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Voltage Stability Assessment of The Nigerian 330kv Transmission Network Using Artificial Neural Networks

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Abstract- The study looked at Nigerian 330kv transmission network of a 48 bus system. The identified vulnerable buses in the system (Maiduguri bus, Jalingo bus, Yola bus, Damaturu bus and Gombe bus) were optimally compensated using static var compensator. In order to assess the voltage stability of the Nigerian 330KV transmission network after optimal compensation, artificial neural networks were introduced. The artificial neural network was introduced. Artificial neural network simulation showed that blue, green and red plot indicates the training, validation and test mode respectively. The performance regarding each iteration was calculated and the point where the three plots coincided was chosen to be the best performance as it became the best line of fit. The best validation performance during training process is 10.4258 at epoch 4 which indicates how much minimized Mean-Square Error (MSE) occurred during the training. Also, the regression plot of the artificial neural network output against the targets reveals the fitness of the training result. Regression = 1 indicates there is an exact linear relationship between outputs and targets and Regression=0 indicates no linear relationship between the output and the target. The regression plot shows the R value equals to 0.9992 for training, 0.99993 for validation and 0.99855 for testing. This shows that the applied ANN model, training, testing and validation are significantly acceptable and a perfect regression existed between the output and the target.

I. INTRODUCTION

Voltage stability is the ability of power system to maintain steady acceptable voltages at all buses in the system under normal operating conditions and after being subjected to a disturbance. The main factor causing instability is the inability of the power system to meet the demand for reactive power. The heart of the problem is usually voltage drop that occurs when the active power and reactive power flow through inductive reactance associated with the transmission network. It is imperative for power system to continually maintain constant acceptable bus voltage at each node under normal operating conditions after being subjected to disturbances. The non- optimization control and monitoring tool may lead to progressive and uncontrollable drop in voltage results into wide spread of voltage collapse.

Artificial neural networks (ANNs) are computing systems of an interconnected group of nodes, vaguely inspired by biological neural network which loosely model the neurons in a biological brain. Other neurons can receive transmitted signal from each of the interconnected group. The transmitted signal from each interconnected group of nodes is real number and output of each neuron is computed by some non-linear function of the sum of its inputs. Neurons are aggregated into layers. The first layer represents the input layer where signals travel from to the last layer representing the output layer. Though, different layers may perform different transformations on their inputs. For modeling of general relationships, artificial neural networks have emerged as a powerful technique for this purpose. The training of ANN models is by presenting sets of input/output data pairs to the neural network. To capture the implicit mapping in the sets of input/output pairs, the internal weights of the ANN are then optimized. The training of the ANN gives it the ability to predict the correct outputs corresponding to responses it never saw before. This feature is called the generalization ability of the ANN. Modeling of highly nonlinear input/output mappings can be done using the ANN. The training of the ANN gives it extra ability that it can be used for different purposes such as surrogate model of the time-intensive EM simulator, rapidly optimize the parameters of the EM structure, simulations where the ANN models part or all of a given structure [2].

ANN function is known basically by the interconnections between neurons that consist of non-linear functions. The strength of the interconnection is dependent on the weight factor of each input to a neuron and the contribution of that interconnection to the neurons. The ANN can be trained to perform specific functions such as adjusting the values of each input weight factors between the neurons, either by using information from outside the network or by the neurons themselves in response to the input. The ability of ANN to describe complex non-linear, multi-dimensional functional relationship without any prior assumptions about the nature of the relationships is the greatest advantage of ANNs. To develop a well-performing neural network, including its architecture, training functions, training algorithms and other parameters, followed by the training process and the evaluation method, experimental data is needed.

The ANN has the flexibility to allow interconnection with the 330KV network and meets environmental targets. Artificial neuron network is expected to be dynamic, reliable, flexible, adaptable, diverse and fully controllable. This new scenario will enable power operators to maximize energy efficiency such as loss management, demand reduction and data communication [3].

II. REVIEW OF RELATED WORKS

” Reference [1]” proposed artificial neutral network (ANN) controlled VSC-HVDC as a means to enhance the transient stability of Benin bus in the Nigerian 330kv transmission system. They modeled the Nigerian 330kv transmission system in PSAT environment. Simulation of the load flow was done. Analysis on the eigenvalue and damping ratio of the system buses were determined to identify the critical buses. To establish the existing transient stability situation of the grid, the balanced three phase fault was introduced in the critical Benin bus and Ikeja West-Benin transmission line of the transmission network by observing the dynamic response of the generator in the network when the fault was applied. From the result shows that the Nigeria 330kv transmission network is on a critical state. Thus, an urgent control measurer with the aim of enhancing the stability margin of the network to avoid system collapse was required. To this effect, VSC-HVDC was installed along to those critical lines. The inverter and the converter parameters of the HVDC were controlled by the conventional proportional integral (PI) method and artificial neural network. The generalized swing equations for a multi-machine power system are presented. Simulation was done using MATLAB/PSAT. The result showed that 42.86% critical clearing time (CCT) transient stability improvement was achieved when the HVDC was controlled with the artificial neural network against when compared to the PI controllers as can be seen by observing the dynamic response of the generators in the network. The violations at buses 1, 2, 13 and 37 which were 0.930561, 0.922923, 0.922923 and 0.920670 as obtained previously when the VSC-HVDC was being controlled by the conventional PI method are now all improved to 1.000000p.u each.

