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Voltage Stability Enhancement of Nigeria 330 kV Grid Using UPFC Facts ANN and Particle Swarm Optimization Technique (PSO)

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ABSTRACT- The Nigerian Power system network in recent times has witnessed various power system distortions and frequent voltage violations leading to voltage collapse arising from inadequate reactive power support. The paper deals with enhancement of voltage stability in 330 kV Nigeria transmission network using Artificial Neural Network (ann) and Particle Swarm Optimization (PSO) techniques; UPFC FACTS tuned by ANN and determination of weak buses and its transmission line location via PSO optimization algorithm were implemented. By addressing the voltage stability issues in the network, the study aimed to contribute to system reliability and efficiency. Power flow was carried out using PSAT in steady state without UPFC, then with UPFC, and subsequently with ANN and PSO. Without UPFC FACTS, the following buses had least voltages which is a violation. The buses are 3, 6, 7, 8, 11, 22, 30, 34, 40, 54 and 55. Their recorded voltages were (301.26, 300.97, 302.78, 305.46, 301.57, 300.357, 301.71, 300.46, 300.34, 301.62 and 301.1) kV with an average of 301.6 kV. With UPFC, the bus voltages improved to (323.4, 322.25, 322.73, 321.48, 323.43, 321.53, 322.66, 322.75, 321.15, 320.55, 321.29) with an average of 322.09 kV. With the introduction of ANN, the bus voltages improved to (326.5, 327.69, 328.33, 329.99, 329.27, 326.13, 326.45, 326.71, 325.47 and 327.99 kV with an average bus voltage of 327.5472 kV. seventy percent 70% of the data obtained was for the training of the ANN based on Levenberg Marquadt back propagation algorithm and fifteen percent 15% each was for testing and validation. The average steady state voltage improvement with UPFC FACTS is 6.7% whereas with ANN it was 8.6%. In steady state, ANN performed better than UPFC FACTS. In dynamic state, at the generation stations of hydro and gas turbines UPFC performed better than ANN as the amplitude of ANN voltages experienced serious instability and fluctuations; whereas UPFC had a stable voltage of 7.5 kV. The implication is reduced insulation requirements and dimensions of synchronous alternators resulting to lower cost of alternator manufacturing.

KEYWORDS- Unified Power Flow Controller (UPFC), Artificial Neural Network (ANN), Particle Swarm Optimization (PSO), Load Flow, Voltage Stability, Bus, Voltage Profile.

I. INTRODUCTION

Nigeria 330 kV grid has experienced frequent collapse due to many factors amongst which is repetitive voltage instability. Power system voltage stability has been recognized as an important factor for secure system operation [1].

The performance of a power system under normal balanced steady state conditions is of primary importance in power system engineering. The 330 kV Nigeria grid is the main energy corridor in it's power system Network. It is therefore obvious that, the performance of a power system is mainly dependent on the performance of the transmission lines in the system. A power system therefore consists of a number of generators, transformers, lines and compensating equipment for voltage control and maintenance of stability. The power system can be classified in the voltage stability region if it can maintain steady acceptable voltages at all buses in the system under normal operating conditions and after being subjected to disturbance [2].

Voltage stability is associated with the capability of a power system to maintain steady acceptable voltages at al buses, not only under normal operating conditions, but also after been subjected to a disturbance [3]. It is a well-established fact that voltage collapse in power systems is associated with demand beyond certain limits, as well as with the lack of reactive power support in the system caused by limitations in the generation or transmission of reactive power. System contingencies such as generator or unexpected line outages exacerbate, if not trigger the voltage instability problem. Voltage instability is an important problem in modern power systems due to the catastrophic consequences of these phenomena [4]. A slow increase in the system demand, such as that due to normal daily load variations, can have negative effects on voltage stability. If any small increase in loading demand occurs, the reactive power demand will be greater than supply and the voltage will decrease. As the voltage decreases, the difference between reactive power supply and demand increases, and the voltage falls even more until it eventually falls to a small value resulting into voltage collapse.

Singh *et al.* [6] conducted a comprehensive review of various methods for enhancing voltage stability in both steady and dynamic states. The authors presented a tabulated summary of techniques used to mitigate voltage instability, along with the corresponding levels of improvement reported in previous studies. Kisengeu *et al.* [5] implemented a hybrid Ant Bee Colony (ABC) and Particle Swarm Optimization (PSO) algorithm to enhance voltage stability during under voltage load shedding conditions on the IEEE 14-bus test system. Their study successfully identified the weak buses in the system, and optimization with the proposed algorithm led to a significant improvement in voltage stability. A comparison of the system's performance, with and without the ABC-PSO algorithm, and against the Genetic Algorithm (GA), revealed that ABC-PSO offered superior results in both steady-state and dynamic performance.

