PREDICTION OF THE FUTURE EFFECT OF NIGERIA ECONOMY GROWTH ON IMPORT AND EXPORT COMMODITIES

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Abstract
The aim of this study is to develop models that will be used for prediction the effects of Nigeria economy development and growth on international trade based artificial intelligence technique and traditional statistical forecasting tool. The quarterly time-series data obtained from the National bureau of statistics for 2016 Q1 through 2019 Q1 on Imports and exports was employed with three variables namely Agricultural goods, Raw material goods and Solid mineral goods. The result of regression, normal probabilty and performance metric reveals that the models are moderately well specified and could be used for policy analysis. The study reveals that increase participation in global trade particularly in non-oil exports helps Nigeria to reap static and dynamic benefit of international trade. The prediction model based on artificial intelligence technique (Adaptive Neuro Fuzzy Inference System) produced more accurate result than statistical forecasting (Multiple Linear Regressions) model. The Nigerian government could make use of ANFIS to aid her in maximizing profit in the non-oil foreign trade. The analysis for this study was simulated using MATLAB software version 8.3 and Minitab18 software; executed in PC Intel Pentium IV E7400 processor with 2.80 GHz speed and 2.0 GB of RAM.

Keywords: *ANFIS, Economic Growth, International Trade, MLR, Prediction*

Introduction
International trade is the exchange of goods and services across national borders and allows countries to expand their markets for both goods and services that otherwise may not have been available domestically. As a result of international trade, the market contains greater competition, and therefore more competitive prices, which brings a cheaper product home to the consumer (Heakal, 2019).

The growth performance of the Nigeria economy has been less satisfactory during the past three decades until recently when statistics show steady growth in the nation's economy. Apart from oil, Nigeria export mainly primary products and often rely almost exclusively on a limited number of commodities, such exports are characterized by lower prices than manufactured goods plus highly volatile markets. Thus, Nigeria is often on the wrong end of unbalanced trade environment that favours developed countries. Nigeria with the abundant human and natural resources is paradoxically being regarded as one of the poorest countries in the world (Adeleye, Adeteye & Adewuyi, 2015).

The economy of Nigeria has had to navigate a major crisis. The crisis of the past four years reaffirms the vulnerability of the Nigerian economy to oil related shocks. Oil accounts for 90% or more of Nigerian merchandise exports. This heavy dependence of the Nigerian economy on oil as the dominant source of foreign exchange is widely acknowledged. But the mechanisms through which oil price changes affect the economy. By the end of 2015, oil prices had collapsed. At that time, Nigeria got only about USD$40 worth of imports for each barrel of oil exported. By August 2018, prices had rebounded to about USD$65 per barrel or about USD$65 worth of imports for each barrel exported. Businesses in a growing economy require more capital goods and more intermediate inputs. Without progressively more exports, there cannot be progressively more imports of efficient machines, tools, and other technologies that are critical for growth. The only way Nigeria can avoid this stagnant state of affairs is if it does something dramatic about increasing non-oil exports. Agricultural products, Raw material products and solid mineral products are potentially a part of the solution (The Conversation, 2018).

Nigerian economy has grossly underperformed relative to its economic endowment and her peer nations. With about 37 solid minerals types and a population estimate of over 160 million people, one of the largest gas and oil reserves in the world, the economic performance of the country is rather weak when compared to the emerging Asian countries such as Thailand, Malaysia, China, India and Indonesia and even Brazil. These countries had by far lagged behind Nigeria or at par with Nigeria in terms of GDP per capital in 1970s, but later they were better able to transform their economies to emerge as major players on the global economic arena. In 1970, for instance, Nigeria had a GDP per capital of US$233.35 and was ranked 88thin the world, when China was ranked 114with a GDP per capital of US$111.82 (Udeaja & Onyebuchi, 2015). Today, China occupied an enviable position even as the second largest economy after the United State of America, largely owing to her self-esteemed trade position.

Imports to Nigeria rose 2.6% year-on-year to NGN 1002 billion in March 2019, boosted by purchases of energy goods (796.3%); manufactured goods (101.3%); solid mineral (70.8%); raw material (46.9%) and agricultural goods (61.3%). Imports in Nigeria averaged 227104.84 NGN Millions from 1981 until 2019, reaching an all time high of 2209385.78 NGN Millions in August of 2018 and a record low of 167.88 NGN Millions in May of 1984 (Trading Economics, 2019a)

Exports from Nigeria dropped 0.2% year-on-year to NGN 1452 billion in March 2019, amid declines in sales of raw material (-20.5%); solid minerals (-43.1%) and energy goods (-4.8%). In contrast, they grew for agricultural goods (74.5%); crude oil (0.7%) and manufactured goods (353.6%). Exports in Nigeria averaged 432508.24 NGN Millions from 1981 until 2019, reaching an all-time high of 2648881.76 NGN Millions in December of 2011 and a record low of 322.93 NGN Millions in February of 1983 (Trading Economics, 2019b)

Materials and Methods

In this study, Trade (Imports and Exports) data set was obtained from the website of the National Bureau of Statistics of Nigeria (National Bureau of Statistics, 2019). The date set used are for agricultural goods, raw material goods and solid mineral goods.

