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Voltage Collapse Instability Prediction of Nigerian 330kV Transmission Network Using Predictive Optimizer and Arithmetic Moving Average Technique for Enhancement.

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ABSTRACT – The Nigeria 330kV integrated power system currently consists of existing network, national independent power projects (NIPP), and independent power producers (IPP). This network consists of generating stations, transmission lines, and buses. Consequently, the Nigerian power system is gradually transforming into a complex interconnected network of different components. [1] A balance between active and reactive power will ensure a reliable electric power system for the consumer at the receiving end. Low power factor of the system indicates inefficient delivery of active power to the load due to reactive power losses. Voltage collapse incidence may be the resultant effect of voltage instability in the power system network (PSN). This paper considered the application of predictive optimizers with the aim to assess various voltage stability indices (VSI), particularly fast voltage stability index (FVSI), line stability index (LMN), line stability factor (LQP), voltage stability index (LD) and novel line stability index (NLSI), are presented to predict proximity of the line close to voltage collapse. The line voltage stability indices are based on active and reactive power injections into network configuration Five (5) predictive indices [2, 3] examined the predictions of voltage collapse profile for the 330kv transmission network under investigation. Following the trend of the predictive pattern are three (3) indices (NLSI, LMN, FVSI) captured for voltage collapse behaviour in their respective order, especially voltage stability (LD) and line stability factor (LQP) prediction behaviour for voltage collapse, because of its poor dynamic response to system abnormal conditions which indicates that the mean absolute percentages error (MAPE) was used to indicates NLSI has better and faster response terms of performance capacity, followed by line stability index (LMN) and fast voltage stability index (FVSI). The application of Arithmetic Moving Average (AMA) determined the number of voltage collapse in the following years, 2024, 2025, 2026, 2027 and 2028 to be 11, while the expected villages collapses become 10 in the year 2029 – 2032, using Five (5) years moving average technique. It is observed that the number of voltage collapse from 2021 – 2024 was 11 while the year 2025 – 2029 was 10 numbers. The indices, NLSI, LMN and FVSI show high predictive behaviour for yearly system voltage collapse, particularly the Novel line stability index (NLSI) which has better and faster predictive characteristics capacity for determining voltage instability especially, Shiroro (generator-bus), Okpai (generator–bus) Kumbotso (load bus), Jos (load-bus), Markudi (load-bus) Damaturu (load-bus), Ikeja-west (load-bus), Ikot-Ekpene (load bus), Ayede (load bus) Aja (load bus) Egbin (generator bus). The research paper also introduced application of artificial neural network (ANN), to measure system parameters performance, correlation, and validation with input data (FVSI, LMN, LQP, LD, NLSI). The result shows the obtained quantitative value of R = 0.9993 while the validity value was 0.9993 which agrees with the (FVSI, LMN, LQP, LD, NLSI) set parameters relationship. [4, 5]

Keywords- Voltage Instability, Predictive Optimizer, Arithmetic Moving Average, Voltage Collapse, Nigerian 330KV, Artificial Neural Network.

I. INTRODUCTION

The contemporary Power System Network (PSN) represents vast engineering infrastructure, the vitality of which is paramount for sustainable progress of industrial and socio-economic facets within any nation. In many developing economies, such as Nigeria, the continuous expansion and interconnection of bulk power systems have catalyzed economic growth, albeit resulting in a sophisticated network that operates within acceptable stability margins [6].

Voltage collapse is manifested in the form of slow variation in the system operating point because of continuous increase in load which eventually leads to a corresponding decrease in magnitude of the voltage.

This is due to the magnitude of its negative impact on power system infrastructure and in turn, it is highly detrimental in terms of economic impact to the society [7].

