European Journal of
Engineering & Environmental Sciences

RESEARCH ARTICLE

Loss Minimization of the Nigeria 330kv Power Grid Network Using Artificial Neural Network Based Interline Power Flow Compensator

[1]Ude Kingsley Okechukwu and [2]Prof. G. N. Onoh
[1,2]Electrical and Electronics Engineering Department, Enugu State University of Science and Technology, Nigeria

***Corresponding Authors:** Ude Kingsley Okechukwu, Electrical and Electronics Engineering Department, Enugu State University of Science and Technology, Nigeria*

ABSTRACT

Nigeria has since suffered from poor electric generation, transmission and distribution, despite the fact that Nigeria has the largest population in Africa. This situation has impacted negatively on businesses in Nigeria which often rely on off-grid generation to run their businesses. Real power losses in the transmission lines have been identified as one of the country's key causes of inadequate power supply. Against this backdrop, there is therefore an urgent need to address the problem of real power losses in the lines so as to boost the meager power currently available at the national grid. In view of this, this study seeks to minimize real power losses in the transmission lines of the Nigerian 47-bus transmission network using an Artificial Neural Network (ANN) based Interline Power Flow Compensator (IPFC). Thus, the Nigerian 47 bus transmission network was modeled in Simulink/PSAT and characterized using load flow analysis. Continuation Power flow (CPF) was used to identify the weak buses in the network and the result showed that five (5) buses fell below the acceptable voltage level of 0.95pu≤V≤1.05. In addition, the total real power loss on the network was obtained. ANN optimal size predictor and ANN optimal locator were created and trained using ANN fitting tool in Simulink. The trained AI agents were then converted to Simulink models and connected to the test network to ascertain the optimal size(s) and location(s) of the Interline Power Flow compensator (IPFC) modeled to minimize real power losses in the network. The simulation was carried out on the integrated network with optimally sized ANN-based IPFCs deployed at the optimal location. The result showed that the total real power losses were reduced from 0.5182pu to 0.21186pu and the magnitude of the voltage profile of the five weak buses normalized within the IEEE acceptance range of 0.95pu≤V≤1.05pu. This implies that IPFC optimized with ANN will be significantly viable in minimizing real power losses for improving the voltage profile and security of the Nigerian 47-bus transmission network

***Keywords**: Loss Minimization; Continuation Power Flow; Nigeria 330kv Power Grid Network; Artificial Neural Network; Interline Power Flow Compensator*

Introduction

Electricity has a major impact on every aspect of our socioeconomic life. It plays a vital role in the economic, social, and political development of any nation (Energy Commission, Nigeria 2009). Electricity is the most popular and commonly used source of energy in the world today. One significant pattern that has observed is that as the country's population grows, so does the demand of power (Nkalo et al., 2018). Poor transmission capacity, generation, and poor maintenance culture have also contributed greatly to the inadequate supply of electricity to the Nigerian people. This situation has no doubt impacted negatively both socially and economically. Technically speaking, one of the key causes of inadequate power supply is increased transmission line active power losses. High power losses in the transmission lines contribute greatly to network instability, low voltage profile, and network insecurity. This challenge can be addressed by building new power generation stations and transmission lines. However, the construction of new transmission systems is hindered by many factors such as ecological considerations, financial difficulties, and the unavailability of space in overpopulated areas (Ahmad et al., 2014). Instead of building a new power system network, the total transmission line active power loss can be reduced by introducing effective power transmission line compensators like interline power Flow compensators at the right locations and at the optimum size. This reduction in active power loss will also provide an economical business solution to the deregulated power market (Pandey and Chaitanya, 2012; Ahmad et al., 2014) and also enhance the reliability of power supply in the country. Available transfer capability (ATC), a measure of the transfer capability remaining in the physical transmission

***Citation:** Okechukwu, U. K. & Onoh, G. N. (2022). Loss Minimization of the Nigeria 330kv Power Grid Network Using Artificial Neural Network Based Interline Power Flow Compensator. European Journal of Engineering and Environmental Sciences, 6(5), 1-13. DOI: https://doi.org/10.5281/zenodo.7437085*
***Accepted:** November 28th, 2022; Published: December 13th, 2022*

network for further commercial activity (NERC Report, June 1996) depends on active power losses. Reducing active power losses in the line will enhance network ATC thus increasing the level of power that can be delivered from the source area (slack bus) to the sink area (load bus systems).

Against this backdrop, this study focuses on active power loss minimization using IPFC for improved performance of the Nigeria 330kV power transmission grid network.

Literature Review

Electric Power Losses

Electric power has to be moved from the generation place to the consumer's place through some wires for consumption. Some of the electricity that is generated along the route is lost for a variety of reasons. Whether this loss is at its lowest possible range is the question of modern energy efficiency issues. To make it easier to investigate losses it is helpful to divide electric system losses into different categories. A common classification is to use two categories; technical losses and non-technical losses (Mohammed et al., 2002).

As power is transferred from one point to another, some of the power is dissipated along the route due to the natural properties of the conductors and equipment the power is carried upon. Technical losses incurred over individual elements, shorten the element's operational life on the one hand and dictates greater dimensioning of the power system on the other hand. There are many ways to analyze technical losses.

Depending on their origin, technical losses can be divided into resistive, leakage, and corona losses. Resistive (copper) losses are the I^2 R losses that are inherent in all conductors because of the finite resistance of the conductors. The leakage losses are losses owing to the finite resistance of the insulation materials. Corona losses are caused by partial discharges in the air surrounding overhead lines. The air molecules become ionized and conductive as the voltage level is increased.

The ionization generates light, audible noise, radio noise, conductor vibration, and ozone and causes a dissipation of energy that result in line losses. Heavy rain or wet snow results in a dramatic increase in corona due to droplets clinging to conductors which act as sources of point of discharge (Gustafson and Baylor, 1998). One common classification of technical losses is to use the categories to be (Load losses) and Fixed (No-load losses). This classification method is useful when studying the dependence of losses on power flow.

Interline Power Flow Controller (IPFC)

The Interline Power Flow Controller (IPFC) consists of two series converters in different line that is inter-connected by a common DC link. It is a device that provides a comprehensive power flow control for a multi-line transmission system and consists of multiple DC to AC converters, each providing series compensation for a different transmission line. The converters are connected together to their DC terminals and connected to the AC systems through their series coupling transformers. With this arrangement, it provides series reactive compensation in addition any converter can be controlled to supply active power to the common DC link from its own transmission line. Unlike other FACTS, it controls and compensates power flow in a multiple-line transmission system as shown in figure 1.

