions

The study, examined three ANN based forecasting models and a comparison was made using ARIMA model. From the table above as obtained from the analysis, all ANN models better than performed ARIMA model as measured on five performance indices. Results show that ANN based model can forecast inflation rates of the two countries effectively. In the committee of the ANN, BPR produced the best result.

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