Similarly, Al-Wazni and Al-Kubragyi [7] developed a Hybrid Firefly and Particle Swarm Optimization (HFPSO) technique for optimizing distributed generation and appropriately sizing the Distribution Static Compensator (D-STATCOM) for voltage stability improvement. Their approach was tested on the IEEE 33-bus distribution system. Graphical analyses showed that integrating D-STATCOM sized using the HFPSO technique outperformed the use of either method individually, leading to enhanced voltage stability across the network.

Artificial Intelligence based Power System Stabilizers for frequency stability enhancement in multi-machine power systems [8]. The authors utilized a Power System Stabilizer (PSS) for the damping of high frequency oscillations in a 30-bus IEEE Network. The PSS was optimized with Interline Power Flow Controller (IPFC) and the outcome was compared to the system when the PSS was optimized with the GA and Neuro-Fuzzy Controller (NFC). The results generated showed that the use of PSS optimized with IPFC performed better compared with the use of NFC and GA [9] in their write up Artificial Intelligence Techniques for stability analysis and control in smart grids, methodologies, applications and future directions presented a general over view of artificial intelligence for voltage stability in the power system network and control.

From the chart and tables presented, voltage stability improved by 5.2% and the proposal showed a good attempt to improve on the system protection. The applications of Artificial Intelligence in distribution power system operation carried out a systematic review on the application of artificial intelligence modelling on voltage stability of power system network [10]. The outcome showed voltage stability improvement of 2.3%. Voltage stability improvement with Genetic Algorithm (GA) and Artificial Intelligence (AI) model (ANN) [11]. While GA was deployed for the implementation of the STATCOM FACTS, ANN was utilized for voltage stability improvement with the outcome compared with use of FACTS alone. The result showed that the use of ANN improved the voltage stability by 5.5%. The GA identified the point of placement of the FACTS device and ANN model. The authors in their paper, proposed the use of generalized approximate reasoning based intelligent control indicator system to determine the weak bus location and voltage profile [12]. The result obtained showed that voltage stability obtained was 3.4% for IEEE 118 bus and 5.2% for IEEE 30-bus system.

Zhang [13] in this work, the authors carried out a detailed review of the importance of utilizing artificial intelligence model in data gathering for voltage stability studies and use of ANN in voltage stability enhancement. The outcome showed that, the ability of ANN on data gathering has not been in contention, but its ability to reduce voltage abnormality remains in doubt as the maximum voltage enhancement was paltry 4.4%. [14] Ezeonye et al. (2024) in their work developed a flow diagram for modeling and determination of voltage profile of a 48-bus 330 kV Network. [15] Anyanor et al., (2020) inserted STATCOM on Bus 7 (Maiduguri substation on 54-bus Nigeria Network to improve voltage profile.

From the literatures reviewed, it is evident that, most of the researchers did their test on IEEE bus system. The researchers did not provide comparison on the effect of UPFC, ANN and PSO on the improvement of voltage profile on the high voltage transmission line corridors.

The work here, is done on a real time Nigeria 330 kV, 58 bus system using UPFC, ANN and PSO, for improvement of voltage profile on the identified five weak buses having the least voltage magnitude in electrical power transmission along the lines in steady state and dynamic state analysis at the generation stations.

A. Load Flow Study

Power flow studies form an integral part and backbone of power system analysis and design. The study determined if the system voltage remain within specified limits under various contingency conditions. It helps to identify the need for additional inductive or capacitive VAR support and the location of reactors and or capacitor to main system voltage within limits. The main interest in this study using PSAT, and NEPLAN Software is to obtain the voltages at various buses and power injection into the Nigeria 58 buses, 22 generators, 87 transmission lines, 36 load buses and one slack bus. The load flow study determines if the system voltage remain within specified limits under various contingency and scenarios, Additionally, load flow studies are used to ensure that electrical power transfer from generators to consumers through the grid system is stable, reliable and economic [9].

The introduction of UPFC is expected to improve the bus voltages by a certain and positive margin.

B. Overview of PSAT and Artificial Intelligence Techniques of ANN and PSO

PSAT is a software tool for power flow analysis. It is a MATLAB tool for electric power system analysis and simulation. It includes power flow, optimal power flow, small signal stability analysis and time domain simulation.

Artificial Intelligence (AI) is a subfield of computer science concerned with developing algorithms and systems capable of performing tasks typically associated with human intelligence, such as perception, reasoning, learning, and decision-making [16], [14]. These tasks include perception [18], reasoning [15], learning [17], and decision-making, which are vital cognitive abilities. Within the domain of power systems, AI has been extensively applied to improve the performance, reliability, and stability of electrical grids [8], [9].

Therefore, Artificial Neural Network (ANN) is a powerful machine learning technique that can be used for Voltage stability studies. ANN are inspired by the structure and function of biological neural network and they consist of a large number of interconnected nodes or neurons that process information and learn from experience. The basic building block of an ANN is the neuron which receives the raw data performs computations and sends output data to other neurons. Neurons are arranged in layers and there are typically three main layers; the input, hidden and output layers. The input layer receives the raw data, the hidden layer performs the complex computations and the output layer sends the results of the computation.

