IMPLEMENTING ARTIFICIAL NEURAL NETWORK BASED DVR TO IMPROVE POWER QUALITY OF RUMUOLA-RUMUOMOI 11kV DISTRIBUTION NETWORK

Kingsley Okpara Uwho, Hachimenum Nyebuchi Amadi and Okechi Chikezie

Department of Electrical Engineering, Rivers State University, Port-Harcourt, Nigeria

Email: (kingsley.uwho@ust.edu.ng**)**

ABSTRACT

The most vexing problem plaguing Rumuomoi's 11kV distribution network is voltage sag and swell, which degrades power quality. There has been no effective mitigation control implemented. The purpose of this research is to address the issue of power quality by implementing artificial neural network (ANN) control with an embedded dynamic voltage restorer (DVR). To begin, the artificial neural network is trained using the input and desired data obtained during simulation using a proportional integral (PI) controller. To limit the amount of data obtained during training, the Levenberg-Marquardt feed forward back method is utilized, and the result for each iteration is determined in Matlab software. The desired dynamic voltage restorer system was tested using a replicated model of Rumuomoi 11kV and it was determined that Bus 7 is 0.938p.u, Bus 8 is 0.9244p.u, Bus 9 is 0.9148p.u, Bus 10 is 0.9035p.u, Bus 11 is 0.8912p.u, and Bus 12 is 0.8811p.u, all of which exceeded the statutory limit condition of 0.95-1.01p.u. There were no bus voltage violations after network optimization with DVR, demonstrating that DVR is effective at enhancing power quality by removing voltage sag and swell in the distribution network.

Key Words – Implementing, Artificial Neural Network, Dynamic Voltage Restorer, Distribution, Network, Rumuola

I. Introduction

Before now, the quality of power delivered to consumers was not Paramount in the minds of utility companies rather, the interest was on delivering power with no interruptions but as technology advances, sensitive loads are produced which disturbs voltage stability and also, the knowledge of end users of electricity has increased therefore, researchers and power system engineers are now focusing on how to improve the quality of power delivered to consumers.

Power quality (PQ) is seen as a group of electrical limits within which a piece of equipment can performed as expected without great loss of performance or life expectancy[1].Electrical energy among the various types of energy has a significant impact on how a society operates. As a result, it is critical for a government to provide among other things, quality power to meet the growing demands of its citizens [2]. It involves supplying electric power with negligible distortions and thus, maintaining a near sinusoidal signal waveform at a frequency of 50Hz and at required load voltage. Voltage, current, and frequency are all indicators of poor power quality [3]. Among the many types of distortion are voltage swell and sag, voltage fluctuation, and harmonic distortions. Along with power system breakdowns, heavy machinery start-stop operations, and switch operations, nonlinear loads are regarded to be the primary source of power quality concerns [4]. Power quality issues exist in various countries' distribution systems around the world, including Nigeria, Libya, India, and some developed countries, and are considered a global issue. Concerns about power quality can have a wide range of consequences, ranging from equipment failure to complete equipment breakdown. The imperative to mitigate power quality issues and generate high-quality electricity has propelled power system engineers, equipment makers, researchers, and legal organizations to the forefront of methodological progress. There are several approaches to improve power quality today in order to accommodate the distribution network's ever-increasing applications of sensitive and non-linear loads. Historically, synchronous capacitors, capacitor banks, static reactive power compensators (SVCs), and auto-switched reactive power compensators have been used to control reactive power and improve power factor, albeit with drawbacks such as instability, high transient generation during on/off switching, and so on [5]. Recently, custom electrical devices such as distributed static compensators (DSTATCOM), unified power quality conditioners (UPQCs), and dynamic voltage restorers (DVRs) have been investigated as more effective methods of improving power quality; however, their performance is dependent on the type of controller used. Proportional integrals (PI), proportional integral differentiators (PID), and similar functions are useful but have a long response time and perform badly when parameter values vary. Researchers use Artificial Mind controls (Al) such as the Artificial Neural Network (ANN), ambiguous logic (FL), and others [6] because they provide superior performance in terms of response time and operation under variable loads.

1.1 Problem Statement

The numerous power saving components and heavy equipment in everyday applications has brought in supply quality challenges in power system.

These issues, such as voltage sag, voltage swell, and harmonics, adversely influence the performance of sensitive loads used in the process and automation sectors, as well as in homes and offices, resulting in financial losses. Undervoltage and overvoltage are significant power quality issues in the Rumumoi distribution system network [7].

Objectives of the Study

The objectives of the research are :

i. To simulate 11kV distribution network of Rumuola Rumuomoi network using Matlab software
ii. To improve the power quality of Rumuola Rumuomoi 11kV distribution network using ANN based DVR

II. Literature Review

2.1. Extent of Past Works

The use of precise components has brought about the demand for good energy quality. As such, the quality of power supply needs to be measured and monitored.

The analysis of energy quality involves data acquisition by measuring instruments, manual or automatic data analysis, and interpretation into useful information. The ultimate goal of power quality measurement and monitoring is to improve quality power supply. [8] discussed various issues relating to power quality monitoring including detailed application of Al technique. Several instrument which include harmonic analyzers, disturbance analyzers, energy monitors, wiring and grounding test devices and oscilloscopes are used for measuring and monitoring quality of power supply. The sensitivity of today's sophisticated equipment has significantly magnified the effects of power quality problems. Some associated effects are failure or malfunctioning of equipment, loss of data, data processing errors, over heating in motors, flickering of lighting and screens etc. [4]. Circuit breakers tripping, equipment malfunctioning and failing, cable and transformer heating are all common occurrences in distribution networks. There are several typical side effects [3, including data recording issues, metering issues, and insulation failures]. In more severe circumstances, power quality disturbances can cause damage to any type of equipment [9], including computers. According to a study conducted by [10], the quality of Nigeria's electricity supply is less than 10% of the time. It was mentioned that evaluating the quality of power in Nigeria is challenging because data is nearly completely lacking in the country. [11] claimed that, with the deregulation in the electricity industry and promotion of energy saving devices, there is need to address power quality problems in the distribution systems.[12] noted that in Libya, one of the fastest growing North African countries also experiences power quality problems. It was revealed that measurements taken at various points on the Misurata city in Libya shows the occurrence of voltage sag, swell, fluctuation harmonic distortions in the distribution network. [13] noted that power quality is greatly considered in some developed countries, where great investments are made in renewable energy resources for power supply improvement. However, it was further revealed that the installation of small scale photovoltaic and wind power sources in the lower level distribution grid, give birth to power quality challenges such as overvoltage, frequency deviation, harmonics, voltage dip, and voltage unbalance in the distribution system.