” reference [6]” proposed online monitoring, evaluation and improvement of steady state voltage stability for electric power system using artificial neural networks techniques. The training data was three sets of data obtained by performing load flow and voltage stability analysis for different load factors such as 0.8, 1.0 and 1.2. The ANN was tested with data corresponding to load factors of 0.75 and 1.3 to determine the effectiveness of the proposed method. The selected objective function gave minimum deviation of the reactive power control variables, which lend to the maximization of minimum Eigen value of load flow jacobian. The considered reactive power control variables were switchable VAR compensators, OLTC transformers and excitation of generators. The method was modified on IEEE 30 bus test system. The result obtained clearly shows that the voltage profile increased from 0.86 to 0.968 at bus 26 as minimum Eigen value increased from 0.194 to 0.214 and the power loss reduced from 24.27MW to 20.46MW.

” reference [5]” proposed power system voltage stability assessment through artificial neural network. A voltage stability index with respect to a load bus was formulated from the voltage equation derived from a two bus network and computed using thevenin equivalent circuit of the power system referred to a load bus. Buses with values of voltage stability factors close to 1.0 are identified as the critical buses. ANN was developed for voltage stability monitoring.

” reference [9]” proposed power system voltage stability analysis and assessment using artificial neural network. Artificial neural network model was used along with continuation power flow methods to assess the voltage stability of a power system. The modal analysis method was first implemented to identify the most vulnerable load buses of the system. Hundreds of loading patterns were generated by varying the real and reactive power. With the help of input patterns and the target outputs, the neural network with the back propagation error architecture was developed using MATLAB and was applied to 14 bus system. It was observed that the selected neural network was efficient in calculating the voltage stability of L-INDEX for the vulnerable load buses. And the L-index value from the ANN was very close to the actual L-index from the analytical method.

” reference [8]” proposed artificial neural networks for on line assessment of voltage stability using FVSI in power transmission systems. The ANN model of the system was developed via on line checking of the load of the weak bus, then calculated the fast voltage stability index (FVSI) and line stability factor (LQF). The developed ANN technique was tested in IEEE 30 bus test system and on-line monitoring of 2 bus Indian southern power grid parameters found out the stability limit for the system without any classical calculation. ANN model was trained with a number of input training vector set to meet convergence criterion.

III. MATERIALS AND METHOD

3.1 Nigerian 48 Bus 330kv Network

NEPLAN software simulation result of the modeled 330kv transmission network of a 48 bus system presented in figure 3.1 below and refers to as Pre-upgrade network. The 5 buses with red color show the unstable state of the system.

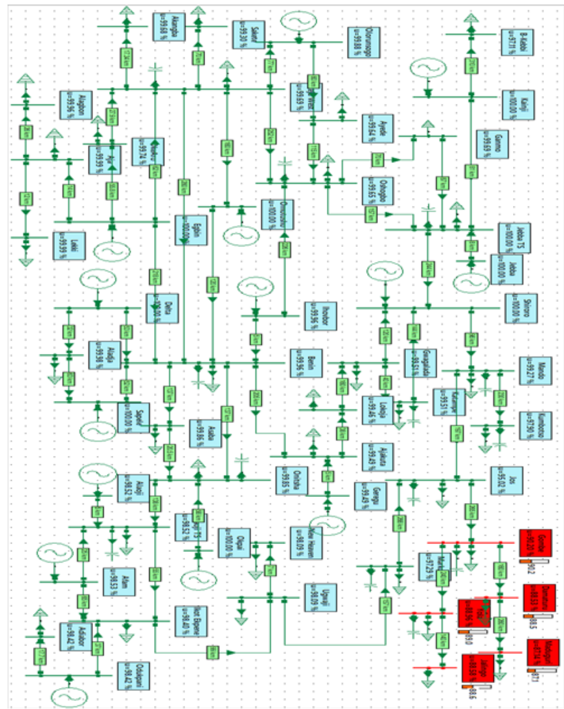

Figure 3.1: Pre-Upgrade Network Simulation in NEPLAN Software

3.2 Bus Operating Voltage for Nigerian 48 Bus 330kv Network

Table 3.1 below shows the nominal and operating voltage of the 330kv transmission network of a 48 bus system.

