International Journal of Interdisciplinary Research in Statistics, Mathematics and Engineering
ISSN: 2992-9261| Impact Factor : 7.62
Volume. 10, Number 3; July-September, 2023;
Published By: Scientific and Academic Development Institute (SADI)
8933 Willis Ave Los Angeles, California
https://sadijournals.org/index.php/ijirsme | editorial@sadijournals.org

VOLTAGE STABILITY IMPROVEMENT OF INTERCONNECTED GRID NETWORK USING ANFIS TECHNIQUE

Noble Chidi Njoku and Chizindu Stanley Esobinenwu
Electrical and Electronic Engineering Department, University of Port Harcourt, Rivers State, Nigeria. Email: trinitynoble4life@gmail.com and chizindu.esobinenwu@uniport.edu.ng
https://doi.org/10.5281/zenodo.8272937

ABTRACT: *The paper examined a heavily stressed Nigeria 330kV network that operates closer to its thermal limits. The total forced outage recorded by Transmission Company of Nigeria (TCN) in the year 2020 was 53.4%, 42.43% in 2019 and 35.1 % in 2018. The inconvenience and economic cost of the occasioned forced outage on the public residence are enormous and unpleasant. With these statistics, this paper tends to evaluate the existing South-South 330kV grid for voltage stability improvement using Adaptive Neuro-Fuzzy. The network consisting of seven (7) generating station, sixteen (16) buses, and nineteen (19) transmission lines was modeled in NEPLAN 555 using Newton Raphson power flow algorithm to determine the operating condition of the existing network. Modal analysis and V-Q sensitivity was used to identify buses near voltage collapse. The result obtained from the base simulation shows that the 1st mode is the most critical in the network with the least eigenvalue of 35.5598 and the highest participating buses that showcased their proximity to voltage collapse in the mode are 12 (New Heaven, 0.4668) and 18 (Ugwaji, 0.4640). The P-V curve plot for base case simulation shows that at 710MW loading the operating point of Bus 12 (New Heaven) and 18(Ugwaji) are 93.925% and 93.956% respectively. The loadability can be increased by 1597.5MW and before a voltage collapse can be seen beyond which the system will not recover at 58.198% and 58.069% at 2307.5 MW loading. However, with ANFIS controlled SVC installed at Bus 12 and 18 respectively, the operating point increased to 98.437% and 98.508% at 710.0 MW loading and can be increased by 2840 MW before a voltage collapse can be seen beyond which the system will not recover, at 76.821% and 76.801% at 3550 MW loading. Therefore, increasing the loadability of buses by 1242.5MW with ANFIS controlled SVC.*

Keywords: Voltage, Reactive power, ANFIS, Q-V Sensitivity, Q-V Modal Analysis, Loadability,

1.1 INTRODUCTION

Power plants that produce electrical energy are typically positioned far from load centres. In order to harness the power generated, a network of conductors must connect the power plants and the load centres. This conductor is called the transmission lines and the interconnection of all major generating stations and load centres in the country is called the grid (Robinson 2019). In Nigeria, the 330KV ultra high voltage level is referred to as the national grid system and the transmission company of Nigeria (TCN) is charge with the responsibility of managing the grid system. In recent time, the grid system has advance size and complexity with extensive interconnection due to the skyrocketed demand electrical power in the country and the transfer of energy from one point to another makes it more complex thereby altering the stability of the grid as the driven operate close to their limits and disposing it to different forms of system disturbance such as limitation in the quantity of power

evacuated, increased power loss especially in congested lines, loss of synchronization at the generating stations that may trigger cascading outages thereby resulting in system collapse (Ademola et al, 2016)
The lack of a monitoring and controlling tool may cause a gradual and unpredictable decline in voltage that spreads across a large area. As a result, the deployment of artificial intelligence systems is required for the operation, control, and monitoring of power systems. If artificial intelligence is fully incorporated into the power system, it can efficiently handle complicated network problems as well as carry out real-time infrastructure monitoring and control. (Hague, 2012).
Rastgoufard (2018) asserts that the speed, resilience, and relative insensitivity to missing data of artificial intelligence tools make them ideal for use in power systems. The study suggested using adaptive neuro-fuzzy inference system (ANFIS) in addition to existing expert systems like artificial neural network (ANN) and fuzzy logic inference system (FIS) to increase voltage stability in a network of interconnected power systems. He further noted that some of the benefits of ANFIS that makes it useful for parameter estimation, control, and modelling in complex systems are;

i. Training data without relying entirely on expert knowledge to develop a fuzzy logic model.
ii. The model benefits from having both linguistic and numerical expertise of Fuzzy and ANN
iii. It makes use of the ANN's capacity to categorize data and spot trends.
iv. It is less prone to memorization errors than the ANN and is more transparent to the user.

