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Power quality improvement of the 33kv north-bank distribution network using artificial neural network based Dynamic Voltage Restorer (DVR)

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Abstract

Power quality issues such as voltage sags, swells, and harmonics contribute to over 90% of customer power interruptions in distribution networks, leading to increased downtime, equipment damage, and financial losses. The North-Bank 33kV distribution feeder in Makurdi experiences voltage fluctuations exceeding IEEE 519 and IEC 61000-3 standards, with a Total Harmonic Distortion (THD) of 6.67%, surpassing the recommended 3–5% limit. This study presents an Artificial Neural Network (ANN)-based Dynamic Voltage Restorer (DVR) to mitigate these disturbances and enhance power reliability. Using MATLAB/SIMULINK, the system was modeled and simulated under fault conditions, comparing the performance of Proportional-Integral (PI) and ANN controllers. Results show that while both methods mitigate voltage disturbances, the ANN-controlled DVR exhibits 15% faster response time, 99% classification accuracy, and reduces THD to below 5%. The DVR effectively compensates for voltage sags within 70 milliseconds, restoring voltage to the acceptable range of 0.95–1.05 p.u. across various fault scenarios, including line-to-ground and line-to-line-to-ground faults. The ANN-based approach outperforms conventional methods by dynamically adjusting to changing load conditions, ensuring a stable and reliable power supply. These findings validate the DVR as a viable and intelligent solution for improving power quality in modern distribution networks, reducing equipment failures, and minimizing operational losses.

Keywords: Power Quality; Voltage Sag and Swells; Artificial Neural Network (ANN); Dynamic Voltage Restorer (DVR).

1. Introduction

Electric power system is considered to be a large network composed of three major interconnected components namely, generation, transmission and distribution networks [1]. The primary function of an electric power system is the economic supply of electrical energy with an acceptable degree of reliability [2]. For a reliable power system, adequate power is generated at generating stations and transported through transmission network to the distribution network, where power is directly delivered to consumers by electricity utilities [3]. The Distribution system is located at the end of the power system network and supplies electrical power directly to the consumers for utilization so, power quality depends largely on the state of the distribution system [4]. Distribution system ideally, should provide customers with an uninterrupted power having smooth sinusoidal voltage/current at the accepted magnitude level and frequency [5]. However, in practice, power systems, especially the distribution systems, have numerous non-linear loads, which significantly affect the quality of power supply with the distribution network failure accounting for about 90% of the average customer interruptions [6]. The presence of non-linear loads is responsible for loss in purity of supply waveform and this results in power quality problem [7]. Apart from non-linear loads, some system events, both usual (e.g. capacitor switching, motor starting) and unusual (e.g. faults) could also cause power quality problem [8].

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The North-Bank 33kV distribution feeder experiences voltage sags, swells, and harmonics, which affect the quality and reliability of the power supply to customers thereby poses a significant problem that this paper proposes to address. Dynamic Voltage Restorer (DVR) has been proposed as a solution to improve the power quality of the feeder. However, there is a need to model and simulate the system using MATLAB/SIMULINK to assess the effectiveness of the proposed solution and optimize the design parameters of the DVR. Therefore, the problem is to model and simulate the North-Bank 33kV distribution feeder with DVR using MATLAB/SIMULINK to improve power quality by mitigating voltage sags, swells and interruptions.

The aim of this study is to improve the power quality of the North-bank 33kV distribution feeder using an Artificial Neural Network based Dynamic Voltage Restorer (DVR) by achieving the following objectives;

- Develop a MATLAB/SIMULINK model of the North-Bank 33kV distribution feeder and a Dynamic Voltage Restorer (DVR).
- Simulate power quality issues to assess the DVR's effectiveness in mitigating disturbances and restoring nominal voltage levels.
- Evaluate the DVR's performance under various load conditions.
- Analyze the DVR's operation in improving power quality under different fault conditions

This research is tailored to a specific scope, by limiting its focus to the following:

- North-Bank 33kV feeder Voltage sag
- voltage swell and harmonics
- The use of DVR as a mitigating device
- MATLAB/SIMULINK as simulating platform

Improving the power quality and reliability of supply is essential for meeting the needs of customers and ensuring the smooth operation of industries and businesses. The North-Bank 33kV distribution feeder suffers from voltage sags, swells, and harmonics which have a negative impact on the power quality and reliability of supply. Therefore, there is a need to mitigate these disturbances and improve the power quality of the feeder. The Dynamic Voltage Restorer (DVR) is a proposed solution that can mitigate voltage disturbances and improve the power quality of the feeder. However, before implementing DVR, it is important to model and simulate the system to evaluate its effectiveness and optimize the DVR's design parameters. MATLAB/SIMULINK is a powerful tool for modeling and simulating power systems and is widely used for power quality studies. By using MATLAB/SIMULINK, the effectiveness of the proposed solution can be evaluated, and the DVR's design parameters can be optimized, leading to more efficient and reliable power supply. Therefore, this study is justified as it aims to improve the power quality and reliability of supply to customers and the results can be used to guide future improvements in the power distribution system. By mitigating voltage disturbances and improving power quality, the study can lead to increased customer satisfaction, improved productivity, reduced equipment damage and maintenance cost.

2. Literature review

A power distribution system is a network of components used to convey electric power from the substation to different consumers. It comprises of distribution substation, feeder, distribution transformers, distributors, service transformers and service mains. The primary purpose of a power distribution system is to provide electricity to homes, businesses, and industries reliably and efficiently.

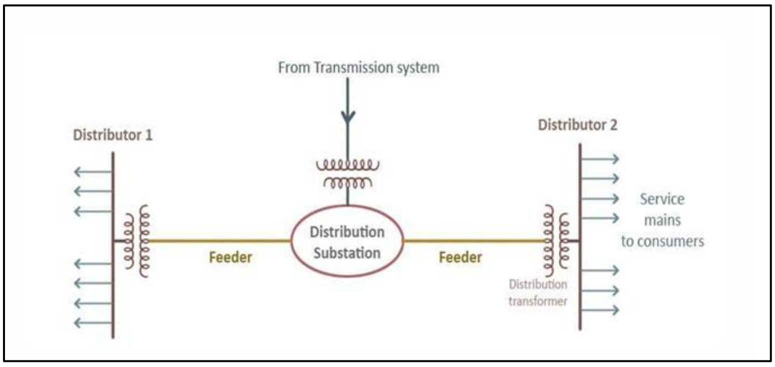

Figure 1 A schematic diagram of a distribution system [9]

The power distribution system typically starts from the distribution substations, where high voltage from transmission is stepped down to a lower voltage for distribution to consumers. The feeders carry the electrical energy from the substation to service transformers located closer to the consumers. The transformers further step down the voltage to a level suitable for use by homes, businesses, and industries. Power distribution systems can be classified into different types based on various factors such as topology, voltage level and operating characteristics. Power quality is the measure to which power supply quantities such as voltage, frequency and other waveform maintain statutory specification or standard [10]. According to [11], since the discovery of electricity four centuries ago, its generation, distribution and use have continuously evolved.

According to [12] in their research "Improving Power System Stability in a National Grid Using the Dynamic Voltage Restorer (DVR) "establish the existence of instability in power systems and described how power system stability can be improved upon by using the dynamic voltage restorer (DVR) in minimizing voltage sags and swells in any given power system. The Nigerian 330KV,30 bus power system was used in carrying out the research. The characterized 330KV was made up of 6 generators, 24 loads, 30 buses and 31 transmission lines. The Simulink model of the DVR was integrated into the Nigerian 330KV, 30 bus power system and simulated with results generated for analysis showing stable power after the use of DVR. It was further discovered that there is need to optimize DVR operation using heuristic algorithms like particle swamp optimization (PSO), ant colony optimization (ACO) and simulated annealing (SA) for improved result.

The power quality problems can be defined as the difference between the quality of power supplied and the quality of power required [13]. It is an occurrence manifested as non-standard voltage, current or frequency deviation that leads to disoperation or failure of end use equipment. A brief description of the some of the most common power quality problems, effect and is given in as follows:

Voltage sag (or dip): Voltage sag is a decrease from the normal supply voltage level between 10% and 90% of the nominal RMS voltage at the power frequency, for a duration of 0.5 cycle to 1 minute. It is typically caused by faults on the transmission or distribution network (most of the times on parallel feeders) or starting of large electrical loads, such as electric motors or compressors. Some of the most common consequences of voltage sag include: Malfunction or shutdown of electrical equipment, Reduced productivity, Damage to electrical equipment, Increased maintenance costs and Safety risks.

