Comparative Study of Inflation Rates Forecasting Using Feed-Forward Artificial Neural Networks and Auto Regressive (AR) Models

Bayo Mohammed, Onimode[1]; John Kolo, Alhassan[2]; Solomon A., Adepoju[3]

[123]Computer Science Department,
Federal University of Technology, Minna
Minna, Niger State, 234-920271, Nigeria

Abstract

The paper examines the efficacy of neural networks application for inflation forecasting. In a simulated out-of-model forecasting investigation using recent Nigeria inflation rate data obtained from the appropriate authorities, the neural networks did better than univariate autoregressive models on normal rate for short periods of quarter one and quarter two; quarter one and quarter three; and quarter one and quarter four. A clear-cut condition of the model of neural network and specialized evaluation trial from the neural networks literature exemplify the important roles in the achievement of the feed-forward neural network model.

Keywords: *Inflation, Forecasting, Neural Networks, Feed-forward, Model Selection, Linearity, Forecasting*.

1. Introduction

In this paper, the result of Consumer Price Index (CPI) estimates from an artificial neural network (ANN) using foremost economic indicator data are demonstrated. The outcome shows that the neural network (NN) predicts the level of the CPI with a higher measure of accuracy. In recent times, there has been significant attention in the applications of artificial neural networks in the economics and business texts, particularly in the areas of fiscal statistics and exchange rates (Serletis *et' al*, 2003). Comparatively, relatively fever researches have applied artificial neural network methods to macroeconomic time series analysis (William and Car, 1970). Inflation Forecasting is a foremost concern for businessmen and economists. Most investigators (researchers) have relied upon numerical techniques with their strict data hypothesis and very stumpy correctness rates to forecast changes in inflation rates, but only a very few have explored how neural networks can improve these forecasts.

A limitation of the small number of research works that apply artificial neural networks to macroeconomics purposes is that they do not make use regular practice neural networks inference methods, such as "early-stopping" and "pre-processing" (Swanson, 2001). However, the analysis of the nonlinearities in time series statistics is as central to macroeconomic hypothesis as well as prediction, for instance, in the innovative work of Brock and Hommes (1997), Bernett, Medio and Serletis (2003) among others. A good number of closely related works in the literatures to the recent work of Moshiri and Cameron (2000).

In this paper, the usefulness of a neural network model for inflation rates forecasting is examined. Also, the output of the neural networks model is balanced with that of univariate auto-regression models in a simulated out-of-model forecasting research using recent Nigeria inflation rate data obtained from the appropriate authorities. In the process, the importance of standard-practice neural networks assessment methods such as "early-stopping" and "pre-processing" is evaluated (Swanson, 2001). Thus, the Swanson and White's (1997) assumption that these forms of procedures may be of significance considering the comparative failure the other types of model selection criteria such as the Schwarz Information Criterion to pick out the best prediction model is tracked upon.

2. Aims and Objectives

The main aim of this paper is to predict monthly year on year (YoY) inflation for Nigerian by using ANN technique for financial year 2012 (FY13) on the foundation of the available monthly data since November 2011 (Nigerian National Bureau of Statistics (NBS)

October 2012), using feed-forward artificial neural network model.

The objectives of this paper are to:

a) Compare inflation forecasting using the feed-forward artificial neural network and AR (1) models,
b) Predict monthly year on year (YoY) inflation for Nigeria by using ANN technique for the financial year 2012 (FY13)

3. Literature Review

Time series forecasting is a vital forecasting domain. In order to widen up and to also improve time series forecasting models, too much effort is given for many times. This type of studies helps policy makers in reaching better decisions. Most of these methodological progresses are based on statistical methods. Though, very lately new methods are discovered which challenges the old conventional models. This new methodology is known as the Artificial Neural Network (ANN).

The AR model considers linear connection that links time series values. Alternatively, most of the macro-economic variable demonstrates non-linear attribute. At this point the AR model could not be able to catch the non-linear link that exists between series and thus the achievement of forecasting of this models remains limited. ANN is one of the non-linear means that makes the predictions on macroeconomic variables. What is new with ANN is laid down firstly with interval layers amid the input and output layers. The second advancement is that is being employed as an activation function that can roughly compute any non-linear fuction. Briefly, ANN has a very big benefit in forming flexible and curved models (Aryal and Yao-wu, 2003).