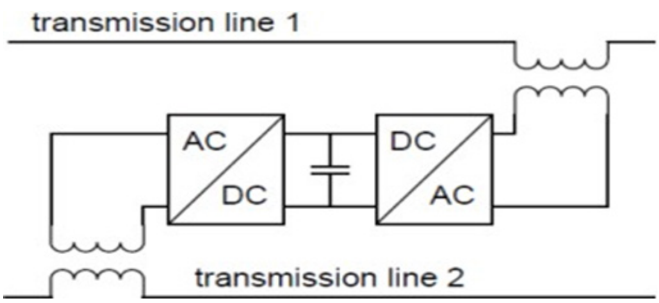

Figure 1: Interline Power Flow Controller Configuration (Source: Yuan, 2010)

Both converters have the capacity to provide a series of compensation on their line as an SSSC. The converters can provide active compensation just as they can exchange active power through a common DC link. This allows the controller to provide both active and reactive compensation for the transmission line lines and thereby optimize the operation of multi-line transmission systems.

Artificial Neural Network ANN

ANNs are computational techniques that try to obtain a performance similar to a human's performance when solving problems. An ANN can be seen as a union of simple processing units, based on neurons that are linked to each other through connections similar to synapses. These connections contain the "understanding" of the network and the patterns of connectivity express the objects represented in the network. The understanding of the network is gotten through a learning process where the connections between processing units are varied through weight changes. ANN is an efficient alternative for problem solutions where it is possible to obtain data describing the problem behavior but a mathematical description of the process is impossible. ANNs have several attractive characteristics. The capacity to adapt to system data and the facility to perform new tasks are some of the advantages of these techniques. ANNs are parallel structures that usually need small amounts of memory and processing time. ANN scans store knowledge in a distributed fashion and consequently have high fault tolerance. Learning algorithms used to train ANN can be supervised or unsupervised. In supervised learning algorithms, input/output pairs are furnished and the connection weights are adjusted with respect to the error between desired and obtained output. In unsupervised learning algorithms, the ANN will map an input set in state space by automatically changing its weight connections. Supervised learning algorithms are commonly used in engineering processes because they can guarantee the desired output (Arturo and Phadke, 2003).

Review of Related Works

Karthik and Chandrasekar (2012) presented the IPFC's main features and limitations while controlling the power flow. In order to observe these advantages and disadvantages, a mathematical model based on the d-q orthogonal coordinates was developed. A 3-phase transmission line model associated with the converter station was developed and incorporated into an IPFC model using SIMULINK. The results indicate that IPFC improves the system. Alievelu et al. (2011) reported the investigation on the development of the steady-state model, the dynamic nonlinear mathematical model of the power system installed with the IPFC for stability studies, and the linearized extended Phillips Heffron model for the design of control techniques to enhance the damping of the lightly damped oscillations modes. In this context, the mathematical models of the single-machine infinite bus (SMIB) power system and multi-machine power system incorporated with IPFC were established. The controllers for the IPFC were designed for enhancing the power system stability. The eigenvalue analysis and nonlinear simulation studies of the investigations conducted on the SMIB and Multi-machine power systems installed with IPFC demonstrate that the control designs are effective in damping the power.

Reddy et al. (2016) noted that a power flow controller (IPFC), is the most versatile device used for controlling power flows in multiple transmission lines. When the load on the transmission line is drastically increased the power losses and voltage deviation increase in the system leading to line outages and the power system network may become unstable. Thus, they proposed an algorithm for the IPFC optimal location. The proposed algorithm improved voltage stability under the overloaded line outage contingency in a power system network. The transmission line outages were calculated and ranked on the basis of their performance index. The proposed method was tested for the IEEE-30 bus system by using MATLAB software and the results were compared with an SVC device for the same configuration of the network. Akhilesh et al. (2011) investigated the use of IPFC, which they understand to be dc/ac converters linked by common DC terminals, in a DG-power system from an economic perspective. They discovered that; because of the common link, any inverter within the IPFC is able to transfer real power to any other and thereby facilitate real power transfer among the lines of the transmission system. Since each inverter is able to provide active compensation, the IPFC is able to carry out an overall real and reactive power compensation of the total transmission system. This capability makes it possible to equalize both real and reactive power flow between the lines, transfer power from overloaded to under-loaded lines, compensate against reactive voltage drops and corresponding reactive line power, and increase the effectiveness of the compensating system.

Methodology

The method adopted in this research entails characterizing the test network (47-bus Nigeria 330kV) first. This is achieved through load flow analysis performed on the network using PSAT as a tool. With the help of load flow analysis, the network parameters (the magnitude of voltage and its phase angle, real and reactive power loss, and real and reactive power injected into the system) at normal operating conditions were determined. In addition, load flow on the network revealed the amount of power transferred from one bus to another as well as the total power transferred by the network. Load flow studies reveals also the total losses on the network as well as the losses on each transmission line. Having done this, a Simulink model of the test network was realized in PSAT. The Simulink model of the test network is very important as the compensating device need to be connected to the network to be able to determine its contribution in minimizing the real power loss of the network. Continuation power flow is then performed on the test network to determine the total real power loss of the uncompensated test network. The total real power loss of the network obtained before compensation with the interline Power flow controller (IPFC) was compared with the total real power loss of the network after compensation with IPFC.

Continuation power flow also helped to extract possible (viable) locations (lines) for the IPFC placement for the realization of minimum total network real power loss in the network. Continuation power flow has the capacity to identify the weakest buses in a network. These weakest buses are usually the best positions for connecting compensation devices for maximum impact. Modeling of the IPFC that will be used for the compensation of the network for the total real power loss is very critical likewise the modeling of an artificial neural network (ANN) controller for determining the optimum size of the IPFC to be connected to the optimum location for maximum total real power loss reduction in the test network. After network compensation with IPFC, simulations are carried out in the test network to determine the overall performance of the technique used.

Implementation of the Test Network Modelin PSAT Simulink

The case study network was modeled in PSAT/Simulink as shown in figure 2

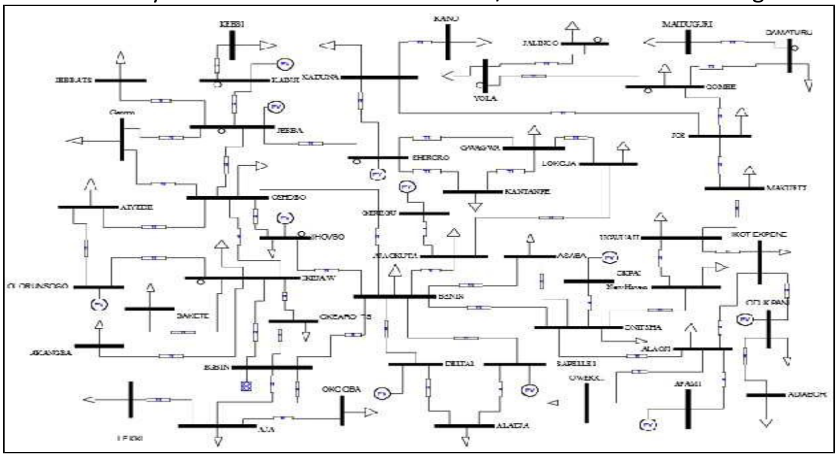

Figure 2: Developed Simulink model of the 47-bus test network

Determination of Possible Location for Placement of IPFC and Computation of ATC of Test Network

To effectively reduce the total real power loss of the test network; the network compensator (IPFC) must be connected to the most vulnerable bus(es). The most vulnerable bus in the test network can be obtained by performing continuation power flow on the test network. The total network real power loss of the test system before and after compensation will be determined using load flow studies.