2.0 LITERATURE REVIEW

Adewuji et al. (2022) applied machine learning and artificial intelligence approaches to the analysis of voltage stability. While acknowledging the dynamic character of voltage stability (VS) problems, the authors made the case that it is possible to approximate VS conditions of power systems using steady state analysis for a variety of voltage stability indices. To track the power systems' allowed voltage stability margin under various loading scenarios, the work specifically utilized an artificial neuro-fuzzy inference system and hybridized it with particle swarm optimization. Obtaining accurate assessments of the power system's proximity to the voltage stability limit is typically the first step in mitigating voltage collapse. An actual machine learning technique was applied to do this. The scientists did, however, point out that choosing the right amount of fine-tuning for the training parameters is the main challenge when using machine learning algorithms. The authors therefore merged the particle swamp optimization approach with an artificial neuro-fuzzy inference system in an effort to enhance the predictive analysis's training performance.
Nor et al. (2017), presented a neural network were used to examine the voltage stability of load buses in an electric power system. The indications for the analysis of voltage stability were the load power margin and the voltage stability margin. Two categories of neural networks were used in the study. The neural network was used in the first category to predict the voltage stability margin and load power margin values. It used a multilayer perceptron back propagation neural network and an adaptive neuro-fuzzy inference system. The probabilistic neural network was used in the second category to categorize the voltage stability margin and load power margin values. The reference electrical power system was determined to be the IEEE 30-bus system.
Bourzami et al. (2021) suggested two ways to monitor the voltage stability of power systems: an adaptive neuro-fuzzy inference system with the moth swamp algorithm, and a multi-layer perceptron neural network. The connection biases and weights of the multi-layer perceptron network were optimized using the moth swamp algorithm, and the tuning parameter for the adaptive neuro-fuzzy inference system model was determined using the proposed hybrid multi-layer perceptron combined with moth swamp algorithm and moth swamp algorithm models. Different statistical measures, including correlation coefficient, root mean square error, and root mean square percentage error, were utilized to assess the suggested models' forecasting effectiveness and capacity. The obtained results show that the proposed adaptive neuro-fuzzy inference system with moth swamp algorithm model had the most accurate and reliable prediction ability and was therefore considered to be the efficient technique for calculating the voltage stability margin of the power system based on readings from phasor measurement unit devices.

Ghaghishpour and Koochaki (2020) noted Artificial Neuro-Fuzzy Inference System model is based on association rules. For monitoring the effective voltage stability margin of a power system, the proposed ANFIS was trained using the Harris-hawks optimization process. Three crucial areas—data estimation, model training, and feature selection—were investigated in the suggested hybrid artificial neuro-fuzzy inference system model's capacity for voltage stability margin evaluation. A multilayer feedforward artificial neural network model for estimating the voltage stability margin has been created, often using an approach called error backpropagation learning. The most frequently used sensitivity for performance analysis has been to link the voltage stability margin and the power system loading conditions.

Adhikari *et al.* (2020) observed that in recent times, methods of machine learning regression have drawn considerable interest to assess voltage stability margin in power systems, especially for online application purposes. And so, the authors presented a research work that compared the voltage stability margin prediction that used various popularly used machine learning algorithms for good operational conditions. Additionally, the work compared the predictive capability of various algorithms for machine learning to network topologies that are not seen. The used algorithms were Artificial Neural Network, and Decision Tree, Gaussian Process Regression, Support Vector Machine. The inputs to the machine learning algorithm were angle at each bus and voltage magnitude so as to evaluate the voltage stability margin. The work was analyzed, and the results show that the Gaussian process regression method was the best among the four algorithms used. Fuzzy Inference system has remained one of the key techniques in Machine learning that is rapidly gaining growing attention by many researchers in recent years. In order to acquire or obtain the appropriate output data, the fuzzy inference system integrates the concepts of artificial neural networks and fuzzy logic.

According to Ashfaq (2018). Artificial Neuro-Fuzzy Inference System has proved to be a useful technique, one that has been used many times to predict power systems parameters, and for determining the actual operating conditions of power systems.

3.0 MATERIALS AND METHODS

3.1 Materials Used

The Materials used for the study includes;

i. Single Line Diagram
ii. Bus Data
iii. Line Data
iv. Neplan 555 Software
v. Fuzzy Logic Toolbox in MATLAB