Imports: The value of total imports roseto N3,703.7 billion, representing an increase of 3.39% in Q1 2019 compared to Q4 2018, and by 25.84% over the corresponding quarter of 2018. The trade balance remained positive at N831.6 billion in Q1 2019. Imported Agricultural products were 7.98% higher in value than in Q4 2018, and 28.1% higher than in Q1, 2018. The value of Raw material imports grew 6.62% more than the value recorded in Q4, 2018 and 20.76% more than the value recorded in Q1 2018. The value of Solid minerals imports was 1.26% more than the value of imports in Q4, 2018 and 35.90% higher than the value recorded in Q1 2018.

Exports: The value of total exports in Q1, 2019 increased by 1.78% against the level recorded in Q4, 2018 but decreased by 3.90% against its value in Q1, 2018. In Q1 2019 the value of agricultural exports was 11.89% lower than in Q4, 2018 but 17.5% higher than Q1 2018. The value of raw material exports in Q1, 2019 was 10.67% lower than the value in Q4, 2018 but 11.57% higher than in Q1 2018. The value of Solid minerals exports increased by 16.88% relative to Q4 2018 but decreased by 66.6% compared to the corresponding quarter in 2018.Total trade grew by 2.50% in Q1,2019 compared to Q4, 2018, and 7.52% relative to the corresponding quarter in 2018.

System Design

Trade (Imports and Exports) data set was obtained from the website of the National Bureau of Statistics of Nigeria from January, 2016 to March 2019, having 39 months in all, implying an initial sample size of n = 39. Adaptive neuro fuzzy inference system was trained with the data set collected for prediction after pre-processing it.

Concept and Structure of Adaptive Neuro Fuzzy Inference System

Adaptive Neuro Fuzzy Inference System (ANFIS) was first introduced by Jang (1993). The ANFIS is a framework of adaptive techniques to assist learning and adaptation. According to Jang, Chuen & Mizutani (1997), if $f\left(x, y\right)$ is a first order polynomial, then Takagi Sugeno Kang (TSK) Fuzzy model is gives as:

$$if\ \ x\ is\ A_j\ \ and\ \ y\ is\ B_k\ \ then\ Z_i = px + qy + r \tag{1}$$

where A and B are fuzzy sets in the rule antecedent part, while $Z_i = px + qy + r = f(x, y)$ is a crisp function in the rule consequent part, and p, q & r are the optimal consequent parameters. Usually $f(x, y)$ is a polynomial in the input variables x and y.
Degree the input matches' number of rule, is typically computed using min operator

$$w_i = \min\left(\mu_{A_i}\left(x\right), \mu_{B_i}\left(y\right)\right) \tag{2}$$

where μ_{A_i} & μ_{B_i} are membership functions that define the fuzzy set A & B, respectively, on the universe x and $i = 1, \ldots, n$.
The final output of the system is the weighted average of all rule outputs, computed as

$$Final\ output = \frac{\sum_{i=1}^{N} \mathrm{w}_i z_i}{\sum_{i=1}^{N} w_i} \tag{3}$$

These rules are combined to get a function define as:

$$R\left(x\right) = \frac{A_1\left(x\right) f_1\left(x\right) + A_2\left(x\right) f_2\left(x\right) + \ldots + A_n\left(x\right) f_n\left(x\right)}{A_1\left(x\right) + A_2\left(x\right) + \ldots + A_n\left(x\right)} \tag{4}$$

This Takagi Sugeno Kang (TSK) fuzzy model produces a real-valued function.
The structure of the proposed model contains five layers, the input and output layers, and three hidden layers that represent membership functions and fuzzy rules. Each layer contains several nodes and the structure of ANFIS was described in (Sagir, 2017).

Fuzzy C-Means Clustering Algorithm

According to Rabunal and Dorado (2006), the Fuzzy C-Means (FCM) has the advantage of less number of rules and it is considered as more efficient. The Fuzzy c- means aims to minimize an objective function:

$$J\left(U, V\right) = \sum_{i=1}^{N} \sum_{j=1}^{c} (U_{ij})^m x_i - v_j^{\,2} \tag{5}$$

U_{ij} is the degree of membership of x_i in the cluster j, v_j is the center of cluster, $\|*\|$ is any norm expressing the similarity between any measured data (e.g. Euclidean and City block distances) and the center, m is any real number $> 1\ (1 \le m < \infty)$. Training Algorithm for FCM can be found in (Saratha and Sagir, 2014).

Performance Metric

Root Mean Square Error is one of the most acceptable indicators that describe the differences between the actual data and the predicted values. The values of premise and consequent parameters can be obtained after network training by directly minimizing the RMSE performance criterion (Ho *et al.*, 2009).

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(y - y'\right)^2} \quad (6)$$

where y and y' are ith desired output and predicted output respectively; and N is the number of total points.