2.2. Solutions of Quality Power Challenges

According to [14] solution of quality power challenges can be achieved by good design of equipment (electrical and electronic) and electrical systems, determination of power quality causes and analysis of symptoms, identification of the medium transmitting electrical disturbance, and use of power conditioning equipment

[5] in their presentation noted that compensating devices such as synchronous condensers, static VAR compensator, motor generator, resonance transformers, tap changing transformers, line voltage compensators, shunt capacitors, surge arresters, passive filters etc. are used to solve power quality problems. However, these devices are characterized by many disadvantages which includes instability, harmonics or transient generation etc. It was further reviewed that to achieve better power quality improvement, filtering techniques such as passive filters and hybrid filters should be considered.

2.3. Custom Devices Controllers for Power Quality Improvement

Several researchers have work on the use of custom devices to mitigate power quality problems.

[15] in a study on the design and simulation of DSTATCOM in Matlab Simulink, modeled a DSTATCOM with PI controller. The model was investigated under fault conditions such as single, and double line to ground, and three phase faults with static non-linear loads. Result of the analysis shows a satisfactory performance of DSTATCOM in distribution network. In the same vein, [16] presented a study on DSTATCOM in controlling reactive compensation and maintaining load voltage level using PI controller. Though excellent result was recorded. However, it was further recommended for the use of multilevel converters with dynamic loads. More recently [17] looked at the importance of custom gadgets in solving power efficiency problems in Nigeria distribution network stating that devices such as DVR, DSTATCOM and UPQC have been widely used in distribution network of developed countries. [18] in their presentation used park's transformation strategy to study the effect of harmonics and under voltage (voltage sag) compensation using DVR. It was revealed that the UPQC compensated for voltage sag and current imbalance. It was further recommended for other power quality problems.

2.4. Artificial Neural Network (ANN)

The creation of ANN is hinged on a set of connected parts known as artificial neurons, used to model the neurons found in a brain.

Every connection, much like the actual human brain, can pass signals to other neurons in the human brain. Then when a signal is received by a neuron, the signal is processed and the neurons connected to it are alerted. The connections are referred to as edges. The connections, call edges and the Neurons have a weight that tries to adjust itself as learning process goes on. The weight can increase or even decrease the signal strength of a joint. It is normal for neuronal activity to be restricted to a specific level, which is commonly referred to as a threshold, and for signal transmission to occur only when the total signal surpasses that level or threshold. Normally, neurons are arranged in layers of differing thicknesses. Different layers can make different adjustments to the inputs that are related to each other. Signals go from the input layer, which happens to be layer number one, to the output layer, after passing through layers a number of times[19].

2.4.1 Types of Artificial Neural Network

Artificial neural networks have been integrated into a diverse range of technologies, advancing the state of the art in a variety of disciplines. There are several types:

i. Static type: A static type is one of the simplest kinds. It consists of one or more static components. This static component consists of the number of layers, the number of units, the unit weight, and the topology.

ii. Type that is dynamic. Dynamic types allow for the evolution of one or more of them through learning. While dynamic types are extremely sophisticated, they can significantly reduce learning times while still producing intriguing results. Certain types may require training to work independently of the person operating them, while others run totally autonomously. Certain neural networks are totally hardware-based, whilst others are entirely software-based and run on general-purpose computers [20].

2.5. Neural Network Training

According to [21], neural networks may be trained to learn.

The training is performed on the inputs and is anticipated to create a result termed the output, building a probability-weighted association between the input and output that is stored in the network's data structure. When training a neural network for a given goal, the training is typically accomplished by determining the difference between the network's processed output, referred to as a prediction, and the targeted output. The disparity between the intended and processed output is referred to as the error. The network's purpose is to alter its own weighted associations in accordance with a set of learning rules. With repeated changes, the neural network's output will become progressively similar to the targeted output. The objective of training is to ensure that the output that is expected is desirable. Then, after making a fair amount of revisions, the training can be terminated based on specified criteria. This is referred to as supervised learning.

2.6. Artificial Neural Network Design

Neural architecture search utilizes machine learning to automate the creation of artificial neural networks. Experts have a variety of ways while examining neural architecture search.

The approaches incorporate networks that enable them to be compared to other systems. A search algorithm, referred to as the basic search algorithm (BSA), must present a candidate model, evaluate it against a collection of data, and then use the assessment results as feedback to teach the neural architecture search network [22]. [23] discussed design issues associated with the creation of artificial neural networks. The issues involve determining the following:

i. the number of network layers
ii. the type of network layerk
iii. the connection of network layers
iv. the size of the network layers
v. the learning rate
vi. the depth
vii. the stride.

III. **Materials and Method**

3.1 **Materials Used**

The materials employed in this research work are :

i. Single line diagram of Rumuola Rumuomoi 11kV distribution network
ii. Load data of Rumuola Rumuomoi 11kV distribution network
iii. Line data of Rumuola Rumuomoi 11kV distribution network

3.2 Method

The artificial neural network (ANN) based DVR is trained in Matlab/Simulink software using data obtained by modifying the existing dynamic voltage restorer (DVR) proportional integrator (PI) controller.

The distribution network of Rumuola injection station is modeled and simulated in Matlab 2018 application software.