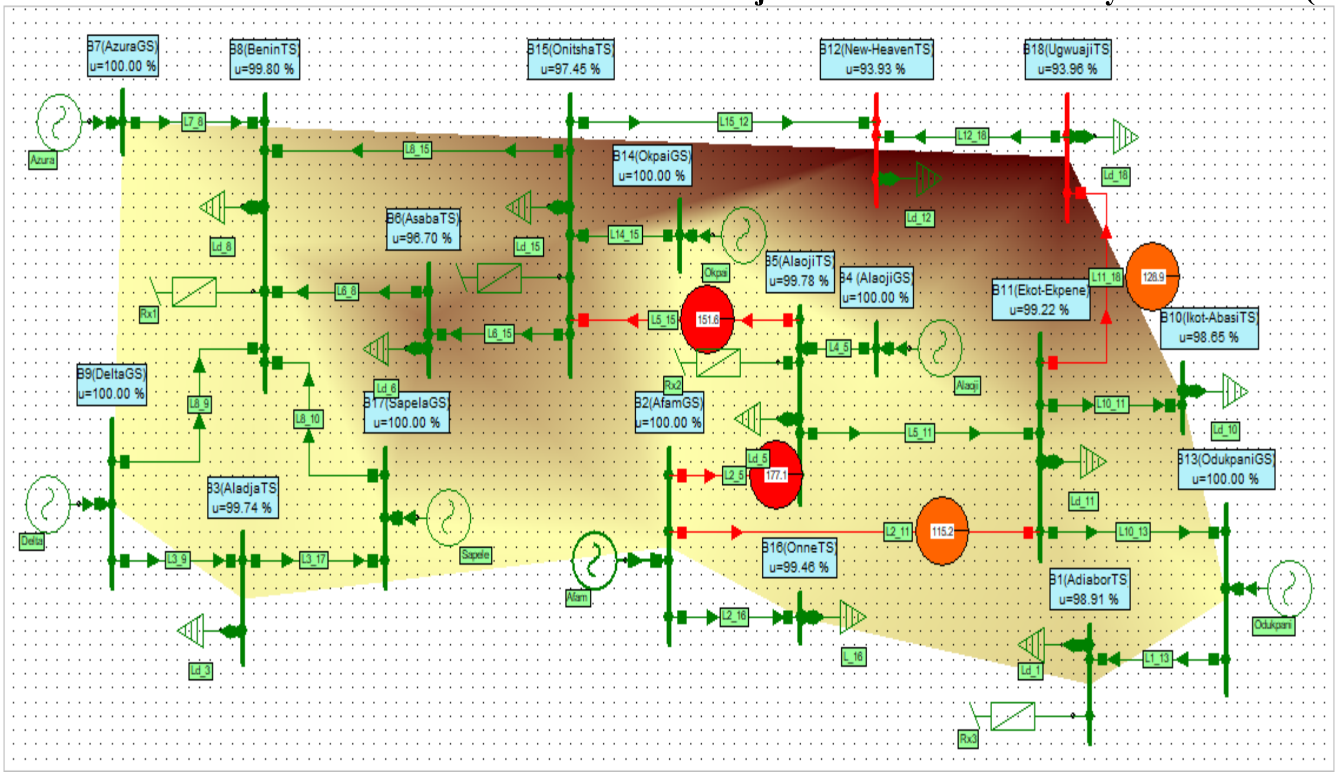

Figure 1: Single Diagram of the existing South-South 330kV grid in NEPLAN

Figure 1 show the existing South-South 330kV grid in NEPLAN consisting of seven (7) generating station, sixteen (16) buses, and nineteen (19) transmission lines was modeled in NEPLAN 555 environment.

3.2 Proposed Method

The proposed ANFIS method controls the loading margin of the buses during contingencies by combining two or more measurable power system parameters such as voltage, reactive power for online monitoring of the buses close to point of voltage collapse. The method involves;

3.2.1 Reducing the Jacobian Matrix from Newton-Raphson Power Flow Solution Using Q-V Modal Analysis.

The traditional Newton-Raphson method fails to converge because of the singularity of the Jacobian matrix at the knee point where any change in the modal reactive power will result in an infinite change in the modal voltage and the system will crash. The Modal analysis is an efficient analytical method for predicting voltage collapse in extensive power system networks. It mitigates the challenge of Jacobian matrix singularity by reducing the Jacobian matrix from the typical power flow solution to linearize its dimension. By putting the value of ΔP =0, in the conventional Newton-Raphson method then solving simultaneously to eliminate the angle part we have

$$0 = J_{11}\,\Delta\theta + J_{12}\,\Delta V \tag{1}$$

$$\Delta Q = J_{21}\,\Delta\theta + J_{22}\,\Delta V \tag{2}$$

From (1) making $\Delta\theta$ subject of the equation we have

$$\Delta\theta = [-J_{12}J_{11}^{-1}\Delta V] \tag{3}$$

Substituting (3) into (2)

$$\Delta Q = J_{21}[-J_{12}J_{11}^{-1}\Delta V]+J_{22}\,\Delta V \tag{4}$$

$$\Delta Q = \Delta V[J_{22} - J_{21}J_{11}^{-1}J_{12}] \tag{5}$$

$$J_R = [J_{22} - J_{21}J_{11}^{-1}J_{12}] \tag{6}$$

The linearized relationship between the small variations in bus voltage (ΔV) and the injection of reactive power (ΔQ).

$$\Delta Q = J_R \Delta V \quad (7)$$

$$\Delta V = J_R^{-1} \Delta Q \quad (8)$$

3.2.2 Determining the most critical Bus using Q-V Sensitivity

The Q-V sensitivity shows the proximity of the system to close voltage collapse. Based on the size of the bus voltage magnitude's sensitivity to the reactive power injection at the same bus, sensitivity analysis is performed to gauge the system voltage stability.

