A Pricing Model for the Nigerian Electricity Transmission Using Artificial Neural Network

B. O. Ogbonna, C. O. Ahiakwo, D. C. Idoniboyeobu and S. Orike

Abstract---For the restructuring of Nigeria's power sector to be effective, efforts must be made to evolve an excellent pricing methodology that will economically be able to accommodate disintegrated units like generating, transmitting and distributing/retailing units. This work is aimed at developing an improved electricity transmission pricing scheme for the Nigerian Network using Artificial Neural Network. A model based on artificial neural network for improved electricity transmission pricing for the Nigerian Network was developed in order to forecast the transmission price for a longer period of time. The performance of the neural network model was evaluated by applying the actual transmission pricing data from Transmission Company of Nigeria to predict the prices. Raw data was collected from Transmission Company of Nigeria, Port-Harcourt district. The data was trained, tested and validated on the MATLAB/Simulink environment. Forecast results revealed that the model performed very well with a mean absolute percentage error of 0.09%, an average mean error of 0.5 and a regression value of 0.99. It was concluded that the improved and modified transmission use of system pricing is the best pricing method which will be acceptable to consumers and also ensure recovery of transmission cost in Nigeria. It was recommended that Artificial Intelligent-based techniques (ANN) in particular, must be implemented for long-term improved electricity transmission pricing forecast for the Transmission Company of Nigeria.

Keywords---Long Run Marginal Cost, Short Run Marginal Cost, Transmission Pricing, Transmission Capacity.

I. INTRODUCTION

THE electricity power sector is very important to any country's economy because it is key to the industrial, technological and social development of the country [1]. Many countries in the world have transformed virtually their integrated electricity companies and thereafter have segmented them into generation, transmission and distribution companies. In most of the cases private participation have been highly encouraged thereby leaving the government to assume the role of supervision and regulation [2]. Chile was the first country to deregulate and privatize their electricity sector in 1982. The next country was England and Wales which restructured theirs in 1990 for competition first in generation sector and thereafter in the retail sector as well [9]. Other countries like US, Germany, Switzerland, Australia etc. followed later. The aim of all this segmentation and privatization is to ensure that the power sector is operated at a certain profit.

Since the electric power sector was reformed the price of electricity has increasingly been attracting attention in every activity of the sector [2]. The main motive behind transmission pricing is to recuperate the costs of investment in the transmission network. In the provision of transmission services pricing is very vital because with it, the economic benefit of provision of transmission services to both the network and the customer can be determined with ease [3]. The process of estimating the pricing of transmission network can be obtained by the analyses of the engineering situations of the network. This approach is one of the ways through which the importance and the costs of provision of transmission services can be obtained [4].

The method employed for pricing of electricity in Nigeria has been uneconomical and unclear since the establishment of the power sector. Previously the provision of electricity in Nigeria was considered as a government welfare program. This has informed the high subsidization of electricity by the government [4].

Prior to 2008, the electricity pricing system in Nigeria was kept constant for so many years irrespective of increase in the cost of fuel [3]. Unfortunately, about 80% of the country's power is generated from liquefied gas. Nigeria's electricity power authority had set the tariff last in February 2002 and averaged from N4.50/kwh to about N6/kwh. The consequence of this fixed price resulted in the authority losing about N2 billion every month and its failure to provide adequate and reliable power supply to the consumers [14]. In 2011, the government approved different prices for the following consumers:

a) From N4.50/Kwh to N6/kwh for users of single-phase line only,
b) From N6/kwh to N8/kwh for users in the industry,
c) From N8/kwh and N12/kwh for those whose demand are higher. In comparison to this prices, the production cost of power was N10 per kwh [15].

Manuscript received on December 10, 2019, review completed on December 11, 2019 and revised on January 04, 2020.

B. O. Ogbonna is with the Department of Electrical Engineering, Rivers State University, Nkpolu-Oroworukwo, Port Harcourt, Nigeria. E-Mail: bartholomew.ogbonna@ust.edu.ng

C. O. Ahiakwo is with the Department of Electrical Engineering, Rivers State University, Nkpolu-Oroworukwo, Port Harcourt, Nigeria. E-Mail: ahiakwo.christopher@ust.edu.ng

D. C. Idoniboyeobu is with the Department of Electrical Engineering, Rivers State University, Nkpolu-Oroworukwo, Port Harcourt, Nigeria. E-Mail: idniboyeobu.d@ust.edu.ng

S. Orike is with the Department of Electrical Engineering, Rivers State University, Nkpolu-Oroworukwo, Port Harcourt, Nigeria. E-Mail: orike.sunny@ust.edu.ng.

Digital Object Identifier: AIML122019003.

The challenges obtained from this pricing mechanism are [21]: The Transmission Service Providers (TSP) are not given a fair share in the pricing system

1) Transmission network users or consumers are not effectively considered in pricing mechanisms.
2) Due to insufficient pricing systems, transmission investment costs are not realized. This therefore has discouraged more investment on transmission network facilities from stakeholders.
3) At the distribution end, the residential consumers feel a high burden of pricing due to inadequate pricing mechanisms.