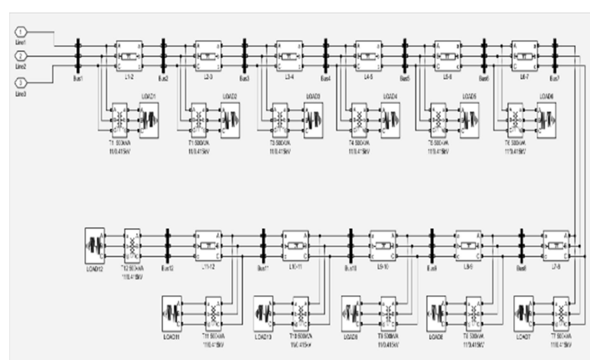

Figure 3.1 : Matlab Simulink Block of Rumuomoi 11kV Network

Figure 3.1 shows the single line diagram of the radiating 11kV distribution network of Rumuomoi feeder consisting of twelve (12) transformers modeled in MATLAB software environment. Table

3.1 and 3.2 shows the load and line data of Rumuomoi 11kV distribution network respectively.

Table 3.1 Load Data (Source: Port Harcourt Electricity Distribution Company PHEDC)

Distribution Substation				I_R	I_Y	I_B	I_N
Bus No	**Bus Name**	**KVA**	**kV**	**(A)**	**(A)**	**(A)**	**(A)**
1	Ohiamini Road	500	11/0.415	270	240	200	80
2	Location Road	500	11/0.415	200	190	210	90
3	Ideogu Estate	500	11/0.415	265	356	314	128
4	Omunakwa Road	300	11/0.415	419	380	400	102
5	Okabie Road	300	11/0.415	420	386	412	150
6	Amadi Road 1	300	11/0.415	460	420	440	60
7	Amadi Road 2	500	11/0.415	332	330	330	80
8	Bakery Road	500	11/0.415	300	380	375	85
9	Silicon Valley Ltd	500	11/0.415	295	385	365	75
10	PHWC	500	11/0.415	310	374	370	82
11	Super Geometrics	300	11/0.415	326	380	375	70
12	Ichiegbo Road	500	11/0.415	358	385	365	96

Table 3.2: Line Data (Source: Port Harcourt Electricity Distribution Company PHEDC)

Line ID	From Bus	To Bus	Impedance (Z)
1-2	Ohiamini Road	Location Road	0.015+j0.057
2-3	Location Road	Ideogu Estate	0.037+j0.049
3-4	Ideogu Estate	Omunakwa Road	0.026+j0.028
4-5	Omunakwa Road	Okabie Road	0.049+j0.041
5-6	Okabie Road	Amadi Road 1	0.083+j0.025
6-7	Amadi Road 1	Amadi Road 2	0.040+j0.011
7-8	Amadi Road 2	Bakery Road	0.058+j0.030
8-9	Bakery Road	Silicon Valley Ltd	0.027+j0.059
9-10	Silicon Valley Ltd	PHWC	0.042+j0.013
10-11	PHWC	Super Geometrics	0.055+j0.047
11-12	Super Geometrics	Ichiegbo Road	0.088+j0.060

3.3 Load Determination

3.3.1 Total Load Current (IL)

The average load current (I_L) of the distribution transformer is giving by

$$I_L = \frac{I_R+I_Y+I_B+I_N}{3} \tag{3.1}$$

Where
I_R is current in the red phase
I_Y is current in yellow phase
I_B is current in the blue phase
I_N is current in neutral

3.3.2 *Apparent Power (KVA)*
The load apparent is giving by
$$KVA_{Load} = \sqrt{3} * I_L * V_s \tag{3.2}$$
Where
I_L is average load current
Vs is the secondary voltage of the transformer

3.3.3 *Real Power (kW)q*
The load real power is giving by
$$kW_{Load} = PF * KVA_{Load} \tag{3.3}$$
Where
PF is the power factor: 0.85
KVA_{Load} is the load apparent power
3.3.4 *Reactive Power (Kvar)*
The load reactive power is giving by
$$Kvar_{Load} = \sqrt{(KVA_{Load})^2 - (kW_{Load})^2} \tag{3.4}$$
Where
KW_{Load} is the load real power

KVA_{Load} is the load apparent power

Table 3.3 Calculated Static Load Data

Distribution Substation		I_L	S	P	Q
Bus No	**Bus Name**	**(A)**	**(KVA)**	**kW**	**kVar**
1	Ohiamini Road	263.33	189.28	160.89	99.71
2	Location Road	230.00	165.32	140.53	87.09
3	Ideogu Estate	354.33	254.70	216.49	134.17
4	Omunakwa Road	433.67	311.72	264.96	164.21
5	Okabie Road	456.00	327.77	278.61	172.67
6	Amadi Road 1	460.00	330.65	281.05	174.18
7	Amadi Road 2	357.33	256.85	218.32	135.30
8	Bakery Road	380.00	273.14	232.17	143.89
9	Silicon Valley Ltd	373.33	268.35	228.10	141.36
10	PHWC	378.67	272.19	231.36	143.38
11	Super Geometrics	383.67	275.78	234.41	145.28

