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APPLICATION OF ARTIFICIAL NEURAL NETWORK ANDMULTIPLELINEARREGRESSIONMODELFORECASTINGOFCONTAINERTHROUGHPUTINAPMTERMINALSAPAPAPORTACOMPARATIVEAPPROACH

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This study is concerned with forecasting of container throughput volume in APM Terminals Apapa Lagos, Nigeria. Using macro-economic variables as the explanatory variables, namely number of container goods, Inflation Rate, Exchange Rate and GDP. The data were obtained from APM Terminals Apapa Port, Central Bank of Nigeria (CBN) and World Bank. Two forecasting methods were compared, namely linear regression model and Artificial Neural Network model, with the purpose of searching among the two models, the model that can provide the most accurate

-ABSTRACT-

prediction for container throughput. The predicted results were compared using coefficient of determination(R^2), root mean squared error (RMSE). It was found out that, in general the multilayer perceptron (MLP) trained with backpropagation algorithm of feed-forward Neural Network was the better model for forecasting container

throughput R^2 with of 0.94 as against 0.61, of the multiple linear Regression (MLR). The result of this study may be helpful to APM terminals for predicting short term demand for container throughput. R statistical software was used as a statistical tool for this research study.

KEYWORDS;- Multiple Linear Regression (MLR), Artificial Neural Network (ANN), Multi-Layer Perceptron (MLP)

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I. INTRODUCTION

Over 90% of world trade is carried by shipping industry (Shipping Facts 2012). Liner shipping is considered as a scheduled shipping service of containerized cargo between this challenges, it is indispensable to use new technologies and facilitate different Ports in different countries and is viewed as the most economical way to transport large volumes of goods worldwide. According to (Agarwal & Ergun 2008) a constant growth of freight transport can be observed up to the world's crisis in 2009. To align with this growth, decision makers need to know the right time to invest in order to handle growth, appropriately. The main challenge is the analysis of vast amount of data comprising of technical and economic data. To overcome, accelerate and increase the accuracy of decision making.

Recent studies have shown that many economic relations are usually non-linear in either parameters or even nonstationary (Assem,2011). Nonlinear least squares methods seems to be the most commonly used in order to obtain the parameters in the non-linear models. However it is very difficult to draw a standard formula for the parameters in these models,(Assem,2011).

The researcher found that there are other techniques that can be applied to such cases and may overcome the problems of non-linearity and non-stationarity. These techniques include Artificial Neural Networks (ANN) methods. This technique has been used in forecasting in many fields and especially in the field of economics. The use of ANN in this domain increased because of their ability to form a complex non-linear systems based on sample data, (Assem,2011).

Interest in neural networks is evident from the growth in the number of papers published in journals of diverse scientific disciplines, (Assem, 2011). A neural network is able to work parallel with input variables and consequently handle large sets of data quickly. The principal strength with the network is its ability to find patterns (Chou, Chang, Chub, and Liang (2008)). ANNs provide a promising alternative tool for forecasters. The inherently nonlinear structure of neural networks is particularly useful for capturing the complex underlying relationship in many real world problems. One of the major application areas of ANNs is forecasting.

APM Terminals Apapa Limited is a container terminal and a branch of AP Moller-Maersk Sea Line Group. It is located inside National Ports Authorities NPA at Wharf road Apapa, Lagos State, Nigeria. Due to Port reform and modernization strategy embarked upon by Federal Government of Nigeria in 2004. The Federal Government decided to transfer the management and operation of the major Port terminals including the container terminal at Apapa Port from the Nigerian Ports Authority to the private sector through a series of operating leases.

The forecasting accuracy of the future throughput is crucial to both of private sectors and government offices for planning and managing their future development. Private sectors will enhance abilities for the growth of containers both of inbound and outbound. The governments' offices such as Nigeria Port Authority, Customs Department and Marine Department will be able to improve daily Port operations to serve the growth throughput and to increase productivity and the efficiency of the Port. The numbers of containers are central to the planning and the operation of organizations and government transportation department at both micro and macro levels (Kasypi, 2010).

Unfortunately, there is no published study to the writers' knowledge that has dealt with forecasting the demand of container throughput in APM Terminals Apapa Port Lagos, which has resulted in financial losses on investment in Port construction and facility enhancement projects (Yitnoe, 1999). According to Peng and Chu (2009), building Port structures usually means a huge loss of time in Port usage or limited access to Port facilities during construction.