There is need therefore for an appropriate pricing policy to be established to achieve fairness and a stable electricity pricing system. Considering the above challenges the country established the Nigerian electricity regulatory commission (NERC). The commission is saddled with the provision of a new pricing system that will depend on requirements of the industrial revenue. A new tariff system was instituted through Multi–Year Tariff Order (MYTO) in 2008 [14]. The MYTO tariff system of pricing is based on econometric method of analyzing and computing transmission pricing on a five year financial planning basis [19]. This method is unable to forecast transmission pricing for a longer period. An accurate forecast of electricity prices has become a very important tool for producers and consumers. This paper presents a successful application of using an artificial neural network approach to forecast electricity transmission prices in Nigeria for a longer period.

II. RESEARCH BACKGROUND

A. *Policies in Pricing Electricity*

The policy in pricing electricity is such that the pricing is divided into:

1) **Static Prices:** The price of electricity in this group do not change no matter the change in demand of energy.
2) **Dynamic Prices**: In this group the price of electricity changes with change in demand of the product [12].

Some of the different kind of static pricing policies are summarized as follows:

Flat Rate Pricing: In this principle the price remains the same irrespective of change in power demand. Transmission users enjoy this scheme because they do not face incessant changes in cost of power supply due to changes in power demand. Therefore consumers do not face any chance of receiving high cost of electricity bills because of high consumption of electricity [12].

Block Rate Pricing: This scheme differentiates from one customer to another on the basis of the amount of electricity consumed [13].

Seasonal Pricing: This pricing method is such that prices change according to different seasons so as to tally with changes in the level of demand within the seasons. At the season the demand is high, transmission price is high. The price decreases at the season demand is low [12].

Time of use (TOU) Pricing: This method consists of fixed network charges. It includes charges for return on capital, depreciation, operation and maintenance. This charges varies differently with the time of the day. At peak demand hours it is high and at off peak demand hours it is high. In Nigeria, the charge is uniform throughout the times of day and in the whole country. This method can be applied effectively for long or short terms [12].

Critical pricing at peak times (CPPT): In this method, customers are charged an increased price during the first peak times and thereafter the price is reduced by a certain percentage at other times of the day. This method causes consumers to reduce unnecessary load consumption so as not to attract a higher charge [13].

Transmission Use of System (TUOS) Pricing: The TUOS charge is normally levied on distributor/retailers. This is a system where the consumer is billed on per unit of energy metered to them at the points of bulk supply. The TUOS charge comprises the network's fixed charges. They include, the capital returns, depreciation and fixed operation and maintenance. The charge is uniform throughout Nigeria [15].

The Improved Transmission Pricing Scheme (ITPS): The ITPS is defined as that network that minimizes the overall operation and investment cost within a certain period of time. This scheme is normally applied for pricing purposes because of the relationship that exists in optimization of transmission network [5].

B. *Introduction to Artificial Neural Network*

Artificial neural networks are models that were developed on the basis of the brain structure. The idea was that the brain learns by experience and so the scientist at the time wanted to develop something that will use this ability to learn. The neural cell in the brain was discovered in 1836 [8]. An organism does not seem to regenerate itself and has the ability to provide the human with the power to remember and think [9]. The neuron is a complex organism and biological research is still ongoing in terms of its functions. A simple neuron structure is shown in Figure 1.

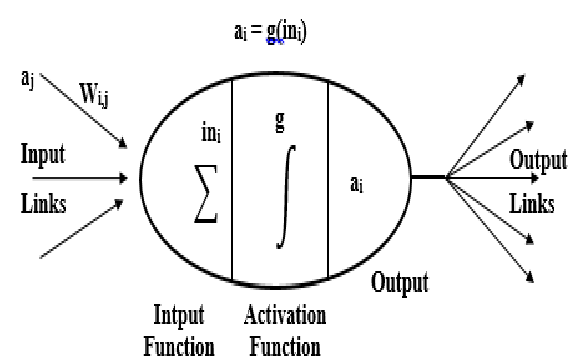

Fig 1: Artificial Neuron and its Components [13]

It works in a more simplistic way as compared to the real neuron. A real neuron receives input signals from different types of sources, combines them in a generally non-linear manner, and then produces the result. The artificial neuron behaves in much the same way but the difference is that the function is known whereas the biological neuron's processing system is known.

C. Description of Artificial Neural Network Component

An ANN is a system of interconnected neurons. They are useful in producing solutions to specific complex problems [13]. ANNs are based on biology, in particular, the interactions between the neurons in the brain and the processing strategy and the results produced [16]. The major components of an artificial neuron are discussed as follows;

Weighting functions: A neuron may receive a number of input signals at the same time. Each input has a weighting of a magnitude that causes the input to have an impact on the summation function of the processing element depending on the strength of the connection between the input and the neuron [16]. The weights are adaptive coefficients that can be increased or decreased where necessary. This occurs during the training regime as mentioned earlier.

Summation Function: This function does the summing of the different inputs supplied to the neuron [2]. The inputs and corresponding weights are represented as vectors and so the dot product of these two vectors result in the total input signal.

Transfer Function: This component receives output from the summation function and then is transformed to an output that will be used for work [7]. Transfer functions that are used are:

- Hard limiter
- Ramping function
- Sigmoid functions

When the output summation is higher than a certain limit, the neuron produces some signal. However if the summation is less then there will be no production of signal.