12	Ichiegbo Road	401.33	288.48	245.21	151.97

3.4 Description of Dynamic Voltage Restorer (DVR)

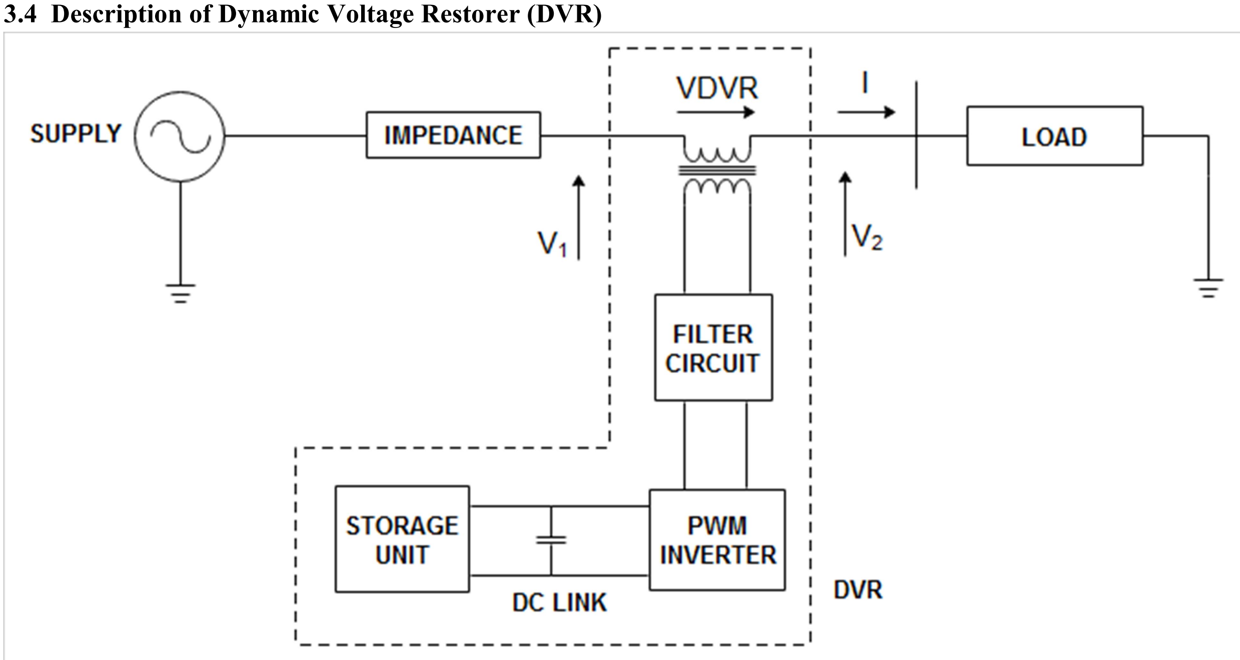

Figure 3.2: Block Diagram of DVR

The block diagram of the Dynamic Voltage Restorer (DVR) used in this investigation is shown in Figure 3.2. The unique device described above is a series-shunt compensator comprised of a converter, a filter, a series transformer, and a controller. The converter converts the alternating current source voltage to direct current. Additionally, it uses a pulse width modulation (PWM) structure to regulate the gate turn off (GTO) thyristor and subsequently converts it to ac voltage in the event of power quality faults. The converter's ac output is filtered to generate a pure voltage waveform that is transmitted to the power system via the coupling series transformer. The injected voltage's amplitude and phase angle enable for management of both actual and reactive power exchange.

3.5 Modelling of Dynamic Voltage Restorer (DVR)

3.5.1 Determination of dc Voltage Level

DC link voltage of DVR is giving by

$$V_{dc} = \sqrt[a]{2}V_{rms}V_{si(pu)}$$

(3.5)

Where

V_{rms} is the phase to ground rms voltage

$V_{si(pu)}$is the voltage sag level to be compensated

a is turn ratio of series transformer

3.5.2 Determination of DVR Rating

The rating of DVR is giving by the injected power

$$S_{series} = V_{series} * I_L \tag{3.6}$$

Where

V_{series} is the injected voltage

I_L is the load current

3.5.3 Determination of Modulation Index

$$k = \frac{\sqrt{2}V_0}{V_{dc}} \tag{3.7}$$

Where

V_0 is nominal load voltage

Vdc is the dc link voltage

3.5.4 Determination of Filter Factor

$$FF = \left(\frac{k^2 - 3.75k^2 + 4.07k^5 - 1.25k^6}{1440}\right)^{1/2} \tag{3.8}$$

Where

K is modulation factor

3.5.5 Determination of Inductance

The inductance is given by

$$L = \frac{V_0}{I_0 f_s}\left(FF\frac{V_{dc}}{V_h}\left(1 + 4\pi^2\frac{f_r^2}{f_s^2}FF\frac{V_{dc}}{V_h}\right)\right)^{1/2} \tag{3.9}$$

Where

V_h is the total harmonic of the load voltage

fr is fundamental frequency

fs is switching frequency

I_0 is the load current

3.5.6 Determination of Capacitor

The capacitance is given by

$$C = FF\frac{V_{dc}}{Lf_s^2V_h} \tag{3.10}$$

Where

Vdc is the dc link voltage

FF is the filter factor

L is the inductance

fs is switching frequency

V_h is the total harmonic of the load voltage

3.6 Data Collection for Training in ANN

Data used for ANN training is obtained by modifying the existing DVR PI controller.

The data obtained are inputs and target. The objective of the training is to obtain an anticipated output for all input values feed into the network and also minimize the error function. The ANN learns through an iterative process and modifies weights of input to be trained accordingly. In neural network, information is stored in terms of weights. A systematic way of modifying the weight is known as learning rule.

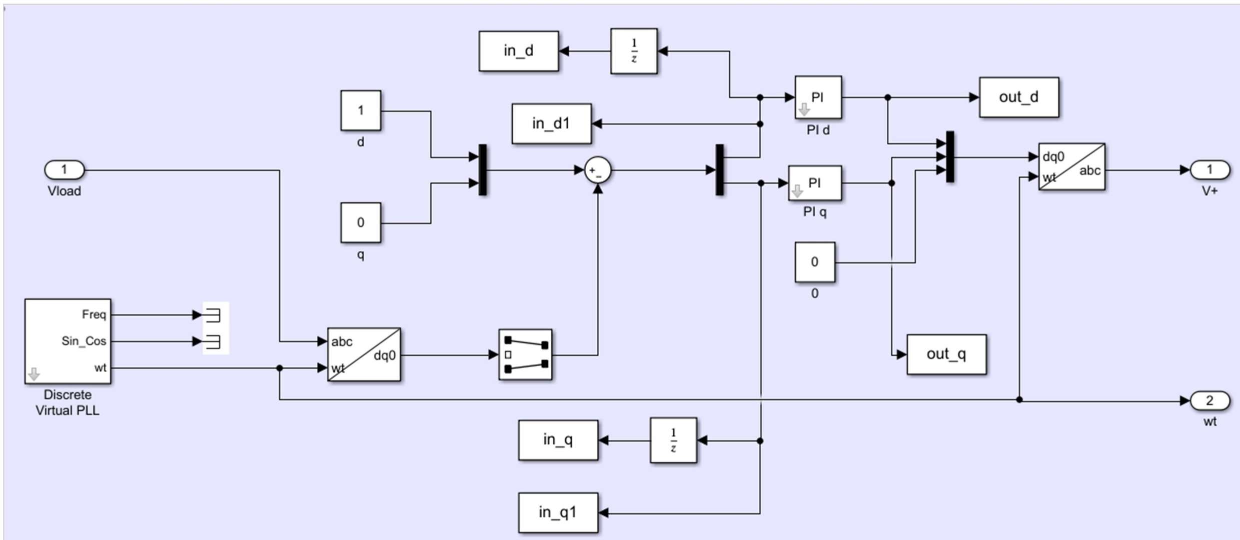

Figure 3.3 : Modified DVR PI Controller for ANN Data Collection

IV. Results and Discussion

4.1 Simulation Result of 11kV Distribution Network of Rumumoi with ANN Based DVR Controller

The 11kV distribution network of Rumumoi is simulated in Matlab software with ANN based DVR controller using data gotten from the Port-Harcourt Electricity Distribution Company (PHED) and is found successful. The power supply to the network is from feeder 1 from 2×15MVA 33/11kV injection substation at Rumuola and is given in figure 4.1.