Determination of the Equivalent Circuit Diagram of IPFC

The schematic diagram of an IPFC is shown in figure 3. From figure 3, the two converters' equivalent electrical circuit model of figure 4 was derived. The two converter-based injection model of the IPFC shown in figure 5 was obtained from a further simplification of figure 3.

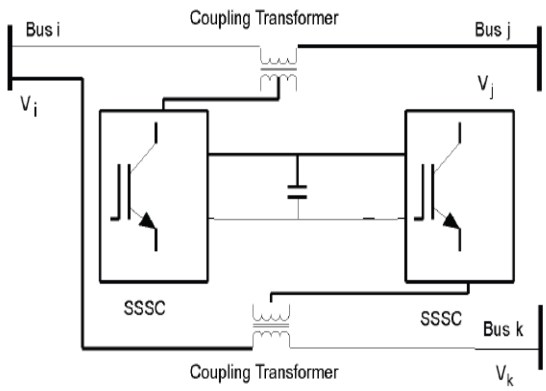

Figure 3: *Schematic diagram of an IPFC (Source: Sreejith et al, 2013)*

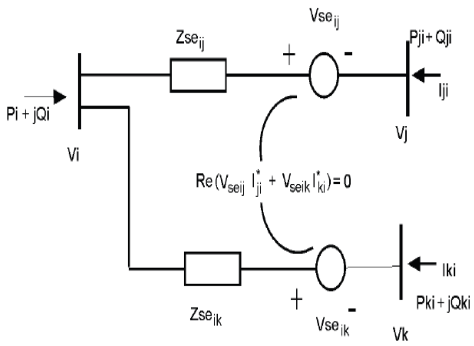

Figure 4: *Equivalent Circuit of Two Converter IPFC (Source: Sreejith et al, 2013)*

In figure 3, V_i, V_j, and $V_k$are the complex bus voltages at the buses i, j and k respectively, and they are defined as;

$V_x - \theta = V_x \angle \theta_x$ for $X = i, j, and\ k$ (1)

Where Vse_{in} is the controllable series injected voltage source, defined as;

$Vse_{in} = Vse_{in} < \theta se_{in} (n = j, k)$ (2)

Where $Zse_{in} = (n = j, k)$ is the series coupling transformer impedance.

The active and reactive power injections at each bus is determined as follows;

$P_{inj,i} = \sum_n = j, kV_i Vse_{in} b_{in} \sin(\theta_i - \theta se_{in})$ (3)

$Q_{inj,i} = -\sum_n j, kV_i Vse_{in} b_{in} \cos(\theta_i - \theta se_{in})$ (4)

$P_{inj\backslash n} = -V_n Vse_{in} b_{in} \sin(\theta_n - \theta se_{in})$ (5)

$Q_{inj,n} = V_n Vse_{in} b_{in} \sin(\theta_n - \theta se_{in})$ (6)

Where n = j,k

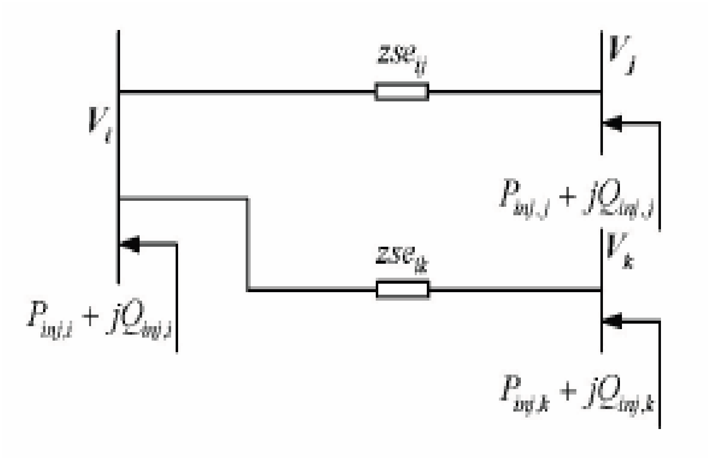

Figure 5: *Power injection model of two converter IPFC (Source: Eti-Ini et al., 2020)*

Implementation of the Simulink Model of the IPFC Model in PSAT

The Simulink model presented in this section was derived from the two-converter based injection model of IPFC shown in figure 5. The various component blocks are obtained from PSAT Simulink library. The component blocks used include: an AC PV generator, bus bars and pie model transmission line blocks.

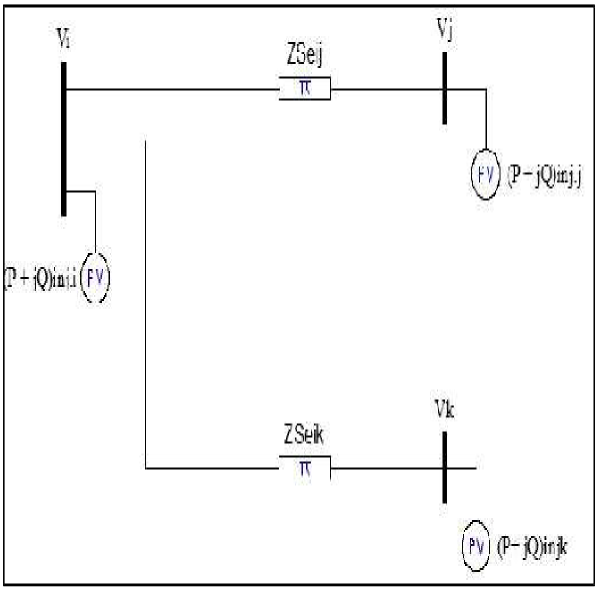

Figure 6: PSAT Simulink Based Injection Model Of IPFC

Figure presents the PSAT based Simulink model of the IPFC injection model proposed for compensating the test network for an improved ATC
$(P+jQ)_{inj.i}$,$(P+jQ)_{inj.j}$ and $(P+jQ)_{inj.k}$ are the voltages injected by the IPFC at buses I,j and k respectively. ZSe_{ik} and ZSe_{ij} are the impedances of the two coupling transformers in the IPFC schematic diagram of figure 5. For optimum compensation and maximum ATC enhancement, the sizes of the injection generators in figure 6 shall be determined optimally using Artificial Neural network (ANN).