II. PROBLEM FORMULATION

This is indeed a problem that requires determination of optimal points for each new collapse scenario. Fast voltage stability index techniques are useful predictive optimizers, but in-depth analysis of such techniques has revealed their inherent code complexity coupled with a system approach to solving problems. [8]

Analysis 1: Fast voltage stability index (FVSI) given as;

$$FVSI_{ij} = \frac{4 \times Z_{ij}}{V_i^2 x_{ij}} \tag{1}$$

This analysis tool is considered for stable operation of the system that is the value of FVSI should be maintained less than one (1) numerically. The values close to one indicates, that particular line is close to instability point; that may lead to voltage collapse in the system. [9]

Where,

Z_{ij} : impedance between bus *i* and *j*

V_i : voltage at sending-end

X_{ij} : reactance at bus *i* and *j* respectively

Analysis 2: Line Stability Index (LMN)

According to Moghavemmi et al. (2019), LMN is proposed based on power flow. This involves a single-line, two-bus system, represented mathematically as;

$$lmn = \frac{4X_{ij}Q_j}{V_i \sin(\theta_{ij} - \delta)} \tag{2}$$

That is the values of LMN close to one indicate that system is losing its stability leading to voltage collapse. This mean that for stable operation of a system, the value should remain less than one, to enhance reliable power supply.

Analysis 3: Line Stability Factor (LQP)

Essentially, Moghavverni *et al.* (2019) formulated LQP based on the same concept of power flow equations, given as;

$$LQP = 4\left(\frac{X_{ij}}{V_i^2}\right)\left(Q_j \frac{p_i^2 X_{ij}}{V_i^2}\right) \qquad (3)$$

That is for stable operation,
LQP <1

Analysis 4: Voltage Stability Index (LD)

The index is also developed to determine voltage stability conditions, this is expressed mathematically as;

$$= \frac{\sqrt[4]{(\ ^2+\ ^2)(\ ^2+\ ^2)}}{\ ^2} \qquad (4)$$

This mean that the system condition to be in proximity to voltage collapse for any value of LD close to one.

Analysis 5: Novel Line Stability Index (NLSI)

The NLSI are developed to describe behaviour of system conditions, for purpose of avoiding voltage instability. This is expected mathematically as; [10]

$$NLSI = \frac{p_i R_{ij} + Q_j X_{ij}}{0.25 V_i^2} \qquad (5)$$

III. CASE STUDY

The network modelled and simulated 330Kv transmission network. The Network comprises of 5 × 120 MVA, 330/132KV transformers up to 33KV feeders.

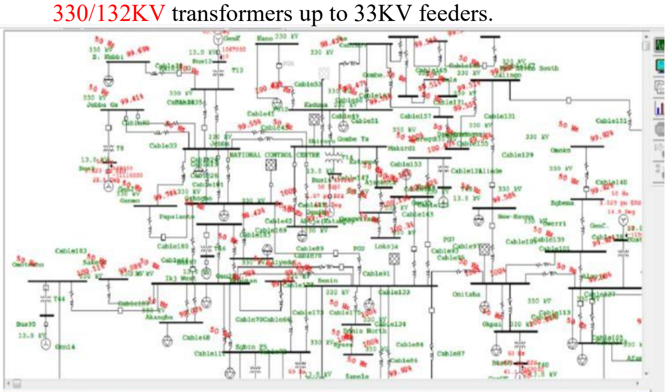


Figure 1: Shows the Single-Line Representation of the Existing Study Case (330KV Nigerian Network Simulated)

IV RESULT AND DISCUSSION

In order to verify the result of the study case under investigation, the network was modeled in ETAP environment and load flow was run on the network before the simulation base on the system line data of table 1.

TABLE 1: COMPARISON OF RESULT OF THE STUDY CASE BEFOERE AND AFTER

	Before	After
Total active loss	2.159MW	2.0871MW
Minimum Voltage	0.99162p.u	0.99179p.u
Maximum Voltage	0.9999p.u	0.9999p.u
Minimum Voltage Bus	25	25
Maximum Voltage Bus	34	34

From the result obtained there was reduction in the active power loss which represent 3.3% gain in the power. Maximum voltage remained unchanged while the minimum voltage improvement was 0.02%.

Table II: Results for the Comparison Test Analysis of the Five (5) Predictive Indices (FVIS, LMN, LQP, LD and NLSI)

