PENERBIT UMT
Menjana Khazanah Ilmuwan

Journal of Mathematical Sciences and Informatics
Journal Homepage: https://journal.umt.edu.my/index.php/jmsi
eISSN: 2948-3697
DOI: http://doi.org/10.46754/jmsi.2022.12.005

FORECASTING NIGERIAN ECONOMIC GROWTH-BASED CORPORATE INCOME TAX

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ARTICLE INFO

Article History:
Received 27 November 2022
Accepted 14 December 2022
Available online 31 December 2022
Section Editor:
Maharani Abu Bakar

Keywords:
Artificial neural network;
corporate income tax;
economic growth;
forecasting;
multiple regressions.

ABSTRACT

Developing countries like Nigeria have been hit hard by recent economic crises, and uncertainty is one of the characteristics that all prices and revenues share. A forecast of Nigerian economic growth was attempted using an artificial neural network (ANN) and statistical model to analyse the contribution of non-oil income tax generation to Nigerian economic development. While the primary objective is to develop and implement the proposed models capable of simulating a real non-oil income tax and evaluate their performances. The dataset (Corporate Income Tax) from 2015–2020 was obtained from the National Bureau of Statistics of Nigeria (NBSN). Three training algorithms for ANN were adopted such as conjugate gradient back-propagation with Fletcher-Reeves restarts, Bayesian regularisation, and gradient descent with an adaptive learning rate, whereas in the statistical part, multiple linear regressions were applied. Comparing all the models revealed that the Bayesian regularisation produced more accurate results than the other models.

2020 Mathematics Subject Classification: 62J05; 68T07 © Penerbit UMT

INTRODUCTION

For a market economy like that of Nigeria, the motivation for revenue collection comes from the need to fulfil policy obligations such as providing public goods and services and ensuring economic stability [1]. To meet these duties, the government must fully use all available national and international revenue streams [2]. Revenues from various sources need to be utilised effectively for the best results. Revenue generation aims to increase the comfort of a nation's population, with a focus on encouraging economic growth by providing the facilities required for bettering public services through effective administrative and structural systems. Nigeria's development operations had difficulty generating money because of numerous insurgency tactics like avoidance, neglect, and unethical behaviour. These actions are seen as economic sabotage and are frequently cited as the cause of the nation's problems [3].

The revenues from products sold on international markets that are not crude oil are known as "non-oil revenues" [4]. The non-oil revenue sector comprises manufacturing, telecommunications services, tourism, real estate, banking, construction, and healthcare. Exports of non-oil commodities formed in the agricultural, quarrying and mining. The industrial sectors of the country are made to generate income for economic development [5]. Some researchers such as [6], [7], [8], [9], [10], [11], [12], [13] and [14] use ANNs and statistical models for prediction purposes. Economic development is the total generated by products and services and can be negative and positive. Negative growth is

associated with recession and stagnant wages. Gross national product is sometimes used instead of gross domestic product [15].

The challenges of generating revenue include tax evasion, a completely fraudulent practice in which taxpayers use illegal means to reduce their tax liability [16]. Tax evasion can occur through willful omission or commission, a crime under tax law. Such violations include income tax, failure to file tax returns, surveillance of tax returns, requests for personal income tax exemptions, under-reporting of income, reporting of deceitful transactions, wastage, and breakdown to respond to requests [17]. It is also true that economic development and regional or national crises cannot be viewed as general concepts simultaneously. Thus, the intrusion of oil exploration facilities by militants in the Niger Delta had a significant impact on the economy of Nigeria as a whole [18].

Nigeria reportedly lost 211,000 barrels of oil daily to militant attacks and cut oil production by 455,000 per day. In contrast, exports of the same commodity are down 20% yearly [19]. Due to gas outages at major power plants, the country's power generation has fallen by more than 25% due to ongoing combat activity [20]. This was direct evidence of deteriorating revenues from oil exploration by the Nigerian government. Since it was first detected in late 2019, the spread of COVID-19 has exacerbated difficulties in the global economy and disrupted global supply chains [21]. As a result, global demand for petroleum products has declined. Falling oil prices have spurred require in Nigeria, where gas and oil are the main economic markets, significantly reducing government oil revenues. These restrictions increase the economic impact of COVID-19 and make it more complicated for governments to find a lasting solution to the crisis [22]. On the other hand, forecasting non-oil income taxes (Corporate Income Tax and VAT) is one of the most important tasks in the supply chain, as exchange rates greatly affect the import and export prices of traded goods.