Particle swarm optimization (PSO) is a computational method inspired by the social behavior of birds or fish in a flock or school. In PSO, a swarm of particles (representing potential solutions of a problem) moves around the search space, and the "fitness" of each particle is evaluated according to a fitness function. The particles then communicate with each other and move toward the more fit particles in the swarm. This process is repeated until the swarm converges on a solution that satisfies the fitness function. PSO has been successfully applied to voltage stability analysis and other system problems. In voltage stability studies, the object function of the PSO algorithm is typically the minimization of the load curtailment required to maintain voltage stability.

II. METHODOLOGY

The following materials were deployed in achieving the work on the enhancement of voltage stability of Nigeria 330 kV transmission network using UPFC, ANN and PSO.

- Real-time data from National Control Centre, Osogbo.
- PSAT, NEPLAN and PowerLib software.
- MATLAB 2023a.

The flow diagram of figure 1 describes the procedure for determining the voltage profile of the 330KV power network of Nigeria grid.

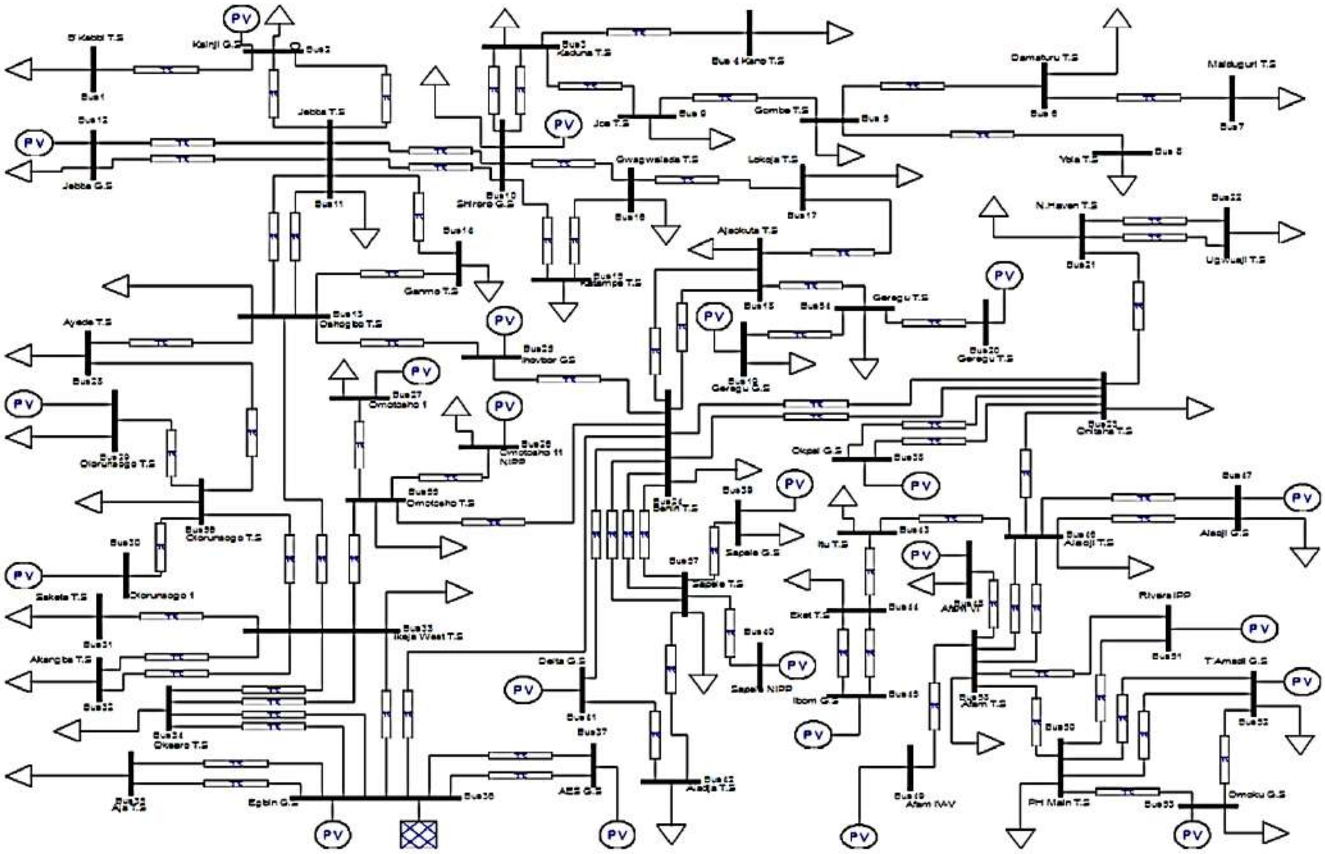

Figure 1: Diagram of power system model in PSAT

The power flow determination is based on continuation power flow equations using Jacobian matrix

Power flow equations can be written in matrix form as follows.