Line Parameters (line/buses)	FVSI, stability	LMN, stability	LQP, stability	LD, stability	NLSI, stability
line/buse1	0.895	0.89456	0.0002975	0.00151002	1.04077135
line/buse2	0.6366	0.87038	0.0005705	0.00221575	1.28595043
line/buse3	0.8055	1.4418	0.011586	0.00184258	1.01464
line/buse4	0.7464	0.851	0.001031	0.00155636	1.38236
line/buse5	1.1973	0.6017	0.0002616	0.00151636	1.3336
line/buse6	1.5776	0.97676	0.0002484	0.00102357	2.05075
line/buse7	0.5817	1.26689	0.0003291	0.0005774	2.0945
line/buse8	1.6501	1.8946	0.00028447	0.00140646	1.58657
line/buse9	2.0249	1.5097	0.0003291	0.00174867	1.7834
line/buse10	1.1153	1.67577	0.00029085	0.001	1.26216
line/buse11	2.1001	0.9912	0.0003218	0.00125772	1.5319
line/buse12	1.2102	1.6002	0.00031728	0.001296	2.2352
line/buse13	0.0972	0.9187	0.00040336	0.001462	1.11178
line/buse14	0.0819	0.7395	0.00033941	0.0004925	1.52417
line/buse15	0.0123	1.5248	0.0012367	0.001508	1.97825
line/buse16	0.00958	1.5097	0.0011979	0.00149734	2.050687
line/buse17	0.00835	1.5474	0.0011529	0.00149307	1.54134
line/buse18	0.00635	0.8905	0.00111488	0.00150813	2.02218
line/buse19	0.004616	2.69	0.0014659	0.001325	2.261296
line/buse20	0.0056	0.9574	0.0016041	0.001454	2.006205
line/buse21	0.008009	0.7463	0.001628	0.007847	2.26873
line/buse22	0.0936	0.9961	0.00117847	0.00130865	1.59887
line/buse23	0.00368	1.0154	0.00135865	0.00135752	1.365904
line/buse24	0.149	0.753	0.00132482	0.00152434	1.570648

Table III: Shows Results for the Comparison Test for Fire Predictive Indices

Line Parameters(line/ buses)	FVSI, stability (Xo)	LMN, stability (X_1)	$\lvert X_0 - X_1 \rvert$	LQP, stability (X_2)	$\lvert X_0 - X_2 \rvert$	LD, stability (X_3)	$\lvert X_0 - X_3 \rvert$	NLSI, stability (X_4)	$\lvert X_0 - X_4 \rvert$
line/buse1	0.895	0.89456	0.00044	0.0002975	0.8947025	0.00151002	0.89348998	1.04077135	-0.14577135
line/buse2	0.6366	0.87038	-0.23378	0.0005705	0.6360295	0.00221575	0.63438425	1.28595043	-0.64935043
line/buse3	0.8055	1.4418	-0.6363	0.011586	0.793914	0.00184258	0.80365742	1.01464	-0.20914
line/buse4	0.7464	0.851	-0.1046	0.001031	0.745369	0.00155636	0.74484364	1.38236	-0.63596
line/buse5	1.1973	0.6017	0.5956	0.0002616	1.1970384	0.00151636	1.19578364	1.3336	-0.1363
line/buse6	1.5776	0.97676	0.60084	0.0002484	1.5773516	0.00102357	1.57657643	2.05075	-0.47315
line/buse7	0.5817	1.26689	-0.68519	0.0003291	0.5813709	0.0005774	0.5811226	2.0945	-1.5128
line/buse8	1.6501	1.8946	-0.2445	0.00028447	1.64981553	0.00140646	1.64869354	1.58657	0.06353
line/buse9	2.0249	1.5097	0.5152	0.0003291	2.0245709	0.00174867	2.02315133	1.7834	0.2415
line/buse10	1.1153	1.67577	-0.56047	0.00029085	1.11500915	0.001	1.1143	1.26216	-0.14686
line/buse11	2.1001	0.9912	1.1089	0.0003218	2.0997782	0.00125772	2.09884228	1.5319	0.5682
line/buse12	1.2102	1.6002	-0.39	0.00031728	1.20988272	0.001296	1.208904	2.2352	-1.025
line/buse13	0.0972	0.9187	-0.8215	0.00040336	0.09679664	0.001462	0.095738	0.11178	-0.01458
line/buse14	0.0819	0.7395	-0.6576	0.00033941	0.08156059	0.0004925	0.0814075	1.52417	-1.44227
line/buse15	0.0123	1.5248	-1.5125	0.0012367	0.0110633	0.001508	0.010792	1.97825	-1.96595
line/buse16	0.00958	1.5097	-1.50012	0.0011979	0.0083821	0.00149734	0.00808266	2.050687	-2.041107
line/buse17	0.00835	1.5474	-1.53905	0.0011529	0.0071971	0.00149307	0.00685693	1.54134	-1.53299
line/buse18	0.00635	0.8905	-0.88415	0.00111488	0.00523512	0.00150813	0.00484187	2.02218	-2.01583
line/buse19	0.004616	2.69	-2.685384	0.0014659	0.0031501	0.001325	0.003291	2.261296	-2.25668
line/buse20	0.0056	0.9574	-0.9518	0.0016041	0.0039959	0.001454	0.004146	2.006205	-2.000605
line/buse21	0.008009	0.7463	-0.738291	0.001628	0.006381	0.007847	0.000162	2.26873	-2.260721
line/buse22	0.0936	0.9961	-0.9025	0.00117847	0.09242153	0.00130865	0.09229135	1.59887	-1.50527
line/buse23	0.00368	1.0154	-1.01172	0.00135865	0.00232135	0.00135752	0.00232248	1.365904	-1.362224
line/buse24	0.149	0.753	-0.604	0.00132482	0.14767518	0.00152434	0.14747566	1.570648	-1.421648
Total			13.842475		14.99101231		14.98115656		23.88097678
$\frac{1}{n}\sum\left(\frac{X_o - X_i}{X_0}\right) X$	100 where n = 24		0.57676979		0.624625513		0.624214857		0.995040699
%			57.6769792		62.46255129		62.42148567		99.50406993