The merits of ANN are being considered by lots of authors and being insight source in their studies. For example, in economic variable predictions, beside the conventional models, neural networks can also be used and is exposed theoretically and the matching of both techniques is emphasized by Kuan and White (Kuan and White, 1994). In economy literature, there are some researches that compare forecasting output of linear autoregressive models and neural networks (Maaoumi et'al, 1994, Swanson and White 1997, Kohzadi et'al. 1995, Tkacz & Hu 1999, Li et'al. 1995 and Tkacz 2001). Though ANN is been used in inflation forecasting quite limitedly.

In the current time of forecasting, there exists a huge concern in studying the neural network forecasting in engineering, monetary, business and fiscals applications as well as the Gross Domestic Products (GDP) growth of a country, electricity demand and supply, construction demand and supply, stock market returns, currency in circulation and exchange rates amongst others. The innovative works of Brock and Hommes (1997), Barnett, Medio and Serletis (2003) among others are good number of closely related works in the literatures to the present paper is Moshiri and Cameron (2000). Fernandezn-Rodriguez, Gonzalez-Martel and Sosvilla-Rivero (2000); Redenes and White (1998) and many others have also worked in this area. Many central banks, for instance, Bank of Canada (Tkacz and Hu, 1999), Czech National Bank (Cada et'al, 2005), Bank of Jamaica (Serju, 2002) etc, are presently applying their forecasting models based on Artificial Neural Network methodology for forecasting various macroeconomic indicators. Using predictions based on this methodology one may build accurate classification and assessments such as bond rating, stock selection, property valuation, credit allotment, and many others (Chen, Racine and Swanson, 2001; Swanson and White, 1997; Stock and Watson, 1998).

Inflation rate forecasting is applied as guide in the formulation of the monetary policy by the various monetary authorities in the world. Monetary policy verdicts are based on inflation rates forecast that are mined from the information from various models and their and other information that are suggested by the relevant economic indicators of the economy. The comparison of the prediction performance of the artificial neural network model with that of univariate AR (1) based model was also done. It is observed that forecasts based on artificial neural network are more precise than those that are based upon AR (1) model.

4. Methodology

Regardless of its suggestive name, a neural network (NN) is simply a parameterized non-linear function that can be fixed to data for prediction functions. The non-linear function is built as a mixture of non-linear structural blocks, known as the transfer functions. A very common example of a NN transfer function is the hyperbolic tangent function. The composition of the NN is described, in neural networks jargon, by the amount of "layers" and "neurons" in the NN. Increasing the numbers of the transfer functions (adding more layers and neurons) also increases the flexibility of the NN.

The major appeal of NN's is their flexibility in approximating a wide range of functional links between inputs and outputs. Indeed, ample intricate neural networks are able to estimate random functions arbitrarily well. Thus, there is a close link between the NN approach and the older economics literature on stretchy functional forms such as the translog function. The algorithms used to approximate NN's are known as "training algorithms". These algorithms are much like the standard minimization routines that is applied, for example, in non-linear least squares. Loosely speaking, the training algorithms iteratively alter the parameters in the direction of the negative gradient of mean squared error (MSE). (Sosvilla-Rivero, 2000). Though, standard-practice NN estimation approaches differ from econometric evaluation techniques in many significant ways. In order to evade "overfitting", the NN training algorithm is often discontinued before a local minimum is reached. Instinctively, overfitting occurs when the NN provides a near-perfect fit in-sample but poor forecasts out-of-sample. NN's are thought to be particulaly susceptible to overfitting because of their suppleness in approximating different functional forms.

One of the most common types of early stopping procedures is the following cross-validation based approach.

* First, the data are divided into a training set and a validation set.
* Next, the training algorithm is run on the training set until the MSE starts to increase on the validation set (which usually occurs long before the minimum MSE is attained on the training set).

I estimate a very simple neural network for inflation,

$\hat{\pi}_{t+j} = L_1 \cdot \tanh(I_1 \cdot x_{t-1} + b_1) + L_2 \cdot \tanh(I_2 \cdot x_{t-1} + b_1) + L,$ -- - **(1)**

Where:

$\hat{\pi}_{t+j}$ is the NN inflation forecast j quarters in advance,

x_{t-1} is a vector of lagged inflation variables $[\pi \cdot x_{t-1}, x_{t-2}]$,

tanh is the hyperbolic tangent function, and

$L_1, L_2, I_1, I_2, b_1, b_2,$ and b_3 are parameters.

In NN jargon, L_1 and L_2 are "layer weights", I_1 and I_2 are "input weights" and b_1, b_2 and b_3 are "biases".

It is noticed that the NN depends on two lags of inflation. Thus, like Stock and Watson (1998), considering only univariate inflation forecasting models.