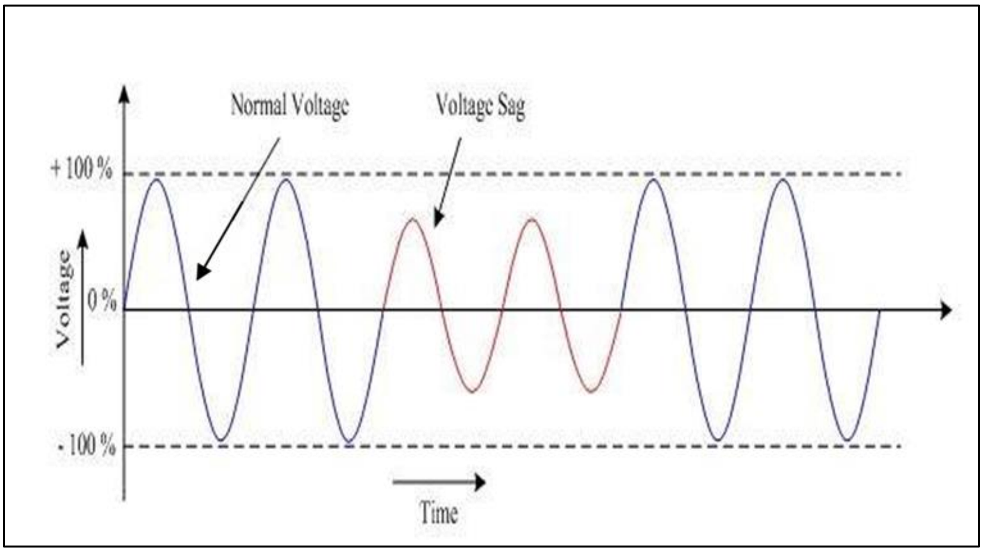

Figure 2 Voltage Sag [14]

Very Short/Long Interruptions: Very short interruption occurs when there is complete interruption of electrical supply for a brief period lasting from few milliseconds to one or two seconds. It can be caused by the opening and automatic closure of protection devices to decommission a faulty section of a network, equipment fault, insulation failure, lightning and insulator flashover. While, Long interruptions occur when there is a total interruption of electrical supply for duration greater than 1 to 2 seconds. It is caused by severe weather events, equipment failures, and grid disturbances and leads to productivity and data loss in sensitive equipment.

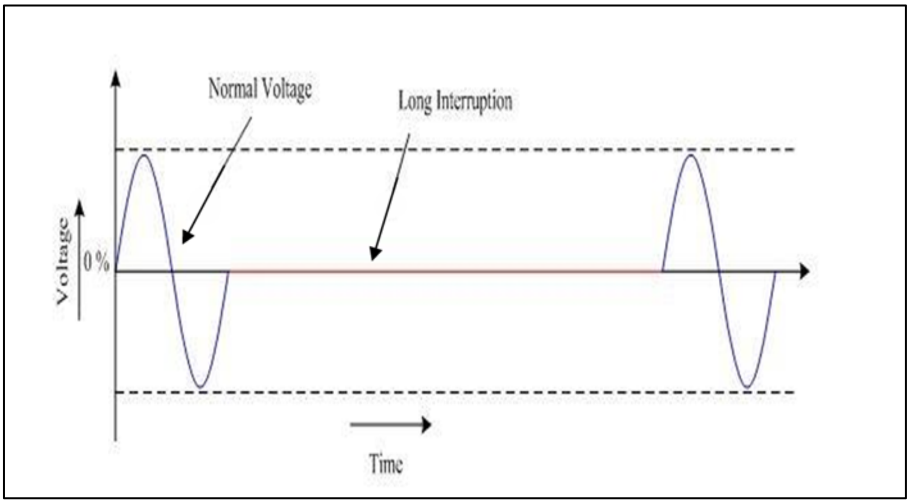

Figure 3 Long Interruption [14]

Voltage fluctuation: Voltage fluctuation occurs when the amplitude of the voltage oscillates, typically modulated by a signal with a frequency range of 0 to 30 Hz. This phenomenon can be triggered by various factors, including load variations, grid disturbances, and voltage regulation issues. The most noticeable effect of voltage fluctuations is flickering of lighting and screens, which can create the perception of visual instability. Additionally, prolonged voltage fluctuations can lead to overheating in electrical equipment, compromising their reliability and potentially causing equipment failure. Effective voltage regulation and monitoring systems are essential to minimize the adverse effects of voltage fluctuations on sensitive devices and equipment.

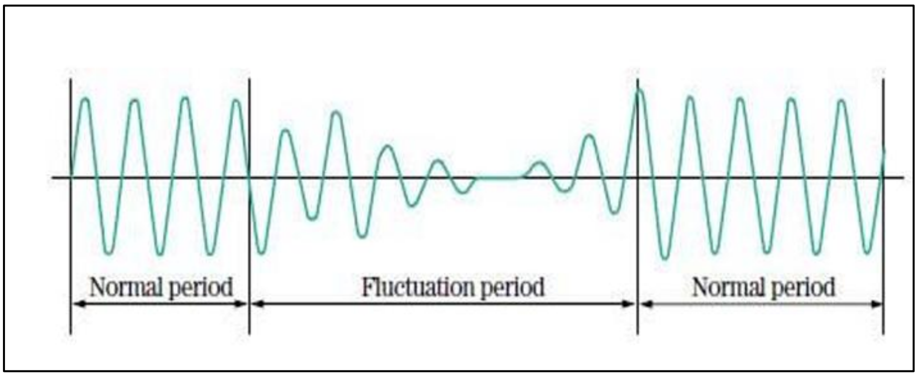

Figure 4 Voltage Fluctuations [14]

Voltage Swell: A voltage swell refers to a temporary and brief increase in the RMS voltage of an electrical power supply, typically lasting only a few cycles. These voltage spikes can occur due to various factors, such as sudden changes in load, grid disturbances, or switching operations. While short-lived, voltage swells can cause significant issues, including data loss, flickering of lights and screens, and potentially the stoppage or damage of sensitive equipment, especially if the voltage levels exceed safe operational thresholds. Proper voltage regulation and protection systems are crucial to mitigate the impact of swells on critical electrical systems.

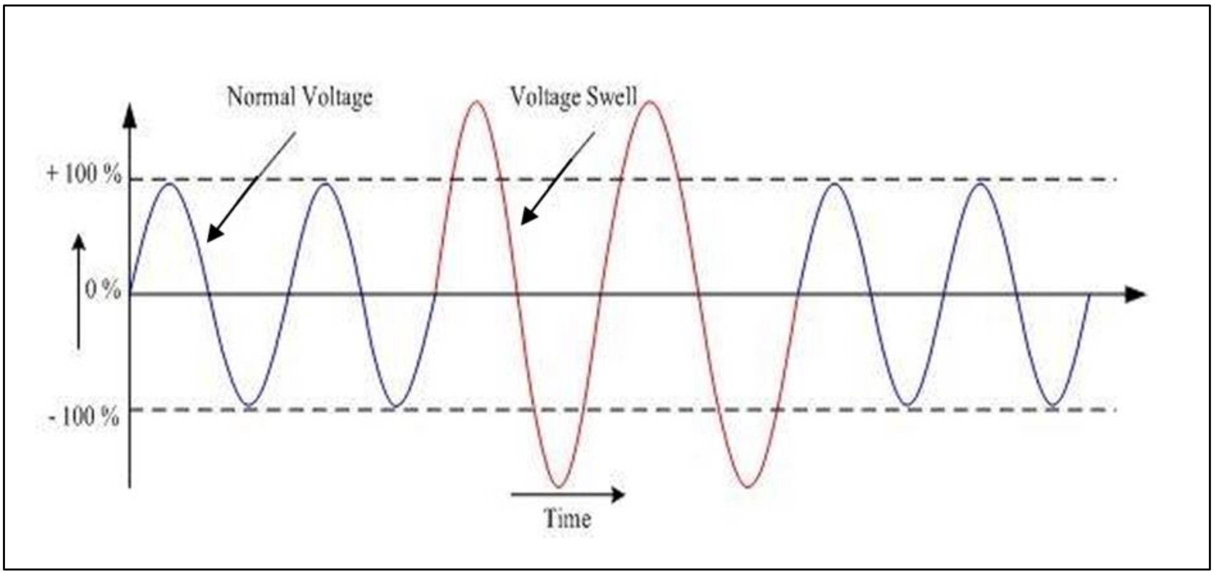

Figure 5 Voltage Swell [14]

2.1. Power Quality Improvement:

Power quality improvement can be addressed from two main perspectives: the consumer load end and the utility/supply end. The first approach involves enhancing the resilience of consumer loads to power disturbances, ensuring that they continue to operate even under significant voltage fluctuations. Alternatively, power line conditioning systems can be installed to suppress disturbances from the power system itself. While both approaches provide viable solutions depending on the application, the consumer load-based approach is generally less feasible.