Many researchers and scholars have been interested in the relationship between and the volumes (1976 - 1985)factors of economics of import and Dollar export. studied the regression method to analyze the relationship between the outward orientation and per capita GDP growth. The results have implied that trade liberalization and exchange rate could improve growth performance in many poor countries. Greenaway and Nam (1988) analyzed the various indicators of industrialization and macroeconomic. Ram (1985) used a regression model to analyze the relationship between the exports and economic growth. Their study has confirmed the strong relationship of the export performance and the economic growth. Chou, Chub and Liang (2008) presented the importance of the non-stationary relationship between the volumes of containers and the macro-economic variables. They used volumes of export containers, volumes of import containers, population, industrial production index, GNP, GNP per capita, wholesale GDP, agricultural GDP, industrial GDP and service GDP for the factors in the regression analysis.

Thus this study is based on the absence of reference model for forecasting container throughput in APM Terminals Apapa Port and also according to Peng and Chu [2009]. They suggested exploring other forecasting methods which apply the latest technologies such as neural, network, artificial intelligence and advance data mining to predict container throughput volume. As there is no existing forecasting technique for container throughput volume in APM Terminals Apapa Port, the comparison of linear regression and artificial neural network model is necessary to find the most appropriate for predicting the container throughput in APM terminal.

The commercial shipping industry has experienced the increasing size of vessels and this presents the Port with a challenge in terms of infrastructure to accommodate larger vessels (Ng, 2003). Several Ports are planning to upgrade their facilities and APM Terminals Apapa is faced with the same challenge. Furthermore Since there is absence of forecasting method. Therefore, this study strives to search among two models, for a model that is capable of generating the most accurate prediction of container throughput useful for Port authorities in a short time which can be achieved through;

- 1. Identifying Nigeria's macro-economic variables that affect container throughput of cargo goods.
- 2. Finding a better linear regression model
- 3. Finding the most suitable ANN model.
- 4. Comparing the two methods based on their coefficient of determination (R-square) and the Root Mean Square Error (RMSE).
- 5. Give the relevant recommendations based on the results of the comparison that we obtained above.

These can assist APM Terminals Apapa Port and Nigeria Port planners to make a decision on a limited investment budget, scope, and size of the expansion project, as well as estimating actual cost of handling cargo in the company.

II. METHODOLOGY

This section describes the process of the research, which is divided into the following steps

Data Source and Collection Method

a) Dependent Factor

Volume of container throughput: Port container traffic (throughput) measures the flow of containers from land to sea transport modes, and vice versa, in twenty-foot equivalent units (TEUs), a standard size container Transhipment traffic is counted as two lifts at the intermediate port (once to off-load and again as an outbound lift) and includes empty units)Annual data from APM Terminals Apapa Lagos, Nigeria.

Unit: in TEU (Twenty-foot equivalent unit) **Source:** *Cargo Statistics, Planning Department APM Terminals Apapa Port, Nigeria.*

b) Independent Factors

GDP: Gross Domestic Product is the sum of gross value added by all resident producers in the economy of Nigeria plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant local currency (Naira).

Unit: Billion Nigeria Naira, Gross domestic product include; Agricultural GDP, Industrial GDP, Service GDP, private consumption index and other GDP's.

Source: Central Bank of Nigeria website http://www.cbn.gov.ng/documents/Statbulletin.asp

Inflation rate: Inflation refers to an overall increase in the Consumer Price Index (CPI), which is a weighted average of prices for different goods. The set of goods that make up the index depends on which are considered representative of a common consumption basket. Therefore, depending on the consumption habits of the majority of the population of Nigeria, the index will comprise different goods. Some goods might record a drop in prices, whereas others may increase, thus the overall value of the CPI will depend on the weight of each of the goods with respect to the whole basket. Annual inflation, refers to the percent change of the CPI compared to the same month of the previous year.

Unit: Average annual (%) Source: *World Bank Data development website* http://data.worldbank.org/data-catalog/world-development-indicators

Exchange Rate: Official exchange rate refers to the exchange rate determined by national authorities or to the rate determined in the legally sanctioned exchange market. It is calculated as an annual average based on monthly averages.

Unit: Nigeria Naira currency units relative to the U.S. dollar. **Source:** *World Bank Data development website* http://data.worldbank.org/data-catalog/world-development-indicators

III. METHOD OF DATA ANALYSIS

Multilayer Perceptron (MLP)

Trained with backpropagation algorithm of Artificial Neural Network (ANN) forecasting techniques.