i. if all the V-Q sensitivities are positive, the system is voltage stable
ii. if V-Q sensitivity is negative for at least one bus, then the system is voltage unstable

By computing V-Q sensitivities on every bus in the system, help in identifying buses in close proximity to voltage collapse.

$$J_R = \lambda \phi \xi \quad (9)$$

$$J_R^{-1} = \lambda^{-1} \phi \xi \quad (10)$$

Where

ϕ: right eigenvector matrix of J_R

ξ: left eigenvector matrix of J_R

λ:diagonal eigenvalue matrix of J_R

Substituting (10) into (8)

$$\Delta V = \lambda^{-1} \phi \xi \Delta Q \quad (11)$$

$$\Delta V = \frac{\phi_i \xi_i}{\lambda_i} \Delta Q \quad (12)$$

$$\phi_i \xi_i = 1 \quad (13)$$

$$\Delta V = \frac{1}{\lambda_i} \Delta Q \quad (14)$$

Table 1: Input Data for ANFIS Training

Bus 12		Bus 18		Bus 12		Bus 18	
P(p.u)	V(p.u)	P(p.u)	V (p.u)	P(p.u)	V (p.u)	P(p.u)	V(p.u)
0.710	0.094	0.710	0.094	0.973	0.091	0.973	0.091
0.717	0.094	0.717	0.094	0.980	0.091	0.980	0.091
0.724	0.094	0.724	0.094	0.987	0.091	0.987	0.091
0.731	0.094	0.731	0.094	0.994	0.091	0.994	0.091
0.738	0.094	0.738	0.094	1.001	0.091	1.001	0.091
0.746	0.094	0.746	0.094	1.008	0.091	1.008	0.091
0.753	0.093	0.753	0.094	1.015	0.091	1.015	0.091
0.760	0.093	0.760	0.093	1.022	0.091	1.022	0.091
0.767	0.093	0.767	0.093	1.030	0.090	1.030	0.090
0.774	0.093	0.774	0.093	1.037	0.090	1.037	0.090
0.781	0.093	0.781	0.093	1.044	0.090	1.044	0.090
0.788	0.093	0.788	0.093	1.051	0.090	1.051	0.090
0.795	0.093	0.795	0.093	1.058	0.090	1.058	0.090
0.802	0.093	0.802	0.093	1.065	0.090	1.065	0.090
0.809	0.093	0.809	0.093	1.072	0.090	1.072	0.090
0.817	0.093	0.817	0.093	1.079	0.090	1.079	0.090
0.824	0.093	0.824	0.093	1.086	0.090	1.086	0.090
0.831	0.093	0.831	0.093	1.093	0.090	1.093	0.090
0.838	0.093	0.838	0.093	1.101	0.090	1.101	0.090
0.845	0.093	0.845	0.093	1.108	0.090	1.108	0.090
0.852	0.092	0.852	0.092	1.115	0.089	1.115	0.089
0.859	0.092	0.859	0.092	1.122	0.089	1.122	0.089
0.866	0.092	0.866	0.092	1.129	0.089	1.129	0.089
0.873	0.092	0.873	0.092	1.136	0.089	1.136	0.089
0.880	0.092	0.880	0.092	1.143	0.089	1.143	0.089
0.888	0.092	0.888	0.092	1.150	0.089	1.150	0.089
0.895	0.092	0.895	0.092	1.157	0.089	1.157	0.089
0.902	0.092	0.902	0.092	1.164	0.089	1.164	0.089
0.909	0.092	0.909	0.092	1.172	0.089	1.172	0.089
0.916	0.092	0.916	0.092	1.179	0.089	1.179	0.089
0.923	0.092	0.923	0.092	1.186	0.089	1.186	0.089
0.930	0.092	0.930	0.092	1.193	0.088	1.193	0.088
0.937	0.092	0.937	0.092	1.200	0.088	1.200	0.088
0.944	0.091	0.944	0.091	1.207	0.088	1.207	0.088

3.2.3 ANFIS Application for Voltage Collapse Prediction

The Takagi-Sugeno fuzzy inference system is the foundation for artificial neuro-fuzzy inference system (ANFIS). Firstly, the training data are loaded to the neuro fuzzy designer toolbox. Grid partitioning technique for clustering data based on similarity is used to create the ANFIS. After which, the ANFIS is trained using a hybrid learning rule. The least squares estimation (LSE) and the gradient methods are combined to create the hybrid learning rule. Membership functions for the fuzzy logic controller are built based on the input-output relationships of the ANFIS which are supplied by the training data it receives. Based on the ANFIS's execution, the rule basis for the fuzzy logic controller is developed. Figure 2 shows the ANFIS structure used for voltage collapse prediction.