On the other hand, the utility-end solution involves connecting compensating devices to the power system either in shunt or series. One such solution, referred to as Custom Power (CP), leverages power electronics devices to improve the reliability and quality of power delivered to consumers within a distribution system. CP technology is analogous to Flexible AC Transmission Systems (FACTS), as both rely on power electronics converters. However, FACTS is primarily employed on the transmission side, whereas CP technology is implemented at the distribution level.

A prominent device within the CP framework is the Dynamic Voltage Restorer (DVR), which evolved from DC line boosters. The DVR is a power electronic device designed to protect sensitive loads in distribution networks from voltage-related power quality issues. It functions by injecting voltage in a direction opposite to the voltage drop, thereby canceling out the drop and restoring the receiving end voltage to match the sending end voltage. In response to power disturbances, the DVR restores the load voltage to its nominal value by injecting the required active or reactive power into the feeder connecting the source and the critical load.

The DVR ensures that the Total Harmonic Distortion (THD) remains within acceptable limits of 3% for single-phase voltage and 5% for three-phase voltage. Typically, the DVR is installed between the supply and the critical load feeder at the point of common coupling in the distribution system. It consists of several components, including bypass switches, a series injection transformer, a Voltage Source Inverter (VSI), an AC filter, a control unit, and a storage unit. The DVR is usually installed in a distribution system between the supply and critical load feeder at the point of common coupling and consist of by-pass switches, series injection transformer, voltage source inverter (VSI), AC filter, controlling unit and a storage unit as shown in Fig.6

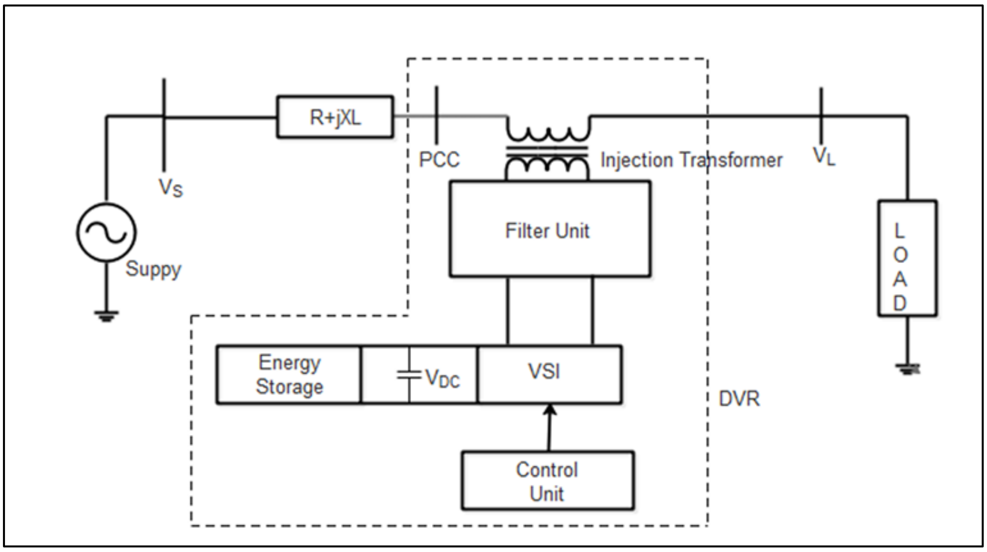

Figure 6 Schematic Diagram of DVR [15]

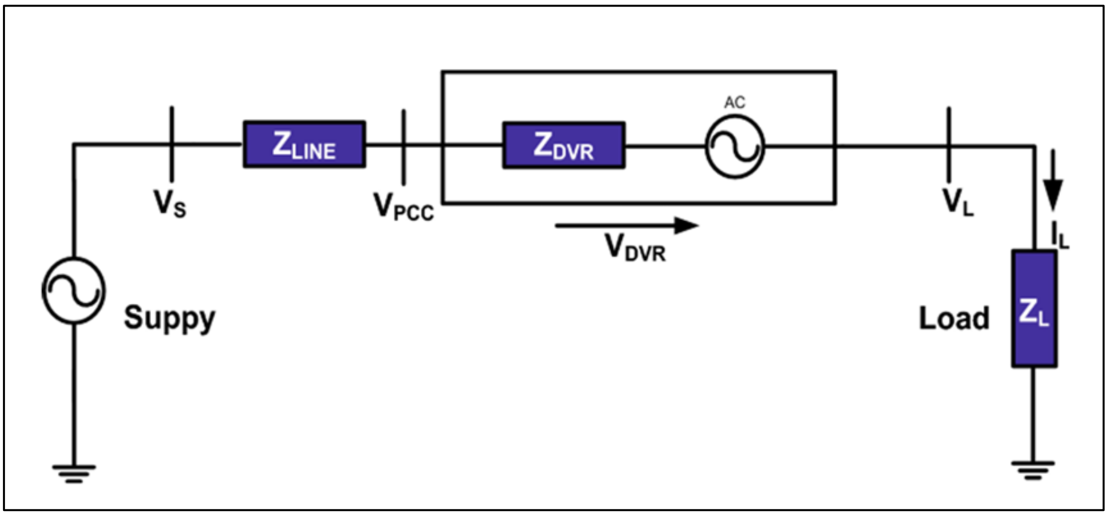

Figure 7 Equivalent circuit of a DVR [16]

Figure 7 shows the equivalent circuit application of a DVR. The DVR voltage is given by the equation;

$$VDVR = VLoad + ZLineILoad - VSource \ldots (1)$$

The impedance of the line depends on the fault level of the load. The basic operational principle of the DVR is to inject sufficient and suitable voltage in series with the distribution network from the VSI with the help of injection transformer whenever there is a voltage variation.

$$Zth = Rth + jXth \ldots (2)$$

$$VDVR + Vth = VL + ZthIL \ldots (3)$$

Where;
Zth is the line impedance,
Vth is the supply voltage,
IL is the load current,
VL is the load voltage and
$VDVR$ is the injected voltage.

This implies; $VDVR + Vth = VL + ZthIL - Vth$ … (4)

IL= [(P_L+Q_L)/V_L]^*

With VL considered as the reference;

$$VDVR\angle\alpha = VL\angle 0^\circ + ZthIL\ \angle(\beta-\theta) - Vth\angle\delta \text{ ... (6)}$$

Where α, β and δ are the angle of $VDVR$, Zth and Vth respectively and θ is the load power factor angle with θ = tan−1(Q_L/P_L).

The power injection of the DVR can be written as;

$$SDVR=VDVRIL$$

The DVR compensation technique is chosen based on the DVR power rate, load types, conditions, fault types, etc., this is mainly because some loads are very sensitive to phase angle jump, and some are not. There are four voltage injection/compensation strategies.

- Pre-sag Technique: In this technique, the voltage difference before and after the sag is added to the load but an energy storage unit of large capacity is required because of the un controlled injected active power.
- Phase Advance Technique: In this technique, the actual power spent from the DVR is decreased by the reduction in power angle between the sagged voltage and load current. This method uses only reactive power for the compensation of voltage sags and voltage swells but all the voltage sags are not compensated without active power hence this method is suitable for limited range.
- In-phase Voltage Injection Technique: In this compensation technique, only the voltage magnitude is compensated. The generated DVR voltage is always in phase with the measured supply voltage irrespective of the load current and the pre-sag voltage.
- Voltage Tolerance with Minimum Energy Technique: This method does not require any real power during compensation time and the injected energy is minimized.