Modelling of the Imports and Exports Goods with Multiple Linear Regressions Model

This method uses the sum of the least squared errors to fit a curve to a data set. Using Minitab 18, a linear regression analysis was performed on the data set. Three variables were used as the independent variables (*Xi*), that is, $X_1,\ X_2\ and\ X_3$ be the Agricultural Goods (*Agricultural Goods*), the Raw Material Goods (*Raw Material Goods*) and Solid Mineral Goods (*Solid Mineral Goods*), respectively. The dependent variable is termed *Y*, is the value of Imports or Exports (*Imports/Exports*).

Four assumptions checks were carried out on the data set: (i) Normality (ii) Homoscedasticity (iii) The Independence of errors and (iv) Linearly.

The Multiple Linear Regressions formula is as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots + \beta_n X_n + \varepsilon \quad (7)$$

where Y is the response variable, β_0 is the constant, $\beta_1,\ \beta_{2,}\ \ldots,\ \beta_n$ are the coefficients, $X_1,\ X_2\ ,\ldots,\ X_n$ are the values of the term.

Results and Discussions

From the materials and methods that were experimented with the data collected, the results from the two different models were recorded and analyzed.

Implementation of the ANFIS model

This research work introduces an improved hybrid approach for training the adaptive network based fuzzy inference system (ANFIS), it incorporates hybrid learning algorithms least square estimates with Gradient Descent algorithm to get the initial values of the conclusion parameters and calculates the premise or antecedent parameters are updated.

Table 1 to Table 4 shows the RMSE prediction performances for three input variables with Month-on-Month predictions based on data sample length of 39 observations (January, 2016 to March, 2019).

Table 1: Performance Results on Training Data set for Imports

No. of Iterations	1000	2000	3000	4000
RMSE	89873.7031	74590.6162	1074.6741	47351.7429
Error Mean	-13985.5483	-20837.0658	0.11895	1081.5611
Regression, R^2	0.13413	0.29055	0.89974	0.45799

Table 1, shows the performance results on training data set for imports. The best regression $R^2 = 0.89974$ is closer to 1 after 3000 iterations, indicates the strongest linear relationship between dependent variable (imports) and independent variables (Agricultural goods, Raw material goods and Solid mineral goods). The linear relationship is positively perfect with error mean found to be 0.11895 and the standard error, RMSE gave an adequate error as 1074.6741.

Table 2:Performance Results on Testing Data set for Imports

No. of Iterations	1000	2000	3000	4000
RMSE	182350.6914	89759.2422	4013.7743	72601.1316
Error Mean	-40485.5351	33424.5265	-1344.7153	19683.8596
Regression, R^2	0.57273	0.36254	0.89777	0.49485

Table 2, presents the performance results on test data set for imports. The best regression $R^2 = 0.89777$ is closer to 1 after 3000 iterations, indicates the strongest linear relationship between dependent variable (imports) and independent variables (Agricultural goods, Raw material goods and Solid mineral goods). The linear relationship is positively perfect with error mean found to be -1344.7153 and the standard error, RMSE gave an adequate error as 4013.7743.

Table 3: Performance Results on Training Data set for Exports

No. of Iterations	1000	2000	3000	4000
RMSE	456.1808	461.2981	415.2176	473.1704
Error Mean	-4.4174	-3.4503	-48.016	10.0193
Regression, R^2	0.99485	0.99431	0.99737	0.99017

Table 3, indicates the performance results on training data set for exports. The best regression $R^2 = 0.99737$ is closer to 1 after 3000 iterations, indicates the strongest linear relationship between dependent variable (exports) and independent variables (Agricultural goods, Raw material goods and Solid mineral goods). The linear relationship is positively perfect with error mean found to be -48.016 and the standard error, RMSE gave an adequate error as 415.2176.

Table 4: Performance Results on Testing Data set for Exports

No. of Iterations	1000	2000	3000	4000
RMSE	934.467	880.8453	563.1550	1146.2013
Error Mean	46.2278	351.0044	-33.026	42.2345
Regression, R^2	0.97661	0.98128	0.99242	0.93664

Table 4, indicates the performance results on training data set for exports. The best regression $R^2 = 0.99242$ is closer to 1 after 3000 iterations, indicates the strongest linear relationship between dependent variable (exports) and independent variables (Agricultural goods, Raw material goods and Solid mineral goods). The linear relationship is positively perfect with error mean found to be -33.026 and the standard error, RMSE gave an adequate error as 563.1550.

The data set was divided into training set of 70%and the testing set 30%.ANFIS model performance was measured by the coefficient of determination (R^2) and the performance of the Root Mean Squared Error with least error. The coefficient of determination is a measure of the accuracy of prediction of the trained network models. Higher (R^2) values indicate better prediction than lower values. The test data set was used for testing the proposed model and results show that exports result outperformed imports result with lower error (RMSE) and higher regression values as presented in Table 2 and Table 4. However, the results of train data set are presented in Table 1 and Table 3.