Table 3.1: Bus Operating Voltage for Pre-Upgrade Network Condition

No	Bus Name	Nominal (kV)	Operating Voltage (KV)	Operating Voltage (P.U.)	Operating Voltage (%)
1	Adiabor	330	324.786	0.9842	98.42
2	Afam	330	325.149	0.9853	98.53
3	Aja	330	329.967	0.9999	99.99
4	Ajakuta	330	328.317	0.9949	99.49
5	Akangba	330	328.944	0.9968	99.68
6	Aladja	330	329.934	0.9998	99.98

7	Alagbon	330	329.868	0.9996	99.96
8	Alaoji	330	325.116	0.9852	98.52
9	Alaoji TS	330	325.116	0.9852	98.52
10	Asaba	330	329.538	0.9986	99.86
11	Ayede	330	328.812	0.9964	99.64
12	Benin	330	329.868	0.9996	99.96
13	B-Kebbi	330	320.463	0.9711	97.11
14	Damaturu	330	292.149	0.8853	88.53
15	Delta	330	330	1.00	100.00
16	Egbin	330	330	1.00	100.00
17	Ganmo	330	328.977	0.9969	99.69
18	Geregu	330	328.317	0.9949	99.49
19	Gombe	330	297.66	0.902	90.20
20	Gwagalada	330	328.383	0.9951	99.51
21	Ihovbor	330	329.868	0.9996	99.96
22	Ikeja West	330	328.977	0.9969	99.69
23	Ikot Ekpene	330	324.72	0.984	98.40
24	Jalingo	330	292.314	0.8858	88.58
25	Jebba	330	330	1.00	100.00
26	Jebba TS	330	330	1.00	100.00
27	Jos	330	313.566	0.9502	95.02
28	Kainji	330	330	1.00	100.00
29	Katampe	330	328.383	0.9951	99.51
30	Kumbotso	330	323.07	0.979	97.90
31	Lekki	330	329.967	0.9999	99.99
32	Lokoja	330	328.218	0.9946	99.46
33	Maiduguri	330	287.562	0.8714	87.14
34	Mando	330	327.591	0.9927	99.27
35	Markudi	330	321.057	0.9729	97.29
36	New Heaven	330	323.697	0.9809	98.09
37	Odukpani	330	324.786	0.9842	98.42
38	OkeAro	330	329.142	0.9974	99.74
39	Okpai	330	330	1.00	100.00
40	Olorunsogo	330	329.604	0.9988	99.88
41	Omotosho	330	330	1.00	100.00
42	Onitsha	330	329.505	0.9985	99.85
43	Oshogbo	330	328.845	0.9965	99.65
44	Sakete	330	327.69	0.9930	99.30
45	Sapele	330	330	1.00	100.00
46	Shiroro	330	330	1.00	100.00
47	Ugwaji	330	323.697	0.9809	98.09
48	Yola	330	293.568	0.8896	88.96

Table 3.1 above is the first NEPLAN simulation result of the operating voltage of the system. The following buses (Maiduguru, Jalingo, Yola, Damaturu and Gombe), violates the bus voltage statutory limit condition of 0.95p.u - 1.05p.u (0.8714p.u, 0.8858p.u , 0.8896p.u, 0.8853p.u , 0.9020p.u) respectively.

3.3 Modeling of the Static VAR Compensator (SVC)

The SVC used for this work is the Thyristor Controlled Reactor-Fixed Capacitor (TCR-FC) type. The TCR-FC functional diagram and its equivalent circuit are showcased below in figure 3.2 and 3.3.

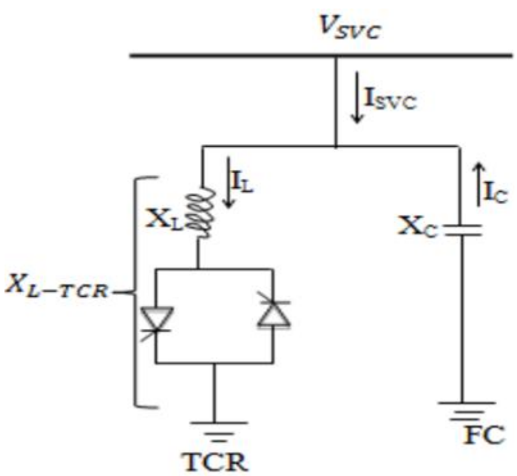

Figure 3.2: Functional Diagram of a TCR-FC SVC [7].

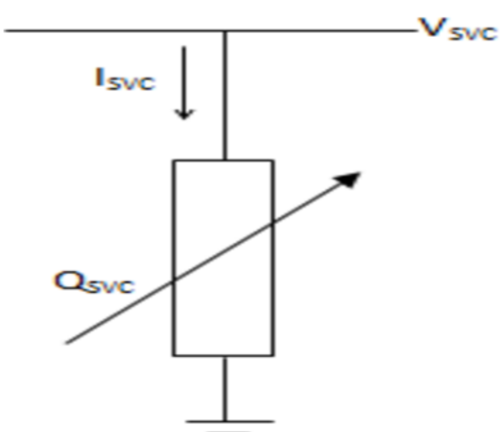

Figure 3.3: Equivalent circuit of the SVC [7].