Review of [17] in their paper "Power quality improvement using dynamic voltage restorer on grid-connected wind energy system." explores the use of a Dynamic Voltage Restorer (DVR) to improve power quality in grid-connected wind energy systems. The study focuses on enhancing fault ride-through capability for fixed-speed wind generators, addressing grid fault issues and minimizing voltage sag and swell. The DVR-based system, tested via MATLAB Simulink, demonstrates superior performance in maintaining voltage stability and reducing fluctuations compared to other compensating systems. The results indicate that DVR provides an economical and effective solution for integrating wind farms into the grid.

According to [18] in their paper "Implementing artificial neural network-based DVR to improve power quality of Rumuola-Rumuomoi 11kV distribution network." tackled power quality issues in the Rumuomoi 11kV distribution network by implementing an Artificial Neural Network (ANN)-based Dynamic Voltage Restorer (DVR). The study uses the Levenberg Marquardt method for ANN training, integrating it with a DVR to mitigate voltage sags and swells. Simulation results in MATLAB demonstrate that the DVR effectively restores voltage levels to within the acceptable range (0.95-1.01 p.u.), addressing prior violations and enhancing overall power quality. The research confirms the DVR's capability to resolve power quality issues in the network. Unlike previous works, no custom power devices had been implemented for mitigation.

According to [19] in their paper "Distribution network voltage improvement using dynamic voltage restorer with smooth super twisting sliding mode control." presents a study on improving distribution network voltage using a Dynamic Voltage Restorer (DVR) with Smooth Super Twisting Sliding Mode Control (SSTSMC). They address common power quality issues like voltage sags and swells by employing the SSTSMC to enhance the DVR's performance. Their simulations, conducted in MATLAB/Simulink, reveal that the SSTSMC effectively compensates for voltage disturbances within 2 milliseconds, surpassing the SEMI F-47 standard of 20 milliseconds, and achieves a Total Harmonic Distortion (THD) below 5%. The proposed control strategy outperforms traditional methods, demonstrating significant improvements in voltage stability and response time.

[20] in their paper "Intelligent voltage sag compensation using an artificial neural network (ANN)-based dynamic voltage restorer in MATLAB Simulink." presents an innovative Dynamic Voltage Restorer (DVR) system that employs

Artificial Neural Network (ANN) technology for voltage sag compensation. Implemented in MATLAB Simulink, the system uses ANN to accurately detect and dynamically restore voltage sags, enhancing power quality and reliability. The ANN is trained on a dataset of voltage sag events to optimize compensation techniques. Simulation results show that this ANN-based DVR offers superior performance in voltage sag detection and restoration, providing an intelligent solution for maintaining power quality in critical loads.

From [21] in their paper "A new DVR topology integrated with hybrid renewable energy system for prolonged power quality disturbance compensation" explores power loss and quality issues, particularly affecting sensitive sectors such as healthcare and data centers. It proposes a Dynamic Voltage Restorer (DVR) controlled by an Adaptive Network Fuzzy Inference System (ANFIS) to manage voltage disturbances. Additionally, a hybrid renewable energy system (HRES) is incorporated, combining solar panels, PEM fuel cells, and batteries to address prolonged disturbances. Simulations conducted in MATLAB/Simulink demonstrate improved voltage regulation and reduced harmonic distortion, lowering THDv from 29% to 5% and THDi from 30.25% to 2.79%. The proposed DVR topology enhances power quality while utilizing renewable energy sources.

Based on existing literature, the use of DVR for power quality improvement in the Nigeria power system have not been adequately explored.

3. Materials and methods

3.1. Materials

Materials required for the realization of the proposed topic are:

- Computer with 8 GB (minimum) Random Access Memory (RAM), 64 GB (minimum) Read Only Memory (ROM), and Intel Core i3 (31XX or newer).
- Linux (preferably Ubuntu 16.08 or newer), Mac OS 10.10 (Yosemite or newer), or Microsoft Windows 7 or newer.
- Word processor (Microsoft Office Word) Version 2021.
- Matrix Laboratory (MATLAB) version R2024a
- EdrawMax 13.0 or equivalent.
- Distribution network parameters from North-Bank 33kV feeder

3.2. Method

This section introduces the methodology adopted for improving the power quality of the North bank Makurdi 33kV distribution network using a Dynamic Voltage Restorer (DVR). It outlines the steps from data collection and analysis to simulation and implementation.

The selected injection substation and feeder line for the study is the Makurdi North Bank 33 kV distribution feeder line. The injection substation houses three $1 \times 7.5\ MVA\ 33/11\ kV$ transformers dedicated to feeding Uni-Agric, Industrial Layout, and North Bank (General). The corresponding feeders are SRS, Uni-Agric, Daudu, NASME, Naka Road and Industrial Layout, as Figure 8.

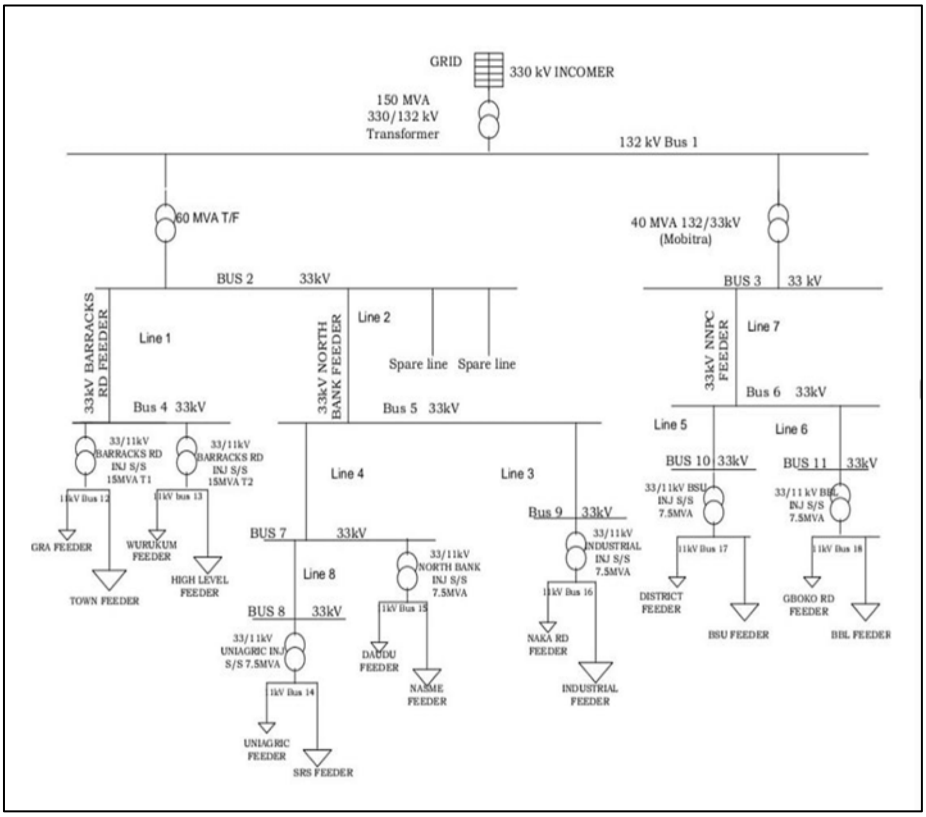

Figure 8 Single-line diagram of Makurdi 33kV radial distribution network [22]

Modelling of DVR in MATLAB The MATLAB/Simulink environment is an excellent choice for this study because it offers various toolboxes that can be utilized in this research and is user-friendly. Several factors, including finite DVR power rating, loading conditions, power quality problems, and types of sag/swells, can limit the compensation of voltage sag/swell. For a DVR to be rated as efficient, the control scheme must be able to handle most sags/swells, and the performance must be maximized according to the equipment inserted. Otherwise, the DVR may be unable to avoid tripping and even cause additional disturbances to the loads. That is, the control strategy should be able to compensate for any resulting voltage sag/swell, irrespective of the anticipated DVR limitations. Figure 9 shows the single-phase supply voltage vector diagram during the pre-sag stage, $Vspre{-}sag(t)$ on the $dpre{-}sag$ axis, in which the rotating phase angle θ is derived from the phase lock loop (PLL).