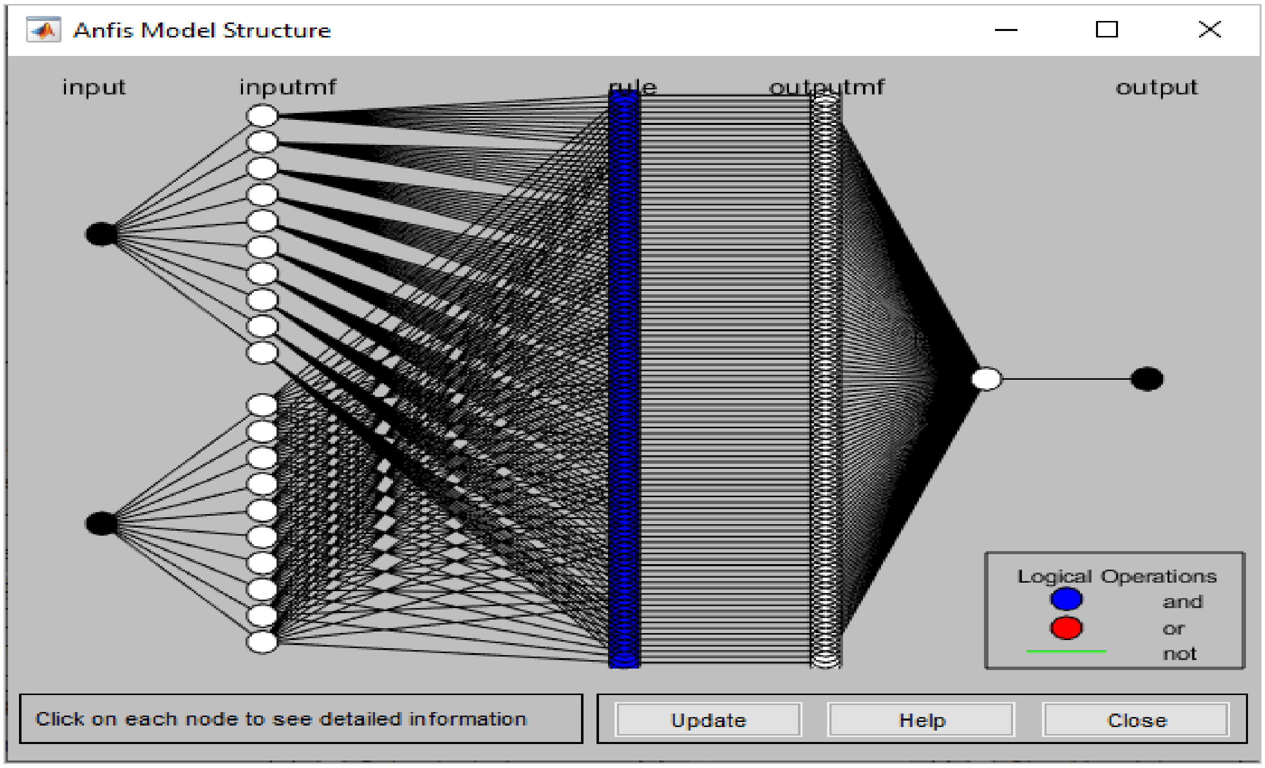

Figure 2: ANFIS architecture Used for Voltage Collapse Prediction

Figure 2 shows a five (5) layer ANFIS architecture. Mathematical model for implementation of ANFIS is given below.

Layer1: Let the inputs be: x and y

$$\text{Input } x = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix} \quad (15)$$

$$\text{Input } y = \begin{bmatrix} B_1 \\ B_2 \end{bmatrix} \quad (16)$$

Layer 2: to determine the firing strength of the rule

$$w_1 = A_1(x) * B_1(y) \quad (17)$$

$$w_2 = A_2(x) * B_2(y) \quad (18)$$

Layer 3: normalization process takes place in each and every node

$$\overline{w_1} = \frac{w_1}{w_1+w_2} \quad (19)$$

$$\overline{w_1} = \frac{w_2}{w_1+w_2} \quad (20)$$

Layer 4: to determine the contribution to the overall output

$$\overline{w_1} * F_1 = \overline{w_1}(P_1x + q_1y + r_1) \quad (21)$$

$$\overline{w_2} * F_2 = \overline{w_2}(P_2x + q_2y + r_2) \quad (22)$$

Layer 5: to determine the overall output

$$f = \overline{w_1} * F_1 + \overline{w_2} * F_2 \quad (23)$$

4.0 RESULTS AND DISCUSSION

Table 2: V-Q Sensitivity Analysis

Bus ID	Bus Name	Sensitivity %/Mvar	Voltage (p.u)	Ranking
1	Adiabor TS	0.0048	0.992	7
3	Aladja TS	0.0052	0.989	6
5	Alaoji TS	0.0005	0.998	11
6	Asaba TS	0.0071	0.987	5
8	Benin TS	0.0005	0.998	10
11	Ekot-Ekpene TS	0.0024	0.997	9
10	Ikot-AbasiTS	0.0125	0.967	3
12	New-Heaven TS	0.0137	0.939	1
15	Onitsha TS	0.0036	0.995	8
16	Onne TS	0.0123	0.975	4
18	Ugwuaji TS	0.0136	0.940	2

Table 2 shows the V-Q sensitivity analysis was carried out on load buses to assess the system voltage stability based on the size of the bus voltage magnitude's sensitivity to the reactive power injection at the buses. Table 2 demonstrates that the system is voltage stable due to the positive V-Q sensitivity for all buses. This implies that if reactive power is introduced into a bus, the voltage at any given bus will rise. To inform the user of the bus voltage's sensitivity as the system's reactive power is changed. A quick look at table 2 shows that New Heaven (0.0137 %/Mvar, 0. 939p.u) and Ugwaji (0.0136 %/Mvar, 0.940p.u) are the most critical buses. The ranking is an indication of bus proximity to voltage collapse. Figure 3 shows the V-Q sensitivity plot.