In this paper, artificial neural networks and statistical models are used to predict economic growth in Nigeria. Data was collected from the Nigerian National Bureau of Statistics, preprocessed, trained, surveyed, and analysed. Three different ANN algorithms are employed to improve accuracy. The mean squared error (MSE) and the coefficient of determination will be used to establish the best model. This paper is structured as follows: Section 1 provides an introduction while Section 2 describes the research materials and methods. This led to Section 4 where experiments, results and discussions were recorded and analysed. Section 5 completes the work.

MATERIALS AND METHODS

Machine Learning Model

Developing any machine learning model consists of training and testing (Figure 1). However, a dataset is required for the learning, which usually needs to be converted to a suitable format before being used; thus, the following steps are performed in the modelling process.

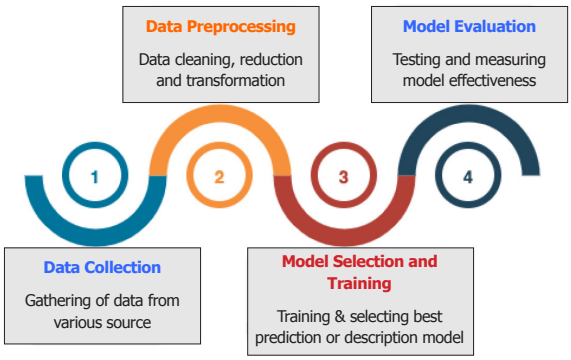

Figure 1: Machine learning architecture

Data Collection

Below are the details of how the data obtained from the National Bureau of Statistics of Nigeria [23], the system design and the proposed training functions have been described in this section.

A Description of Input Attributes

The dataset is obtained from [23]. Detailed information regarding the input variables is revealed in Table 1 below. The CIT is based on the Nigerian currency (Naira).

Table 1: Corporate Income Tax (=N=)

Year (2015-2020) Quarterly	Input Variables				
	Agricultural & Plantation	**Banks & Financial Institutions**	**Breweries, Bottling & Beverage**	**Hotels & Catering**	**Professional Service Telecommunication**
Q1	7.60E+08	1.17E+10	5.10E+09	9.05E+08	1.93E+10
Q2	8.17E+08	4.60E+10	4.39E+09	1.12E+09	3.88E+10
Q3	5.69E+08	3.25E+10	1.90E+10	8.26E+08	9.92E+10
Q4	8.28E+08	2.07E+10	5.23E+09	1.07E+09	1.51E+10
Q1	5.23E+08	1.90E+10	4.68E+09	1.17E+09	1.77E+10
Q2	1.21E+09	6.45E+10	5.81E+09	1.76E+09	3.74E+10
Q3	7.01E+08	2.43E+10	1.67E+10	1.49E+09	7.19E+10
Q4	6.07E+08	1.61E+10	2.77E+09	1.08E+09	2.10E+10
Q1	4.30E+08	1.59E+10	4.55E+09	4.93E+08	1.92E+10
Q2	1.32E+09	7.45E+10	6.93E+09	7.87E+08	3.81E+10
Q3	2.14E+09	2.11E+10	2.08E+10	1.37E+09	6.94E+10
Q4	6.12E+08	2.62E+10	3.12E+09	7.87E+08	2.70E+10
Q1	5.55E+08	1.10E+10	4.39E+09	3.30E+08	2.26E+10
Q2	2.40E+09	7.23E+10	1.16E+10	6.64E+08	2.50E+10
Q3	2.84E+09	4.05E+10	1.50E+10	1.45E+09	5.07E+10
Q4	6.42E+08	1.63E+10	9.59E+09	9.84E+08	3.54E+10
Q1	5.25E+08	1.45E+10	4.91E+09	6.69E+08	2.74E+10

Q2	1.07E+09	7.46E+10	1.49E+10	9.29E+08	3.80E+10
Q3	3.25E+09	3.52E+10	1.79E+10	9.55E+08	8.31E+10
Q4	2.31E+09	1.84E+10	1.07E+10	7.86E+08	2.94E+10
Q1	1.16E+09	1.30E+10	5.42E+09	1.28E+09	2.88E+10
Q2	1.19E+09	4.90E+10	2.26E+10	3.96E+08	6.38E+10
Q3	1.94E+09	2.41E+10	1.41E+10	9.05E+08	5.55E+10
Q4	1.58E+09	1.04E+10	1.11E+10	7.46E+08	3.22E+10

Model Design Based on Artificial Neural Network

The Nigerian non-oil income tax, as described in Table 1 was collected quarterly from the first quarter of 2015 to the fourth quarter of 2020, for a total of 24 quarters, implying an n = 24 sample size. An artificial neural network model was trained on the data set collected for the prediction after preprocessing. Matlab software will be used for simulation and data analysis.