Networks that contain more than one layer of artificial neurons, which allows only unidirectional forward connections of inputs and outputs, are called multi-Layer Perceptrons (MLP) or multi-layered feed-forward Neural Networks. The underlying structure of a MLP consist of neurons and synapses (Haykin,2008). The neurons are organized in layers, which are usually fully connected by synapses. The input layer consists of all covariates in separate neurons and the output layer consists of the response variables. The layers in between are referred to as hidden layers, as they are not directly observable. Input layer and hidden layers include a constant neuron relating to intercept synapses or bias, (i.e. synapses that are not directly influenced by any covariate called the intercept). Figure 2 gives an example of a neural network with one hidden layer that consists of three hidden neurons. This neural network models the relationship between the two covariates A and B and the response variable Y and it is called a MLP feed-forward Neural Network.



Fig.2. Architectural graph of Multilayer Perceptron with one hidden layer.

Source: The R Journal Vol. 2/1, June 2010

To each of the synapses, a weight is attached indicating the effect of the corresponding neuron, and all data pass the neural network as signals. The signals are processed first by combining all incoming signals and second by the activation function transforming the output of the neuron. The MLP with one hidden layer can be represented mathematically as:

$$Y_{k}(x) = \varphi \left(w_{o} + \sum_{j=1}^{J} w_{j} \varphi \left(w_{oj} + \sum_{j=1}^{m} w_{ij} x_{i} \right) \right)$$
$$= \varphi \left(w_{o} + \sum_{j=1}^{J} w_{j} \cdot \varphi \left(w_{oj} + w_{j}^{T} x \right) \right)$$

Where W_o denotes the intercept of the output neuron and W_{oj} denote the intercept of the *j*th hidden neuron. Additionally, W_j denotes the synaptic weights corresponding to the weights starting at the *j*th hidden neuron and leading to the output neuron, $W_j = (w_{1j}, ..., w_{mj})$ the vector of all synaptic weights corresponding to the synapses leading to the *j*th hidden neuron, and $X = (x_1, ..., x_m)$ the vector of all explanatory variables.

Although more hidden units in the system normally result in better forecast, more hidden units may lead to overfitting on sample data. Limit the number of hidden layers is based on trial and error. (Kamruzzaman, Begg, and Sarker, (2006).

For our research purpose, we will make use of one hidden layer, with hidden neuron increased from 1 through 5 units (neurons) and a sigmoid activation function.

Parameters of MLP for the research Study

No. of Inputs = 3 Hidden layer =1 Hidden neuron: 1- 5 No. of Output =1 Learning rate=0.1,0.05 and 0.01 Epoch or No. of Repetition = 5 cycles Threshold =0.01 Algorithm = backpropagation Activation function = sigmoid (logistic) function The back-propagation algorithm for the MLP adopted for finding a better MLR is given below

Backpropagation Algorithm

The backpropagation approach consists of four steps:

- I. The Algorithm determines a random value of initial parameters θ_0 .
- II. The calculation of the difference between the output and the target value. The gradient of the error function is propagated backward respectively from the output layer to hidden layer.
- III. Updating the network weights to reduce the error using the Equation.

$$\theta_{k+1} = \theta_k + a X_j \varphi_k(v) (1 - \varphi_k(v)) \left(T_k - \varphi_k(v) \right)$$

- IV. Repeat (2-3)until the gradient of the error function gets close to zero. Backpropagation is based on three factors: The learning rate a, the distance between the actual output and predicted output $(T_k - \varphi_k(\theta_k, X_k))$ and the activation function $\varphi(v)$ or $\varphi_k(\theta_k, X_k)$.
 - a) **Multiple Linear Regression (MLR):** Multiple regression is a tool to measure the model which a dependent variable is explained by more than one explanatory variable (Brooks,2010). The general equation can be written by;

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$$Y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_k x_k + \epsilon$$

Where $\beta_0, \beta_1, ..., \beta_K$ are called regression coefficients, and \mathcal{E} is called the disturbance or error term, the parameters β_j represents the expected change in the response Y per unit change in the X_j when all the remaining independent variables $X_i (i \neq j)$ are held constant. The term 'linear' because the equation (3.24) is a linear function of the unknown parameters $\beta_0, \beta_1, ..., \beta_K$.