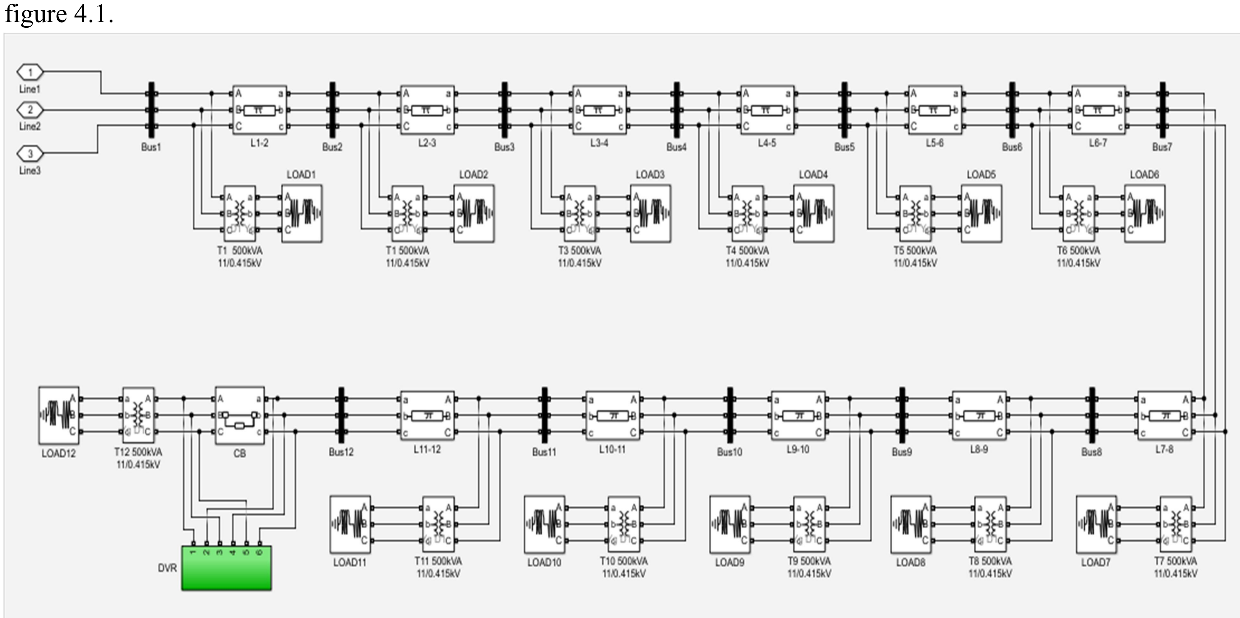

Figure 4.1 : Simulation Result of 11kV Distribution Network of Rumumoi with ANN Based DVR Controller

Table 4.1: Bus Voltage with ANN Based DVR Controller

Bus No	Bus Name	Nominal (kV)	Operating (p.u)

1	Ohiamini Road	11	0.9828
2	Location Road	11	0.9826
3	Ideogu Estate	11	0.9824
4	Omunakwa Road	11	0.9821
5	Okabie Road	11	0.9819
6	Amadi Road 1	11	0.9817
7	Amadi Road 2	11	0.9815
8	Bakery Road	11	0.9901
9	Silicon Valley Ltd	11	0.9813
10	PHWC	11	0.9811
11	Super Geometrics	11	0.9809
12	Ichiegbo Road	11	0.9807

Table 4.1 shows the bus voltages result with ANN based DVR controller and their respective per unit (p.u) values.

Table 4.2 Sample Data used in ANN Training

Input 1	Input 2	Target	Output	Error
0	0.000166125	0.0066450109	-0.1185351464	0.1251801573
0.000166125	0.000180024	0.0072022313	-0.1184985558	0.1257007871
0.000180024	0.000176203	0.0070507989	-0.1186936104	0.1257444094
0.000176203	0.000168274	0.0067349682	-0.1189963304	0.1257312987
0.000168274	0.000164779	0.0065964809	-0.1191101858	0.1257066666
0.000164779	0.000166349	0.0066605529	-0.1190369497	0.1256975026
0.000166349	0.000166115	0.0066524584	-0.1190511615	0.1257036198
0.000166115	0.000166047	0.0066510191	-0.1190531250	0.1257041441
0.000166047	0.000166073	0.0066533382	-0.1190518802	0.1257052183
0.000166073	0.000165998	0.0066516403	-0.1190549145	0.1257065548
0.000165998	0.000165980	0.0066521822	-0.1190554121	0.1257075943
0.00016598	0.000165954	0.0066524399	-0.1190563668	0.1257088066
0.000165954	0.000165958	0.0066538409	-0.1190561648	0.1257100057
0.000165958	0.000165886	0.0066522509	-0.1190590195	0.1257112703
0.000165886	0.000165868	0.0066528149	-0.1190595028	0.1257123177
0.000165868	0.000165842	0.0066530691	-0.1190604619	0.1257135309
0.000165842	0.000165846	0.0066545048	-0.1190602244	0.1257147292