The components of the forecast for Nigerian Economic Growth based on Corporate Income Tax are as follows:

(i) Agricultural & Plantation (AP)

(ii) Banks & Financial Institutions (BFI)

(iii) Breweries, Bottling & Beverage (BBB)

(iv) Hotels & Catering (HC)

(v) Professional Service Telecommunication (PST)

The predicted value CIT is taken as a function of the stated input variables above for the proposed ANN model as:

$$CIT = f\,(AP,\ BFI,\ BBB,\ HC,\ PST) \tag{1}$$

Network Architecture

ANN can be termed a computer forecasting technique that originates from the work of artificial intelligence (AI) and specifically aims to mimic the human ability to adapt to changing circumstances and the current environment. The general artificial neuron model has five components, which consist of an input layer, weighting schemes (W), thresholds (u), transfer (activation) functions (F), and layer output (Y) (Figure 2).

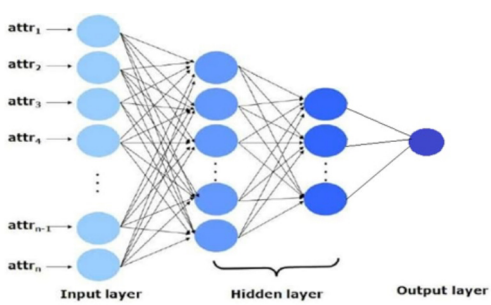

Figure 2: Neural network model architecture

Optimisation Techniques Used

Training is a procedure where an artificial neural network is adjusted to do a particular job. In other words, this is the process by which the free parameters (i.e., weights) of the network are initialised to obtain optimal values. There are several ways in which training can take place using either supervised, unsupervised, or reinforcement learning models. For conjugate gradient back-propagation with Fletcher-Reeves restarts, Bayesian regularisation, and gradient descent with an adaptive learning rate, which uses supervised learning models, specific output nodes are trained to respond to specific input patterns and result in changes in connection weights due to learning, which will be shown below.

The Conjugate Gradient Back-propagation with the Fletcher-Reeves Restarts Method

The conjugate gradient method was chosen because of its steepest descent convergence properties. The method can be greatly improved by modifying the method and considering the conjugate direction using the gradient of the function.

In general, the method can be described as follows:

Step 1: Find the search direction S_i $as\ S_i = -\nabla f_i + \beta_i S_{i-1}\ where\ \beta_i = \frac{|\nabla f_i|^2}{|\nabla f_{i-1}|^2}$

Step 2: Determine the optimal step length $\lambda_i = \frac{\nabla f_i^T \nabla f_i}{S_i^T A S_i}$

In the direction of S_i and set $X_{i+1} = X_i + \lambda_i S_i$

Step 3: Test the optimality for the new point X_{i+1}

Bayesian regularisation is a mathematical technique that transforms nonlinear regression into a proper statistical problem of the ridge regression type. These regularisations are more robust than standard back-propagation networks and can reduce or eliminate the need for time-consuming cross-validation. A mathematical model was obtained as below.

$$\eta(\vartheta / \kappa) = \frac{\eta(\kappa / \vartheta) * \eta(|\vartheta)}{\eta(\kappa)} \tag{2}$$

The Equation (2) above could be rewritten using X as input variables instead of, κ and Y as output instead of ϑ.

The category with the highest successive probability is the outcome of the prediction.

From successive probability (P(y|x)),

$$P(y|x) = \frac{P(x|y)\ P(y)}{P(x)} \tag{3}$$

$$X = (x_i, x_2, x_3, ---, x_n) \tag{4}$$

Such that:

$$P(y|x_i), - - -, x_n = \frac{P(x_1|y)P(x_2|y) - - - P(x_n|y)P(y)}{P(x_1)P(x_2) - - - P(x_n)} \tag{5}$$

By injecting this into Equation (5), we obtain:

$$P(y|x_1, - - -, x_n) \propto P(y) \prod_{i=1}^{n} P(x_i|y) \tag{6}$$

Now to find y, we said:

$$y = argmax_y \, P(y) \prod_{i=1}^{n} P(x_i|y) \tag{7}$$

Gradient descent with an adaptive learning rate: This algorithm also called Adagrad is an algorithm for gradient-based optimisation that adapts the learning rate to the parameters, performing smaller updates for parameters associated with frequently occurring features and larger updates for parameters associated with infrequent features. One of Adagrad's main benefits is that it eliminates the need to tune the learning rate manually. Most implementations use a default value of 0.01 and leave it at that.