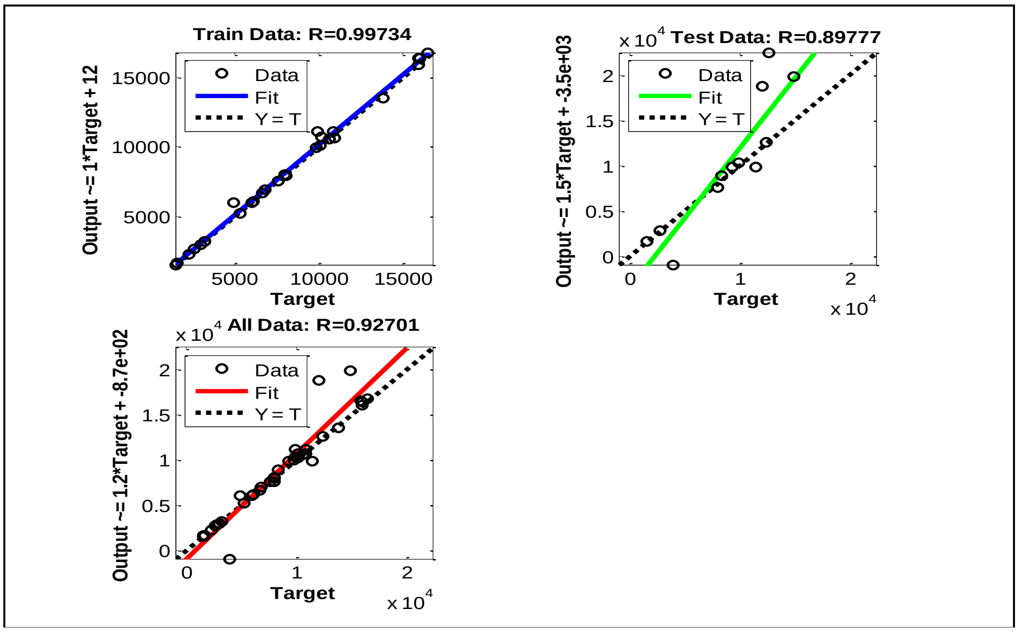

Figure 1: The best graphs showing the training, testing and all regression values for Imports

The performance of training, testing and combined data for imports in terms of regression analysis was illustrated in Figure 1. In regression plot, the perfect fit which shows the perfect correlation between the predicted outputs and the targets is indicated by solid line. The dashed line indicates the best fit produced by the algorithm. Training data set produced $R = 0.99734$, combined data $R = 0.92701$ and test data $R = 0.89777$.

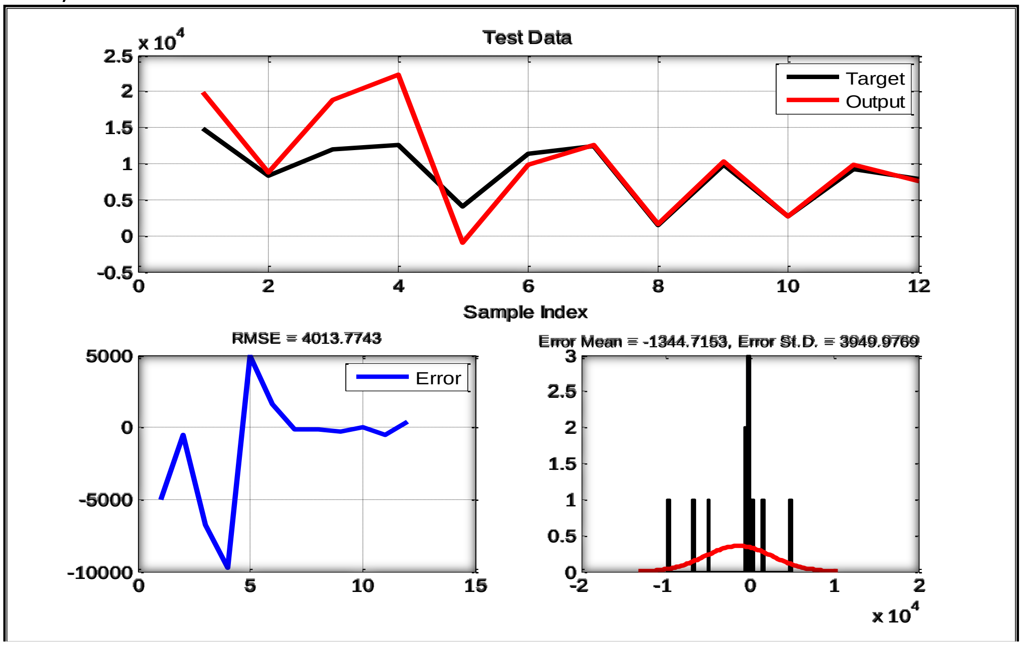

Figure 2: Best Plots of Test Dataset, RMSE and Error Mean for Imports

Figure 2, shows the best plots of test data set for performance error (root mean square error) and error mean for imports. It can be observed that the root mean square error (RMSE) and Error mean are decreased as iterations reached 3000. However, as the number of iterations increases above 3000 the network is over trained and the root mean square error increases. The best performance was obtained at 3000 iterations at which the RMSE is 4013.7743 and error mean is -1344.7153.