0.000165846	0.000165774	0.0066528933	-0.1190631024	0.1257159956
0.000165774	0.000165757	0.0066534799	-0.1190635608	0.1257170407
0.000165757	0.000165732	0.0066537541	-0.1190645010	0.1257182551
0.000165732	0.000165737	0.0066552307	-0.1190642238	0.1257194545
0.000165737	0.000165665	0.0066536177	-0.1190671056	0.1257207233
0.000165665	0.000165648	0.0066542383	-0.1190675295	0.1257217677
0.000165648	0.000165624	0.0066545449	-0.1190684394	0.1257229843
0.000165624	0.000165630	0.0066560698	-0.1190681160	0.1257241858
0.00016563	0.000165559	0.0066544750	-0.1190709829	0.1257254578
0.000165559	0.000165543	0.0066551400	-0.1190713633	0.1257265033
0.000165543	0.000165520	0.0066554907	-0.1190722322	0.1257277230
0.00016552	0.000165528	0.0066570707	-0.1190718570	0.1257289276
0.000165528	0.000165457	0.0066555127	-0.1190746908	0.1257302035
0.000165457	0.000165443	0.0066562321	-0.1190750195	0.1257312516
0.000165443	0.000165421	0.0066566377	-0.1190758375	0.1257324752
0.000165421	0.000165431	0.0066582786	-0.1190754054	0.1257336840
0.000165431	0.000165361	0.0066567757	-0.1190781887	0.1257349644
0.000165361	0.000165349	0.0066575584	-0.1190784582	0.1257360166
0.000165349	0.000165329	0.0066580290	-0.1190792160	0.1257372451
0.000165329	0.000165340	0.0066597359	-0.1190787229	0.1257384588
0.00016534	0.000165306	0.0066596624	-0.1190800927	0.1257397551
0.000165306	0.000165303	0.0066608102	-0.1190801115	0.1257409217
0.000165303	0.000165295	0.0066617613	-0.1190804209	0.1257421821
0.000165295	0.000165304	0.0066634141	-0.1190800187	0.1257434328
0.000165304	0.000165267	0.0066631827	-0.1190815407	0.1257447234
0.000165267	0.000165262	0.0066642804	-0.1190815965	0.1257458769
0.000165262	0.000165253	0.0066651661	-0.1190819665	0.1257471327
0.000165253	0.000165262	0.0066668167	-0.1190815612	0.1257483779
0.000165262	0.000165221	0.0066664297	-0.1190832370	0.1257496667
0.000165221	0.000165215	0.0066674861	-0.1190833213	0.1257508074
0.000165215	0.000165204	0.0066683170	-0.1190837422	0.1257520592
0.000165204	0.000165214	0.0066699725	-0.1190833273	0.1257532998
0.000165214	0.000165169	0.0066694454	-0.1190851422	0.1257545876
0.000165169	0.000165163	0.0066704702	-0.1190852466	0.1257557167
0.000165163	0.000165151	0.0066712567	-0.1190857086	0.1257569653
0.000165151	0.000165161	0.0066729243	-0.1190852779	0.1257582022
0.000165161	0.000165112	0.0066722729	-0.1190872166	0.1257594896
0.000165112	0.000165106	0.0066732756	-0.1190873328	0.1257606084
0.000165106	0.000165093	0.0066740285	-0.1190878261	0.1257618546
0.000165093	0.000165103	0.0066757152	-0.1190873734	0.1257630886
0.000165103	0.000165052	0.0066749557	-0.1190894205	0.1257643762

0.000165052	0.000165045	0.0066759459	-0.1190895401	0.1257654860
0.000165045	0.000165032	0.0066766755	-0.1190900551	0.1257667306
0.000165032	0.000165043	0.0066783881	-0.1190895744	0.1257679625
0.000165043	0.000164990	0.0066775370	-0.1190917140	0.1257692510
0.00016499	0.000164983	0.0066785242	-0.1190918290	0.1257703532
0.000164983	0.000164969	0.0066792410	-0.1190923560	0.1257715971
0.000164969	0.000164981	0.0066809860	-0.1190918418	0.1257728278
0.000164981	0.000164926	0.0066800598	-0.1190940580	0.1257741178
0.000164926	0.000164919	0.0066810533	-0.1190941604	0.1257752137
0.000164919	0.000164905	0.0066817676	-0.1190946900	0.1257764576
0.000164905	0.000164918	0.0066835510	-0.1190941370	0.1257776880
0.000164918	0.000164862	0.0066825665	-0.1190964136	0.1257789801
0.000164862	0.000164855	0.0066835752	-0.1190964959	0.1257800711
0.000164855	0.000164841	0.0066842970	-0.1190970188	0.1257813157
0.000164841	0.000164855	0.0066861246	-0.1190964220	0.1257825466
0.000164855	0.000164798	0.0066850984	-0.1190987431	0.1257838414
0.000164798	0.000164792	0.0066861310	-0.1190987980	0.1257849289
0.000164792	0.000164779	0.0066868700	-0.1190993051	0.1257861751
0.000164779	0.000164794	0.0066887472	-0.1190986601	0.1257874073
0.000164794	0.000164736	0.0066876957	-0.1191010096	0.1257887053
0.000164736	0.000164731	0.0066887606	-0.1191010302	0.1257897907
0.000164731	0.000164718	0.0066895262	-0.1191015130	0.1257910392
0.000164718	0.000164735	0.0066914578	-0.1191008157	0.1257922735
0.000164735	0.000164677	0.0066903974	-0.1191031779	0.1257935753
0.000164677	0.000164673	0.0066915023	-0.1191031576	0.1257946599
0.000164673	0.000164661	0.0066923036	-0.1191036078	0.1257959114
0.000164661	0.000164679	0.0066942938	-0.1191028547	0.1257971485
0.000164679	0.000164621	0.0066932406	-0.1191052140	0.1257984546
0.000164621	0.000164618	0.0066943930	-0.1191051467	0.1257995397
0.000164618	0.000164608	0.0066952385	-0.1191055564	0.1258007949
0.000164608	0.000164627	0.0066972911	-0.1191047445	0.1258020356
0.000164627	0.000164570	0.0066962607	-0.1191070856	0.1258033463
0.00016457	0.000164568	0.0066974676	-0.1191069658	0.1258044333
0.000164568	0.000164559	0.0066983653	-0.1191073276	0.1258056928
0.000164559	0.000164580	0.0067004835	-0.1191064543	0.1258069378
0.00016458	0.000164524	0.0066994912	-0.1191087625	0.1258082537
0.000164524	0.000164524	0.0067007588	-0.1191085850	0.1258093438
0.000164524	0.000164516	0.0067017161	-0.1191088921	0.1258106082
0.000164516	0.000164539	0.0067039026	-0.1191079555	0.1258118581
0.000164539	0.000164484	0.0067029631	-0.1191102163	0.1258131794
0.000164484	0.000164486	0.0067042973	-0.1191099767	0.1258142739