Creating and Training an Ann Controllers for Determining the Optimum Size and Location of the IPFC Based Compensator

In this work, two ANN controllers were created and trained. The controllers are The ANN optimum size predictor and the ANN optimum location predictor. The Optimum size predictor determines the optimum size of the IPFC for each location while the optimum location predictor determines the best location for the placement of the IPFC based on the location that gave the minimum total network loss. The ANN controllers were developed to help determine the optimum size and optimum location for the installation of the IPFC so as to enhance the network voltage profile, improve its ATC and reduce total network losses.

To achieve this, repeated load flow was carried out on 5 selected possible locations of IPFC to determine the optimum IPFC size and optimum power loss on the lines. The result obtained from the selected five lines were then used to train the ANN controllers to predict optimum IPFC sizes and minimum loss at other possible locations. With the training data generated, the ANN controllers were then created, trained, and converted to the Simulink model for easy simulation.

Creating and Training the ANN optimum Size Predictor

The ANN optimum size predictor is created using the fitting application of the ANN toolbox in Simulink/MATLAB. The ANN architecture of figure 7 shows that the ANN optimum size predictor has three inputs (real power loss, reactive power loss, and voltage drop on the five-line). The target is the corresponding optimum IPFC size obtained for the respective five lines). As can be seen from the architecture, the chosen number of hidden layers is 10 while Levenberg Marquardt was used as a training algorithm. The training data is divided into three parts, 70% is used for

Vol. 6, No. 5 | 2022 | pp. 1-13 | DOI: https://doi.org/10.5281/zenodo.7437085
https://ejees.deqepub.org

actual training, 15% was used for testing and the remaining 15% is used for validation. The ANN training environment is shown in figure 7

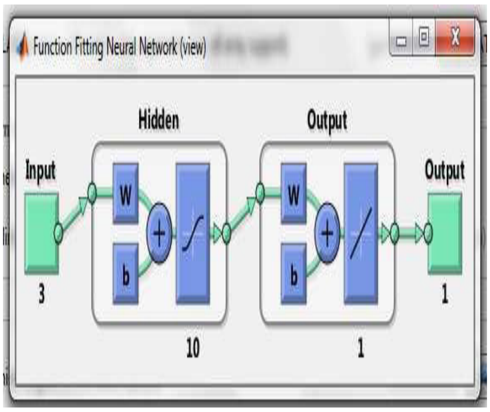

Figure 7: ANN Optimum Size Predictor Architecture

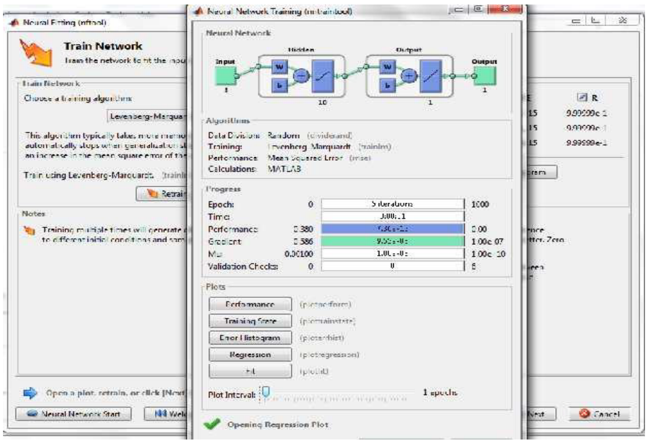

Figure 8: ANN Size Predictor Training Environment in Simulink

From the training performance plot, the training converged after 5 iterations with a best validation performance mean square error (MSE) of 6.9551e-15. The closeness obtained MSE error to zero suggests that the training completed with negligible error. This is also confirmed by the one to one (between input and target data) value obtained in the regression plot. After a successful training, the ANN optimum size predictor model is then converted to a Simulink model for use in predicting the optimum sizes of IPFC at various lines in the test network.

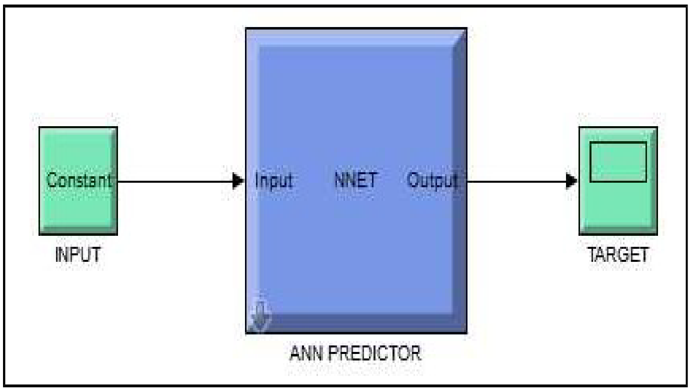

Figure 9: Deployed ANN Size Prediction Model

Vol. 6, No. 5 | 2022 | pp. 1-13 | DOI: https://doi.org/10.5281/zenodo.7437085
https://ejees.deqepub.org

The deployed Simulink model of the ANN optimum size predictor is shown in figure 10 shows the internal structure of the ANN Simulink model.

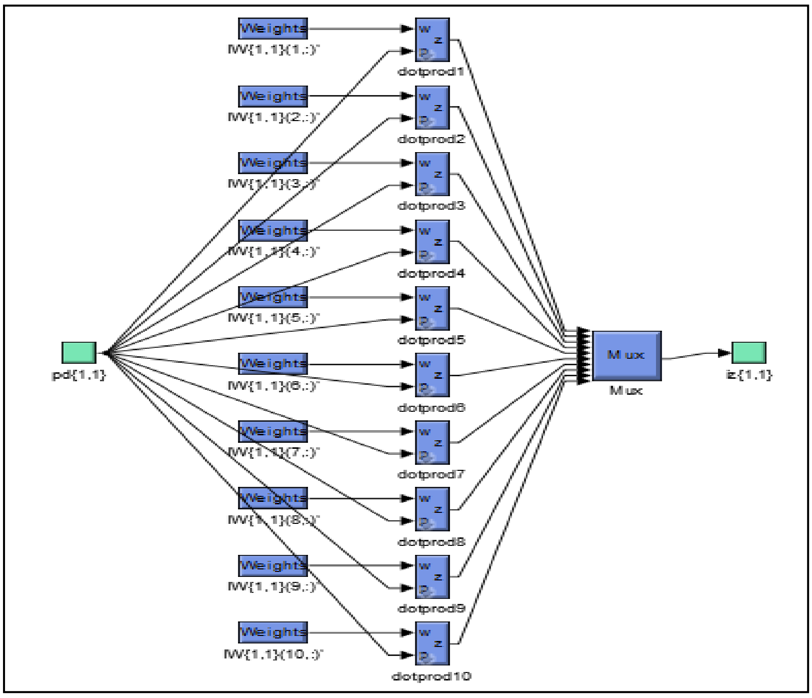

Figure 10: Internal Structure of the Deployed ANN Simulink Model

Creating And Training of the ANN Optimum Locator

Having developed the ANN optimum size predictor that computes the optimum size of IPFC for each line, it is also necessary to determine which of the lines cause optimum loss reduction when optimum-sized IPFC is installed. To achieve this, there is a need to create and train an ANN loss predictor for each line if an optimally sized IPFC were to be installed. The input data for the ANN loss predictor will be the characteristics (line losses and voltage drop) of the five lines used for the ANN optimum size predictor. The determined optimum IPFC size for the selected five lines (that under-went repeated load flow) will be an additional variable in the input data. There is therefore a total of four inputs derived from the five lines that under-went repeated load flow.