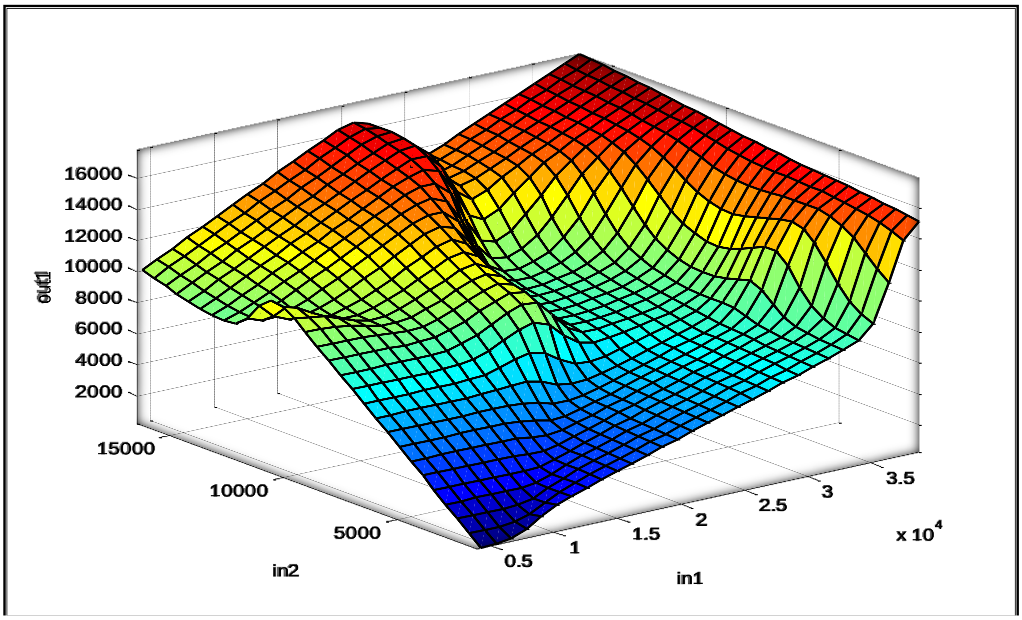

Figure 3: Surface graph showing relationship of Output with Inputs for Imports

In order to visualize the surface obtained from the test data set for imports after training the model for 3000 iterations, the three dimensional plot (3D surface) of the model is generated as shown in Figure 3.

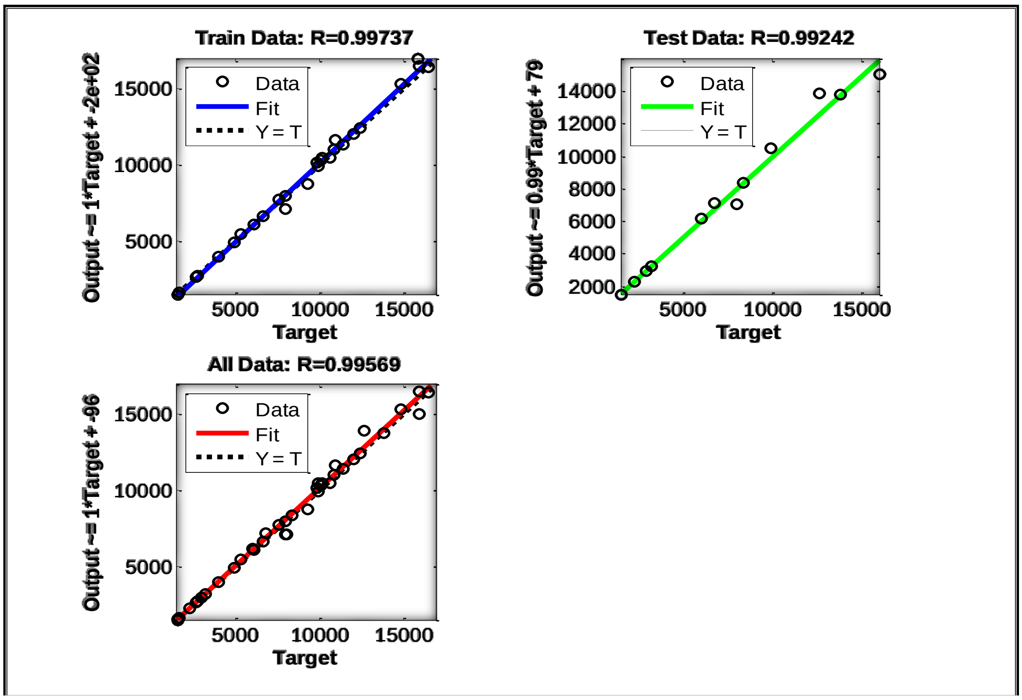

Figure 4: The best graphs showing the training, testing and all regression values for Exports

Figure 4, illustrates the performance of training, testing and combined data for exports in terms of regression analysis. In regression plot, the perfect fit which shows the perfect correlation between the predicted outputs and the targets is indicated by solid line. The dashed line indicates the best fit produced by the algorithm. Training data set produced $R = 0.99737$, test data $R = 0.99242$ and all data $R = 0.99569$.