$$\begin{bmatrix}\Delta P\\ \Delta Q\end{bmatrix} = \begin{bmatrix}J_{p\delta} & J_{pv}\\ J_{q\delta} & J_{qv}\end{bmatrix}\begin{bmatrix}\Delta\delta\\ \Delta V\end{bmatrix} \qquad (1)$$

Also, this equation can be represented as

Ps = P(□,V) and Qs = Q(□,V) (2)

Reorganizing the equation in compact form becomes:

$$\begin{bmatrix}\frac{\partial F}{\partial\delta} \frac{\partial F}{\partial V} \frac{\partial F}{\partial K}\end{bmatrix}\begin{bmatrix}\Delta\delta\\ \Delta V\\ \Delta K\end{bmatrix} = [-F(\delta, V, K)] \qquad (3)$$

Finally, the equation can be written as:

$$J.[\Delta\delta\ \Delta\delta\ \Delta\delta]^T = [= F(\delta, V, K)]$$
$$[\Delta\delta\ \Delta V\ \Delta K]^T = J^{-1}.[-F(\delta, V, K)] \qquad (4)$$

where J is the Jacobian matrix.
Near the point of voltage collapse, the Jacobian matrix, J approaches singularity; hence it is difficult to calculate J-1 near the collapse point. To overcome the problem one more equation is added assuming one of the variables as fixed. This variable is called the continuation variable.
The following parameters were entered in the power system model in PSAT

- Voltage rating of 330 kV was used (the paper centred on Nigeria 330 kV high voltage grid network).
- For the Nigeria power system model, the power used was 100MW (100MVar for apparent power).
- Since the values of reactance X, resistance R and susceptance B, entered were in per unit (PU), the distance of the transmission lines was zero (source: PSAT Manual).

A. *Network Utilized For Analysis*

The 58-bus of 330KV model with the installation of UPFC and ANN optimized with PSO is shown in figure 2:

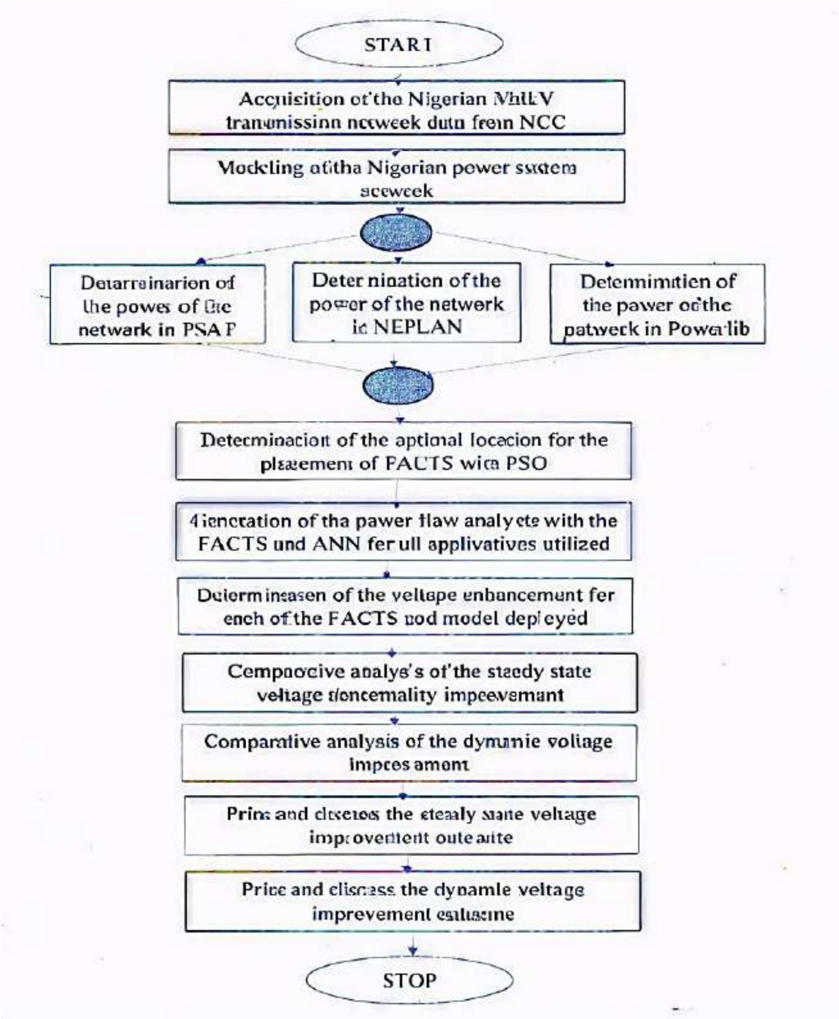

Figure 2: Flow Chart of power system model in PSAT

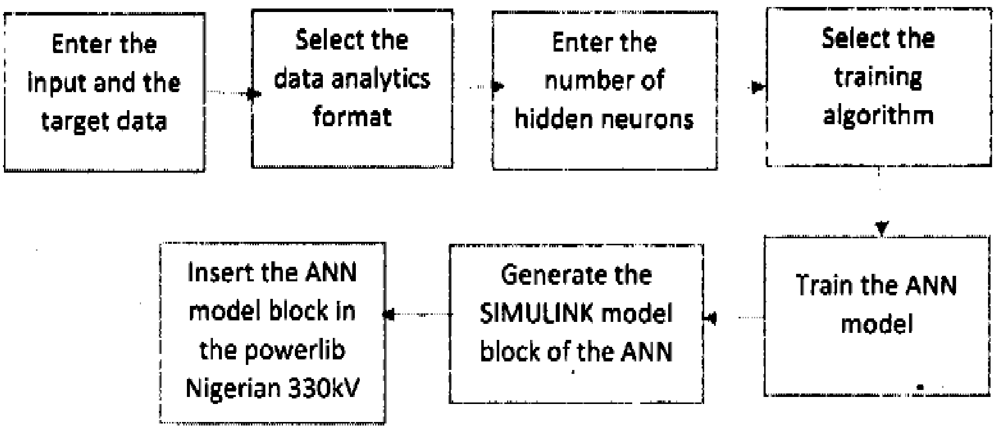

Figure 3: Block diagram

The ANN structure deployed is based on the block diagram bove (see figure 3) and the ANN configuration.

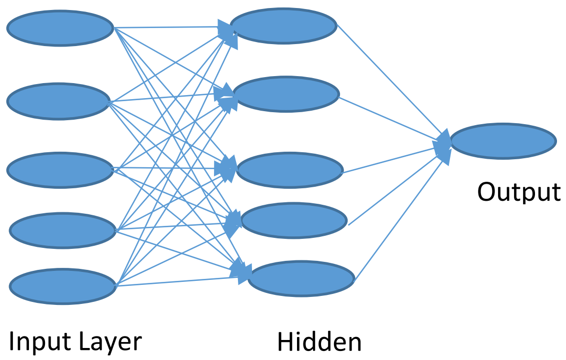

Figure 4: ANN structure

The ANN structure comprises of an input layer of five input neurons which represented the power flow parameters which were voltage, active and reactive power as well as active and reactive losses. The number of hidden neurons in the hidden layer were five and output was one which represented the enhance voltage.

The training algorithm selected for the ANN model was Levenberg Macquart Back propagation network. A choice of the training algorithm was due to the robust nature of handling large data input and training. The data analytics utilized was 70% of the data for training and 15% each for testing and validation.

III. RESULTS AND DISCUSSIONS

The results of the voltage profile when the network is operating without UPFC FACTS and when ANN are incorporated in the network is shown in table 1.

Table 1: ANN incorporated in the network

Bus number	Voltage profile in steady state (kV)	Voltage profile with UPFC (kV)	Voltage profile in ANN (kV)
1	308.1472	320.2151	327.0887
2	309.0579	320.8450	329.9153
3	301.2699	323.2456	326.5073
4	309.1338	323.6586	328.5055
5	306.3236	323.2387	328.3317
6	300.9754	322.2546	327.6956
7	302.7850	322.7350	328.4905
8	305.4688	321.4816	328.3326
9	309.5751	323.7235	325.8907
10	309.6489	320.9448	325.6401
11	301.5761	323.4339	329.9954
12	309.7059	320.9176	325.8556
13	309.5717	321.8424	325.1630
14	304.8538	323.1281	327.8060
15	308.0028	323.9011	329.4093
16	301.4189	320.4056	328.3459
17	304.2176	324.6469	325.9522
18	309.1574	323.8786	326.8446
19	307.9221	322.4340	327.3036
20	309.5949	322.1793	329.9082
21	306.5574	322.2339	325.7820
22	300.3571	321.5317	329.2776
23	308.4913	322.5425	328.2238
24	309.3399	322.5539	326.8814
25	306.7874	324.0881	325.9546
26	307.5774	323.9742	327.1413
27	307.4313	323.2216	327.4101
28	303.9223	321.8930	325.6031
29	306.5548	324.0579	327.9475
30	301.7119	322.6641	326.1309
31	307.0605	321.7536	326.9231
32	300.3183	324.6950	327.9149
33	302.7692	324.3797	326.2590
34	300.4617	322.7508	326.4522
35	300.9713	323.1124	328.0855
36	308.2346	322.9352	326.3264
37	306.9483	321.0387	329.1219
38	303.1710	321.5062	329.9133
39	309.5022	322.3546	328.6512
40	300.3445	321.1524	326.7194
41	304.3874	324.2215	327.9203
42	303.8156	320.9738	325.5388
43	307.6552	321.1296	329.5315
44	307.9520	320.8535	329.3983
45	301.8687	321.1383	329.0888
46	304.8976	322.1785	326.3036
47	304.4559	321.5555	327.9718
48	306.4631	324.6169	325.1126
49	307.0936	322.1510	327.1263
50	307.5469	320.9241	326.5636
51	302.7603	324.5244	325.8074
52	306.7970	324.8987	325.8938
53	306.5510	322.1943	327.1144
54	301.6261	320.5556	325.4711
55	301.1900	321.2903	327.9926
56	304.9836	322.0436	327.3546
57	309.5974	322.9745	328.4797
58	303.4039	321.3111	328.4994

From the voltage of the power system network shown in figure 5, the highest voltage of the power flow was at

309.6489 kV for bus 57 Sapele transmission station. These implies that the voltage was abnormal due to power congestion on the transmission lines which require improvement. The voltage profile of the power system network with UPFC is shown in figure 6.