The ANN optimum loss predictor is created using the fitting application of the ANN toolbox in Simulink/Matlab. The ANN optimum loss predictor has four inputs including real power loss, reactive power loss, voltage drop, and optimum IPFC size for the lines used. The single target (output) is the minimum total network real power loss when the optimal IPFC is connected to a line

The chosen number of hidden layers is 10 while Levenberg Marquardt was used as a training algorithm. As seen in the training of optimum size predictor, the training data is also divided into three parts, 70%is used for actual training, 15% was used for testing and the remaining 15% is used for validation.

From the training performance plot, it is evident that the training converged after 7 iterations with the best validation performance mean square error (MSE) of 1.0401e-19. The one-to-one (between input and target data) value obtained in the regression plot of appendix B4 validates the impressive MSE result obtained during the training. After successful training, the ANN optimum loss predictor model is then converted to a Simulink model.

Progressive Connection of the Optimally Sized IPFCs to the Best Locations for the Determination of Exact Overall Optimum Location and Size of IPFC

The optimum sized and located IPFC is then connected to the most preferred location (line with lowest total network Power loss). Load flow is performed to determine the network total loss. An optimally sized IPFC is then connected to the next preferred location. Load flow is performed. Total network loss is also determined. The result obtained is compared with the one obtained from the first location to confirm an increase a reduction in total power loss. This process is repeated for a few more locations to attain a point where the optimum loss reduction is obtained, such

Vol. 6, No. 5 | 2022 | pp. 1-13 | DOI: https://doi.org/10.5281/zenodo.7437085
https://ejees.deqepub.org

that any further addition of IPFC will cause increase in total network loss. Table 4.46 shows the results of these simulations and the point optimum total network loss is reached

Results and Discussions

Result of Characterization of the Test Network

Table 1: Voltage Magnitude and Angle, Active and Reactive Power at Buses After Load Flow

Bus	V(pu)	phase (rad)	Pgen (pu)	Q gen (pu)	Pload (pu)	Q load (pu)
ALAOJI	0.99774	-0.10303	0	0	3	-0.69
SAPELLE	1	-0.04478	4	-5.36141	0	0
AKANGBA	0.99512	-0.01606	0	0	2.04	0.95
LEKKI	1.00382	-0.01105	0	0	1.2	0.62
SAKETE	0.99039	-0.03045	0	0	2.04	0.95
AJA	1.00167	-0.00156	0	0	1.2	0.62
JEBBA	1	-0.02637	2.78	0.59784	0	0
KADUNA	0.97005	-0.11781	0	0	2	0.97
New Haven	0.99376	-0.09566	0	0	1.13	0.56
OKEAROTS	0.99724	-0.00923	0	0	2.04	0.95
SHIRORO	1	-0.07242	2	6.071	0	0
UGWUAJI	0.98481	-0.11271	0	0	1.6	0.95
ADIABOR	0.99825	-0.11346	0	0	1.82	0.67
AFAM	1	-0.09758	4.5	-2.54152	0	0
AIYEDE	0.99641	-0.02798	0	0	1.39	0.69
AJAOKUTA	1.00285	-0.05126	0	0	0.64	0.323
ALADJA	0.99979	-0.04764	0	0	1.82	0.67
ASABA	1.01252	-0.06247	0	0	0.15	0.076
BENIN	1.006	-0.05012	0	0	1.57	0.8
DAMATURU	0.89612	-0.19033	0	0	1	0.4
DELTA	1	-0.0467	2.5	-3.21335	0	0
EGBIN	1	0	25.04821	-5.51645	0	0
GEREGU	1	-0.04508	2	-1.17521	0	0
GOMBE	0.89641	-0.18913	0	0	1.6	0.95
GWAGWA	0.99999	-0.07123	0	0	2.03	1.02
GANMO	0.99472	-0.0334	0	0	1.39	0.69
IHOVBO	1	-0.03304	2	-5.38415	0.15	0.076
IKEJAW	0.99573	-0.01507	0	0	4.29	2.48
IKOTEKPENE	0.99556	-0.10769	0	0	1.82	0.67
JALINGO	0.88258	-0.19778	0	0	1	0.3
JEBBATS	0.99973	-0.02679	0	0	0.15	0.076
JOS	0.95042	-0.1416	0	0	2.5	1.25
KAINJI	1	-0.01502	5.78	0.02132	0	0
KANO	0.96249	-0.12991	0	0	2	0.97
KANTANPE	0.99872	-0.07208	0	0	2.03	1.02
KEBBI	0.99846	-0.01841	0	0	1.2	0.4
LOKOJA	1.0019	-0.06148	0	0	0.15	0.076
MAIDUGURI	0.8933	-0.19755	0	0	1	0.3
MAKURDI	0.96322	-0.13168	0	0	1.8	0.65
ODUKPANI	1	-0.11233	2.5	1.25492	1.82	0.67
OKO OBA	1.00029	-0.00303	0	0	1.82	0.67
OKPAI	1	-0.07028	2.5	-1.29942	0	0
OLORUNSOGO	1	-0.01229	2.5	-0.28509	0	0
ONITSHA	1.00307	-0.07795	0	0	1.15	0.42
OSHOBO	0.99601	-0.03037	0	0	2.01	1.37
OWERRI	0.99243	-0.11836	0	0	2.04	0.95
YOLA	0.88392	-0.19415	0	0	1	4