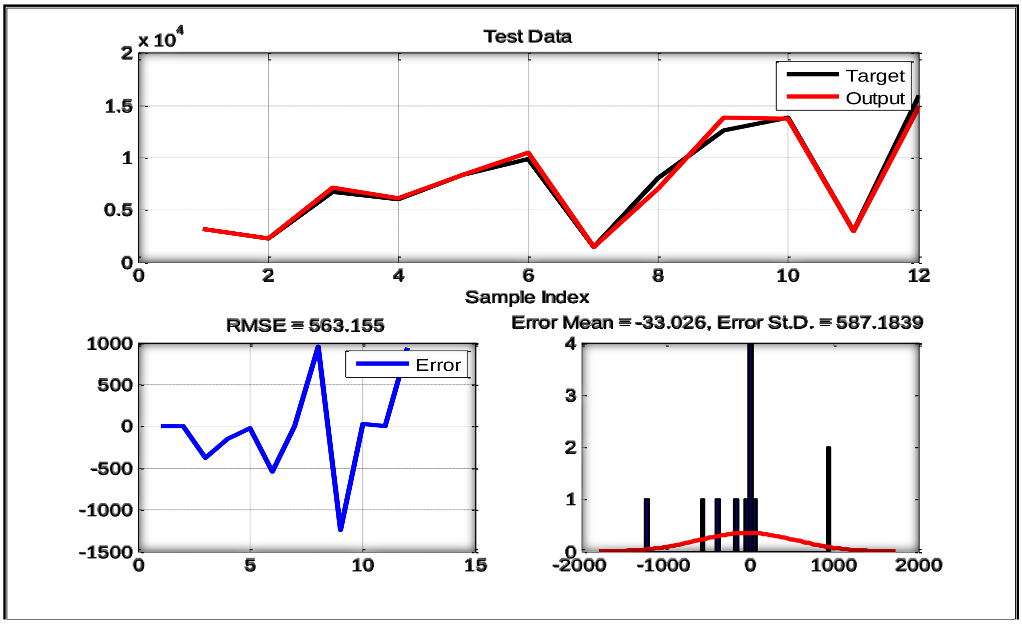

Figure 5: Best Plots of Test Dataset, RMSE and Error Mean for Exports

Figure 5 shows the best plots of test data set for performance error (root mean square error) and error mean for imports. It can be observed that the root mean square error (RMSE) and Error mean are decreased as iterations reached 3000. However, as the number of iterations increases above 3000 the network is over trained and the root mean square error increases. The best performance was obtained at 3000 iterations at which the RMSE is 563.1550 and error mean is -33.026.

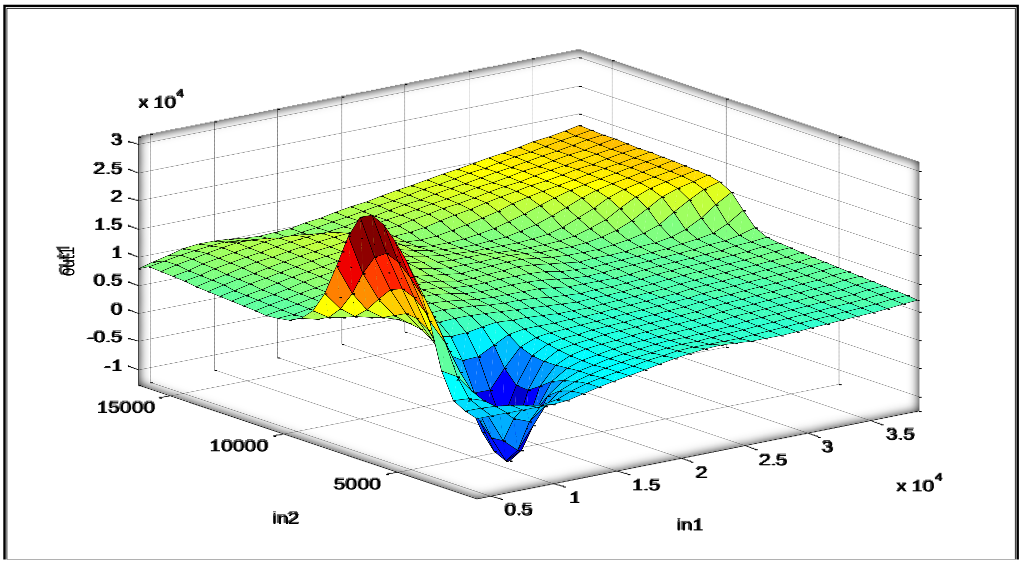

Figure 6: Surface graph showing relationship of Output with Inputs for Exports

In order to visualize the surface obtained from the test data set for imports after training the model for 3000 iterations, the three dimensional plot (3D surface) of the model is generated as shown in Figure 6.

The plot of Figure 1 to Figure 6 present the best graphs showing the training, testing and all regression values, the best plots of test dataset, root mean squared error and error mean; and surface graph showing relationship of output with inputs both for imports and exports.From Figure 1 and Figure 4 indicates that the train which converge to the best line has regression above 0.99737, gives better prediction. Hence, the Mathematical models of ANFIS for Imports and Exports are respectively obtained as:

$$I \square 1.2 * T + (-8.7e + 02) \tag{8}$$

$$E \square 1 * T + (-96) \tag{9}$$

The letter I or E is the Imports or Exports to be predicted while T is used as the training data, which will be used for making prediction.