The five predictive indices are actively evaluated to predict the voltage collapse profile of the characterized 330kV network behavior. Three predictive optimizers, including the Novel Line Stability Index (NLSI), Line Stability Index (LMN), and Fast Voltage Stability Index (FVSI), accurately predicted voltage collapse behavior. However, the Voltage Stability Index (LD) and Line Stability Factor (LQP) are far from predicting voltage collapse, as they exhibit slow dynamic response behavior assessment. These indices lack the capacity to determine and identify system instability conditions leading to voltage collapse. To assess the performance characteristics of the three indices for predicting early system collapse, it is necessary to examine each performance justification using the statistical tool Mean Absolute Percentage Error (MAPE) for verification purposes

Results Presentation for the Correlation ANN Training Regression Plots

Figure 2 shows the regression plot of ANN output against the targets which reveals the fitness of the training result.

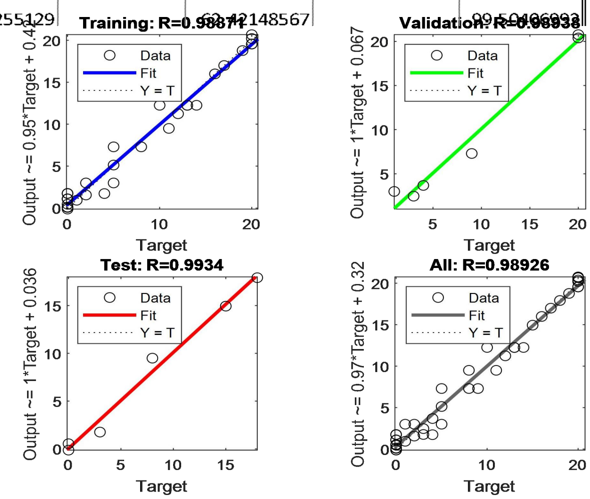


Figure 2: ANN Training Regression Plot

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 the value R equals to 0.9993 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 perfect regression existed between the output and the target.

ANN Training Performances

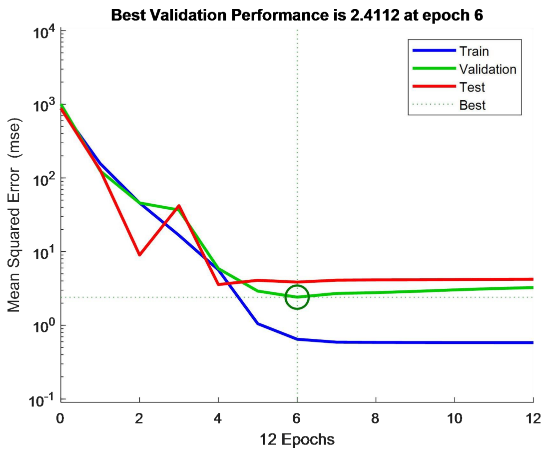
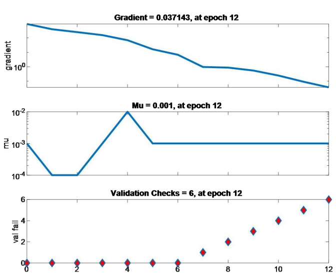
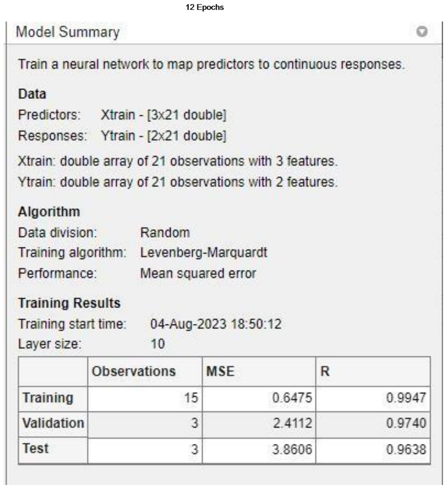