Given the restraints of the data, the simple network "architecture" given by (1) was selected with very minimal search over the alternative network architectures. We train the NN using the Levenberg-Marquardt algorithm, a standard training algorithm from the NN literature. The algorithm is lapsed according to the early stopping procedure described above. The validation set that is used in the early stopping procedure is chosen in a somewhat unusual manner: first, the dataset used to train the NN is divided into "observations" each consisting of t and $x_{t-1,}$ and then every second observation from the dataset is chosen to be part of the validation set (White et'al, 1998). This procedure is related to the innovative approach as applied by Lebaron and Weigend (1998).

Since local minima (and the areas surrounding them) are considerable problems for neural networks, it is standard in the neural networks literature to train the network using a substantial number of random initial values of the parameters, and select only the most successful of these neural networks. Though, it is also detrimental to "saturate" the parameter space with too many random initial values since this approach, in effect, finds the globally minimizing parameter values by trial and error-counteracting the results of the early stopping procedure. In order to balance the concerns of "overfitting" and "over-saturation", training the network using certain random initial values and select the neural network that yields the lowest mean squared error on the training and validation sets. (Lebaron nad Weigend, 1998).

Also, estimating linear autoregressive (AR) models with lag lengths between 1 and 8 of the form:

$\hat{\pi}_{t+j} = a_0 + \Sigma a_i \pi_{t-i,}$ - - - (2)

Where:

$\hat{\pi}_{t+j}$ is the AR model inflation forecast j periods in advance, and

k is the number of lags included in the model.

In NN jargon, L_1 and L_2 are "layer weights", I_1 and I_2 are "input weights" and b_1, b_2 and b_3 are "biases"

Moderately using a model selection criterion to select a particular lag length, simply presenting results for all the possible lag lengths. The data used are the Nigeria GDP deflator for twelve-month period ending in October 2012.

Using a "fixed scheme" pseudo out-of-sample forecasting approach to compare the neural network and AR models (McCracken and West, 2001). Namely, setting aside a couple of the last observations of data (i.e the data for the period Jan2012 (Q2) - Aug 2012 (Q3) for testing purposes, and desist from using this data at any point in the forecasting process as described. Then comparing the AR and NN models on the basis of their success at predicting inflation on the test set. Like Swanson and White (1997), using a model selection approach as opposed to the more traditional hypothesis testing approach of calculating significance levels and confidence intervals (Moshiri *et'al*, 2000).

5. Data Collection

Since the objective of this paper is to compare the prediction of the monthly YoY inflation for Nigeria for FY12using the feed-forward artificial neural network and AR(1) models with 12 hidden, the data for the monthly basis statistics for November 2011 to October 2012 as represented in Table 2 below were used. The mean square error ratio of the NN to AR models was also examined as shown in Table 3 below. Also, the use of the NN ratio estimated with NLLS vs early stopping was also estimated as shown in Table 4 below.

Table 1: Annual Inflation rate as obtained from NBS

Months	Actual Inflation
Nov. 2011	12.63
Dec. 2011	11.93
Jan. 2012	12.11
Feb. 2012	12.91
Mar. 2012	12.73
Apr. 2012	12.86
May 2012	12.91
June 2012	12.93
July 2012	12.89
Aug. 2012	11.79
Sept. 2012	11.39
Oct. 2012	11.78
Average	**12.41**

Source: *National Bureau of Statistics (NBS)*

Table 2: Performance Comparison Based on Yearly Average

Months	Actual Inflation	Forecast by ANN	Forecast by AR(1)
Nov. 2011	12.63	12.68	12.62
Dec. 2011	11.93	11.82	11.60
Jan. 2012	12.11	12.45	12.59
Feb. 2012	12.91	12.98	12.58
Mar. 2012	12.73	12.66	12.56
Apr. 2012	12.86	12.73	12.55
May 2012	12.91	12.59	12.53
June 2012	12.93	12.44	12.52
July 2012	12.89	12.68	12.51
Aug. 2012	11.79	11.92	11.49
Sept. 2012	11.39	11.43	11.48
Oct. 2012	11.78	11.43	11.47
Average	**12.41**	**12.32**	**12.21**