$$g_{t,i} = \nabla_\theta J(\theta_{t,i}) \tag{8}$$

In its update rule, Adagrad modifies the general learning rate η at each time step t for every parameter θ_i based on the past gradients that have been computed for θ_i:

$$\theta_{t+1,i} = \theta_{t,i} - \frac{\eta}{\sqrt{G_{t,i}+\epsilon}} \cdot g_{t,i} \tag{9}$$

Since G_t contains the sum of the squares of the past gradients with respect to all parameters θ along its diagonal, a matrix-vector product Θ was performed between G_t and g_t to vectorise the implementation.

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{G_t+\epsilon}} \odot g_t \tag{10}$$

Model Design Based on Multiple Linear Regressions

The multiple linear regression model presented by [24, 25] and hypothesis testing undertaken by [26] are used in this study for a sample of 24. Minitab software will be used for simulation and data analysis.

The predictor or response variable Y in the following multiple linear regression equation is given by:

$$Y = \omega_1 q_1 + \omega_2 q_2 + \ldots + \omega_n q_n + \phi \tag{11}$$

The independent variables and q_1, q_2, q_3 and q_5 are agricultural & plantation, banks & financial institutions, breweries, bottling & beverage, hotels & catering, and professional service telecommunication, respectively. Whereas ω_1, ω_2, …, ω_n are regression parameters and $\emptyset$ is the Y-intercept.

Model Evaluation

The Mean Squared Error (MSE) of an estimator measures the average magnitude of the error that is the square root of the average squared differences between prediction and actual observation.

$$MSE = \frac{1}{N} \sum_{i=1}^{N} \left(A_v - Y_v \right)^2 \tag{12}$$

where A_v and Y_v represent the actual and forecast values, respectively. N is the number of data points.

RESULTS AND DISCUSSION

The results of three different algorithms were recorded and analysed from the materials and methods experimented with the data obtained.

Implementation of ANN-based Models

Conjugate Gradient with Fletcher-Reeves Restarts

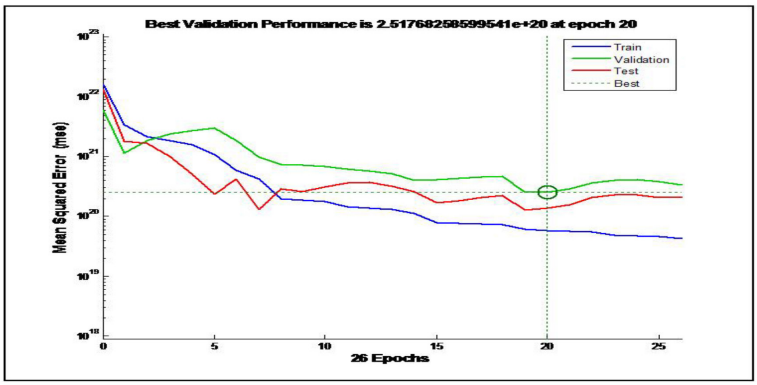

Figure 3: Mean squared error vs. number of epochs

The best validation performance of the conjugate gradient with Fletcher-Reeves restarts is 2.52e+20 at epoch 20 (Figure 3). This means that the epoch with the lowest validation error yields the best performance. The mean squared error was used to find the average squared error difference between the predicted and the actual values, which corresponds to the expected value of the squared error loss.

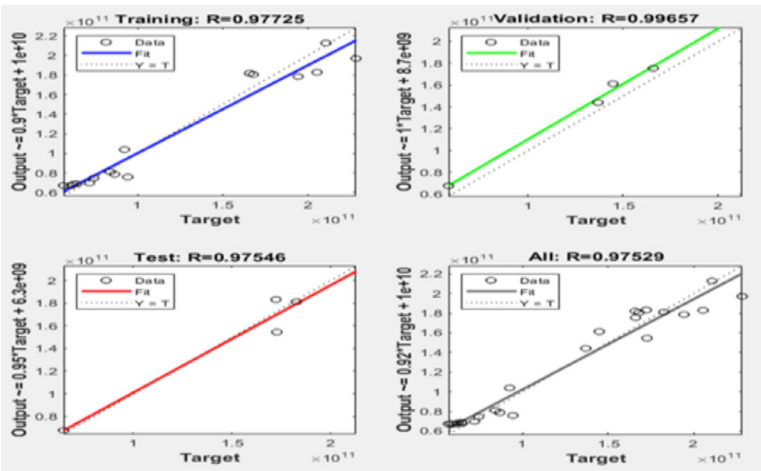

Figure 4: Regressions for the conjugate gradient with Fletcher-Reeves restarts

The analysis from Figure 4 shows that the conjugate gradient with Fletcher-Reeves restarts was trained, tested, validated and maintained an overall regression of 0.97529, and the result is good for research. Moreover, this means that the train converges to the best line with a regression above 0.92, which provides a better prediction formula. Hence, the obtained neural network model based on conjugate gradient back-propagation with Fletcher-Reeves restarts is given by:

$$Y \cong 0.92 * Target + 1e + 10 \tag{13}$$

where Y is the output:

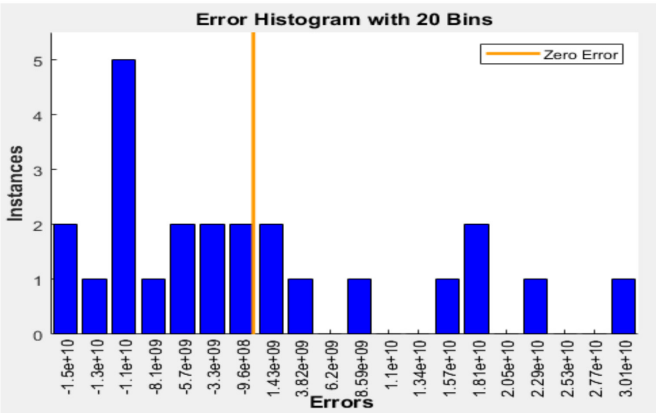

Figure 5: Error histogram

The error histogram of a hidden layer time series neural network indicates the zero mean gaussian distribution and the zero error of the conjugate gradient back-propagation with Fletcher-Reeves restarts is found to be at -9.6E+08 (Figure 5).

Bayesian Regularisation

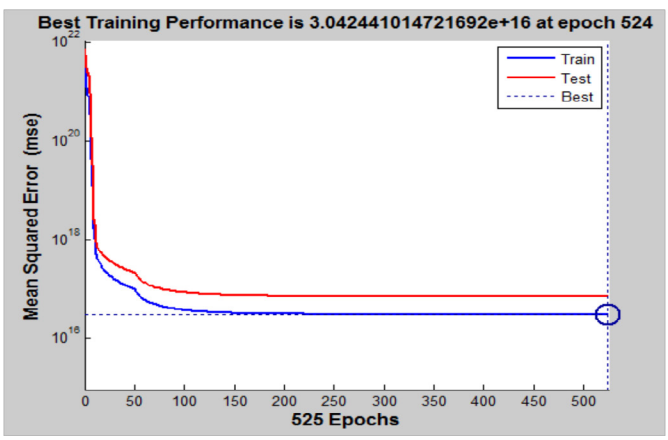

Figure 6: Mean squared error vs. number of epochs

The network was trained with 24 samples (6 years quarterly) for non-oil-generated revenue. The number of epochs exercised for training is 524. The system was tested with previously unseen data by the network in the testing stage. The learning rate was around 0.01-0.99.

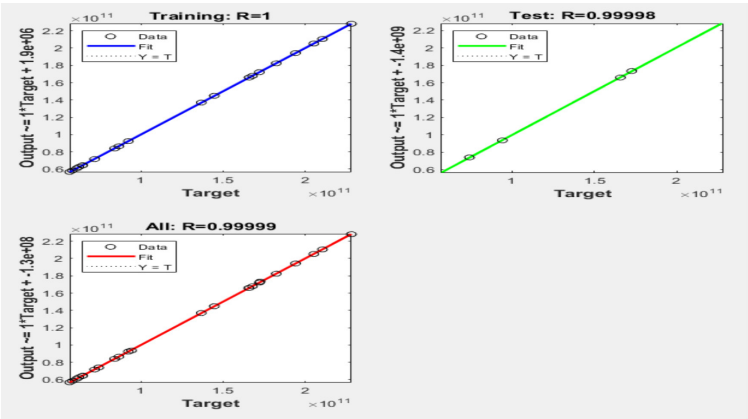

Figure 7: Regressions for Bayesian regularisation

The analysis obtained from Figure 6 shows that the Bayesian regularisation was trained, tested and maintained an overall regression of 0.99999. Moreover, it implies that the train that converges on the best line has its regression at 1, giving a better prediction equation. Hence, the obtained neural network model based on Bayesian regularisation is obtained as:

$$Y \cong 1 * \text{Target} + 1.3e + 08 \tag{14}$$

where Y is the output:

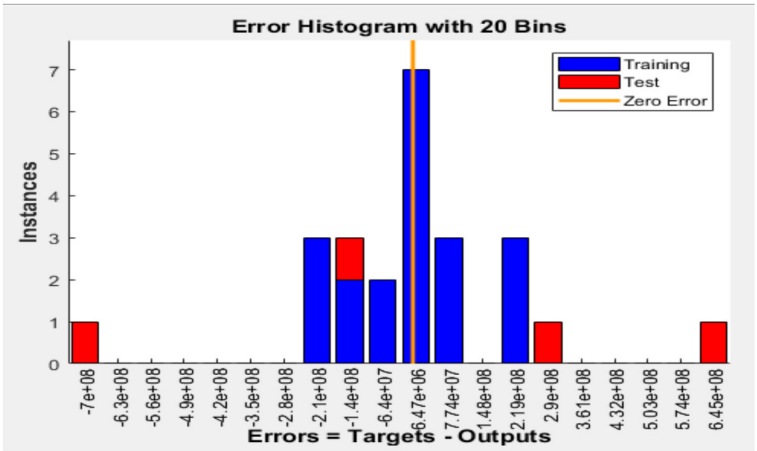

Figure 8: Error histogram

The y-axis represents the number of samples in the dataset in a particular bin. The bins are just the number of the vertical axis in Figure 7. The zero error line corresponds to the zero error value on the error axis (x-axis). This means zero error points are below the bin centred at -6.47E+06 and training values are between 6 and 7 (Figure 8).

Gradient Descent with Adaptive Learning Rate

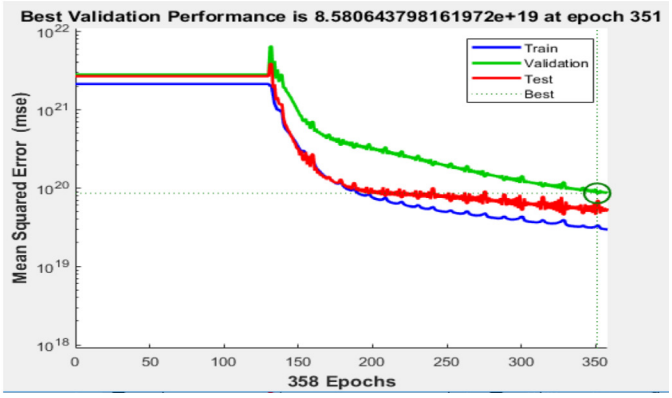

Figure 9: Mean squared error vs. number of epochs

The best validation performance of gradient descent with an adaptive learning rate is 8.58E+19 at epoch 351 (Figure 9). This means we get the best performance from the epoch with the lowest validation error (epoch 351).

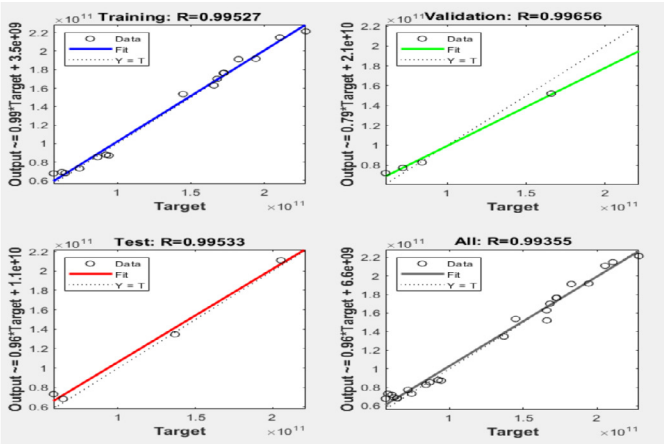

Figure 10: Regressions for gradient decent with an adaptive learning rate

The model has a training regression of 0.99527, was validated using 15% of the original data to obtain a regression of 0.99656 and was tested with 15% of the original data to obtain a regression of 0.99533. The overall regression of the model is 0.99355, indicating a good algorithm. Furthermore, this means that the train that converged on the best line has a regression above 0.96, which gives us a better prediction formula. As a result, the resulting gradient descent neural network model with an adaptive learning rate is given by:

$$Y \cong 0.96 * \text{Target} + 1.1e + 10 \tag{15}$$

where Y is the output.