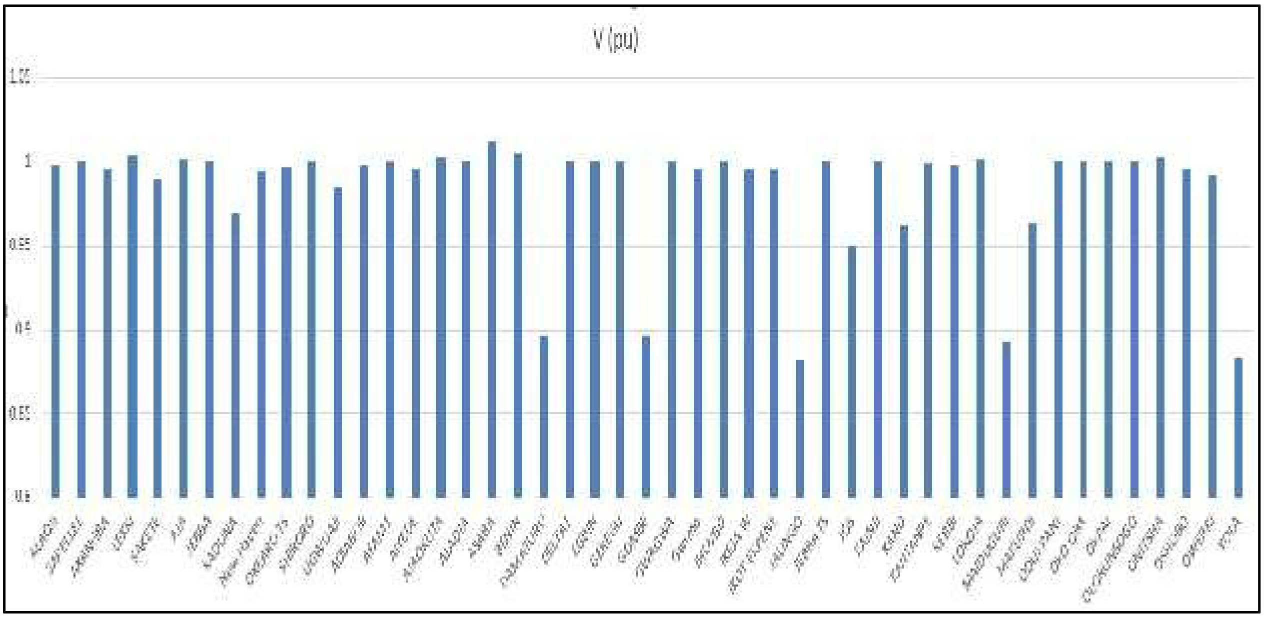

Figure 11: Bar Chart Showing Voltage Magnitude of Test Network Buses After Load Flow.

From table 1 and figure 11, it can be observed that five buses (Maiduguri, Yola, Gombe, Jalingo and Adamawa) fell below the IEEE acceptable range of 0.95pu to 1.05pu for healthy buses. This result suggests that the system was not stable as power network stability requires that all buses maintain a voltage level within the above stated IEEE acceptable range. The result of the continuation power flow revealed that the test network recorded a total network real power line loss of 0.5182pu. To reduce this network line loss and enhance voltage profile and stability, there is need to improve the network Available Transfer Capability (ATC). To enhance the network ATC for an improved voltage profile and reduced line losses, this research proposes the connection of Interline Power Flow Controllers (IPFC) at vulnerable buses. To be able to evaluate the impact of the chosen technique on the enhancement of the test network ATC, there is need to compute the network's ATC before applying the proposed technique on the network.

Results of ANN Model Simulations

To obtain the optimum size of IPFC for each line in the network, the ANN optimum size predictor was simulated. To obtain the optimum IPFC size for Yola-Gombe line for instance, the real and reactive power loss and the voltage difference between the two lines were fed to the input of the ANN optimum size predictor. On simulation, the result obtained was the predicted optimum size of IPFC for the Yola-Gombe line. This simulation is done for the rest of the 47 buses to obtain their corresponding optimum IPFC sizes. The result of the simulation is presented in table 2 and figure 12 0.8pu to 1.6pu. To determine the which of these buses to select as the best location to connect the IPFC for minimum loss and optimum ATC, another simulation will be carried out on each bus to determine the total network minimum loss that will result assuming the predicted optimum IPFC size were to be connected independent of each other.

Table 2: Simulation result showing ANN inputs and Optimum IPFC sizes for all Possible Locations

From Bus	*To Bus*	*Line*	*P Loss*	*Q Loss*	*VD(pu)*	*SIZE (pu)*
DAMATURU	GOMBE	47	0.0027	-0.41633	0.00029	1
DAMATURU	MAIDUGURI	38	0.00798	0.06833	0	0.8715
YOLA	JALINGO	37	0.00379	0.03689	0.00134	0.87
UGWUAJI	IKOT EKPENE	53	0.06884	-0.37645	0.01075	1.09
KANO	KADUNA	10	0.01901	0.16271	0.00756	0.8717
JOS	KADUNA	5	0.13371	1.14414	0.01963	1.18
UGWUAJI	New Haven	8	0.07995	0.55641	0.00895	1.049
YOLA	GOMBE	1	0.057	0.63733	0.01249	0.8692
MAKURDI	UGWUAJI	12	0.25514	1.77558	0.02159	1.3
JOS	MAKURDI	34	0.10467	0.88792	0.03868	1.024
GOMBE	JOS	17	0.66609	5.67931	0.05401	1.442
KADUNA	SHIRORO	3	0.36752	1.50829	0.02995	1.24