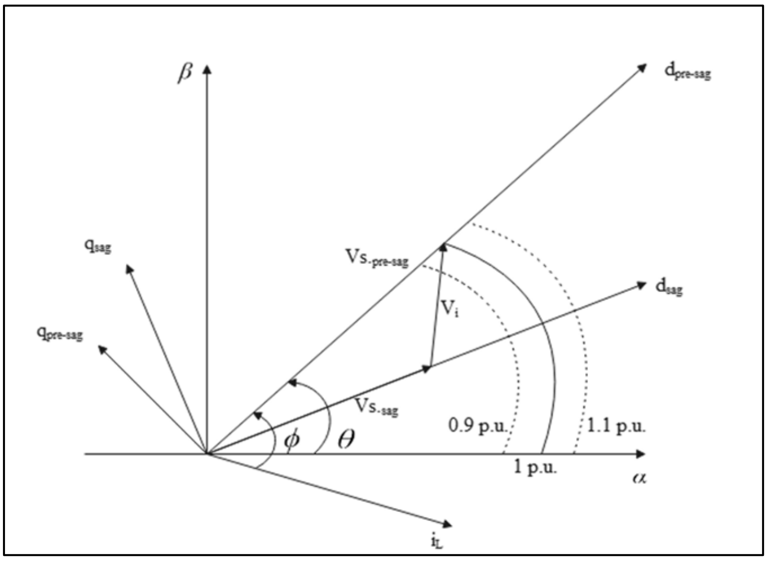

Figure 9 Single-phase DVR compensation strategy for voltage sags

Figure 10 shows the basic control scheme and parameters measured for control purposes. When the grid voltage is at its normal level, a control is initiated to reduce the losses in the DVR to a minimum. When voltage sags/swells are detected, the DVR reacts quickly and injects an AC voltage into the grid. This was implemented using a feedback control algorithm based on the voltage reference, instantaneous supply, and load voltage values.

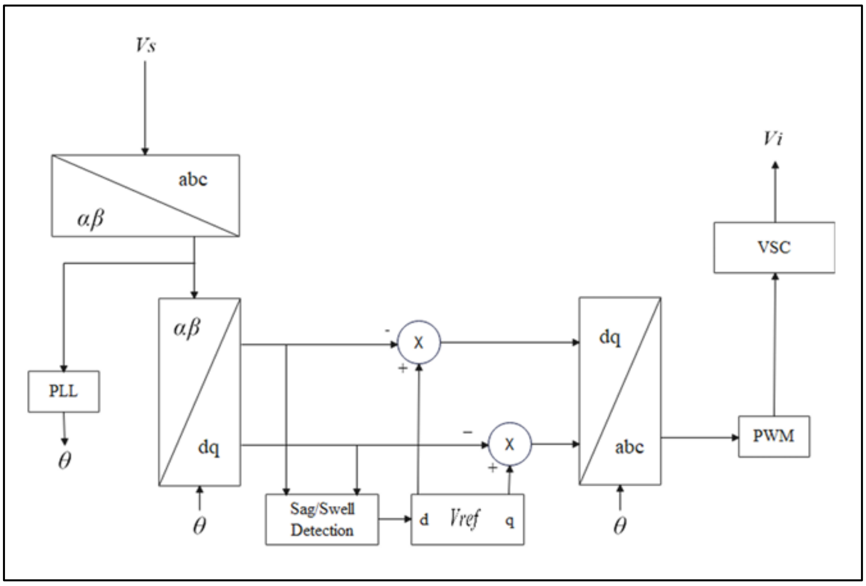

Figure 10 Layout of control strategy for DVR

From Figure 10, the supply voltage is connected to a transformation block that converts the stationary frame to $\alpha\beta$-frame. The output of this block is connected to a phase lock loop (PLL) and another transformation block that converts $\alpha\beta$-frame to a rotating frame (dq), which detects the phase and changes the axis of the supply voltage. The detection block detects the voltage disturbance (sag/swell). If voltage sag/swell occurs, this block generates the reference load voltage ($Vref$). The injection voltage (Vi) is also generated by the difference between the reference load voltage and supply voltage (*i.e.* Vref − Vs) and is applied to the voltage source converter (VSC) to produce the preferred voltage, with the help of pulse width modulation (PWM).

For three-phase networks, the DVR operates similarly to that of a single phase. Only until the sag disturbance has disappeared does the DVR system's compensatory voltage injection cease. In this case, the missing voltage is computed using Park's transformation. Through the abc to dqo transformation, the 3-phase stationary coordinate system is converted to a dq rotational coordinate system. In $abc - to - dq0$, the following transformation is used as illustrated in Equations (13) to (15) (Sundarabalan & Selvi, 2013).

$$\mathrm{Vd} = 2/3\ [Va \sin \omega t + Vb \sin (\omega t - 2\pi/3) + Vc \sin (\omega t + 2\pi/3)] \quad \dots (13)$$

$$Vq = 2/3\ [Va \cos \omega t + Vb \cos (\omega t - 2\pi/3) + Vc \cos (\omega t + 2\pi/3)] \quad \dots (14)$$