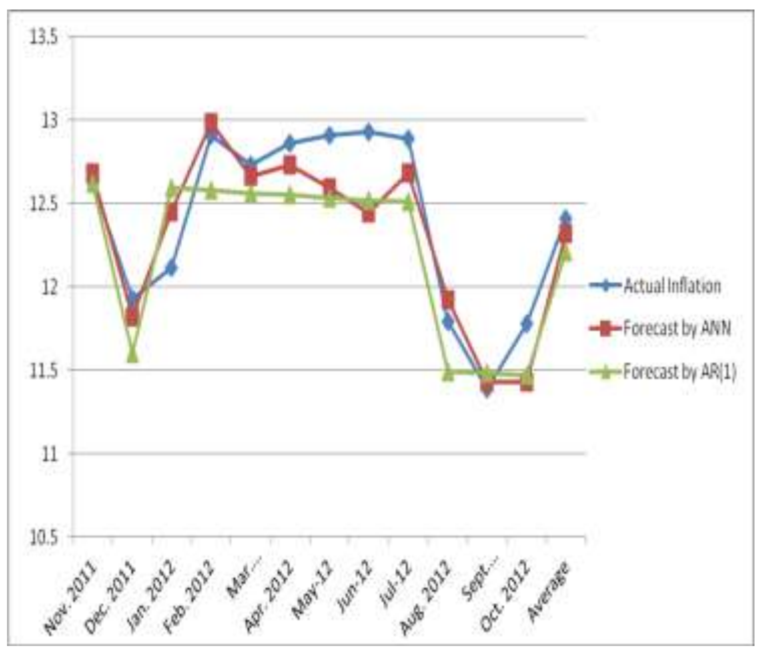


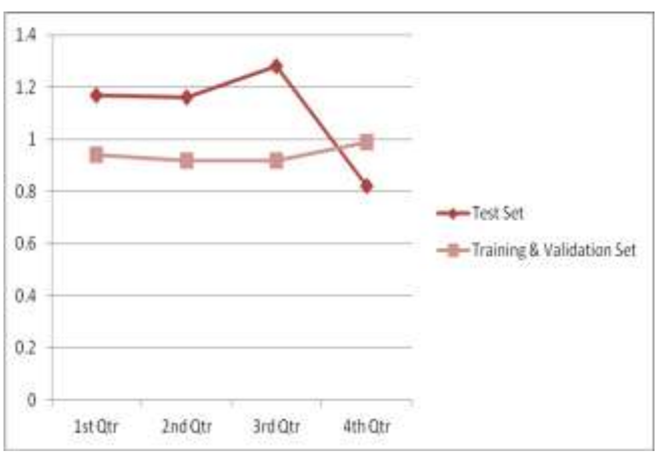
Table 2: Mean Square error ration on NN to AR Models

Test Set Forecast Horizon					Training & Validation Set Forecast Horizon			
Qtrs	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
AR1	0.84	0.77	0.98	1.2	0.85	0.77	0.77	0.72
AR2	0.89	0.84	1.04	1.18	0.86	0.81	0.81	0.73
AR3	0.9	0.83	1.01	1.15	0.9	0.85	0.81	0.73
AR4	0.9	0.82	0.96	1.12	0.9	0.85	0.83	0.72
AR5	0.93	0.8	0.94	1.07	0.9	0.87	0.82	0.72
AR6	0.86	0.79	0.91	1.04	0.92	0.86	0.82	0.72
AR7	0.77	0.75	0.84	0.98	0.94	0.87	0.84	0.74
AR8	0.77	0.75	0.83	0.91	0.93	0.88	0.84	0.76

Table 3: Mean square error ratio of NN estimate with NLLS vs early stopping *

Test Set Forecast Horizon					Training & Validation Set Forecast Horizon			
Qtrs	**Q1**	**Q2**	**Q3**	**Q4**	**Q1**	**Q2**	**Q3**	**Q4**
Mean	1.17	1.16	1.28	0.82	0.94	0.92	0.92	0.99

* Each cell shows the ratio of the mean error of the NN model estimated by NLLS to the mean square error of the NN model estimated using early stopping.



6. Result and Discussion

The first table, Table 1 displays the ratio of the mean MSE of the neural network model to the MSE's of the AR models on the test set. The NN model has a lower MSE for forecast horizons 0f 1 and 2 quarters. The NN model has a similar MSE to the AR model for the 3 quarter horizon, and a higher MSE for the 4 quarter horizon. The MSE ratios on the training and validation sets are generally lower than on the test set as a consequence of the over-fitting problem described above.

The NN estimator has the unusual property that its generates a distribution of parameter values and MSE's for the same dataset, due to the early stopping and random initialization procedures illustrated above. Thus, the results in Table 1 are for the mean MSE in a Monte Carlo experiment in which the training algorithm is run many times. The NN training algorithm plays a significant role in the success of the NN model.