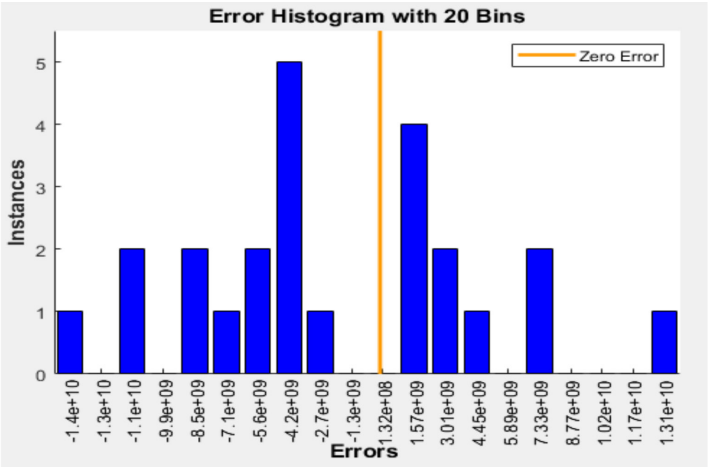

Figure 11: Error histogram

The error histogram in Figure 10 indicates zero mean gaussian distribution and zero error is at 1.32e+08.

Comparison of Results between ANN Training Algorithms

Table 2: Comparison of the results based on regression and performance evaluation

Neural Network Training Algorithm	Regression (Overall Regression)	Model Evaluation (Mean Squared Error)
Conjugate gradient back-propagation with Fletcher-Reeves restarts	0.97529	1.7486e+21
Bayesian regularisation	0.99999	1.3007e+12
Gradient descent with an adaptive learning rate	0.99355	9.0901e+19

According to the results in Table 2, conjugate gradient back-propagation with Fletcher-Reeves restarts has the lowest regression value of 0.97529 and the highest performance error of 1.7486 e+21. The Bayesian regularisation outperformed others with an overall regression of 0.99999, approximately R = 1, with a minimum performance error MSE of 1.3007e+12. If the resulting value of R is 1 or very close to 1, then, the linear relationship is perfect and a value of zero means no relationship. Hence, Bayesian regularisation is the best algorithm for forecasting.

Implementation of Multiple Linear Regressions Model

Multiple regression analysis was performed on normalised data using Minitab version 21. The results of this process for the final model are shown below.

Regression Analysis

The P-value of the regression in the analysis of variance in Table 3 is 0.000; this shows that the level of the model estimated by the regression procedure is significant at a level of 0.05, which indicates that at least one coefficient is different from zero.

Table 3: Analysis of variance

Source	DF	Adj. SS	Adj. MS	F-value	P-value
Regression	5	7.77252E+22	1.55450E+22	3.74333E+11	0.000
Agricultural & plantation	1	2.22977E+19	2.22977E+19	5.36941E+08	0.000
Banks & financial institutions	1	2.10606E+22	2.10606E+22	5.07151E+11	0.000
Breweries, bottling & beverage	1	4.25409E+20	4.25409E+20	1.02441E+10	0.000
Hotels & catering	1	5.51699E+18	5.51699E+18	1.32852E+08	0.000
Professional service telecommunication	1	6.78754E+21	6.78754E+21	1.63448E+11	0.000
Error	18	7.47492E+11	41527337870		
Total	**23**	**7.77252E+22**			

The P-values of the estimated coefficients for agricultural & plantation, banks & financial institutions, breweries, bottling & beverage, hotels & catering, and professional service telecommunication in Table 3 are all 0.000 (0.05), indicating that they are significantly related to Cooperative Income Tax (CIT). According to the adjusted squares, the predicted values explain a significant amount of unique variance, implying that a model with all five factors may be more appropriate.

Table 4: Model summary

S	R-sq.	R-sq. (adj.)	R-sq. (pred.)
203783	90.81%	82.24%	80.70%

From Table 4, the R-square values indicate that the predictors explain 82.24% of the variance in agricultural & plantation, banks & financial institutions, breweries, bottling & beverage, hotels & catering, and professional service telecommunication. The adjusted R-square is 80.70%, which accounts for the number of true predictors in the model (both values indicate that the model fits the data well), and the predicted R-value is 90.81%. However, since the predicted R-value is close to the R-square and adjusted R-square values, the model does not appear to overfit and has the adequate predictive ability.