Hard Limiter: This function as illustrated in Figure 2 has limits between minus one and positive one. This means that the output is either a minus one or positive one for a given input. The threshold can also be between 0 and 1 [7].

Ramping function: The input to the function is mirrored for a certain range and thereafter a hard limit is enforced. In Figure 2, the input and output signals are the same when the range is from 0 and 1 and thereafter the output signal is clipped to a maximum value of one [10].

Sigmoid Function: This component consists of an "S" shaped function that is continuous, differentiable, and non-decreasing and its derivative has the same properties. Sigmoid is made up of two kinds commonly used in ANN architecture [11]. They are the hyperbolic tangent and the logistic function. The logistic function has outputs ranging from zero to one whereas the hyperbolic one has outputs from minus one to positive one [13].

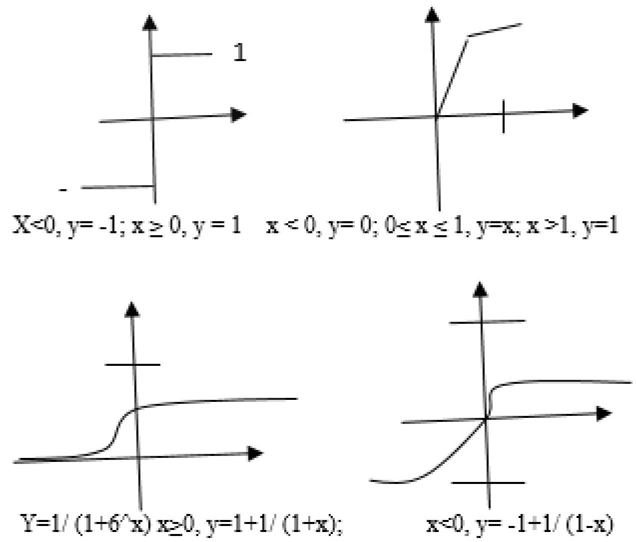

Fig 2: Samples of Transfer Functions

Scaling and Limiting: The result from the transfer function may be passed through further scaling and limiting processes. The output from the transfer function is multiplied by a certain scale factor and then an offset may be added. This decision rests with the designer. Limiting this output ensures that it does not exceed any specified upper and lower bounds [7].

Output Function: Each neuron produces an output after the scaling and limiting of the original output from the transfer function. The neuron releases an output signal to many output neurons. A phenomenon known as competition is sometimes used at this stage (not all network topologies use this technique) [18]. The output from transfer component is modified to include an element of competitiveness among the neurons. The neurons however engages in a competition among themselves thereby inhibiting other neurons except the later neurons have greater strength. [8].

Error Function: This function is calculated as:

Raw Error = Actual output-Desired Output.

The raw error is then taken into an error function and then sent back to a former layer. The error is usually multiplied with the connecting weights to the new layer in order to modify them before the learning cycle [7].

Learning Function: This function is used to change the input weights of every neuron according to the errors propagated backwards as well as other ANN dependent algorithm. The process continues until a desired result is obtained. It is called the adaptation or the learning system [8]. The learning system are of two kinds namely: Supervised and Unsupervised learning.

Learning Rates: A learning rate defines the length of time the network will be trained. The slower the ANN learns the more time spent, the faster the rate the more the network cannot achieve good distinctions required to obtain good target. Factors like network size, architecture type, learning rule type and targeted accuracy must be considered prior to coming up with a learning rate. This rate is usually a positive number, from 0 to 1. If it is bigger than 1, the algorithm may go higher in order to correct the weights whereas when the rate is very small, it may not be quick enough to correct the errors and may lead to convergence problems [20].

D. Feed Forward, Back-Propagation

The Feed-forward, Back-propagation architecture was established in 1970's by several people namely Werbor, Parker, Hinton, Rumelhalt and Williams. By generalizing the delta rule to multiply layer networks and non-linear differentiable functions, the back propagation rule was created [6].

This network is popular, efficient but easy to learn and use especially for problems that are complex such as Electricity transmission pricing systems. It makes use of non-linear solutions to problems that are not determined [7]. Figure 3 shows a typical layout of a Feed-Forward Network [20].

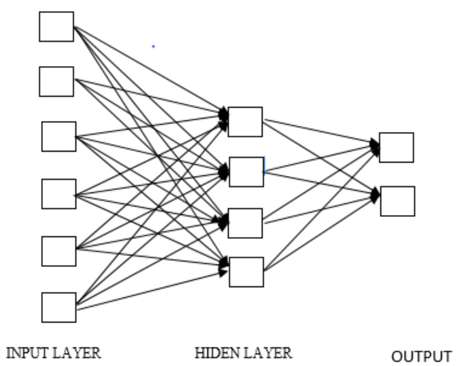

Fig 3: Layout of a Feed-Forward Network [22]

The input layer receives training signals and the target output is compared to the output at the other end of the output layer. At the time of learning, the signal moves pass the network with the information moving from input layer through the hidden layer and finally to the output layer, hence the name feed-forward [19]. The difference between the target and computed outputs (error term) are then sent back to the previous layers. This is normally changed by the transfer function derivative. The weight connections are usually adjusted by the Delta rule [22].