The SVC consumes no active power as one branch of the SVC is purely inductive while the other branch is purely capacitive as depicted in figure 3.2 above. The SVC performs two main purpose of consuming (inductive) reactive power to reduce the system voltage or injects reactive power to increase the system voltage. The reactors current (I_L) is positive since the reactor consumes reactive power while the capacitor current (I_C) is negative since it injects reactive power into the system.

Hence, the SVC current (I_{SVC}) at maximum var could be expressed as:

$$I_{SVC} = I_L - I_C \tag{3.23}$$

Where I_L *and* I_C is given as

$$I_C = \frac{V_{SVC}}{X_C} \tag{3.24}$$

$$I_L = \frac{V_{SVC}}{X_L} \tag{3.25}$$

Where

I_L : Inductive current of the SVC

I_C : Capacitive current of the SVC

X_L : Inductive reactance of the SVC

X_C : Capacitive reactance of the SVC

C : Fixed Capacitance of the SVC

f : Frequency of the system

V_{SVC} : Bus voltage magnitude

Assuming that no real power is consumed by the SVC in Figure 3.5, (i.e. $P_{SVC} = 0$) then:

$$Q_{SVC} = I_{SVC} \times V_{SVC} \tag{3.26}$$

Substituting equation (3.23) into (3.26) gives:

$$Q_{SVC} = (I_L - I_C) \times V_{SVC} \tag{3.27}$$

Equating equations (3.24), (3.25) and (3.27) gives

$$Q_{SVC} = \left(\frac{V_{SVC}}{X_L} - \frac{V_{SVC}}{X_C} \right) \times V_{SVC} \tag{3.28}$$

$$Q_{SVC} = \left(\frac{1}{X_L} - \frac{1}{X_C} \right) \times V_{SVC}^2 \tag{3.29}$$

$$Q_{SVC} = \left(\frac{X_C - X_L}{X_C X_L} \right) \times V_{SVC}^2 \tag{3.30}$$

The design of the SVC controller is in such a way that the TCR-FC is switched ON when the bus voltage becomes lower than the reference voltage and switched OFF when the bus voltage becomes higher than the reference voltage.

Hence, the FC and the TCR are in operation at maximum VAR Injection as such $I_L = 0$, therefore equation (3.29) becomes;

$$Q_{SVC}^{\max} = \left(-\frac{1}{X_C}\right) \times V_{SVC}^2 \qquad (3.31)$$

And $I_C = 0$ at minimum VAR Injection, as such equation (3.29) becomes

$$Q_{SVC}^{\min} = \left(\frac{1}{X_L}\right) \times V_{SVC}^2 \qquad (3.32)$$

3.4 Artificial Neural Network Architecture in Matlab

Artificial Neural Network is the biologically inspired computer simulation performed to confirm the basic connection in a set of data similar to the human brain. The neural network helps to modify the input so that the network gives the best result without redesigning the output.

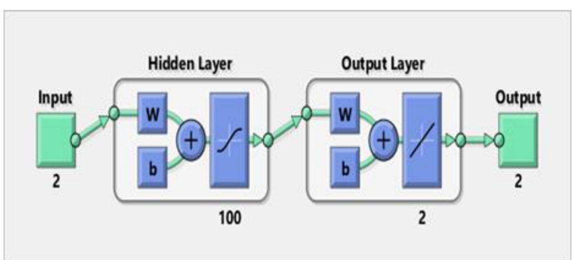

Plate 3.1: Artificial Neural Network Architecture

Plate 3.1 shows a typical neural network architecture containing artificial neurons (units) arranged in a series of layers namely;

(i) Input layer: is made up of nodes that transmit input data (signals) only. They do not calculate the weighted sum and do not use activation function.

(ii) Hidden layer: is the layer between input and output of the neural network. It contains units of artificial neurons that transform the input data (signals) into something the output can use by multiplying the signal by the weight of the signals

(iii) Output layer: is the rightmost layer of the neural network. They contain units of artificial neurons that respond to the information about how the network learned any task and uses activation function to determine the behavior of the layer.

3.4.1 Training in Artificial Neural Network The objective of the training is to obtain an anticipated output for all input values fed into the network and minimize the error. In neural network, information is stored in terms of weights of neurons. The ANN learns through an iterative process and modifies weights of input to be trained accordingly. A systematic way of modifying the weight of the neuron is known as learning rule. For this thesis, supervised learning rule was used because the target for training is already known.

Supervised learning describes a class of problem where input variables (X) and an output variable (Y) use back propagation algorithm to learn the mapping function from the input to output.

$$Y = f(X) \qquad (3.62)$$

In this learning procedure, a back propagation algorithm model is used to learn a mapping between input examples and the target variables.