0.000164486	0.000164479	0.0067053212	-0.1191102226	0.1258155438
0.000164479	0.000164504	0.0067075779	-0.1191092214	0.1258167992
0.000164504	0.000164487	0.0067081635	-0.1191099744	0.1258181379
0.000164487	0.000164499	0.0067098901	-0.1191094648	0.1258193549
0.000164499	0.000164506	0.0067114315	-0.1191092281	0.1258206597
0.000164506	0.000164529	0.0067136323	-0.1191083230	0.1258219553
0.000164529	0.000164508	0.0067140567	-0.1191092318	0.1258232885
0.000164508	0.000164518	0.0067157315	-0.1191087611	0.1258244926
0.000164518	0.000164523	0.0067172045	-0.1191085884	0.1258257929
0.000164523	0.000164546	0.0067194011	-0.1191076822	0.1258270833
0.000164546	0.000164521	0.0067196623	-0.1191087527	0.1258284150
0.000164521	0.000164530	0.0067212910	-0.1191083150	0.1258296060
0.00016453	0.000164534	0.0067227031	-0.1191081992	0.1258309024
0.000164534	0.000164557	0.0067249000	-0.1191072881	0.1258321881
0.000164557	0.000164528	0.0067250102	-0.1191085085	0.1258335187
0.000164528	0.000164536	0.0067265996	-0.1191080981	0.1258346976
0.000164536	0.000164539	0.0067279585	-0.1191080320	0.1258359905
0.000164539	0.000164562	0.0067301601	-0.1191071120	0.1258372721
0.000164562	0.000164530	0.0067301322	-0.1191084698	0.1258386020
0.00016453	0.000164537	0.0067316894	-0.1191080806	0.1258397699
0.00016496	0.000164945	0.0069851663	-0.1190932214	0.1260783877

Table 4.2 shows some of the sample data used in training the artificial neural network for this research.

4.3 Result of Improved Voltage and Current in the Network using DVR

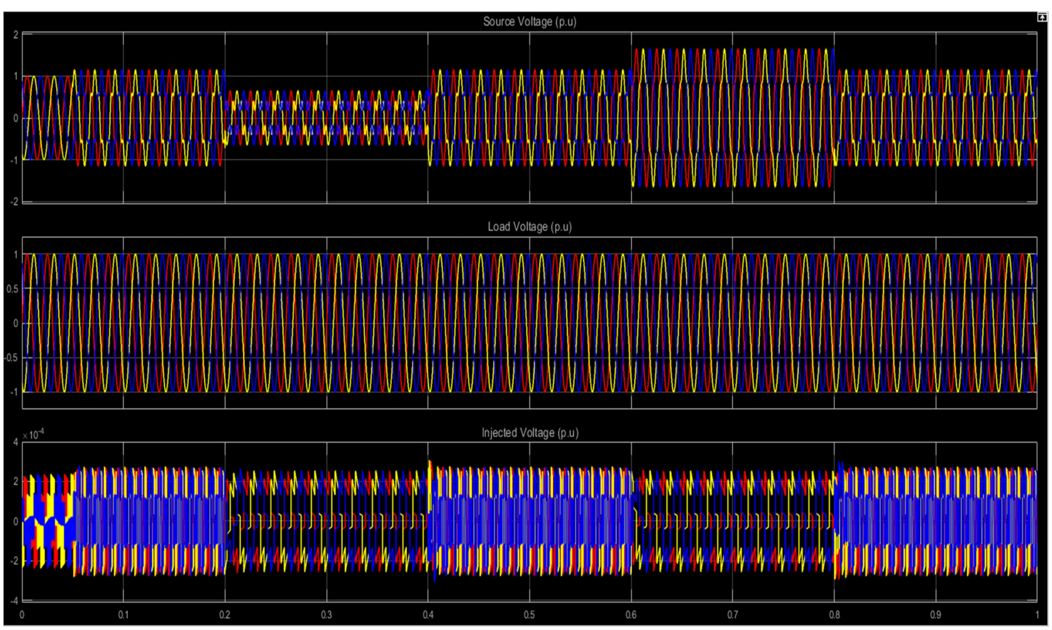

Figure 4.2: plot of Source voltage, Load voltage and Injected voltage signal waveforms

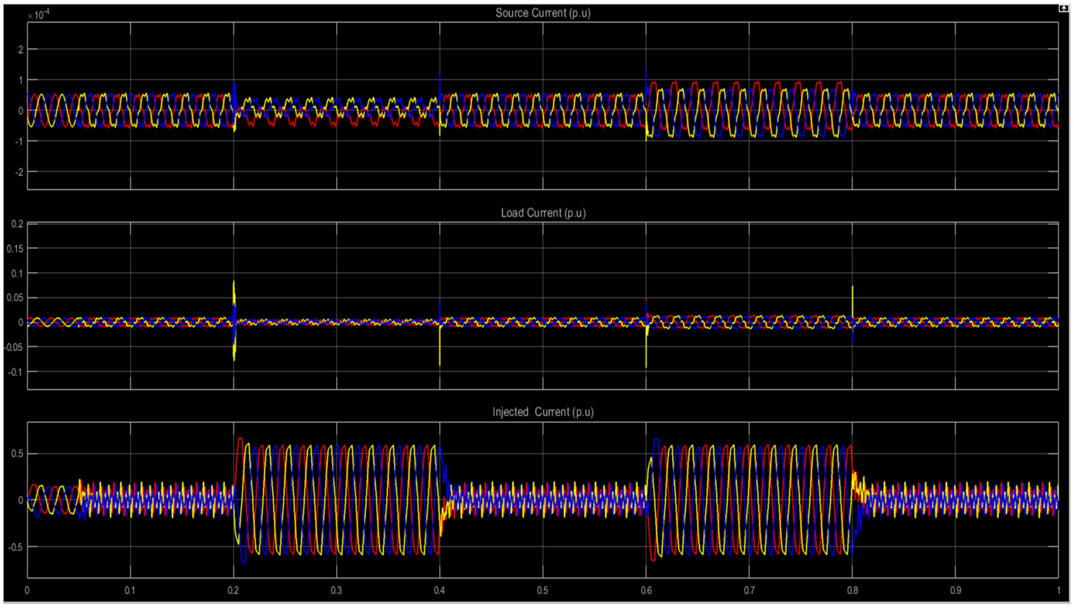

Figure 4.3: plot of Source Current, Load Current and Injected Current signal waveforms