III. MATERIALS AND METHOD

The materials used for this work are:

1. Total Operating Cost (TOC)
2. Return on Capital (RoC)
3. Depreciation Cost (Dep)
4. NERC Regulatory Charge (NRC)
5. Ancillary Service Charge (ASC)

A. Developing the Model for ANN

The procedures and guidelines that were used in formulating this model are described in this section. Figure 4 is a diagram of the steps that are taken in developing a model for price forecasting.

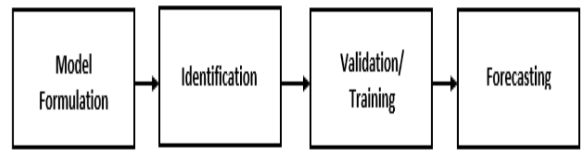

Fig 4: Stages Involved in Developing the Price Forecasting Model

Model Formulation: The type of model need to be decided, say on yearly forecasting basis. The year type is developed according to the information provided and engineer's discretion. The year objectives of the forecast need to be clarified in this stage so that the engineer can proceed to the next stage [8].

Identification: The vital parameters employed by the model are identified. The parameters include the total operating cost, return on capital, depreciation cost, electricity delivered to demand etc [13].

Validation: This is the stage where the model will be tested to see whether it performed as required. The working ability of model is checked here as well and if it does not conform, then the model will have to be re-evaluated and either additional parameters will have to be added so that better accuracy can be achieved [8].

Forecasting Stage: This is the final stage after the validation procedure has been performed. The model is then employed for the actual forecasting of the price [7].

B. Proposed Model

It was decided to develop a fully connected 3 layer feed-forward, back propagation network since it can approximate with ease nonlinear functions. A fully connected network means that each neuron receives information from every input variable.

Derivation of Mathematical Model for the Proposed ANN

Given a set of input *i* and *j* hidden layer neurons as well as *k* output layer neurons, the hidden layer receives the following signal input as [20]:

$$\boldsymbol{h_j = \sum x_i W_j} \quad (1)$$

and produces an output that has been transformed by the transfer function which in this case can be taken as sigmoid or logistic function of the form:

$$\boldsymbol{g = {}^{1}\!/_{1 + e_r^{-b}}} \quad (2)$$

The output of a single hidden layer neuron is expressed as [20]:

$$\boldsymbol{f_j = g(h_j)} \quad (3)$$

Multiply with the hidden layer connecting weight to the neuron output.

$$\boldsymbol{y_k = g\left[\sum\left(W_{jk} f_j\right)\right] = g(V_k)} \quad (4)$$

is the final output of a neuron *k* at the output layer.

For the hidden to output neurons the change in weight is calculated by

$$\Delta W_{jk} = \alpha\left[\sum(t_k - y_k)g''(V_k)f_j\right] \quad (5)$$

Where α is the learning rate.

The partial differential of the error term yields the weight change from input to hidden connections given as:

$$\alpha = \sum k(t_k - y_k)g''(V_k)g''(h_j)x_i \quad (6)$$

The final step is to add the changes to the original weights given by equations (7) and (8) respectively [22]:

$$W_{ij}^{new} = W_{ij}^{old} + \Delta W_{ij} \quad (7)$$

$$W_{jk}^{new} = W_{jk}^{old} + \Delta W_{jk} \quad (8)$$

Figure 6 is a diagram showing a simplified structure of a 3 layer feed forward, back propagation network. The network has three layers, namely the first hidden layer, the second hidden layer and the output layer. The input vector contains the variables that are required to perform the forecast. The model equations were obtained using the MATLAB curve-fitting toolbox and are presented in equations (1) – (5) and equations (6) – (8).

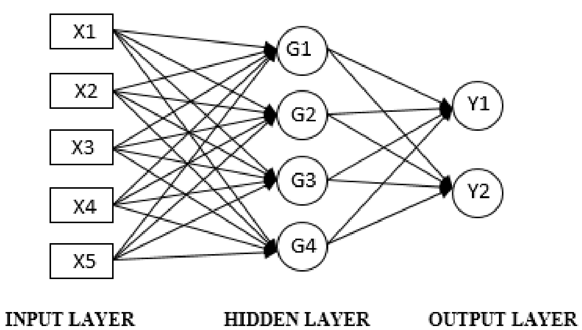

Fig 5 A Simplified Structure of 3 Layer, BP Network

Identification of Parameters

Carrying out an analysis of input variables consists in studying the contribution of each variable to the result of the forecasting model. The input variables were chosen according to the specification (in section 111). A three – layer neural network models were developed. The model has an input vector that consist of 5 variables. The initial hidden layer is the same size as the number of inputs, that is, the number of neurons corresponds to the number of inputs. The number of output neurons equals to each year. The model have a total of 10 neurons in the hidden layer. The transfer function chosen for these layers are the tangent sigmoid functions. The output layer has neurons with a linear activation function so that the outputs can take on any value.

Transmission Revenue Requirement and Tariff in Nigeria

The transmission revenue requirement are:

1) Transmission Asset Value
2) Capital Expenditure

1) Transmission Asset Value: This value is obtained based on the history of the cost of the transmission assets plus recent additional costs incurred towards the asset base. As at 1st July 2008, an initial value of transmission asset was assumed to be at N189.4 billion [17].