The three layered ANN structure shown in plate 3.1 is known as feed forward artificial neural network. In this network, the information or signal propagates in only one direction forward starting from the input neurons through the hidden layers and to the output neuron without forming a cycle or loops. The feed forward neural networks are primarily used for supervision learning where the data to be learned is neither sequential nor time dependent. In training of the feed forward, back propagation algorithm was used in training of the feed-forward neural networks. In this algorithm, there is propagation from each input pattern of the training dataset through network to input layer and to the output layer. The error is computed when the network generated output is compared with the target output as given below [4]:

$$E = \sum_n \sum_p (y_i - t_i)^2 \qquad (3.63)$$

Where:

y_i : is the ANN generated output

t_i : is the component of the desired output/target T

n : is the number of output neurons

p : is the number of training patterns

Through each neuron, this error will be propagated backward and correspondingly the connection weights will be updated.

The back propagation happens when the error signals (inputs) are propagated backward through the network from the output layer to the hidden layer, assigning blames for the error and updating weights as they go. The error for a neuron in the hidden layer is calculated as the weighted error of each neuron in the output layer. Then, the back propagated error signal is accumulated and then used to determine the error for the neuron in the hidden layer.

3.4.2 Determination of Data for Training in ANN

The Nigeria 330kv modeled operating voltages result is used as the input data while the improved result Nigeria 330kv modeled operating voltages is used as the target data for neural network simulation. The quantities used are operating voltage, active power respectively

3.4.3 Algorithm for ANN Training

Step 1. Input training data formatted as [input, target]. For the research work, 3x36 input signals were used. The input signal is giving by

$$Input\ (x) = \begin{bmatrix} x_{1i} \\ x_{2i} \\ x_{3i} \end{bmatrix} \quad (3.64)$$

Where

x_{1i} : Voltage magnitude (p.u)

x_{2i} : Active power loading (MW)

x_{3i} : Current loading (A)

i=1,2,3,4,5+…….36

Step 2. Initialize the weights and bias

$$w = [w_1 \quad w_2 \quad w_3], [b] \quad (3.65)$$

The weighted sum of the output node *i* is giving by

$$v_i = \left([w_1 \quad w_2 \quad w_3] * \begin{bmatrix} x_{1i} \\ x_{2i} \\ x_{3i} \end{bmatrix} \right) + b \quad (3.65)$$

$$v_i = (w_1 * x_{1i}) + (w_2 * x_{2i}) + (w_3 * x_{3i}) + b \quad (3.66)$$

Where

x_{1i} : Voltage magnitude (p.u)

x_{2i} : Real power loading (MW)

x_{3i} : Current loading (A)

w_1 : Weight of x_{1i}

w_2: Weight of x_{2i}

w_3: Weight of x_{3i}

b= bias which is associated with the storage of information

Step 3. Calculate output

$$Ouput\ (y_i) = \emptyset(v_i) \quad (3.67)$$

$$= \emptyset((w_1 * x_{1i}) + (w_2 * x_{2i}) + (w_3 * x_{3i}) + b \quad (3.68)$$

$$\emptyset(v_i) = \left(\frac{1}{1+e^{-v_i}}\right) \quad (3.69)$$

$$Ouput\ (y) = \frac{1}{1+e^{-((w_1 * x_{1i}) + (w_2 * x_{2i}) + (w_3 * x_{3i}) + b)}} \quad (3.70)$$

Where

$\emptyset$: Activation function (Tan Sigmoid Function)

vi : Weighted sum of the output node *i*

x_{1i}: Voltage magnitude (p.u)

x_{2i} : Active power loading (MW)

x_{3i} : Current loading (A)

w_1 : Weight of x_{1i}

w_2 : Weight of x_{2i}

w_3 : Weight of x_{3i}

B : Bias which is associated with the storage of information

Step 4. Calculate the error.

The difference between the output and the target of a neural network

$$e_i = d_i - y_i \quad (3.71)$$

Where

d_i : Target

y_i : Output

Step 5. Calculate the weights

$$w_{ij} = \alpha e_i x_j \quad (3.72)$$

Where

α : Learning rate [0,1]

e_i : Error in node i

x_j : Output from node j where j=1,2,3 and so on.

Step 6. Adjust the weight update using Mini Batch Method. The Mini Batch method has the speed of Stochastic gradient descent (SGD) method and the stability of Batch method.

$$w_{ij} = w_{ij} + \alpha \delta_i x_j \quad (3.73)$$

$$\delta_i = \emptyset^I(v_i) e_i \quad (3.74)$$

$$\emptyset(v) = \left(\frac{1}{1+e^{-v}}\right) \quad (3.75)$$

$$\emptyset^I(v_i) = \emptyset(v_i)(1 - \emptyset(v_i)) \quad (3.76)$$

$$\delta_i = \emptyset(v_i)(1 - \emptyset(v_i)) e_i \quad (3.77)$$

$$w_{ij} = w_{ij} + \alpha \emptyset(v_i)(1 - \emptyset(v_i)) e_i x_j \quad (3.78)$$

Where

vi : Weighted sum of the output node *i*

e_i : Error in node i

x_j : Output from node j where j=1,2,3 and so on.