Implementation of Multiple Linear Regressions Model

Multiple linear regressions analysis was performed on the normalized data using Minitab version 18. The output of this process for the final model is presented below.

Table 5: Multiple Linear Regressions Statistical Outcomes

Regression Parameter	Imports Result (%)	Exports Result (%)
R^2	67.05	74.82
Adjusted R^2	64.23	72.66
R^2 (Pred)	59.23	67.53

Table 5, shows the overall goodness of fit measures. The R^2 (Pred) indicates the strongest or weakness the linear relations are between dependent and independent variables. When the value of R^2 (Pred)is 1 or closer to 1, the linear relationship is positively perfect, and a value zero means no relationship at all. In Table 5, $R^2\left(Pred\right) = 67.53\%$ for exports indicates better linear relationship than that of imports with $R^2\left(Pred\right) = 59.23\%$,and the number of observation $n = 39$ was used in the regression. Hence, the general regression model equation is presented in equation (10).

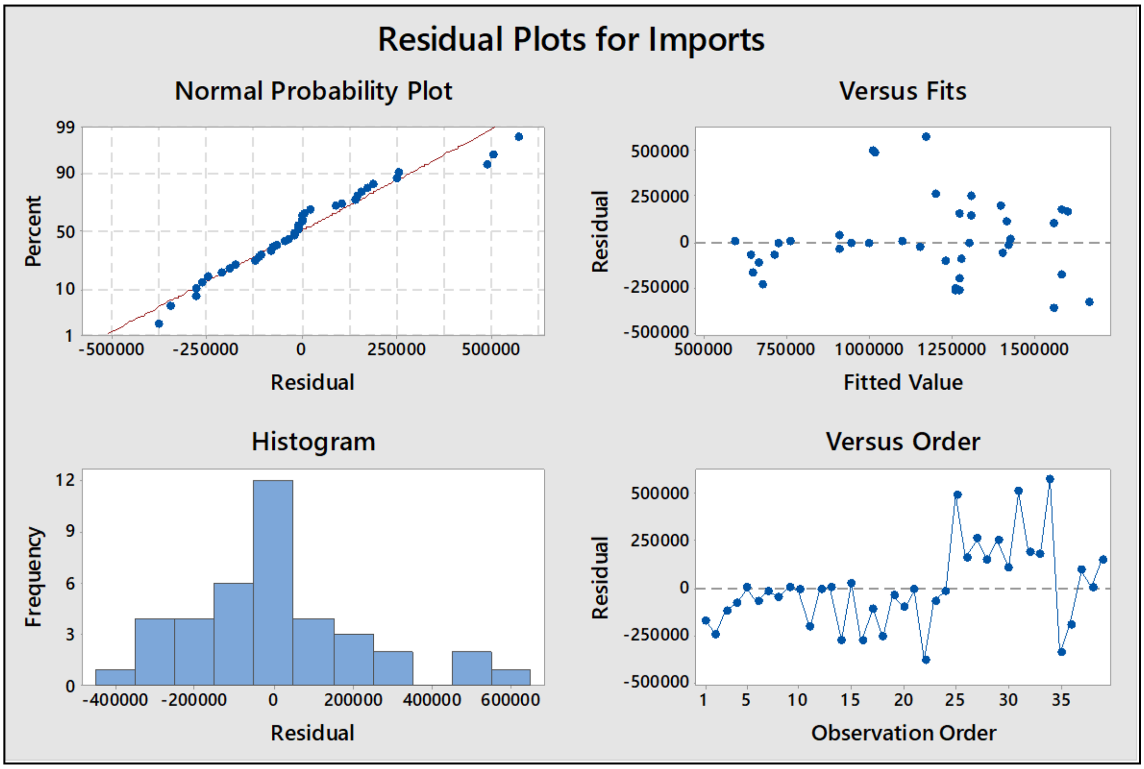

Figure 7: The verification of the regression assumptions in plot forms for Imports

Figure 7, the regression assumptions are verified in plot form for imports data, which show the errors are normally distributed with a zero mean and constant standard deviation. The true relationship between dependent variable and predictor is linear. This plot further illustrates error histogram that presents number of data that falls in different error values.