2) Capital Expenditure: In the calculation of TUOS charge, a significant increase in capital expenditure is allowed by TCN. This includes the expenditure on the system operator (SO) [17].

Transmission Use of System (TUOS) Charge: TCN pays some institutional charges to cover the cost of other departments of the industry. They include [17]:

PHCN HQ charge: This charge is done against energy (MW) leaving the transmission system and delivered to the distributor/retailers at their bulk supply points.

Regulatory Charge: The regulatory charge covers part of the cost of NERC's operations in regulating TCN.

So

Total Annual Revenue Tar is given as:

$$T_{ar} = a + r_c + d_{rp} \quad (9)$$

Where:

a = Annual Operations and Maintenance cost

r_c = Return on Capital

d_{rp} = Depreciation (return of capital)

Therefore, Transmission Cost per MW, T_C (in Naira/MW) is given as:

$$T_c = \frac{T_{ar}}{GWh} \quad (10)$$

In this work, the improved transmission use of system (TUOS) or postage stamp method is employed to determine the best transmission pricing scheme for Nigeria.

Major Parameters Used for TUOS Calculation

NERC in 2012 decided that TCN's initial asset valuation will largely reflect historical costs plus recent additions to TCN's asset base. This provides an initial asset value at the beginning of 2012 to be N189billion. In order to calculate the asset value in each year of the tariff period, the forecast capital expenditures are added to this amount and depreciation plus any reduction in asset values due to optimization are deducted. However, this was reviewed to reflect additional asset base as follows:

Starting balance as at end of 2010 is based on NERC's ODRC (Optimized Depreciated Replacement Cost) valuation of NGN 189 billion.

Recognition of additional asset base that will ressult in higher return of capital (depreciation cost on assets in service) based on:

(i) Recognition of additional transmission assets of NGN 72 billion not captured in the 2010 valuation as reported in PHCN books to have been procured/completed as at December 31st 2013;

(ii) Transfer of NIPP asset received by TCN in 2014 amounting to NGN 310.4 billion:

(iii)Transfer of Investment in plant using internally generated funds and World Bank/other donor (NTDP and NEDP) assisted transmission projects managed by the Project Management Unit (PMU) of PHCN not reflected in valuations used in 2010. These assets together amounted into NGN23.4 billion as at 2013 [15].

ISSN 0974-9667/CIIT–IJ-7927/09/$20/$100 © 2019 CiiT Published by the Coimbatore Institute of Information Technology

Table 1 defines the summary of budgeted and proposed asset value approved by NERC.

TABLE 1
NERC'S APPROVED CAPITAL BUDGETED ASSET VALUE

Year	2017	2018	2019	2020	2021	2022
SB		189				
ATA	72					
AT	310.4					
IT	23.4					
BCAV		594.8	594.8	594.8	594.8	594.8
ECE		265.2	247.82	224.4	202.1	204.78

***Source: MYTO 2012* [18]**

Key
SB – Starting Balance
ATA – Additional Transmission Assets
AT – Assets Transfer
IT – Investment Transfer
BCAV – Budgeted Capital Assets Value
ECE – Estimated Capital Expenditure

Table 2, shows the proposed TUOS tariffs for billing on distributors/ retailers. These charges are made on the basis of each unit of energy transmitted to the users per year. The institutional charges are outlined as shown. The table also indicates the total annual required revenue obtained from aggregation of operations and maintenance costs, return on capital and depreciations.

Pre-Processing of Input Data

The data employed in the training and validating phases were gotten from **TCN.** This is shown in table 2**.** Yearly price data for the years 2018 to 2037 were obtained. The 2018-2037 statistics was employed for training and testing of the ANN system. Therefore all the data had to be pre-processed.

TABLE 2
PROPOSED TRANSMISSION REVENUE REQUIREMENT AND TUOS TARIFF PER MWH IN (N'000)

	2018	2019	2020	2021	2022
Variable Costs	24,661,330	26,821,663	29,171,240	31,726,641	34,505,894
Administrative Costs	3,898,625	4,240,144	4,611,581	5,015,555	5,454,918
Fixed Costs	13,703,040	14,251,162	14,821,208	15,414,056	16,030,619
Total Operating Costs	42,262,995	45,312,969	48,604,029	52,156,252	55,991,431
Return on Capital	21,562,801	65,631,973	44,277,488	48,085,557	51,760,132
Return of Capital (Depreciation)	21,945,819	23,338,791	24,731,763	25,581,506	26,974,478
NERC Regulatory Charge	1,439,607	1,561,124	1,682,756	1,796,810	1,920,043
Ancillary Service Charge	289,809	312,704	585,715	662,971	750,417
Grand Total	87,501,031	136,157,559	119,881,752	128,283,097	137,396,501
Electricity delivered to Distribution (GWh)	23,403	23,403	40,663	42,696	44,831

Prediction Results Using Neural Training Networks

The back-propagation feed-forward neural network is used for training the data obtained from the field. As stated earlier the data training input features are the (TOC), (RoC), (Dep), (NRC) and (ASC). The Electricity Delivered to Distribution (EDD $_{target}$) is used as target (predictor) input for training. The values of these features are numeric quantities and are summarized for a 5 year financial period (i.e., for the years 2018 to 2022 corresponding to 5 columns). Table 2 gives the data representation used for subsequent analysis.