The voltage profile improvement with UPFC as shown in figure 6 has a maximum voltage value of 324.8987 kV as compared to 309.6489 kV without FACTS. Though the outcome shows voltage abnormality, there was voltage improvement when compared to the power system without FACTS.

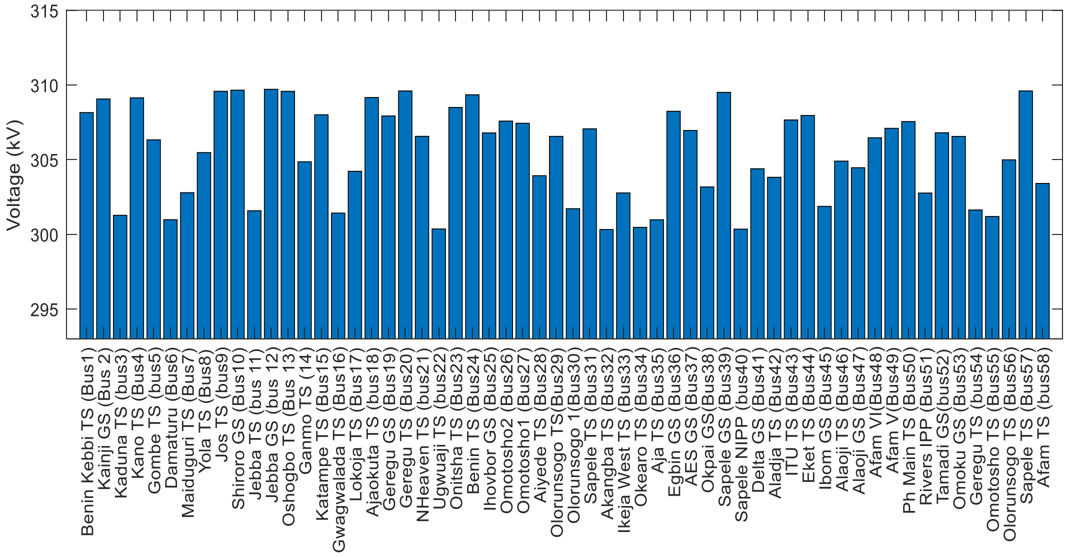

Figure 5: Bar chart of the voltage profile in steady states situation without FACTS using PSAT