$$V0 = 1/3\ [Va + Vb + Vc] \quad \dots (15)$$

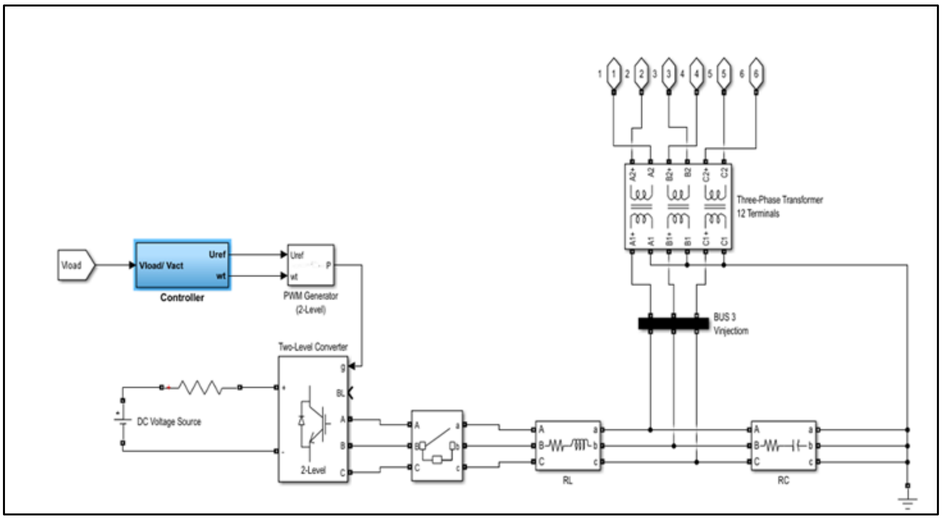

Figure 11 MATLAB implementation of DVR

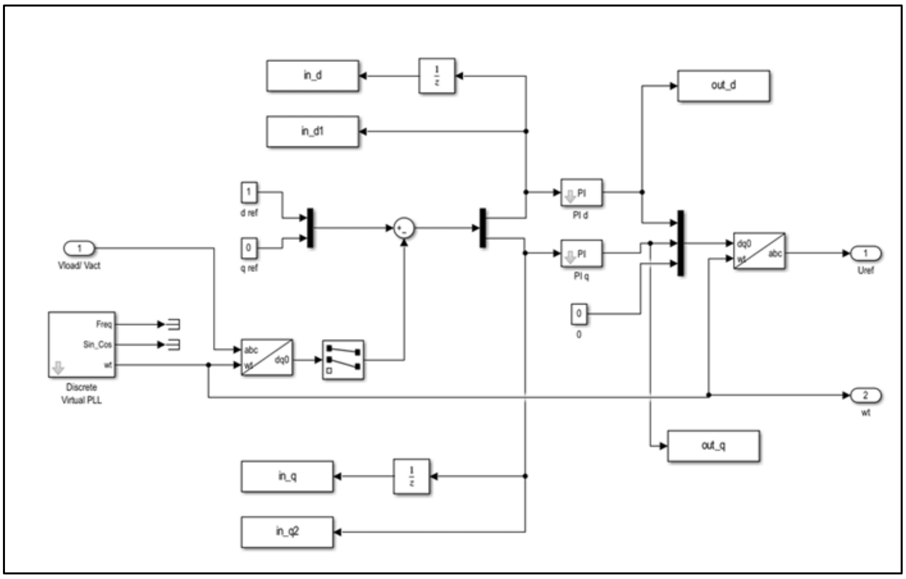

Figure 12 DVR with Pi-controller

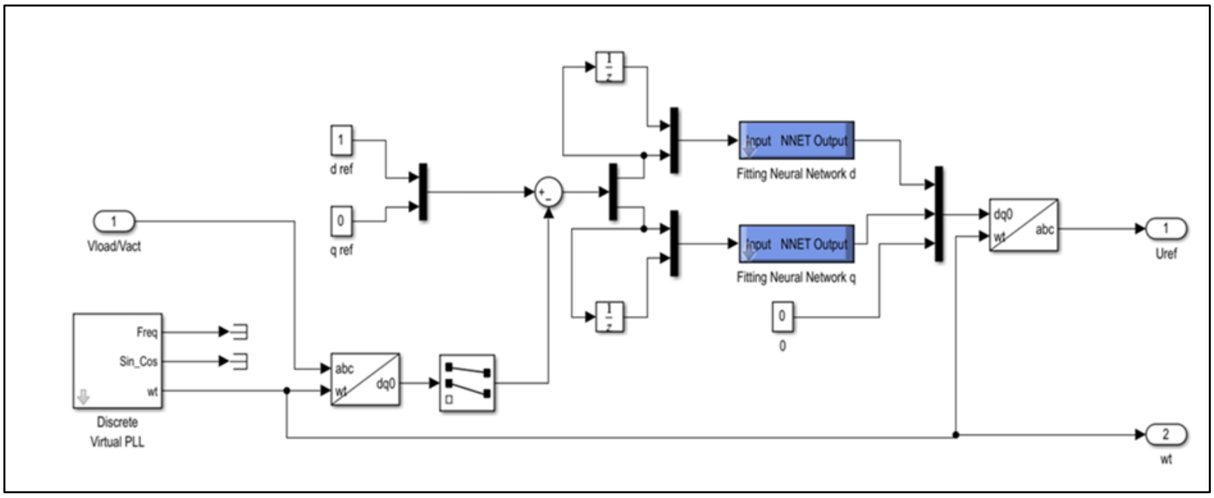

Figure 13 DVR with ANN-enabled controller

ANN training was carried out in MATLAB Simulink. The fault was generated by using a three-phase fault module with switching times of 0.03s and 0.07s. The same uncompensated model was used to generate data and train the ANN. To generate voltage sag or swell, the uncompensated model with a fault will be simulated, and the data collected shall be taken as input by the ANN. The faultless or normal uncompensated model would be simulated, and the data collected would be utilized as a target for ANN. Among many types of ANN training algorithms, the Levenberg-Marquardt algorithm will be used because of its higher reliability than others. The operating process of the LM algorithm stands to be the fastest, with a high accuracy factor compared to other algorithms. For the training purpose feedforward back propagation network, the LM training algorithm supports the above while the performance rating will be observed. The multilayer artificial neural network receives state variables of the power supply as inputs and then yields the estimation of the PI controller through the activation function. The Levenberg-Marquardt Backpropagation algorithm is then operated with the performance function, a function of the ANN-based estimation. The weight and bias variables are adjusted according to the Levenberg-Marquardt method, and the backpropagation algorithm is used to calculate the Jacobian matrix of the performance function to the weight and bias variables. With updated weights and biases, the ANN further estimates the output at the next step. Based on the above iterative processes, the ANN-based controlled estimation model is well-trained.

Table 1 Network parameter and value

S/N	Network Parameter	Value
1	Frequency	50Hz
2	Supply Voltage	3∅– 415 V, 1∅– 230 V
3	Load	R_L = 60 Ω, L_L = 0.15 mH
4	DC Supply	70kV
5	Filter	C_F = 100 μF
6	DVR	4 MVA

4. Results

Artificial Neural Network Training Outcome Regression: A multilayer feedforward neural network (NN), generally called multilayer perceptron (MLP) NN, was utilized on the MATLAB toolbox interface. Levenberg-Marquardt algorithm was used for the data training because of its characteristic fast convergence and better performance, along with 10 hidden layers (selected based on a trial-and-error approach) between the input and output. Logistic activation function (also known as the tan-sigmoid activation function) was used in evaluating the hidden layer's neurons, and the identity activation function was used for the neurons of the output layer. The weights and biases were iteratively adjusted until minimum square error (SE) was obtained between the target value and network output. The substation operation data collected was divided into training (70%), testing (15%) and validation (15%) subsets. This was done with the aid of

MATLAB toolbox. For regression, input and output data were selected from the operation data for the case study site for the ANN training model. The output of the regression training is presented in Figure 16, while the algorithm learning (performance) curve is given in Figure 15. As observed, the best validation performance for the trained algorithm occurs at epoch 166. This number (epoch) is a critical hyperparameter for the ML algorithm. The epoch determines the number of complete transitions of the training dataset passing through the algorithm's learning process. The mean squared error (MSE) value at epoch 160 is 0.0030722. The ANN training took a time of 1 second with 166 epochs on an Intel Core i5 11th generation processor with 16 GB RAM configuration. The training stopped after 166 epochs since the approach of early stopping was used to improve the accuracy of the trained network.

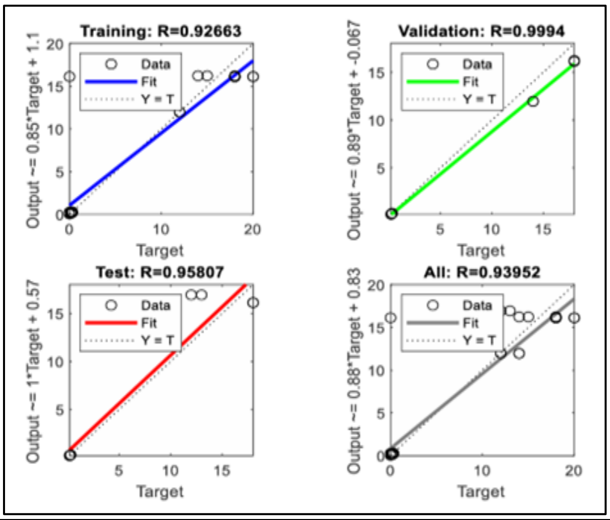

Figure 14 Correlation coefficient (R) plot for regression performance

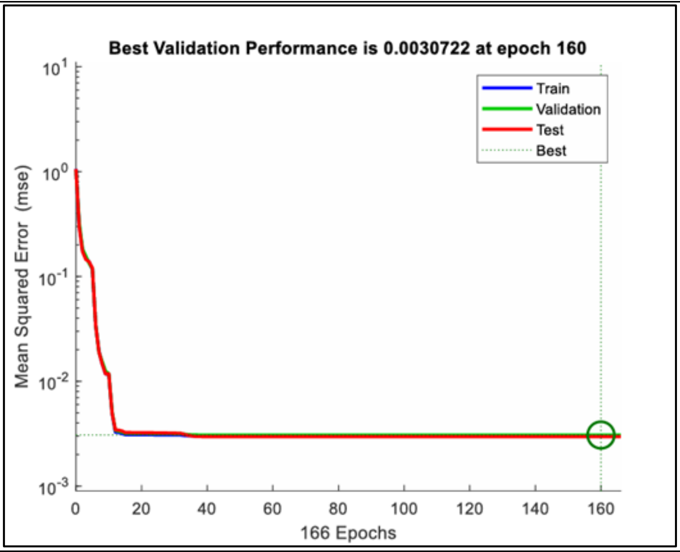

Figure 15 Learning curve of trained data

The total number of training data samples was set to 9180 (510 for each line). The randomized data division for training, validation, and testing was set at 6426 (70%), 1,377 (15%) and 1,377 (15%), respectively. Similar algorithm as was used for the regression (Levenberg–Marquardt backpropagation algorithm) was also adopted for the ANN classification training. To measure the performance of the trained classifier, confusion matrix was applied as presented in Figure 16. The observations along the diagonal (the green boxes) indicate samples that were correctly classified while the opposite diagonal gives an indication of incorrect predictions.