Linear-Spacing and Regression Fitting

When looking at table 3 it is evident that the data values per column i.e. the number of row-wise data sequences are very small. Thus, regression fitting of type polynomial-degree-one and linear spacing was used to expand the data set to about 50 points; the regression-fitting is primarily used to determine the slope and constant terms of a linear model representation of the columns while a linear spacing function is used to expand the input feature set such that it generates a corresponding number of target feature values in the linear model representation. It is imperative to emphasize here that the generated model is based on the set of values registered for each column (year fields considered).

Neural Training

As mentioned earlier, a back-propagation feed-forward artificial neural network (BP-FFAN) is used for the prediction modeling. The number of training epochs of the BP-FFANN is set to 25,000 while a stopping criterion of 1.0*10-7 is used. The activation function proposed in [3] is used; this function has been shown to reduce the effect of vanishing gradients on the BP-ANN.

TABLE 3
DATA FEATURE VALUES

	2018	2019	2020	2021	2022
TOC	42262995	45312969	48604029	52156252	55991431
RoC	21562801	65631973	44277488	48085557	51760132
Dep Cost	21945819	23338791	24731763	25581506	26974478
NRC	1439607	1561124	1682756	1796810	1920043
ASC	289809	312704	585715	662971	750417
EDD $_{target}$	23403	23403	40663	42696	44831

IV. RESULTS AND DISCUSSION

Table 4 shows the forecasted (predicted) targets vs expected (actual) targets for 20 sample points of simulations. The ANN price forecast has almost the same profile as the actual target and this is very good.

TABLE 4
PREDICTED TARGETS VS. ACTUAL TARGETS

Year	Predicted Target	Actual Target
2018	2286	2286
2019	2335	2335
2020	2384	2384
2021	2433	2433
2022	2482	2482
2023	2531	2531
2024	2580	2580
2025	2629	2629
2026	2678	2677
2027	2726	2726
2028	2775	2775
2029	2824	2824
2030	2873	2873
2031	2922	2922
2032	2971	2971
2033	3020	3020
2034	3069	3069
2035	3118	3118
2036	3167	3167
2037	3216	3216

The training and validation procedures for specific network architectures were repeated in order to handle uncertainties of the initial weights and stopping criteria. The performance efficiencies of each trial were recorded and compared. The figure shows the gradient of the plot at 16 iterations (i.e. 16 epochs), the Mu and the validation checks.

Figure 6 comprises three graphical displays. The first display is the graph of learning function against number of epoch. It shows how the values of the gradient varies as the number of iterations increases. The second display shows the learning rate (mu) verses number of epochs. This graph is very vital because it monitors the rate in which the calculated network error reduces at the time the training progress. The third display shows how the validation check is done. This is spontaneously carried out at any time an abrupt alteration is perceived in the calculations of network gradient. During validation check, it was observed that 6 different iterations failed. The results showed a good training of the ANN model.

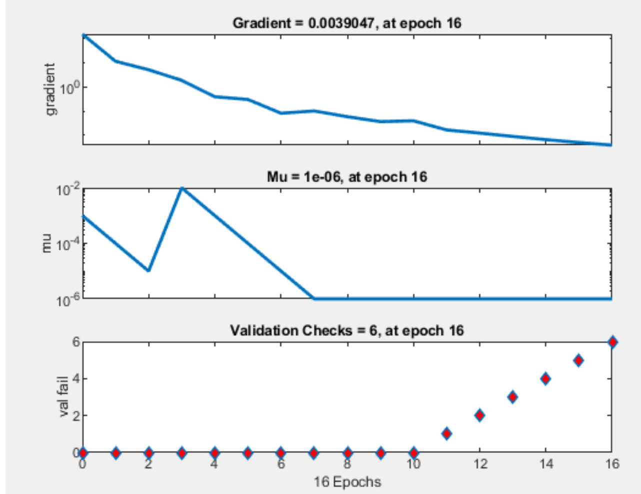

Fig 6: ANN Training Stage

Figure 7 is the simulation showing ANN regression fittings. The graph indicates how the output and the target are closely related. A regression value of one (i.e., R = 1) shows that the relationship between the output and target are very close. The graph reveals that for training section R = 0.9999. The validation section reveals R= 0.9998. The testing section reveals R = 0.9998 and R = 0.9999 for all.

This result indicates that the output and the target are closely related. This result however concludes that the prediction of the network is satisfactory.

Figure 8 is the ANN simulation results showing the relationship between the forecasted (Predicted) price and the TCN expected (actual) price of the electricity transmission network. It can be seen that in figure 3, ANN approximates the forecasted price better for the next ten years, while the TCN price increases steadily. ANN is a more superior tool. This is because ANN is an automated forecasting tool that does not require manual updating of input data. Errors that may be caused by human interference are minimal in ANN.