$\emptyset^I$: Derivative of the activation function $\emptyset$ of node i
α : Learning rate [0,1]
w_{ij} : Previous weight
Step 7. Repeat step 4 to 6 for all training data until the error reaches an acceptable limit. From step 4 to step 6 is known as epoch

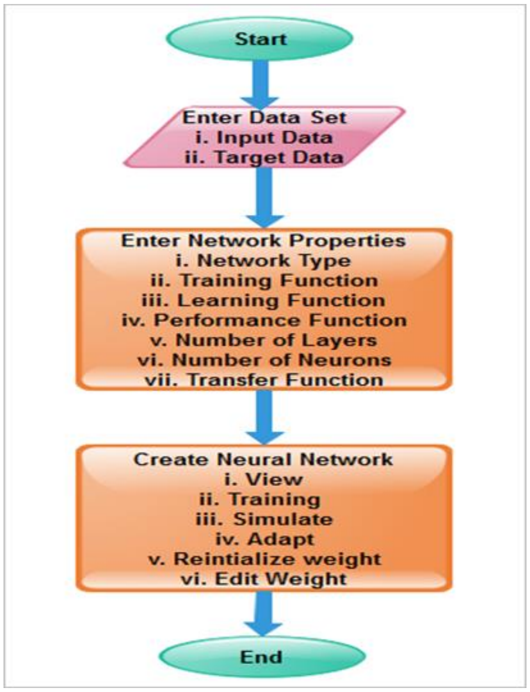

Plate 3.2 Flow chat of ANN Training

IV. RESULTS AND DISCUSSION

4.1 Improved Nigerian 330kv transmission network

NEPLAN software simulation result of the improved 330kv transmission network is presented in figure 4.1 below and refers to as Post-upgrade network. All the buses in green color signify stability state of the system.

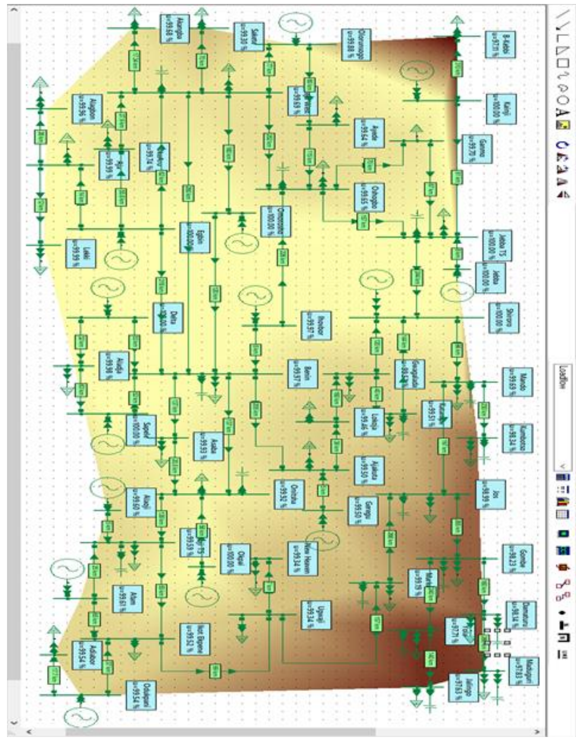

Figure 4.1: Post-Upgrade Networks Simulation in NEPLAN Software

4.1.1 Improved Buses Result

The improved vulnerable buses NEPLAN simulation result is presented in figure 4.2 below showing the improved operating voltages as contained and declared by statutory condition. The buses displaying green color signifies stability of the system.

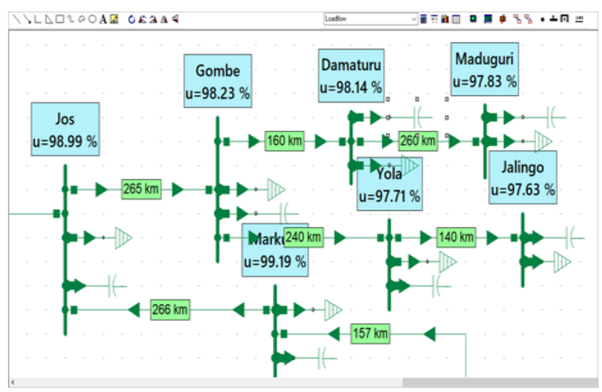

Table 4.1: Bus Operating Voltage for Post-Upgrade Network Condition

No	Bus Name	Nominal (kV)	Post- Upgrade (KV)	Post- Upgrade (P.U.)	Post- Upgrade (%)
1	Adiabor	330	328.581	0.9957	99.57