Procedure for obtaining a better Multiple Linear regression Model is outlined below: Stage 1: Correlation between Dependent variable each Independent variables. and Stage 2: Fit the MLR model using the whole explanatory variables (GDP, exchange rate Inflation and Rate). Test coefficients Stage 3: the slope of the model (T-test and F-test) Stage 4: If both T-test and F-test in Stage 3 is significant, the variable under consideration is excluded from the model. Stage 5: F-test is significant and the t-test is not, check for the presence of multicollinearity using

VIF (Douglas and George 2014). Stage **6:** If the square root of the VIF for a given coefficient is greater than 2, the variable is excluded.(Robert 2011). all Stage7: Go 2, using the remaining variable, satisfied back stage and if Stage 8: Diagnostic check to verify the assumptions of a classical linear regression model such as normality test of the residual, serial correlation test of the error term, heteroscedasticity and test of linear functional form.

Stage9: If stage(3-8) is satisfied, the model is selected as the better model for our research study.

Model Accuracy Measurement

There are several statistical methods available to evaluate forecast performance (Makindakis et al 1998). Among the commonly used forecast accuracy measures, two techniques were selected for this research; the Coefficient of determination and the Root Mean Squared Error (RMSE), the Equation of R^2 and the RMSE are shown as follows:

$$R^{2} = \frac{SSE}{SST} = \frac{\sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^{2}}{\sum_{i=1}^{n} (y_{i} - \overline{y}_{i})^{2}}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_{i} - \hat{y}_{i})^{2}}{n - 2}} = \sqrt{\frac{MSE}{n - 2}}$$
2.3

Where \mathcal{Y}_i and \mathcal{Y}_i are the actual and predicted container throughput volume. And n is the number of observation,

The correlation coefficient measures the strength and the direction of a linear relationship between two variables is given by:

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$$\hat{r} = \frac{n(\sum_{i=1}^{n} X_{i}Y_{i}) - (\sum_{i=1}^{n} X_{i})(\sum_{i=1}^{n} Y_{i})}{\sqrt{[n(\sum_{i=1}^{n} X^{2}_{i}) - (\sum_{i=1}^{n} X_{i})^{2}][n(\sum_{i=1}^{n} Y^{2}_{i}) - (\sum_{i=1}^{n} Y_{i})^{2}]}}$$
2.4

The value of $\hat{\mathcal{V}}$ is between $-1 < \hat{\mathcal{V}} < +1$, the + and – signs are used to denote positive and negative correlation respectively.

Thus, the model with lower R-square and RMSE is chosen to be more precise, (Brooks, 2010).

Normalization

Transformation using min-max normalization function was applied on the original data since ANN fit well when the data is scaled to [0,1]range(Brett Lantz (2015)). Also to enable equal comparison of error and model performance, the same scaled data was used for both linear regression and ANN model. The function is given by:

$$x' = \frac{x - \min(x)}{\max(x) - \min(x)}$$
2.5

Where: x' is the data after being normalized, x is the current data to normalize, $\min(x)$ is the minimum value of the data and $\max(x)$ is the maximum value of the data to be normalized. We note that any transformation applied to the data prior to training the model will have to be applied in reverse later, in order to convert back to the original units of measurement. Thus, R provides a rescaling function which is given by:

$$x = (x - \min(x'))^* (\max(x') + \min(x'))$$
2.6

where: \mathcal{X} is the original data, $\min(\mathcal{X}')$ is the minimum value of the normalized data and $\max(\mathcal{X}')$ is the maximum value of the normalized data (Brett Lantz 2015).

IV. RESULTS AND DISCUSSION

Data Presentation:

Table 4.1 and 4.2 represent the original and the normalized data for research study.