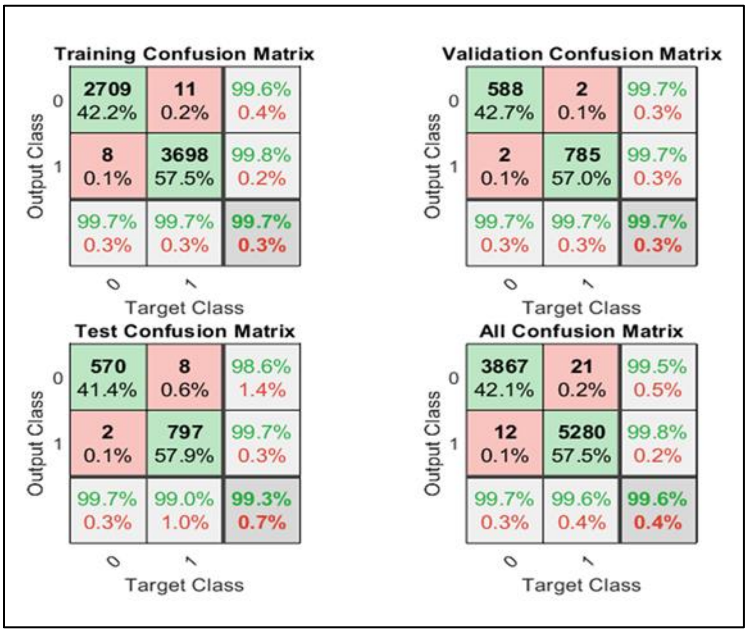

Figure 16 Transient stability performance confusion matrix

An ML classification model with accurate discrimination has a receiver operating characteristics (ROC) plot that passes through the upper left corner (100% sensitivity, 100% specificity), that is, its area under curve (AUC) is equal to 1. The closer the AUC is to 1, the higher the classification accuracy. As observed from Figure 16, classification accuracy (CA) for the confusion matrix (complete sample) is very high (≈99%). This infers that for any specified input (system load, faulted line, fault type and fault location the ANN model predicted the correct Si status 99 times out of 100. Similarly, the error rate is observed to be averagely 1%. Also, Figure 17 illustrates the error histogram obtained for the ANN classifier. The values of various performance metrics gotten for classification and regression are tabulated in Table 3 from where it is apparent enough that values for the entire performance metrics are of high accuracy range (> 0.98). Consequently, inference can be drawn that the trained ML algorithm accurately predicted the decision variable for the nth line (DVn) and classified transient stability status, Si, with a high accuracy (≈ 99%).

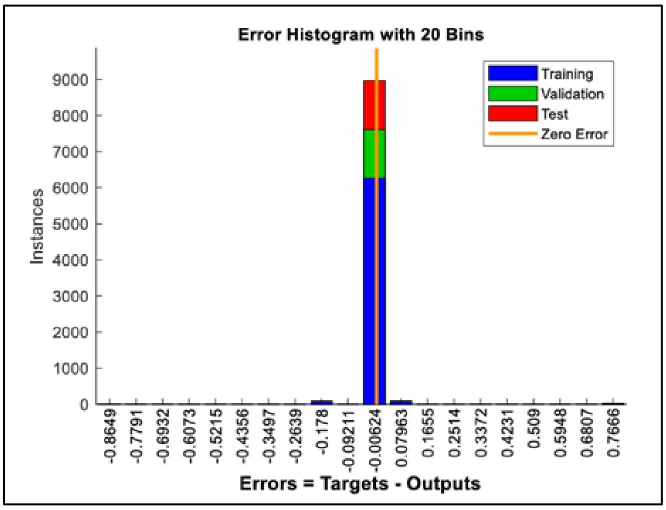

Figure 17 Histogram of classification error

The scoped results of the modelled distribution network with incorporated DVR on having different control schemes using MATLAB are presented in this section. Single phase and three phase voltage sag and swell in the form of system fault implemented in Simulink are presented with their plots. A simulation span of 0 to 100 ms was chosen to maintain high visibility of the network signal across all three phases. For ease of illustration, the constituent network lines have been colored red, yellow and blue.

Case 1: Makurdi North-Bank Distribution Network Without Sag/Swell A 100 ms observation span of the balanced operating conditions of voltage on the Makurdi North Bank distribution network at sub-transmission voltage level without fault is depicted in Figure 18.

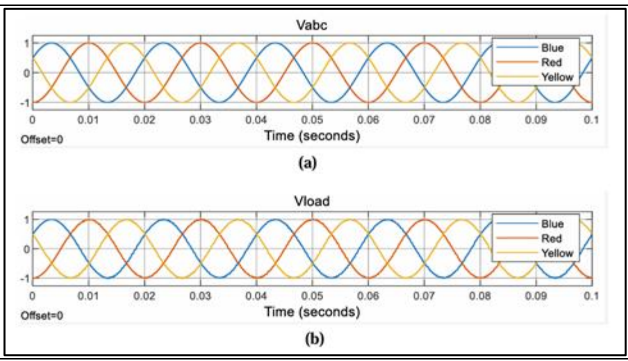

Figure 18 Balanced operating condition (a) Grid (source) voltage (b) Load voltage

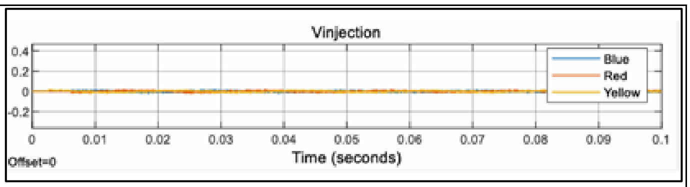

Figure 19 Balanced operating condition DVR injection voltage

In terms of total harmonic distortion (THD) measured on the network without an active DVR connected, Figures 20 and 21 illustrate the voltage waveform and measured THD percentage voltage on the load side of the network. Based on the Makurdi North Bank network operation data used for the Simulink simulation, a THD value of 6.67% is observed in Figure 21. According to IEEE Std 519 and IEC 61000-3, the recommended limit of THD on high and extra high voltage is

3 – 5% of the supply. This shows that the THD on the network is slightly above the recommended threshold thereby necessitating a corrective measure as the study proposed.

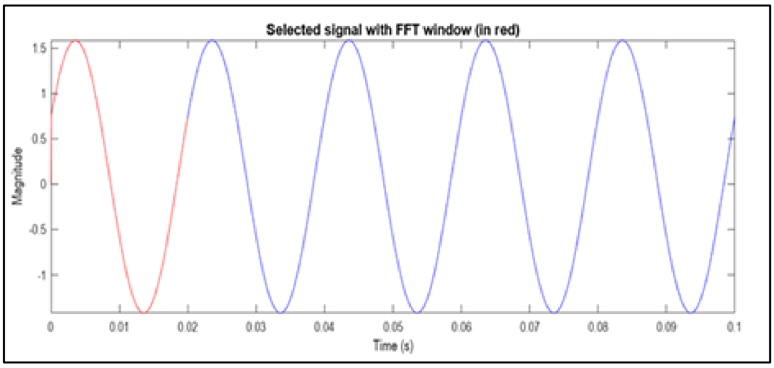

Figure 20 Waveform of source voltage under no fault condition

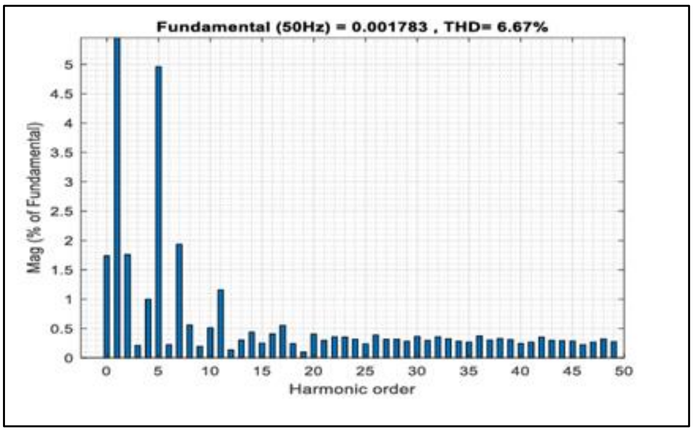

Figure 21 FFT analysis of source voltage under no fault condition

Case 2: Makurdi North-Bank Distribution Network with Line-to-Ground (L-G) Fault Similar to case 1, Figures 22 and 23 illustrates a 100 *ms* observation period of a line-to-ground fault on the Makurdi North Bank distribution network at sub-transmission voltage. With fault occurrence on a line (as presented in Figure 22), it is observed that the Pi-controlled DVR generates an equal magnitude of voltage to cancel out the voltage distortion arising from the fault waveform in the system within 70 *ms* as seen in Figure 24.