2	Afam	330	328.779	0.9963	99.63
3	Aja	330	329.967	0.9999	99.99
4	Ajakuta	330	328.35	0.995	99.50
5	Akangba	330	328.944	0.9968	99.68
6	Aladja	330	329.934	0.9998	99.98
7	Alagbon	330	329.868	0.9996	99.96
8	Alaoji	330	328.746	0.9962	99.62
9	Alaoji TS	330	328.746	0.9962	99.62
10	Asaba	330	329.769	0.9993	99.93
11	Ayede	330	328.812	0.9964	99.64
12	Benin	330	329.901	0.9997	99.97
13	B-Kebbi	330	320.463	0.9711	97.11
14	Damaturu	330	323.862	0.9814	98.14
15	Delta	330	330	1.00	100.00
16	Egbin	330	330	1.00	100.00
17	Ganmo	330	329.01	0.997	99.70
18	Geregu	330	328.35	0.995	99.50
19	Gombe	330	324.159	0.9823	98.23
20	Gwagalada	330	328.416	0.9952	99.52
21	Ihovbor	330	329.901	0.9997	99.97
22	Ikeja West	330	328.977	0.9969	99.69
23	Ikot Ekpene	330	328.515	0.9955	99.55
24	Jalingo	330	322.179	0.9763	97.63
25	Jebba	330	330	1.00	100.00
26	Jebba TS	330	330	1.00	100.00
27	Jos	330	326.667	0.9899	98.99
28	Kainji	330	330	1.00	100.00
29	Katampe	330	328.383	0.9951	99.51
30	Kumbotso	330	324.489	0.9833	98.33
31	Lekki	330	329.967	0.9999	99.99
32	Lokoja	330	328.218	0.9946	99.46
33	Maiduguri	330	322.839	0.9783	97.83
34	Mando	330	328.911	0.9967	99.67
35	Markudi	330	327.459	0.9923	99.23
36	New Heaven	330	327.921	0.9937	99.37
37	Odukpani	330	328.581	0.9957	99.57
38	OkeAro	330	329.142	0.9974	99.74
39	Okpai	330	330	1.00	100.00
40	Olorunsogo	330	329.604	0.9988	99.88

41	Omotosho	330	330	1.00	100.00
42	Onitsha	330	329.736	0.9992	99.92
43	Oshogbo	330	328.845	0.9965	99.65
44	Sakete	330	327.69	0.993	99.30
45	Sapele	330	330	1.00	100.00
46	Shiroro	330	330	1.00	100.00
47	Ugwaji	330	327.921	0.9937	99.37
48	Yola	330	322.443	0.9771	97.71

Table 4.1 shows the nominal and operating voltage of the system for post-upgrade network condition. The post-upgrade network condition is the state when static var compensators are installed. Table 4.1 shows that no buses violate the statutory limit condition of 0.95p.u. (313.5kV) - 1.05p.u. (326.5kV)

4.3 Voltage Profile Comparisons of Pre-Upgrade and Post-Upgrade Network

Figure 4.3 below shows voltage profile of pre-upgrade in (KV) and post-upgrade network in (KV) against bus name where the blue color represents the pre-upgrade while the red color represents the post upgrade.

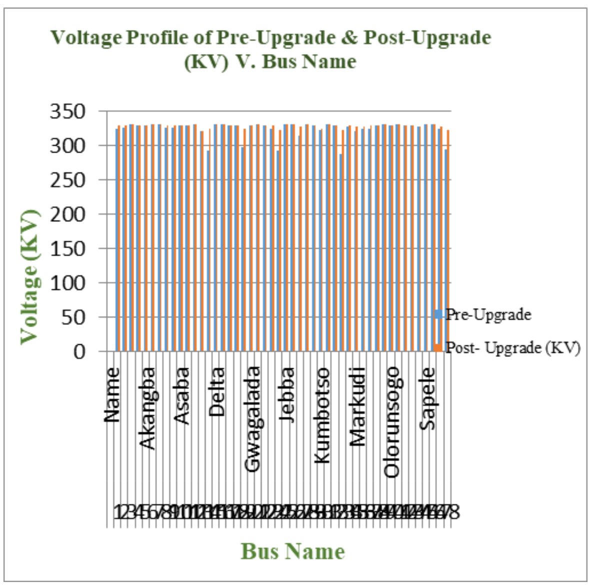

Figure 4.3: Voltage Profile Comparisons of Pre-Upgrade and Post-Upgrade Network

Figure 4.3 depicts comparisons of pre-upgrade maximum voltage loadability and post-upgrade maximum voltage loadability and showcases the improvement achieved. of pre-upgrade maximum voltage loadability is below 300KV while the post-upgrade maximum voltage loadability is above 320KV.

4.4 Voltage Improvement for the vulnerable buses

Figure 4.4 depicts the voltage profile comparison of bus operating voltages without static var compensation and bus operating voltages with static var compensation in (KV). The blue color represents the buses without var compensation while red color represents bus voltages with var compensation.