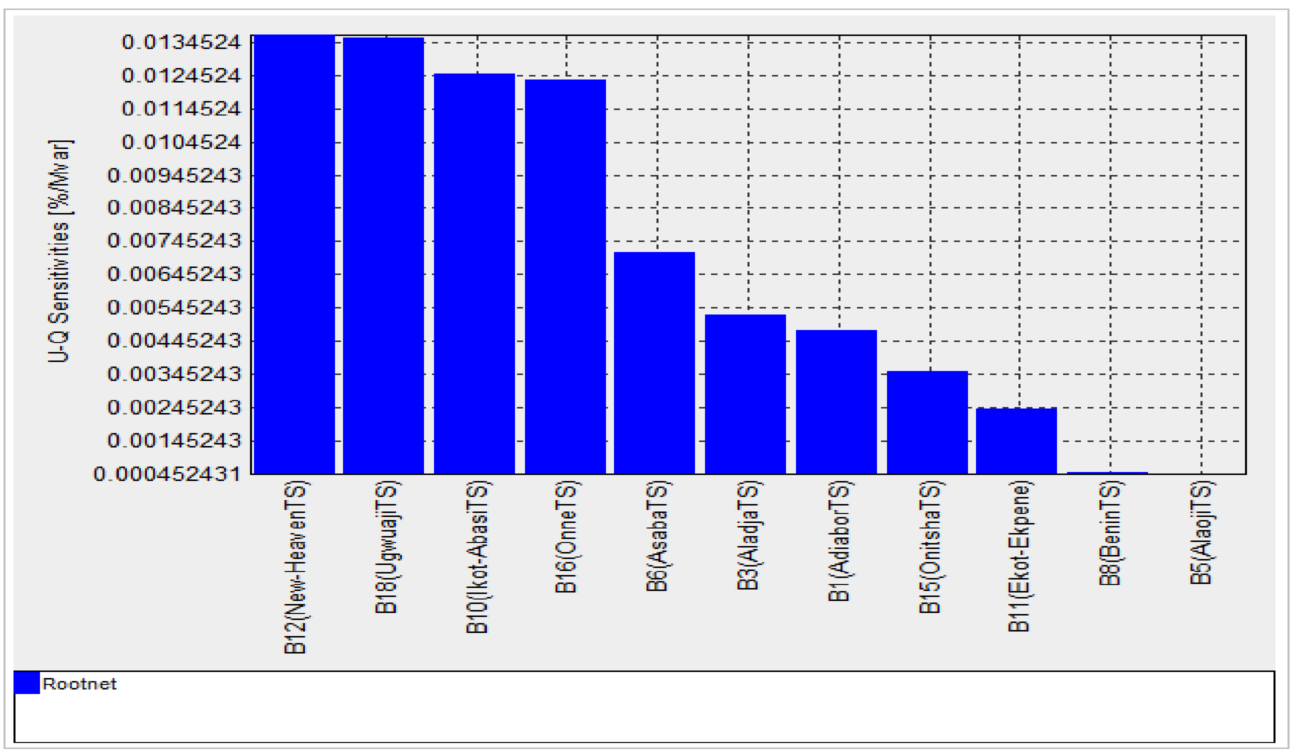

Figure 3: V-Q Sensitivity for Base Case Network Condition

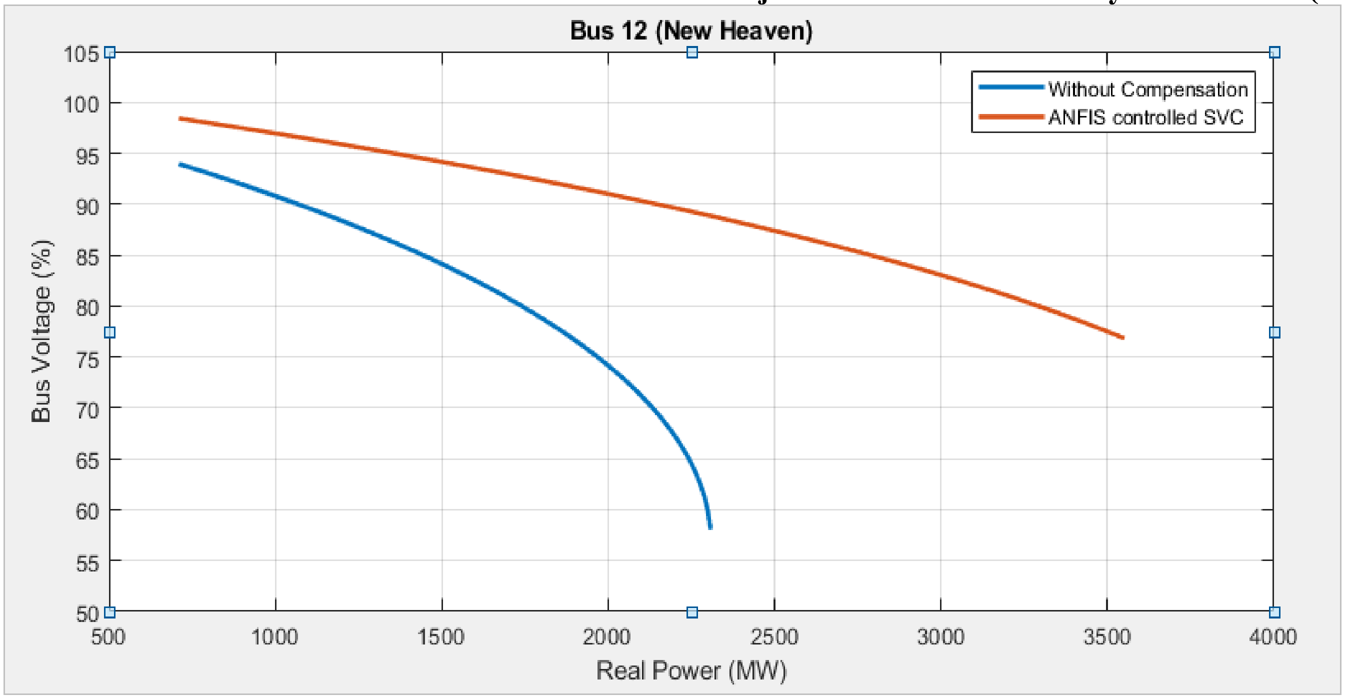

Figure 4 P-V Curve Comparisons for Bus 12 (New Heaven)

Figure 4 shows a comparison P-V plot of Bus 12 (New Heaven). The blue curve shows the existing operating point while the blue curve shows the improved operating point. The plot shows how the bus voltage decreases as real power rises to the point of voltage collapse. A quick look at figure 4 shows that the operating voltage of Bus 12 (New Heaven) is 93.925% at 710.0 MW loading and can be increased by1597.5MW before a voltage collapse can be seen beyond which the system will not recover, the operating voltage at the point of collapse is 58.198% at 2307.5 MW loading. Similarly, when an ANFIS controlled SVC are installed. It is seen from figure 4that the operating voltage is increased to 98.437% at 710.0 MW loading and can be increased by 2840 MW before a voltage collapse can be seen beyond which the system will not recover, the operating voltage at the point of voltage collapse is 76.821% at 3550 MW loading. Therefore, it is seen that by using an ANFIS controlled SVC, the loadability of bus 12 (New Heaven) can be increased by 1242.5MW