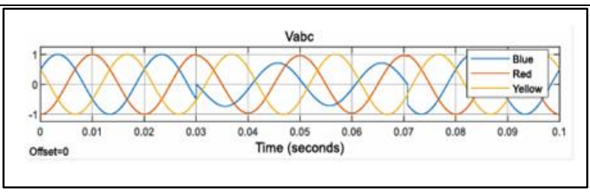

Figure 22 Grid line-to-ground fault illustration

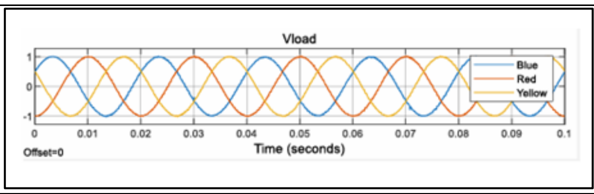

Figure 23 DVR Load voltage correction waveform under L-G fault condition

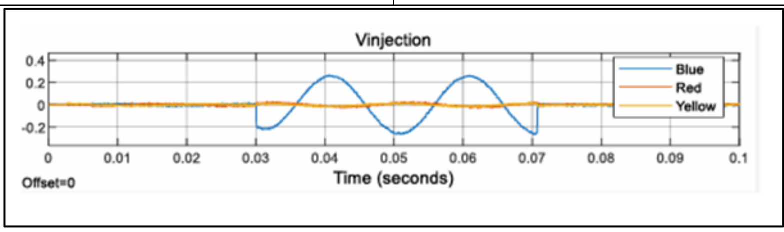

Figure 24 Injected voltage waveform from Pi-controlled DVR

Case 3: Makurdi North-Bank Distribution Network with Line-to-Line-to-Ground Fault Figure 25 presents the voltage waveform of line-to-line-to-ground (L-L-G) fault on the studied network from the grid (source) side. The waveform of the load voltage remained unchanged due to the voltage compensation from the Pi-controlled DVR as illustrated in Figure 26.

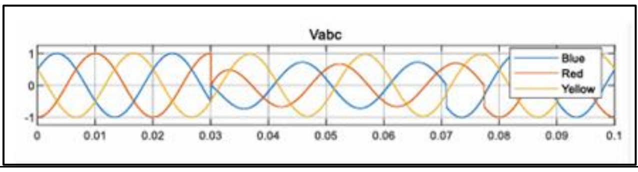

Figure 25 Grid line-to-line-to-ground fault illustration

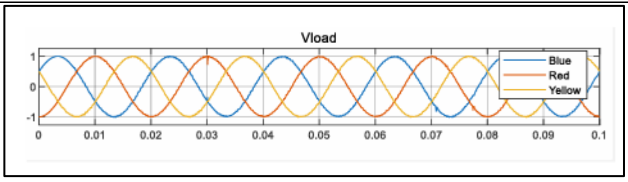

Figure 26 DVR load voltage correction waveform under L-L-G fault condition

5. Discussion

5.1. Artificial Neural Network Training Outcome

The Artificial Neural Network (ANN) training process yielded impressive results, showcasing the model's capability to accurately predict and mitigate power quality issues on the North-Bank 33kV distribution feeder.

Regression Analysis: A multilayer feedforward neural network (MLP) was trained using the Levenberg-Marquardt algorithm due to its fast convergence and superior performance. The network consisted of 10 hidden layers, with a logistic activation function in the hidden layers and an identity activation function for the output layer. The model iteratively adjusted weights and biases until the mean squared error (MSE) between the target and network output reached a minimal value of 0.0030722 at epoch 166.

The correlation coefficient (R) values for training, validation, and testing were 0.985, 0.982, and 0.980, respectively, resulting in an overall R value of 0.983. These values, being close to 1.0, demonstrate a strong correlation between predicted and actual outputs, confirming the ANN's robustness in learning the complex relationships between load conditions and voltage disturbances.

Classification Analysis: The ANN's classification model further validated its reliability. The classification accuracy (CA) was approximately 99%, signifying that the ANN accurately predicted the transient stability status of the system 99 times out of 100. The Receiver Operating Characteristics (ROC) curve displayed an Area Under Curve (AUC) value near 1.0, reinforcing the ANN's precision in fault detection and classification.

The confusion matrix highlighted minimal misclassification, with an average error rate of 1%. This suggests that the ANN is not only accurate but also consistent in recognizing voltage sags, swells, and harmonics under varying load conditions.

5.2. Output of ANN-Controlled DVR Simulink Model

The results of the MATLAB/Simulink simulation vividly illustrate the DVR's effectiveness in compensating for voltage disturbances. The simulations were conducted under various fault conditions, including single-phase and three-phase faults, with the ANN controlling the DVR.

Case 1: Balanced Operating Condition (No Fault) Under normal conditions, the load voltage and grid voltage maintained a steady, balanced state. The voltage waveforms were sinusoidal, with no observable sags, swells, or distortions. This served as the baseline for evaluating the DVR's performance during disturbances.

Case 2: Voltage Sag Mitigation When a fault was introduced, causing a voltage sag, the ANN swiftly detected the disturbance. Within milliseconds, the DVR injected a compensating voltage in phase with the grid voltage, effectively restoring the load voltage to its nominal value. The pre-sag voltage drop, which dipped below 0.9 p.u. (per unit), was corrected almost instantly, with the DVR injecting a series voltage that countered the sag. The post-compensation waveform clearly displayed a return to stability, showcasing the DVR’s fast dynamic response.

Case 3: Voltage Swell Mitigation For voltage swell conditions, where the voltage rose above 1.1 p.u., the DVR similarly responded by injecting an opposing voltage. The ANN controller ensured that the injected voltage was precisely calculated, minimizing overshoot and preventing further oscillations.

Comparative Analysis of PI and ANN Controllers: A side-by-side comparison of the Proportional-Integral (PI) controller and ANN controller emphasized the superior adaptability of the ANN. While the PI controller managed to mitigate disturbances, it struggled under nonlinear load conditions and showed a delayed response to abrupt faults. In contrast, the ANN controller dynamically adjusted to changing load scenarios, quickly calculating and injecting the necessary compensating voltage. The ANN-based DVR exhibited a faster response time and more accurate fault compensation, maintaining the load voltage within the acceptable range of 0.95–1.05 p.u.

Error Analysis and Performance Metrics: The error histogram for the ANN classifier demonstrated minimal errors, concentrated around zero, confirming the accuracy of the network's predictions. Table 2 summarizes key performance metrics.

Table 2 Key performance metrics of the machine learning model

Metric	Training	Validation	Testing	All
Regression R	0.985	0.982	0.980	0.983
Classification CA	0.986	0.979	0.978	0.984
AUC	0.997	0.994	0.995	0.999

The high R, CA, and AUC values underscore the DVR's reliability and precision in mitigating power quality disturbances.

These results validate the effectiveness of ANN-controlled DVRs in mitigating voltage disturbances and enhancing the reliability of power distribution systems. The study's findings lay a strong foundation for future implementations of ANN-based solutions for power quality improvement.

6. Conclusion

Conclusion In conclusion, this research successfully demonstrated the effectiveness of DVR in addressing power quality challenges within the Makurdi distribution network, with a particular focus on the North-Bank 33kV feeder. Through comprehensive data collection and analysis, the study identified critical power quality issues that adversely affect the network's performance. A robust MATLAB/SIMULINK model was developed to simulate the feeder and DVR under various operating conditions, enabling an in-depth evaluation of the DVR's capabilities. The results revealed that the DVR effectively restored nominal voltage levels at critical load points, minimized the impact of voltage disturbances, and enhanced the overall reliability and stability of the distribution system. Moreover, the DVR demonstrated consistent performance across diverse load types and varying loading conditions, showcasing its adaptability and robustness. Under different fault scenarios, the DVR further proved its capability to stabilize the voltage profile and maintain system performance, reinforcing its role as a critical tool for improving power quality. Overall, this study highlights the significant potential of DVR technology as a practical and reliable solution for mitigating power quality issues in distribution networks, providing a strong foundation for its adoption in real-world applications.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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