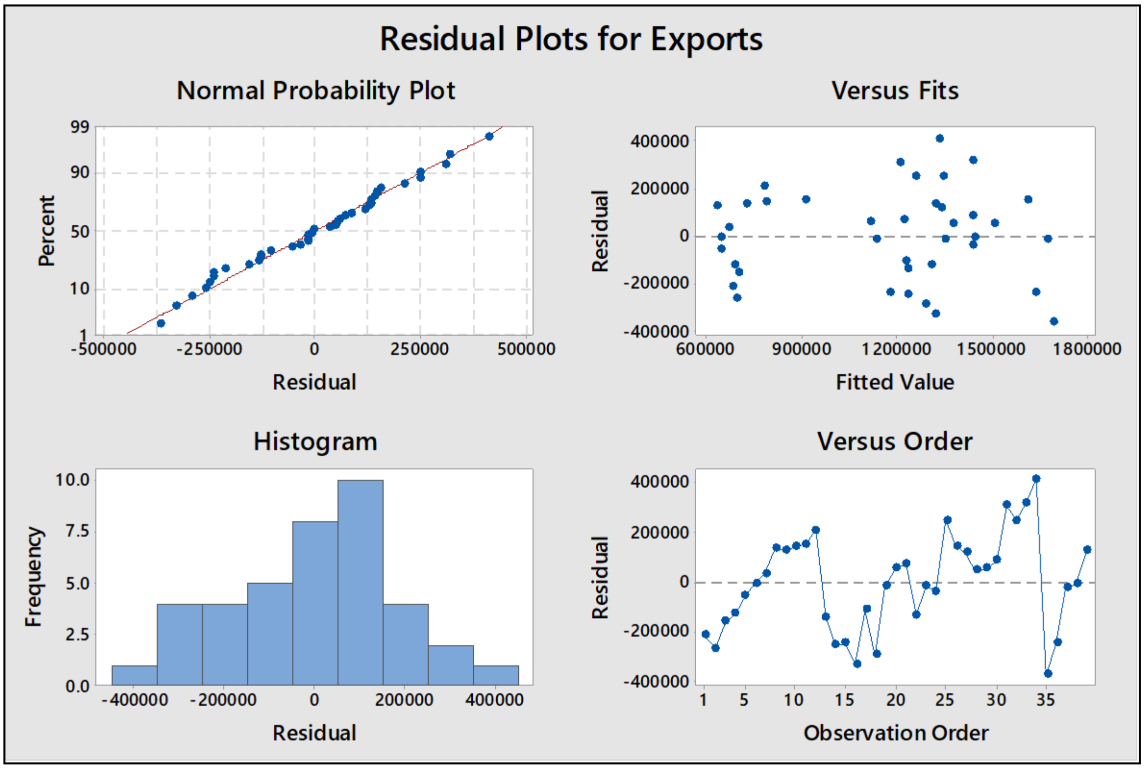

Figure 8: The verification of the regression assumptions in plot forms for Exports

Figure 8, the regression assumptions are verified in plot form for exports data, which show the errors are normally distributed with a zero mean and constant standard deviation. The confidence intervals for predictions and confidence intervals for coefficients are accurate. The true relationship between dependent variable and predictor is linear. This plot further illustrates error histogram that presents number of data that falls in different error values. However the plot of residuals versus observation order verified that the residuals are independent from one another.

All the assumptions of regression analysis were verified; therefore the multiple linear regression models seemed appropriate. Hence, from equation (7), the Regression model equation is obtained as:

$$Imports / Exports = \beta_0 + \beta_1 AgriculturalGoods + \beta_2 RawMaterialGoods + \beta_3 SolidMineralGoods \quad (10)$$

From equation (10), the following equations (11) and (12) are obtained as:

$$Imports = 223410 + 6.57 AgriculturalGoods + 56.04 RawMaterial\,Goods + 4.0\,SolidMineralGoods \quad (11)$$

where $\beta_0 = 223410$ is the constant, $\beta_1 = 6.57$ is the coefficent of Agricultural goods,

$\beta_2 = 56.04$ is the coefficent of Raw material goods,

$\beta_3 = 4.0$ is the coefficient of Solid mineral goods

$$Exports = 558651 + 6.64 AgriculturalGoods + 31.1 RawMaterialGoods + 99.0\,SolidMineralGoods \quad (12)$$

where $\beta_0 = 558651$ is the constant, $\beta_1 = 6.64$ is the coefficent of Agricultural goods,

$\beta_2 = 31.1$ is the coefficent of Raw material goods,

$\beta_3 = 99.0$ is the coefficient of Solid mineral goods

Table 6: Comparasion of Results Based on R^2 for Test Datasets

Model	R^2	
	Imports	Exports
ANFIS	0.89777	0.99242
MLR	0.59230	0.67530

Table 6 show that the results obtained between the two models. ANFIS result outperformed that of MLR. ANFIS produced high value of $R^2 = 0.99242$ with less performance error than MLR with a very low of $R^2 = 0.67530$ for exports data set. In prediction models, the closer the values of R^2 to 1 with lower performance error, the better prediction results.

Conclusion

Artificial intelligence technique under the machine learning phenomenon was applied for the prediction of the future effect of Nigeria economy. The prediction model based on ANFIS produced more accurate results than MLR. The Nigerian government could make use of ANFIS to aid her in maximizing profit in the foreign trade sector. The goal is to assist government or investors predict continuous imports or exports of goods. Results revealed that exports of goods yields better result than imports. The Nigerian government/investors should therefore pursue aggressive diversification of the economy that will boost non-oil exports than imports.

For future research work, metaheuristic algorithms and other traditional prediction tools such as SAS Advanced Analytics, Microsoft Azure Machine Learning Studio with Non-Linear Regression Model can be used to develop an effective model on the possibilities of using a combination of goods (for example, energy goods, manufactured goods, other petroleum oil products e.t.c) to predict the future of National economic development and growth.

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