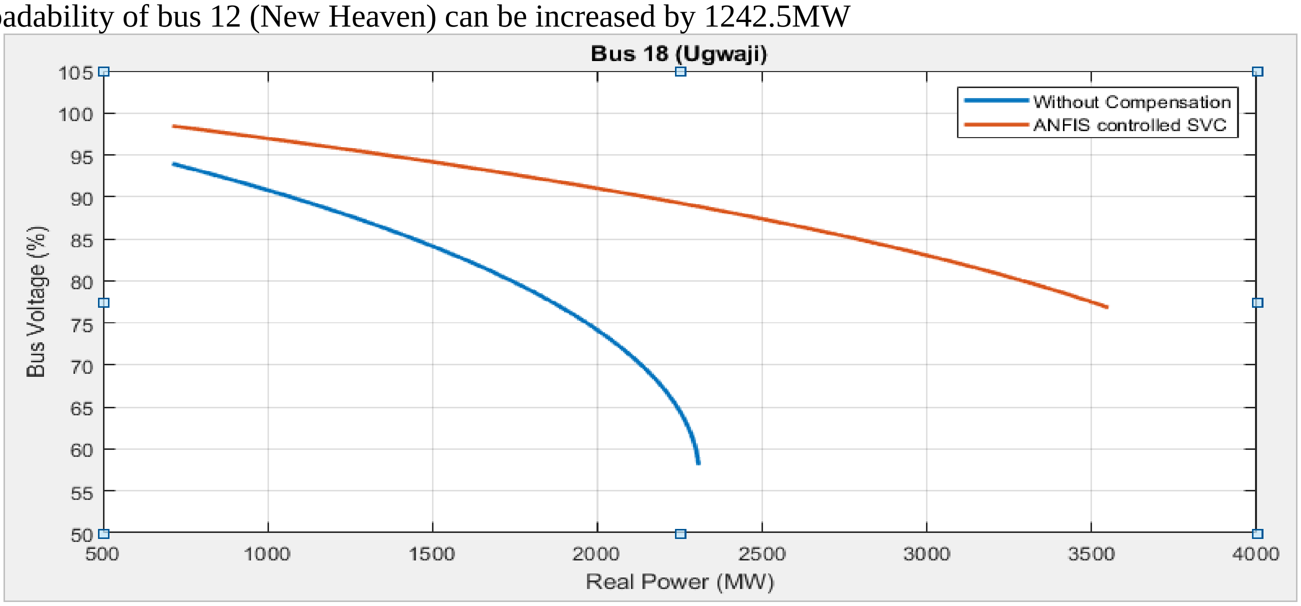

Figure 5: P-V Curve Comparisons for Bus 18(Ugwaji)

Figure 5 shows a comparison P-V plot of Bus 18 (Ugwaji). The blue curve shows the existing operating point while the blue curve shows the improved operating point. The plot shows how the bus voltage decreases as real power rises to the point of voltage collapse. A quick look at figure 5 shows that the operating voltage of Bus 18 (Ugwaji) is 93.956% at 710.0 MW loading and can be increased by1597.5MW before a voltage collapse can be seen beyond which the system will not recover, the operating voltage at the point of collapse is 58.069% at 2307.5 MW loading. Similarly, when ANFIS controlled SVC are installed. It is seen that the operating voltage was increased to 98.508% at 710.0 MW loading and can be increased by 2840 MW before a voltage collapse can be seen beyond which the system will not recover. The operating voltage at the point of voltage collapse is 76.801% at 3550 MW loading. It can be said that with ANFIS controlled SVC, the loadability of Bus 18 (Ugwaji) can be increased by 1242.5MW.

5.0 CONCLUSION

The paper examined a heavily stressed Nigeria 330kV network that operates closer to its thermal limits. The paper tends to evaluate the existing South-South 330kV grid for voltage stability improvement using Adaptive Neuro-Fuzzy. The network consisting of seven (7) generating station, sixteen (16) buses, and nineteen (19) transmission lines was modeled in NEPLAN 555 using Newton Raphson power flow algorithm to determine the operating condition of the existing network. Modal analysis and V-Q sensitivity were used to identify buses near voltage collapse. Based on the result of the V-Q sensitivity analysis, Bus 12 (New Heaven, 0.939pu) and 18 (Ugwaji, 0. 940p.u) showcased their close proximity to voltage collapse and were selected as candidate buses for voltage stability analysis. The operating voltage, active power of the selected buses was used for ANFIS training. It can be said that the paper successfully addressed the major challenges faced by the system. The sensitivities of the buses and their participating factors that will provide insight to system properties to assist in improving voltage stability using modal analysis and V-Q sensitivity was determined. The stability margin in the system in the existing south-south 330KV grid network using PV curve was improved. The loadability margin of the candidate buses was improved using ANFIS controlled technique for reactive power compensation

REFERENCES

Ademola, A., Aremu, A. C., Isaac, A. S., & Ayoade, F. A. (2016). Contingency analysis for assessing line losses in Nigerian 330-kv power lines. *International journal of engineering and advanced technolog*. 5(3), 66-78.

Adewuji B.O.; Folly K.A.; Oyedokun D.T.O. & Ogunwole E.I. (2022). Power system Voltage Stability Margin Estimation Using Adaptive Neuro-Fussy Interference System Enhanced with Particle Swarm Optimization. Retrieved from https://doi.org/10.3390/su142215448.

Ashfraq, H. (2018) *Electrical Power Systems* (5^{th}Edth) CBS Publishers & distributors Pvt. Ltd. 4819/XI, 24 Ansari Road, New delhi

Bourzami A.; Amroune M. & Bouktir T. (2019). On-Line Voltage Stability Evaluation Using Neuro-Fuzzy Inference System and Moth-Flame Optimization Algorithm. Electrical engineering & electromechanics, 2, 47-54.

Ghaghishpour, A. & Koochaki, A. (2020). An Intelligent Method for Online Voltage Stability Margin Assessment Using Optimized ANFIS and Associated Rules Technique. ISA Trans. 102, 91–104.

Haque, M.H, and Rahim A. (2020) 'Determination of first swing stability limit of multi machine power systems through Taylors series expansion'. *IEE proceedings* 136: 373-380

Nor A.F.M.; Sulaiman M.; Kadir A.F.A. & Omar R. (2017). Voltage Stability Analysis of Load Buses in Electric Power System Using Adaptive Neuro-Fuzzy Inference System (ANFIS) and Probabilistic Neural Network (PNN), *Journal of Engineering and Applied Sciences,* 12(5), 1406-1412.

Rastgoufard S. (2018). *Applications of artificial intelligence in power system.* University of New Orleans. Thesis and Dissertation

Robinson, M.H (2019) *Basics of Power Systems* Mil ton Publishers Ltd, First Edition