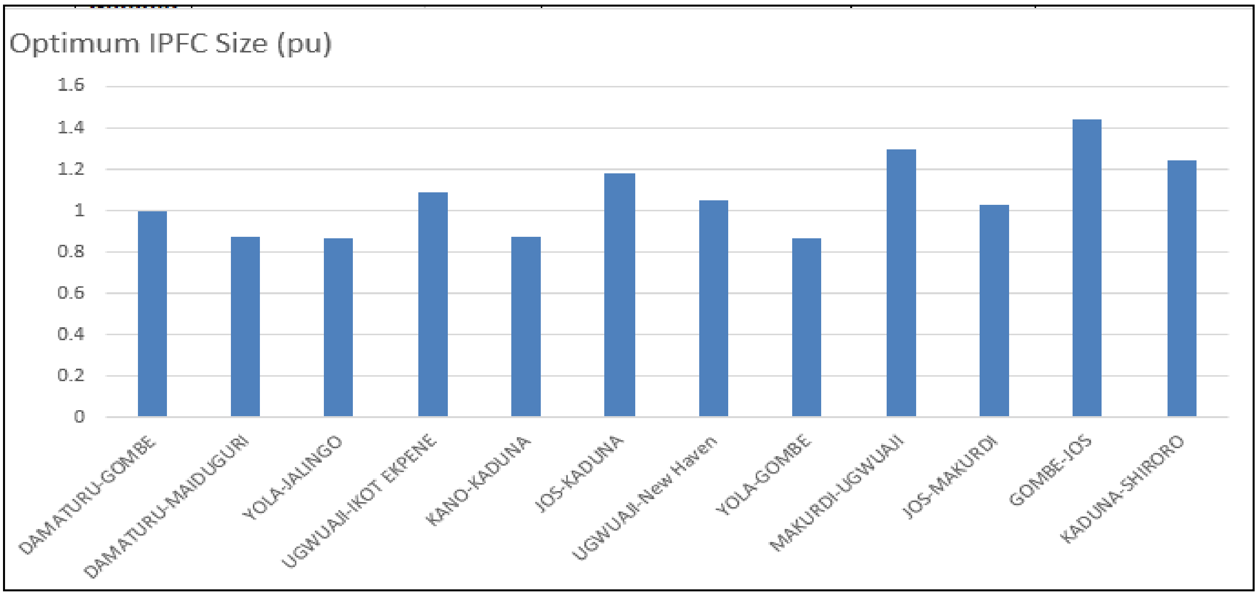

***Figure 13:** Bar chart showing predicted optimum IPFC sizes for possible best IPFC locations of the test network*

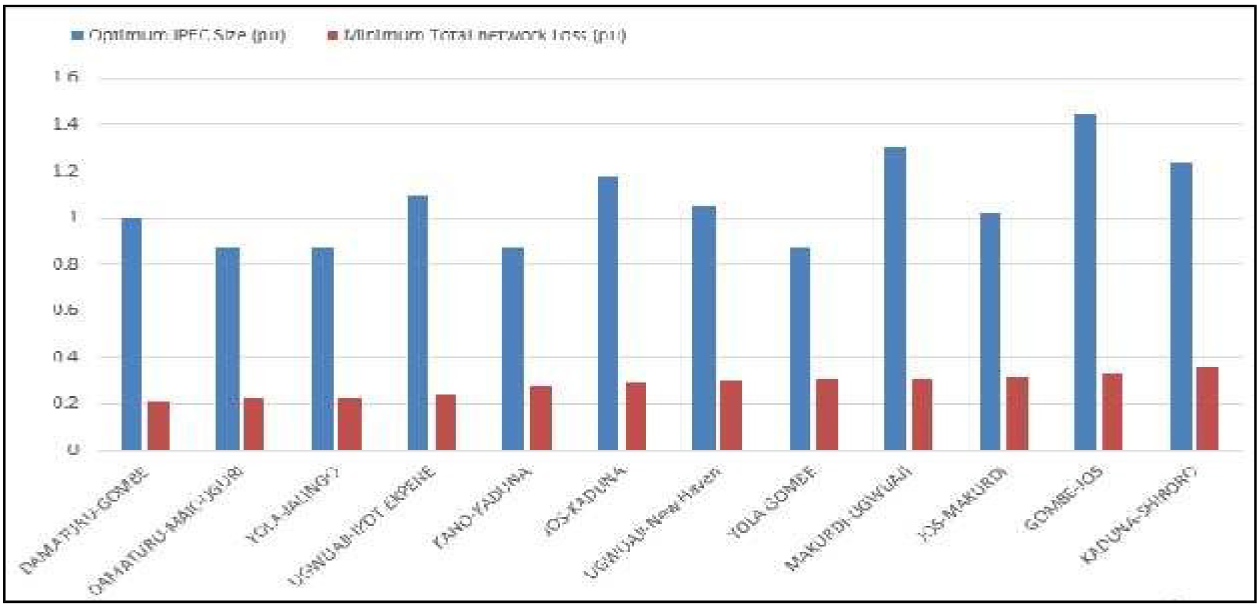

Figure 14: Bar chart showing predicted optimum IPFC size and corresponding minimum total network for each line when optimally sized IPFC is connected to each line independently.

Table 3: Loss Obtained from Progressive Connection of IPFC at the Best Locations

IPFC Location	*Total Network Real Power Loss (pu)*
NIL	0.51821
DAMATURU-GOMBE	0.21186
DAMATURU-MAIDUGURI	0.43253
YOLA-JALINGO	0.96889
UGWUAJI-IKOTEKPENE	1.45661