Table 5: Coefficients of the proposed MLR model

Term	Coef.	SE Coef.	T-value	P-value	VIF
Constant	162498	144836	1.12	0.277	
Agricultural & plantation	1.50004	0.00006	23171.89	0.000	1.53
Banks & financial institutions	1.50000	0.00000	712141.91	0.000	1.11
Breweries, bottling & beverage	1.50000	0.00001	101212.55	0.000	4.62
Hotels & catering	1.49969	0.00013	11526.09	0.000	1.14
Professional service telecommunication	1.50000	0.00000	404284.65	0.000	3.87

Except for breweries, bottling & beverage business, the variance-indicating factors for agricultural & plantation businesses, banks & financial institutions, and hotels & catering are all around one, as shown in Table 5; this indicates that the predictors are correlated; VIF values less than 5-10 indicate that the regression coefficients are adequately estimated.

All assumptions of the regression analysis were validated. Therefore, a linear regression model seemed appropriate. The multiple regression model equation is:

$$CIT=1.50004Agricultural\&Plantation+1.50000Banks\&FinancialInstitutions+1.50000Breweries,Bottling\&Beverage+1.49969Hotels\&Catering+1.50000ProfessionalService-Telecommunication+162498 \quad (16)$$

Equation (16) is explicitly expressed in Equation (11).

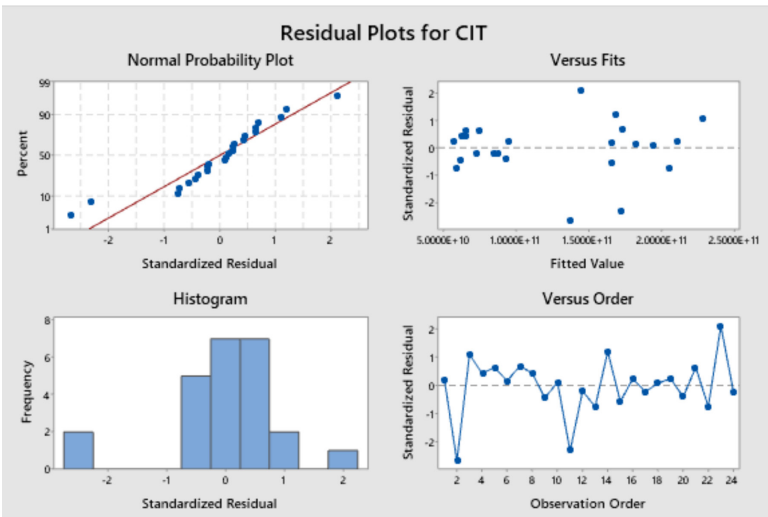

Figure 12: Validation of regression assumptions in diagram form

The histogram shows outliers in the data, as indicated by the two bars on the far right and left (Figure 12). The normal probability plot shows approximately linear patients fitting normal distribution, with two outliers in the upper and lower corners (right and left, respectively). These are the same points that indicate unusual observations in the output. In Figure 11, the verses fit the plot and residuals. Fitted values show that the residuals decrease as the fitted value increases as the reference line is approached. This may indicate non-constant variance.

Table 6: Comparison of results between ANN and MLR models

Model	Regression	Model Evaluation (Mean Squared Error)
Conjugate gradient back-propagation with Fletcher-Reeves restarts	0.97529	1.7486e+21
Bayesian regularisation	0.99999	1.3007e+12
Gradient descent with adaptive learning rate	0.99355	9.0901e+19
Multiple linear regression	0.90810	7.77252E+22

Table 6 shows the results obtained between models ANN and MLR. The multiple linear regression model has a multiple R of 0.90810 with MSE of 7.77252E+22; this revealed that its linear relationship is not as perfect as those of conjugate gradient back-propagation with Fletcher-Reeves restarts, Bayesian regularisation, and gradient descent with an adaptive learning rate, with regressions of 0.97529, 0.99999 and 0.99355, respectively. The Bayesian regularisation outperformed all other models with a regression of 0.99999, approximately 1, with a minimum performance error of 1.3007e+12. If the value of R is 1 or close to 1, the linear relationship is perfect. Hence, Bayesian regularisation is the best algorithm for forecasting.

CONCLUSION

Non-oil income tax is very useful to Nigeria due to the problems of oil bunkering and insurgency in many parts of the country. Forecasting the non-oil income tax is one of the major topics of discussion in the 21st century in Nigeria. Most researchers adopt the conventional way of forecasting the price of both oil and non-oil taxes. This research is almost one of a kind as it uses artificial neural networks and multiple linear regression models to forecast economic growth based on non-oil income tax (Corporate Income Tax) in Nigeria. It has been found that among the four models used, Bayesian regularisation is the best as it produces a better overall regression of 0.99999. The government can make use of the ANN model to yield positive forecasts.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

ACKNOWLEDGEMENTS

The authors express their appreciation to the National Bureau of Statistics of Nigeria for providing the dataset.

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