Table 2 shows the ratio of the MSE's for the NN estimated by Nonlinear Least Square (NLLS) against the MSE estimated by the NN training algorithm described above. In the case of the NLLS minimization algorithm, using many random initial values as used in the Stock and Watson (1998) – a considerably larger number than in the NN algorithm. Table 2 shows that NLLS yields a higher MSE than the NN training algorithm for the 1, 2, and 3 quarter horizons, but a lower MSE for the 4 quarter ahead horizon.

Existing applications of NN's to macroeconomic estimation, such as Stock and Watson (1998) and Swanson and White (1997) find that NN's perform poorly relative to linear models. Thus, table 2 shows that a significant reason for the positive results showed here is the early stopping procedure. Indeed, Table 2 shows that the early stopping procedure makes an important enough contribution to the fit of the NN model for horizons of Q1-Q3 that we could have established a slight advantage in using the NN without the early stopping procedure-even for short horizons. The early stopping procedure would probably be even more important for more complicated NN's since these NN's suffer more from over-fitting.

Though, Table 2 also reminds us that the early stopping procedure is not perfect, as is sometimes advised in the NN literature. The MSE associated with the Q4 ahead forecast is actually higher with the early stopping procedure. Eventually, early stopping is only one way of avoiding the over-fitting setback, and functional form assumptions – such as those imposed by the linear models – are another. While the NN early stopping approach is preferable for short horizon inflation prediction, the advantage disappears for longer horizons.

7. Conclusion

This paper applied a simple univariate feed forward artificial neural network model to predict monthly YoY inflation for Nigeria by using NN methodology for the FY 2012 on the basis of monthly data for November 2011 to October 2012. The existing uses of NN's to macro-economic prediction find that NN's execute better relative to linear models. Coming to a more somewhat positive conclusion observing the usefulness of NN's for inflation forecasting: the NN model performs well and better relative to AR models for the horizons of Q1 and Q2 on the test set December 2011-November 2012. The results suggest that the early stopping procedure adds considerably to the predictive success of the NN approach, and thus should be incorporated into future forecasting experiments that involve NN's. Moreover, simple (for example two lag) specifications of neural networks should not be overlooked when data are limited, as is the case for many macroeconomic variables.

Acknowledgments

We are most grateful for the help and support of Mr. Ibrahim T.O. of Central Bank of Nigeria, Mr. Joseph Kolade of the National Planning Commission and Mr. Steve Adegbola and Mr. Moses Mathew of the National Bureau of Statistics for helping in providing the needed inflation data. We also appreciate Dr. M.B. Abdullahi, the Head of Department, and all other staff of the Computer Science Department, for helping in producing this paper on Comparative Study of Inflation Rates Forecasting Using Feed-Forward Artificial Neural Networks and Auto Regressive (AR) Models. We also acknowledge the original works of Emi Nakamura of the Harvard University, Recept Durgun as well as Adnan Haider and Muhammad Nadeem Hamif and other authors for their various works on Inflation Forecasting Using Neural Network.

References

[1] Aryal, D. R. and Yao-Wu. (2003). Neural Network Forecasting of the Production Level of Chinese Construction Industry, *Journal of Comparative Management 6, 45-64.*

[2] Barnett, W. A., Alfredo M. and Apostolos S. (2003). Nonlinear and Complex Dynamics in Economics, *Working Paper.*

[3] Brock, W. A. and Hommes, C.H., 1997. A Rational Route to Randomness, *Econometrica,* 6 (5), 1059-1095.

[4] Central Bank of Nigeria (CBN) (2012, November), 2013 Annual National Inflation forecast No. 1095.

[5] Chen, X., Racine, J., and Swanson N. (2001). Semi parametricARX Neural Network Models with an Application to Forecasting Inflation, *IEEE Transactions on Neural Networks,* 12, 674-683.

[6] Fernandez-Rodriguez, Fernando, Christian Gonzalez-Martel, and Simon Sosvilla-Rivero (2000), On the profitability of technical trading rules based on artificial neural networks: Evidence from the Madrid stock market Economics Letters, 69 (1), 89-94.

[7] Gonzalez, Steven, (2000). Neural Network for Macroeconomic Forecasting: A Complementary Approach to Linear Regression Models. Finance Canada Working Paper 2000-07.

[8] Hornik, K., Stinchcombe, M. and White, H. (1989). Multilayer feed-forward networks are universal approximators, *Neural Networks*, 2,359-366.