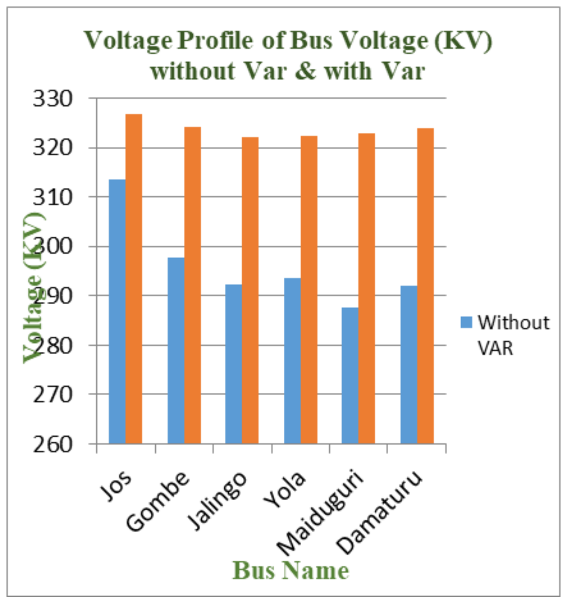

Figure 4.4: Voltage Improvement for the vulnerable buses

The graph shows the improvement achieved after optimal placement of static var compensator on the vulnerable buses and also showcases the maximum voltage loadability of the buses without static var compensator placement being below 300KV and the maximum voltage loadability of the buses after static var compensator placement being above 320KV.

4.5 ANN Training Regression Plot

Figure 4.5 shows the regression plot of the ANN output against the targets which reveals the fitness of the training result.

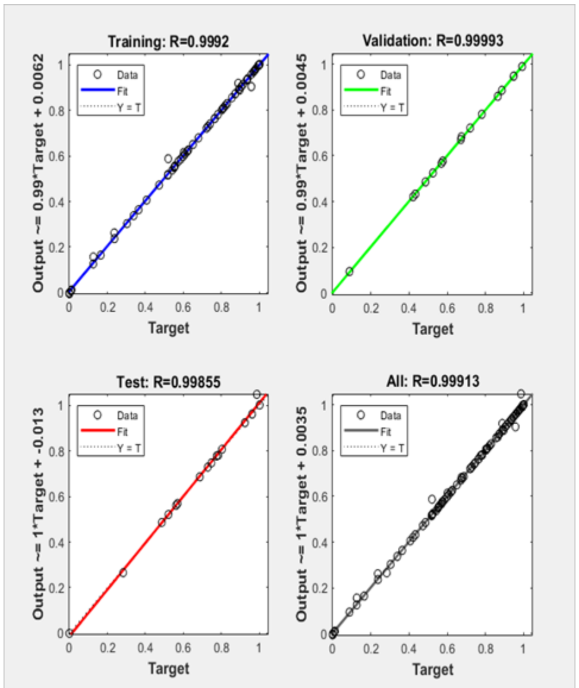

Figure 4.5: ANN Training Regression Plot

Regression (R) = 1 indicates there is an exact linear relationship between outputs and targets and Regression (R) = 0 indicates no linear relationship between the output and the target. Figure 11 shows the R value equals to 0.9992 for training, 0.99993 for validation and 0.99855 for testing. This shows that the applied ANN model, training, testing and validation are significantly acceptable and a perfect regression existed between the output and the target

4.6 ANN Training Performances

Figure 4.6 below shows the performance plot of the ANN training. The blue, green and red clolrs represent the training, validation and test mode respectively.

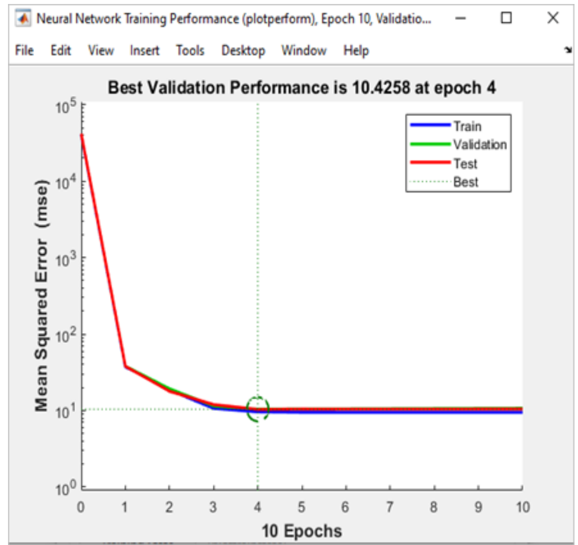

Figure 4.6: ANN Training Performances

During training, the performance for each iteration is calculated and the point where the three plots almost coincided is chosen to be the best performance. At that point, the training process is stopped and no further training is required else the results maybe predicted wrongly. From the performance plot the best validation performance during training process is 10.4258 at epoch 4 which indicates how much minimized errors occurred during the training.

CONCLUSION

Following the completion of the research, it can be observed that the research successfully addressed the objectives set out at the beginning of the research. Artificial neural network applications were able to asses and predict the voltage stability of the Nigerian 330KV transmission network using regression supervised learning that deals with prediction of numerical label.

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