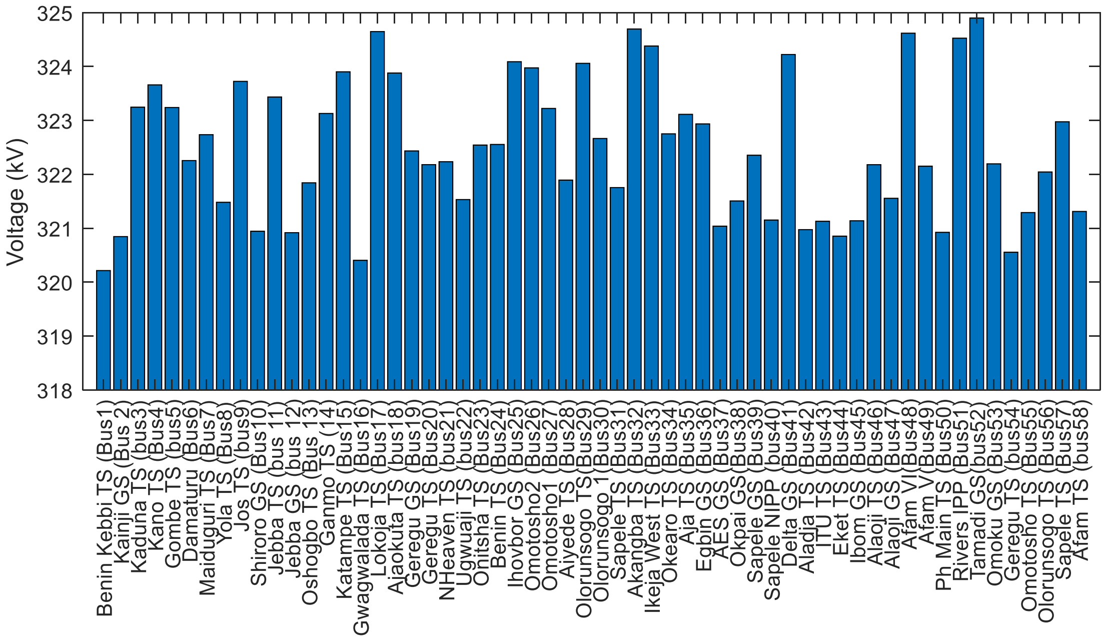

Figure 6: Bar-chart of the voltage profile with UPFC in PSAT

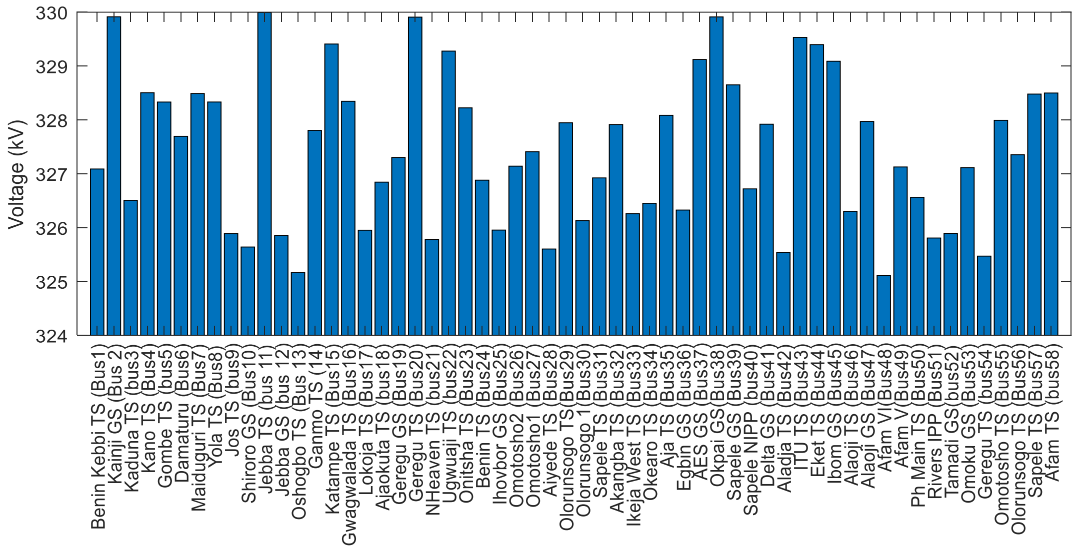

Figure 7: Bar chart of the voltage profile using ANN

A. *Comparative analysis at steady state power flow-*

The comparative analysis indicating the performance of UPFC and ANN controllers in improving the voltage profile.