Table 4.1 Original Data

Year	Inflation.Rate	Exchange.Rate (\$)	GDP(N)	Container Throughput
2006	8.38	128.65	28662.47	877679
2007	5.42	125.81	32995.38	431950
2008	11.52	118.55	39157.88	612982
2009	12.59	148.90	44285.56	653584
2010	13.77	150.29	54612.26	685937
2011	10.85	153.86	62980.40	839977
2012	12.24	157.49	71713.94	880597
2013	8.51	157.31	80092.56	992666
2014	8.05	158.55	89043.62	1063486
2015	9.00	192.44	94144.96	939379
2016	15.62	253.49	101489.49	976459

Year	Inflation.Rate	Exchange.Rate	GDP	Container Throughput
2006	0.2906	0.0749	0.0000	0.7058
2007	0.0000	0.0538	0.0595	0.0000
2008	0.5979	0.0000	0.1441	0.2867
2009	0.7026	0.2249	0.2145	0.3509
2010	0.8181	0.2352	0.3563	0.4022
2011	0.5322	0.2617	0.4712	0.6461
2012	0.6685	0.2886	0.5911	0.7104
2013	0.3027	0.2872	0.7062	0.8879
2014	0.2574	0.2964	0.8291	1.0000
2015	0.3509	0.5476	0.8992	0.8035
2016	1.0000	1.0000	1.0000	0.8622

Table 4.2 Normalized Data

Result Presentation

The results are presented in the order of the stated Objectives of the study,

i. Identifying Nigeria's macro-economic variables that affect container throughput of cargo goods in APMT. **RESULT:** Bivariate correlation matrix, see Figure 4.2 below

ii. Finding a better linear regression model. **RESULT:** After satisfying all the assumptions, the variable exchange rate was excluded (VIF=4), a better model was found with R2 = 0.61 to be expressed as:

$Y = 0.323 + 0.698X_1 - 0.105X_2$

Where Y=Container Throughput, $X_1=GDP$ and $X_2=$ Inflation rate.

iii. A comparison of predicted and actual volume of container throughput in APMT using MLR model is presented in Figure 4.5. below.



Fig.4.2 Bivariate Correlation Matrix of the Variables





By increasing the number of units in the hidden layer and subsequently increasing the learning rate, we found the most suitable MLP model with the lowest RMSE as shown in Figure 4.11 below;

Learning Rate	0.1	0.05	0.01
min RMSE with 1 Unit in hidden layer	0.129	0.130	0.130
min RMSE with 2 Unit in hidden layer	0.072	0.075	0.075
min RMSE with 3 Unit in hidden layer	0.071	0.133	0.129
min RMSE with 4 Unit in hidden layer	0.064	0.076	0.059
min RMSE with 5 Unit in hidden layer	0.072	0.062	0.054

Table 4.11 Lowest Minimum RMSE results of ANN model for Container Throughput.

Figure 4.7: Artificial Neural Network Predicted and Actual Container Throughput





ITEM	MLP	MLR
R^2	0.94	0.61
RMSE	0.054	0.2
NO. of YEARS	11	11

Discussion Of Results

It can be observed from the table above that the RMSE of MLR model is 0.2, and the RMSE of MLP is 0.05 And the value of R-square of ANN model (R^2=0.94) suggest that 94% variation in container throughput volume data is explained by the model independent variables which is more preferable when compared to the R-square value of MLR model 0.61 that accounts only 61% variation in container throughput data. Finally, we can conclude that from the above discussion that the results of the MLP of ANN model are much more better than the MLR model result and it is more efficient when using macro-economic variable to forecast container throughput in AMPT.

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V. CONCLUSION

The performance of a model depends on how properly independent variables are used in the model. Since in the case of the MLR model, multicollinearity was a major issue as seen in the research, the variable Exchange rate was deleted. Proper explanatory variables for generating model should be related to the demand and business activity in the country, which was indicated by the high correlation between container throughput and GDP (0.78). Before generating model, the test of correlation between independent variables and dependent variable should be made.

Moreover, the result of the forecast is also consistent with the economic viewpoint as the value of the Gross Domestic Product (GDP) of a country increases; the value of container throughput also increases. Also if exchange rate is high, import and export of cargo goods tends to be high, as seen from the correlation matrix. The ANN model used backpropagation algorithm with five (5) units in the hidden layer and the learning rate equals 0.01 is the best model for forecasting container throughput based on the findings from the research. The use of linear regression models in forecasting economic data does not give results with high efficiency, since most economic variables are non-linear in nature. The ANN model performs very well in economic data, since the use of a differentiable activation function of the network which applies a linear to non-linear mapping between input variables is a major advantage of the method as compared to other forecasting techniques.

We recommend that more conduct of research and comparison to ascertain the most suitable forecasting technique for container throughput should be made. Also we recommend that all bodies involved in port planning, management and in economic sphere should use the artificial neural networks methods. Furthermore, the use of artificial neural networks as a forecasting technique in other fields, such as medical research, genetics research, etc. should be considered as well.



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