Figure 3: ANN Training Performance

Figure 3 shows the performance plot of the ANN training. The blue, green and red colour represents the training, validation, and test mode respectively.

During the training process 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 10.3257 at epoch 6 which indicates how much minimized errors occurred during the training.





Model Summary

Train a neural network to map predictors to continuous responses.

Data

Predictors: Xtrain - [3x21 double]
Responses: Ytrain - [2x21 double]

Xtrain: double array of 21 observations with 3 features.
Ytrain: double array of 21 observations with 2 features.

Algorithm

Data division: Random
Training algorithm: Levenberg-Marquardt
Performance: Mean squared error

Training Results

Training start time: 04-Aug-2023 18:50:12
Layer size: 10

	Observations	MSE	R
Training	15	0.6475	0.9947
Validation	3	2.4112	0.9740
Test	3	3.8606	0.9638

Figure 4: Plots of Gradient and Validation checks

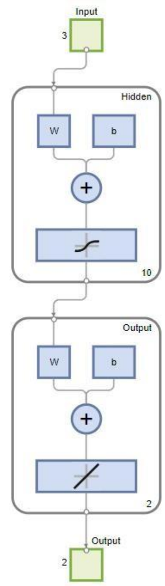


Figure 5: Block Representation, of the ANN-model Architecture of Input and Output.

Table IV: Artificial Neural Network, Predictions Data for checking Relationship, Performance, Validation Test.

INPUT DATA(XTRAIN)	OUTPUT DATA-TARGET (YTRAIN)			
0.895	0.895	0.000298	0.00151	1.040771
0.6366	0.87038	0.000571	0.002216	1.28595
0.80055	1.44177	0.011587	0.001843	1.01464
0.746377	0.851	0.001031	0.001516	1.38236
1.197276	0.6017	0.000262	0.001516	1.3336
1.57755	0.97676	0.000248	0.001024	2.05075
0.58174	1.26689	0.000329	0.000577	2.0945
1.65096	1.8946	0.000284	0.001406	1.58657
2.024289	1.5097	0.000329	0.001749	1.7834
1.115306	1.67577	0.000291	0.001	1.26216
2.100115	0.9912	0.000322	0.001258	1.5319
1.21018	1.600208	0.000317	0.001296	2.2352
0.097156	0.9187	0.000403	0.001462	1.11178
0.0819	0.7395	0.000339	0.004925	1.52417
0.0123	1.5248	0.001237	0.001508	1.97825
0.00958	1.5097	0.001198	0.001497	2.050687
0.00835	1.5474	0.001153	0.001493	1.54134
0.00635	0.8905	0.001115	0.001508	2.02218
0.004616	2.69	0.001466	0.001325	2.261296
0.0056	0.9574	0.001604	0.001454	2.006201
0.008009	0.7463	0.001628	0.007847	2.26873
0.0936	0.9961	0.001178	0.001309	1.59887
0.00368	1.0154	0.001358	0.001358	1.365904
0.0149	0.753	0.001325	0.001524	1.570648

V. CONCLUSION

The Nigerian power network comprises a limited number of generating stations, predominantly situated in remote areas near raw fuel sources. These stations are often linked to load centers by extensive transmission lines. The generation, transmission, distribution, and marketing of electricity in Nigeria are statutory functions handled by the electricity

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utilities, notably the Power Holding Company of Nigeria, among others.