[9] Kohzadi, N., Boyd, M. S., Kaastra, I., Kermanshahi, B. S., and D., Scuse. (1995). Neural Networks for Forecasting: An Introduction, *Canadian Journal of Agricultural Economics* 43, 463-474.

[10] Kuan, C. M., and White, H. (1994). Artificial Neural Networks: An Econometric Perspective, *Econometric Reviews* 13, 1-91.

[11] Lebaron, B. and Weigend, A.S. (1998). A bootstrap evaluation of the effect of data splitting on financial time series, IEEE Transactions on Neural Networks, 9 (1), 213-220.

[12] Li, Y., Ng. K. C., Haeussler, A., Chow, V. C.W. and Muscatelli, V. A., (1995). Macroeconomics Modeling on UK GDP Growth by Neural Computing, *Technical Report CSC-95009.*

[13] Maaoumi, E., Khotanzad, A., and Abaye, A. (1994). Artificial Neural Networks for some Macroeconomic Series: A first Report, *Econometric Reviews* 13, 105-122.

[14] McCracken, M. W. and West, K. D. (2001). Inference About Predictive Ability, in Michael Clements and David Hendry, eds., A Companion to Forecasting, Oxford, UK: Blackwell Publishers.

[15] Moshiri N., Saeed K. U. and Norman C. (2000). Econometrics versus ANN Models in Fotrecasting Inflation , Journal of Forecasting 19, 201-217

[16] Nigeria National Bureau of Statistics (NBS) (2012 October): Consumer Price Index, No. 512.

[17] Refenes, A. P. and H. White (1998), Neural Networks and Financial Economics, International ajaournal of Forecasting, 6 (17).

[18] Stock, James H. and Mark W. Watson (1998), A Comparison of Linear and Nonlinear Univariate Models for Forecasting Macroeconomic Time Series, NBER Working Paper (6) 607.

[19] Swanson, Norman R. and Halbert White, (1997). A Model Selection Approach to Real-Time Macroeconomic Forecasting Using Linear Models and Artificial Neural Networks," The Review of Economics and Statistics, 79 (4), 540-550.

[20] Tkacz, G., and Hu S. (1999). Forecasting GDP Growth using Artificial Neural Networks, *Bank of Canada Working Paper*, 1-24.

[21] Tkacz, G., (2001). Neural Network Forecasting of Canadian GDP Growth, *international Journal of Forecasting* 17, 57-69.

Author's Biography

B. M. Onimode is of the Department of Computer Science, in the School of Information and Communication Technology, Federal University of Technology, Minna, Niger State, Nigeria. He obtained a B.Sc Computer Science at the University of Jos, Jos - Nigeria, and a Master of Technology (M.Tech) Degree in Computer Science at the Federal University of Technology, Minna, Nigeria. His research has focused on Enterprise Database Management; Management Information Systems (MIS); Health MIS; Networks and Computer Security Models; Cyber Security Systems and Health Informatics. He is a Professional member of BCS – The Chartered Institute for IT, UK; Association for Computing Machinery - ACM, USA; Computer Professionals (Registration Council) of Nigeria, CPN; Nigeria Computer Society, NCS; Nigeria Institute of Management (Chattered), NIM; Institute Public Management, Nigeria, IPM; and IT Service Management Forum (itSMF), UK.

Dr. J. K. Alhassan obtained B.Tech (Mathematics / Computer Science) at the Federal University of Technology, Minna. M.Sc (Computer Science) at University of Ibadan, Nigeria in 2006, and PhD (Computer Science), at Federal University of Technology, Minna, Nigeria. He carried out part of his PhD research at United Institute of Informatics Problems, National Academy of Sciences of Belarus (UIIP NASB) Minsk, Republic of Belarus. He is currently the Acting Head, at the Department of Cyber Security Science, Federal University of Technology, Minna, Niger State, Nigeria. His research interest includes Artificial Intelligence, Data Mining, Internet Technology, Database Management System, Software Architecture, Machine Learning, Human Computer Interaction and Computer Security. He is a member of Computer Professionals (Registration Council) of Nigeria (CPN).

S. A. Adepoju holds B.Tech (Mathematics/Computer Science) and M.Sc (Computer Science) from the Federal University of Technology, Minna and University of Ibadan respectively. His research interests include Human Computer Interaction, Web Mining and Information and Communications Technology for Development (ICT4D). He is a member of Computer Professionals (Registration Council) of Nigeria (CPN); Association for Computing Machinery - ACM, USA; IACSIT and IAENG.