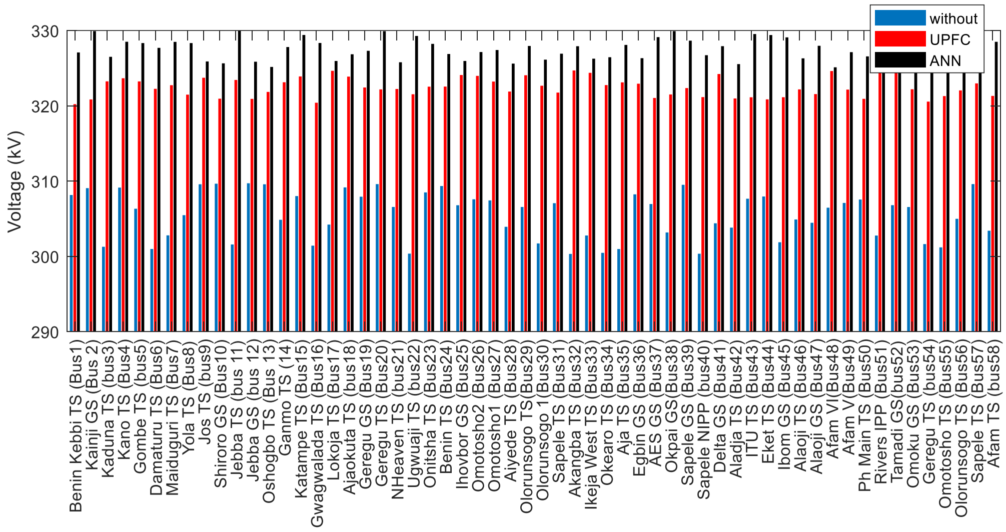

Figure 8: Comparative Analysis at Steady State Power Flow

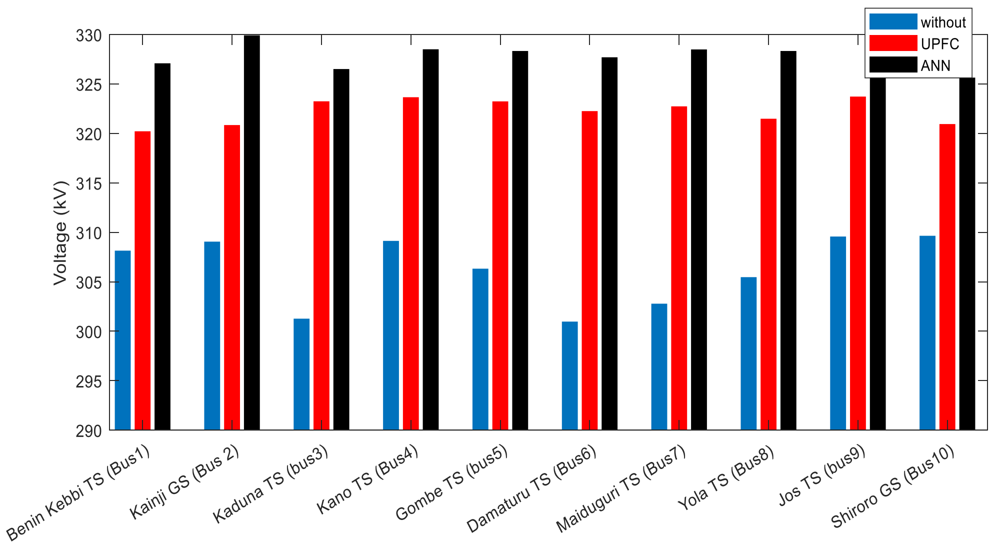

Figure 9: Comparative analysis for the voltage profile on selected buses

B. Dynamic State Results

Voltage stability improvement can be carried out also on the transmission lines and load buses or on the generation stations. Therefore, the effect of UPFC and Ann were tested on Kainji generation station as shown in figure 9 and on Afam VI gas turbine generation station as shown in figure 10. The results showed that UPFC performed better than ANN as voltages at dynamic state without UPFC and ANN suffered instability as the amplitudes were continuously varying compared to UPFC that had a flat voltage profile but with generated output of approximately 8KV. This implies that generators should be designed for less insulation requirement and dimension.

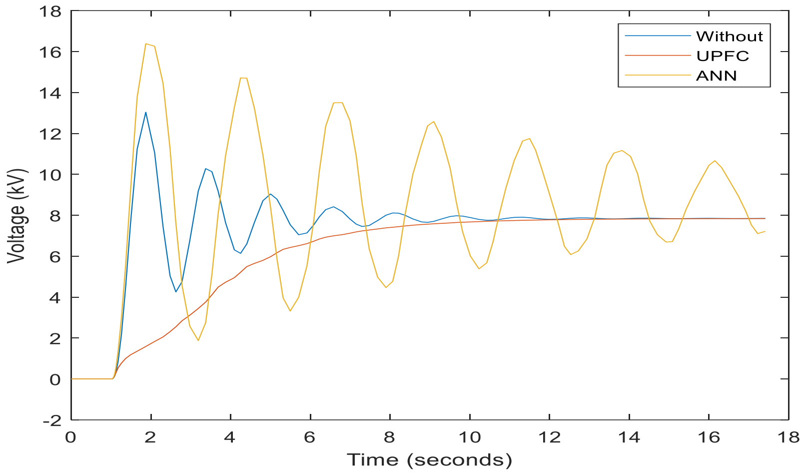

Figure 10: Voltage stability for Kainji GS

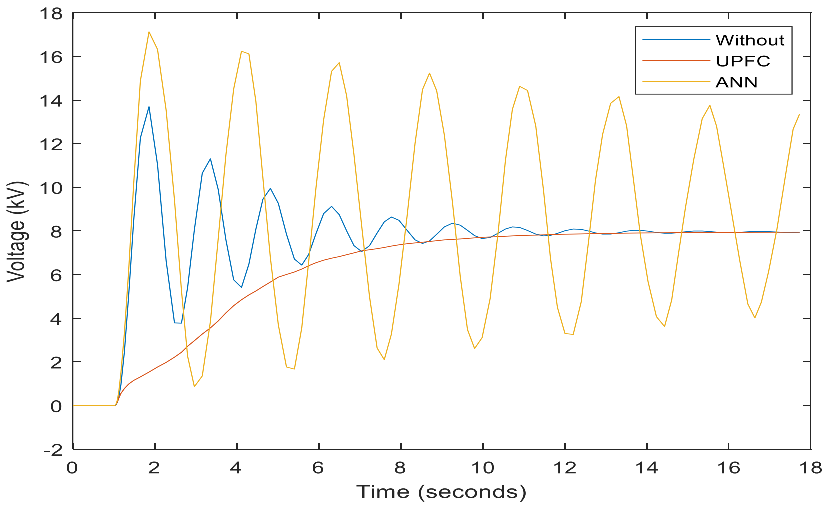

Figure 11: Voltage stability for Afam VI GS

IV. CONCLUSION

From the results of the power flow analysis at steady state, the introduction of UPFC and ANN; it can be seen that the bus voltages after the introduction of UPFC and ANN improved greatly. Also, PSO was utilized to determine the optimal bus for appropriate placement of the UPFC and ANN models. The objective functions for the optimization were the model for the buses with least power and voltage values and transmission lines with most power losses (both active and reactive).

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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