Currently, the installed generating capacity stands at approximately 12,522MW, with a maximum dispatch capacity of about 4000MW, serving a population exceeding 200 million people. This represents a gross inadequacy in meeting the demand for electric power supply to consumers at the receiving. Voltage stability is imperative for optimal system performance. Variations in load demand can trigger system overloads or disturbances that may lead to total outages or blackouts.

The study adopted the three-year and five-year moving average techniques to analyze the annual number of voltage collapses between 2000-2021 and 2021-2032. The predictive models indicated highest number of expected voltage collapses to be 12, occurring in the years 2021, 2022, and 2023, followed by 11 collapses expected between 2024-2028, and 10 collapses predicted for 2029-2032.

The research study has also developed a mathematical framework integrating active and reactive power load flow into a simple 2-bus network. This framework, termed the "predictive optimizer," which has been characterized as second-order quadratic polynomial. Its purpose is to determine the receiving-end voltage (Vy) in relation to the sending-end voltage (Vx), as well as the reactive power at the receiving end (Qy). The study introduced the application of artificial neural network (ANN) to measure system parameters, perform correlation, and validate input data (FVSI, LMN, LQP, LD, NLSI). A regression value (R) of 1 indicates an exact linear relationship, while R = 0 denotes no relationship between inputs and outputs (targets). The quantitative value of R = 0.9993 during validation demonstrates a high level of agreement among data set analyzed.

Five voltage stability indices (NLSI, FVSI, LMN, LQP, LD) has been employed to assess and predict the maximum capacity limit in each scenario of voltage collapse in 330kV long transmission network. Among these indices, NLSI, FVSI, and LMN exhibit predictive behaviors regarding system voltage collapse from the indices of the Novel Line Stability Index (NLSI) provides and rapid predictive capabilities in identifying voltage instability critical nodes includes Shiroro, Okpai, Kumbotoso, Jos, Makundi, Damaturu, Ikeja-west, Ikot-Ekpene, Ayede, Aja, and Egbin—classified as critically overloaded buses surpassing their maximum loadability limits identified by NLSI.

The study introduces the use of simple moving average technique, which examines historical data, to predict and forecast voltage collapses. This novel approach has not been previously utilized in the prediction and forecasting of voltage collapse in the 330kV power system network.

The paper implemented the application of three-year and five-year moving average techniques to ascertain the expected number of voltage collapses from the periods 2000-2021 and 2021-2032.

VI. APPENDIX A1.1

Error Analysis For System Accuracy

Using Mean Absolute Percent Error (MAPE)

From the comparison table in Appendix A1 we have

$$\text{MAPE} = \frac{\Sigma(o-)}{} \text{ X } 100$$

$$\left.\begin{array}{l}
\text{MAPE (FVSI/LMN)} = \frac{18.842475}{24} \text{ X } 100 = 78.676\% \\
\text{MAPE (FVSI/LQP)} = \frac{14.99101231}{24} \text{ X } 100 = 62.462\% \\
\text{MAPE (FVSI/LD)} = \frac{14.98115656}{24} \text{ X } 100 = 62.421\% \\
\text{MAPE (FVSI/NSLI)} = \frac{23.8809768}{24} \text{ X } 100 = 99.504\%
\end{array}\right\} \text{NLSI > LMN > FVSI}$$

From the above calculations, we rank the five optimizers as follows: NLSI > LMN > FVSI >LQP > LD.

Which agrees with the graph in fig 4.5a

APPENDIX A2

Solving for Reactive Power for the Nigerian 330kV Power Network

The Reactive Power needed in the Network is determined using the conventional governing reactive power equation (Q_c) as stated below:

$$Q_c = \frac{}{_1} \sin(\cos^{-1} \quad)_1 - \frac{}{_2} \sin(\cos^{-1} \quad)_2$$

Where P = 1300MW, =existing maximum load = Active power for the load

Pf_1 = 0.65 existing power factor, Pf_2 = 0.85 proposed power factor

$$Q_c = \frac{1300}{0.65} \sin(\cos^{-1}(0.65)) - \frac{1300}{0.85} \sin(\cos^{-1}(0.85))$$

= 2000 x Sin [0.863211] – 1529.41176470 x Sin [0.554811032]

= 2000 x 0.759933629 – 1529.41176470 x 0.52678268680

= 1519.867258 – 805.6676386321

=714.19961 ≈ 800MVAR

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