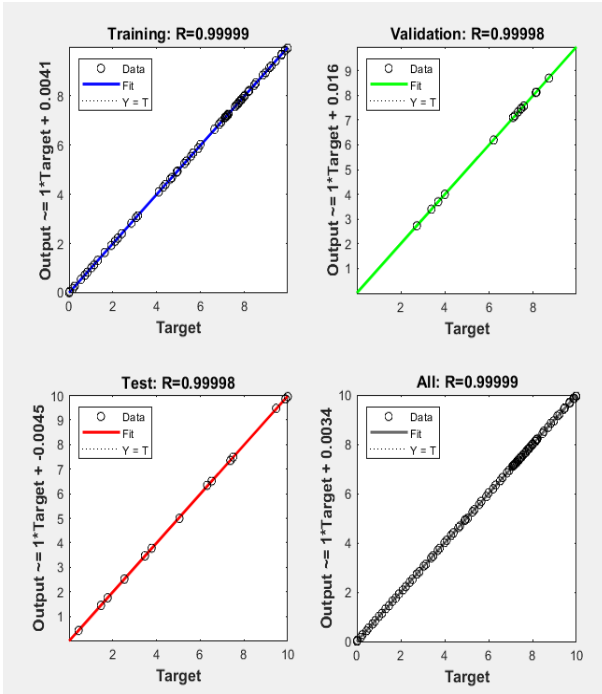

Fig 7: ANN Model Training Regression Plot

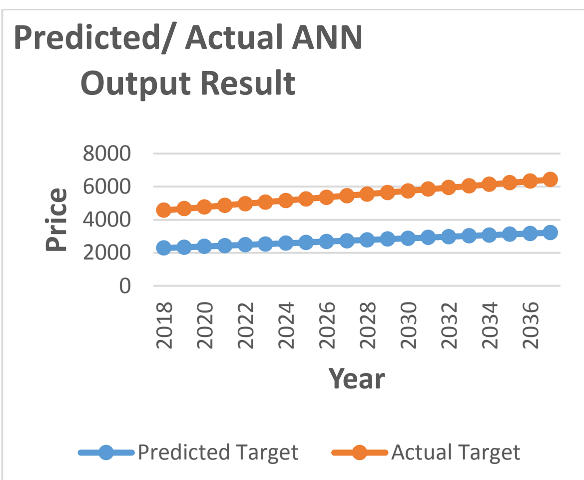

Fig 8: Predicted/Actual ANN Output Result

The actual performance of the ANN can also be measured by the following quantities.

The Mean Absolute Percentage Error (MAPE). It is expressed as:

$$\boldsymbol{\ell} = \frac{\mathbf{1}}{\boldsymbol{N}}\sum \frac{|\boldsymbol{x_j} - \boldsymbol{x_k}|}{\boldsymbol{x_j}} \times \mathbf{100} \qquad (11)$$

Substituting with the values shall give:

$$\text{MAPE} = \frac{1}{20} \times \frac{10}{550274} \times 100 = 0.0908\%$$

Root mean square error (RMSE) expressed as

$$\boldsymbol{\alpha} = \sqrt{\frac{\mathbf{1}\sum_{\mathbf{1}}^{\boldsymbol{N}}(\boldsymbol{x_j} - \boldsymbol{x_k})^{\mathbf{2}}}{\boldsymbol{N}}} \qquad (12)$$

Replacing with the values results to:

$$\text{RMSE} = \sqrt{\frac{100}{20}} = 2.2361$$

Average (mean) error, AME expressed as

$$\boldsymbol{\varepsilon} = \left(\frac{\sum_{i=1}^{N} \boldsymbol{x_j} - \boldsymbol{x_k}}{\boldsymbol{N}}\right) \qquad (13)$$

By substituting with the values, we get

$$\text{AME} = \left(\frac{10}{20}\right) = 0.5$$

From the above values obtained, The MAPE which gave a value of 0.09% showed that by using ANN the forecasted value of transmission pricing is nearly identical with the actual price value and this is very good.

V. Conclusion and Recommendations

The evaluation of electricity transmission price variations when subjected to the action of the Artificial Neural Network showed a better price prediction. This good performance depends on the choice of the ANN network architecture that was applied. Simulations of the input data by ANN indicates that with ANN, a forecast of the electricity transmission price for about 20 years was achieved. ANN has been able to define the nonlinear connection that exists between the old price data that was supplied during the training stage. On this basis a prediction of what the price would be for 20 years was made. With ANN, the transmission price forecast variations are gradual between each year for a period of 10 years and this shows the best forecast. The implication is that consumers are conveniently carried along. The transmission service providers are encouraged for more investment and reliability of service is ensured.

Research however has revealed that ANN has been employed in many engineering applications such as load forecasting, spot pricing of electricity etc. As the conventional engineering methods of Mw-mile, contract path, MVA-mile etc. makes the order of electricity transmission pricing determinations to be clumsy, the required tariff over many years can be obtained by the application of the Artificial Neural Network (ANN). Because of its ability to approximate nonlinear functions from all inputs, ANN therefore makes the determination (or prediction) of electricity pricing to become simple and easy. This phenomenon is very good because the operations of ANN saves time and very cost effective which is a very vital tool for making decisions in industries.

It is however recommended that Artificial Intelligent-based techniques, ANN in particular, must be implemented for long-term improved electricity transmission pricing forecast for the Transmission Company of Nigeria.