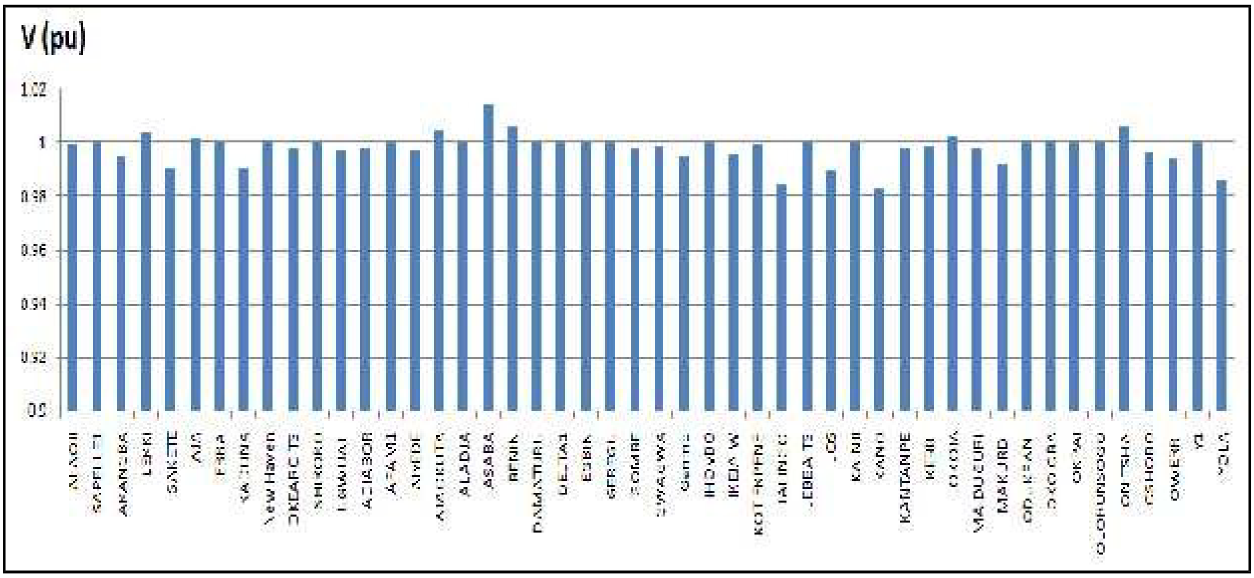

Figure 15: *Load Flow Result After IPFC Based Compensation*

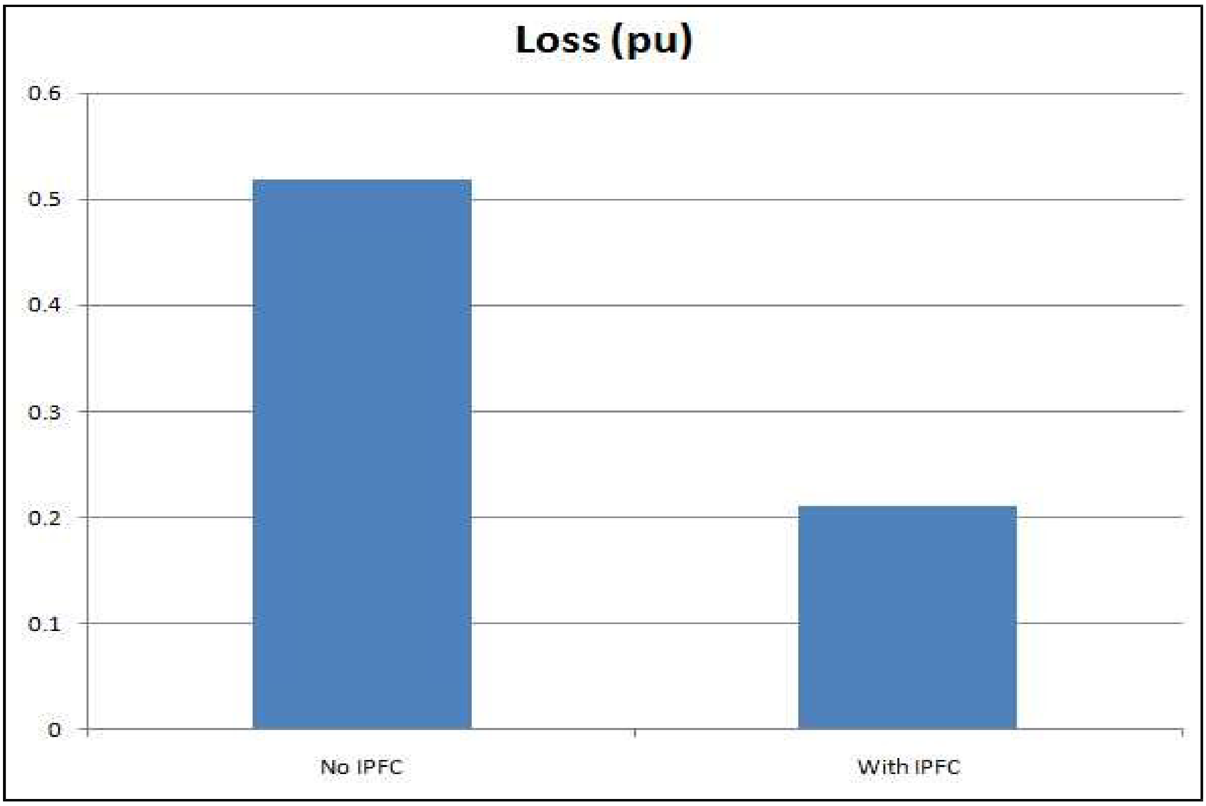

Figure 16: *Bar Chart Showing Total Network Losses with and Without IPFC*

Conclusion

This research work targeted at enhancing the Available Transfer Capability (ATC) of the Nigeria 47 bus 330kVA transmission line network using an optimally sized and placed interline Power Flow Controller. To achieve this, Load flow and continuation load flow was performed on the test network to determine the test network ATC, total network real power loss, and voltage profile. The continuation power flow also helped to determine the best likely optimal positions for the IPFC controllers. An ANN controller (optimum size predictor) was then created and trained to predict the optimum IPFC sizes for the identified likely best locations. Another ANN controller (ANN optimum location predictor) was also created and trained to determine the optimum location for the likely best locations. The ANN models are then simulated to determine the optimum IPFC size and optimum location. With the Damaturu-Gombe line chosen as the best location with an optimum IPFC size of 1.0pu, load flow and continuation load flow were performed again to determine the reduction in total network real power loss and the improvement of the proposed method on the network ATC and voltage profile.

The connection of an optimally sized IPFC at an optimal location increased test network ATC from 8.94pu to 54.26pu. This represents an increase of 45.32pu. This impressive result is a result of the excellent compensation effect of the optimally sized and best-located IPFC. Also, as evident in figure 16, the connection of an optimally sized IPFC at an optimal location reduced total network real power loss from 0.51821pu to 0.21186pu. This represents a reduction of 0.306pu in total network loss.
It can also be observed from figure 15 that the connection of an optimally sized IPFC at an optimal location increased the voltage profile of all 5 weak buses above the acceptable voltage profile limit of 0.95pu.

References

Ahmad, A. S., Mark, N. N., and Agbachi E. O (2014). Available Transfer Capability ATC a Index for Transmission Network Performance – A Case Study of Nigerian 0kV Tran mi in Grid*. International Journal on Electrical Engineering and Informatics,* 6 (3), 479-486.

Akhilesh A. N., Chinmoy, K. P., Ajaya, K. M. (2011). *International Electrical Engineering Journal (IEEJ)* 2 (3), 550-554

Alievelu, M. P. (2011). Modeling and control of interline power flow controller for power system stability enhancement. A PhD thesis submitted to Univeristi Teknologi Petronas.

Arturo, B. & Phadke, A. (2003). Artificial neural networks in power system restoration IEEE Transactions on Power Delivery

Chandrasekar, K., & Rsmana, N. V. (2011). A fast computational techniques to Assess total transfer capability using brodon- Shamanski. *Global J. f Researches in Engineering*, 11 (5), 13–15.

Gustafson M. W and Baylor, J. S (1989). Approximating the System Losses Equation. *IEEE Power Engineering Review*, 9 (8), 31-32. doi: 10.1109/MPER.1989.4310867.

Karthik B. and Chandrasekar S (2012). Modeling of IPFC for power flow control in 3-phaseline

Mohammed, O. O. Otuoze, A. O. Salisu, S.. Abioye, A. E. Usman A. M. and Alao R. A. (2020). The challenges and panaceas to power distribution losses in Nigeria. *Arid Zone Journal of Engineering, Technology & Environment AZOJETE*, 16(1), 120-136

NERC Report, June 1996 NERC, *Available Transfer Capability Definitions and Determination.*

Nigerian Power sector review report, December 2009, African development.

Nkalo, U.; Ekwe, O.; Ukoima, K. N. & Agwu, E. (2018). Impact of Electricity Supply on Economic Growth: A Nigerian Case Study.

Pandey, R. K. & Duvvury, V. S. B. (2012). An effective approach for ATC enhancement with FACTS device - A case study. 1-6. 10.1109/APCET.2012.6301989.

Reddy, B.; Sujatha, P.; Reddy, Y. (2016). Interline Power Flow Controller (IPFC) to Improve the Voltage Stability and Contingency Analysis in Power System. *International Review of Electrical Engineering (IREE)* 11109. 10.15866/iree.v11i1.6790.