References

[1] Ahiakwo, C.O. Chukwu, U.C and Dike, D.O. (2008). Optimal Transmission Line Pricing Algorithm for a Restructured Power System. IEEE Transactions on Power Systems. Vol. 978, no.1, PP.4244-4250

[2] Anderson, D., & McNeil, G. (2006). Artificial neural networks technology: A DACS State-of the Art Report, Data & Analysis Center for Software, 1-35

[3] Anireh, V.I., & Osegi, E.N. (2016). A Modified Activation Function with Improved Run-Times for Neural Networks. Advances in Multidisciplinary and Scientific Research Journal 3 (02).

[4] Araneda, J.C. (2002). Foundations of Pricing and Investment in Electricity Transmission. A Thesis Submitted to the University of Manchester Institute of Science and Technology for the degree of Master of Philosophy.

[5] Desai, K. and Dutta, G. (2013). A dynamic pricing approach to electricity prices in the Indian context. International Journal of Revenue Management, Vol.7 No.3-4. p.268.

[6] Galkin I. (2005). Crash introduction to artificial neural networks.

[7] Green, R. (2000). England and Wales - A competitive Electricity Market, University of California Energy Institute (UCEI). PWP-060 paper.

[8] Hans-Joachim Bodenhofer and Norbert Wohlgemut (2001). Power transmission pricing: issues and international experience. International Energy Symposium Ossiach.

[9] Happ, H., (1994). Cost of Wheeling Methodologies. IEEE Transactions on Power System, Vol, 9. No. 1, pp.147-156.

[10] Illic, M. (1997). Toward Regional Transmission Provision and its Pricing in New England. Utility Policy, Vol. 6, No. 3, pp.245-256.

[11] Komane T (2001). Short term peak load forecasting using neural networks, Department of Electrical Engineering, University of Cape, 2001

[12] Lima, J. Allocation of Transmission fixed charges: an Overview (1996). IEEE Transactions on Power Systems, Vol.11, No. 3, pp. 1409-1418

[13] Mohammed, S. (2002) Market Operations in Electric Power System. Pp. 374,

[14] MYTO document (2008).

[15] MYTO document (2012).

[16] Murali, M. Kumari, M.S. Sydulu, M. (2014). A Review of Transmission Pricing Methods in Restructured Electricity Market and Case Studies. International Electrical Engineering Journal (IEEJ) Vol. 5 No. 1, pp. 1186-1197.

[17] Ogbonna, B.O, C.O.Ahiakwo, D.C. Idoniboyeobu, S. Orike (2019). Improved Electricity transmission pricing for the Nigerian Network. Journal of Newviews in Engineering and Technology (JNET). Vol 1,

[18] Saheed L.B. (2013) Evaluating the Methodology of Setting Electricity Prices in Nigeria. International Association for Energy Economics. Fourth quarter, pp. 31-32.

[19] Singh A, Chen H, Canizares A.C, "ANN-based short term load forecasting inelectricity markets", Proceedings of the IEEE power engineering society transmission and distribution conference, 2001, pp2:411-415

[20] Stergiou C and Siganos D, (2004). Neural Networks found on http://www.doc.ic.ac.uk/~nd/surprise 96/journals /vol4/cs11/report.html.

Bartholomew Odinaka Ogbonna is undergoing Ph.D. degree program in power systems at the Rivers State University, Nigeria. He holds a B.Tech degree in Electrical Power Engineering from the Rivers State University of Science and Technology, Port Harcourt; M.Eng degree in Power Systems & Machines from the University of Port Harcourt, Nigeria. He is a member of the Nigeria Society of Engineers (MNSE). He currently works with the University of Port Harcourt. His main research area is in Power Systems, Machines and Artificial Intelligence.

Christopher O. Ahiakwo received his M. Tech. and PhD in Electrical Engineering from Rivers State University of Science and Technology, Port Harcourt, Nigeria. Professor Christopher Ahiakwo is a Professor of Electrical Engineering, with research interest in electrical power system and Renewable energy. He is a member of several professional bodies, including: Fellow, Nigerian Society of Engineers, Fellow, Nigerian Institution of Electrical Electronics Engineers, Member. Institute of Electrical Electronics Engineers, Council for the Regulation of Engineering in Nigeria, etc. Professor Ahiakwo is currently the Dean, Faculty of Engineering, Rivers State University, Port Harcourt, Nigeria. He was a former Rector, Federal Polytechnic, Ekowe, Bayelsa State, Nigeria.

Dikio C. Idoniboyeobu is a Professor in the Department of Electrical Engineering, Rivers State University, Port-Harcourt, Nigeria He holds B. Eng. Degree in Electrical Engineering, Ahmadu Bello University, Zaria, Nigeria; M. Sc. and PhD Degrees in Electrical Engineering, University of Manchester, United Kingdom. He is registered with Council for the Regulation of Engineering in Nigeria (COREN), and a member of several Professional Organisations.

Sunny Orike obtained his Bachelor of Technology in Computer Engineering from Rivers State University of Science and Technology, M. Sc in Computing from Robert Gordon University, Aberdeen, United Kingdom. Ph.D in Artificial Intelligence from Heriot-Watt University, Edinburgh, United Kingdom. He is a Senior Lecturer and currently the Head, Department of Computer Engineering, Rivers State University, Port Harcourt, Nigeria. His research interests are in the areas of Artificial Intelligence, Deregulated power systems, Big Data Analytics and Cloud Computing. He is registered with Council for the Regulation of Engineering in Nigeria (COREN), and an active member of several professional bodies.