Figure 4.2 illustrates the source, load, and injected voltages for sag and swell in the power system. It indicates that Sag is detected in the source voltage range of 0.2 to 0.4 sec and swell is recorded in the range of 0.4 to 0.6 sec. DVR transmits voltage compensating signals to the power system, which maintains the load voltage at a constant amplitude compensating sag and swell in the power system.

Figure 4.3 depicts the source current, load current and injected current from the DVR during a power quality disturbance. The first waveform depicts the source current when disturbances are present. The third waveform shows the waveform when DVR injects current that attenuates the disturbance. Finally, the second waveform depicts the load current without any disturbance, demonstrating that the DVR impacted the system positively in mitigating power quality problems that affect the distribution system thereby, improving the power quality of Rumuola Rumuomoi network.

V. Conclusion

Quality and sufficient power supply is a source of concern presently in developing countries such as Nigeria therefore, researchers and power engineers are now proffering solutions to these problems.

From the research, Rumuola Rumuomoi network is simulated in Matlab software using available data from PHED. During ANN training, the performance for each iteration is calculated and the point where the three plots almost coincide 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. The validation performance during the training process is 10.4258 at epoch 4 which indicates how much minimized errors occurred during the training. It is found that sag is seen in source voltage within 0.2s to 0.4s and swell is seen within 0.4s to 0.6s but DVR is able to inject a corresponding voltage to compensate for the shortfall and thus, the load voltage is maintained with constant amplitude resulting to improved power quality. Also, DVR is able to inject a current of corresponding waveform to attenuate the disturbance in the source current resulting to a load current without any disturbances hence, enhancing the power quality. The quality power supply at Rumuola Rumuomoi Distribution system owing to sag and swell is solved by employing artificial neural network based DVR.

References

[1] Sankaran C. (2002). Power Quality CRC PRESS

New York USA.

[2] Uwho, K. O., Idoniboyeobu, D. C., & Amadi, H. N. (2022). Design and Simulation of 500kW Grid Connected PV System for Faculty of Engineering, Rivers State University Using Pvsyst software. Iconic Research and Engineering Journals, 5(8), 221-229.

[3] Zahir J.P. (2011). Computational Techniques for Power Quality Data Monitoring and Management; *Phd Dissertation,* Victoria University, Melbourne, Australia.

[4] Joseph, S. (2011). The Seven Types of Power Problems: Schneider Electric Data Center Science Center, 22-30.

[5] Irfan Isak Mujawar, D. R. Patil and Isak Ismail Mujawar (2013). 'Reactive PowerCompensation and Harmonic Mitigation of Distribution System using SAPECompensator'. *International Journal of Engineering Science and Innovative Technology* (IJESIT), 2(3),495-502.

[6] Vinita, V., Rintu, K., & Manoj K., (2013). Improvement of power quality by upqc using different intelligent controls: *International Journal of Recent Technology and Engineering (IJRTE),*2(1), 173-177.

[7] PHED, (2015) Port Harcourt Electricity Distribution Company, Garden City Central Integrated Business Centre, 2-5.

[8] Roger, C.D, Mark F.M, & Wayne B., (2004). Electrical power system quality', Second edition, Mcgraw-Hill Companies.

[9] Shailesh M. Deshmukh, B. D, Gawande, S. P.(2013). A review of' powerquality problems-voltage sags for different faults. *International Journal of Scientific Engineering and Technology*,2(5), 392-397.

[10] Jide, J. P. Akinlolu, A. P. & Thomas, O.A. (2011). Reliability worth assessment of electric power utility in Nigeria: residential customer survey results, 14(3), 217-224.

[11] Ogunyemi, J., Fakolujo, A. and Adcjumobi, l.A. (2012). Power Quality Assessment in Nigerian Distribution Network *EIE 2nd International Conference on Computer, Energy, Robotics and Telecom,* 103-111.

[12] Mohamed, P.S, & Sulinian K.J, (2014). Survey related to Power Quality Issues in Indian Electricity Market, *International Journal of' Electrical and Computer Engineering*,3(1), 37-47.

[13] Christian R, & Stefan H (2014). Power Quality and stability issues in modern distribution grids: identification anti Mitigation', *CIRED Workshop-Rome,*6, 1-5.

[14] Barry, W. K (2000) Power Quality McGraw-Hill, New York San Francisco Washington, D.C.

[15] Mohit, B, Vinay K.D., Ankit K. & Anurag B. (2013). 'Design and Simulation of DSTATCOM for Power Quality Enhancement in Distribution Networks under Various Fault Condition', *International Journal of Emerging Technology and Advanced Engineering,* 3(4), 620—626.

[16] Ahmed, M.F, Oherbi, C. M, Kainel, D. E. & Ameur F. A, (2014). 'Study, Analysis and Simulation of a Static Compensator D—STATCOM for Distribution Systems of Electric Power', *LeonardoJournal of Sciences,* 2(5), 117-130.

[17] Onohaebi S.O.& Omorogiuwa Esosa (20l5)'Prospects of Custom Power Devices inImproving Reliability of Distribution Networks in Nigeria' *International Journal of Electronics Communication and Computer Engineering*,5(5), 1120-1123.

[18] Sundarabalan C. K. & Selvi K. (2013). Power quality enhancement in powerdistribution system using artificial intelligence based dynamic voltage restorer. *International Journal on Electrical Engineering and Informatics* 5(4) 433-446.

[19] Alizadeh E. Lyons S.M., Castle J.M. and Prasad A. (2016). Measuring Systemic Changes in Invasive Cancer cell Shape Using Zernike

Moments. Integrative Biology, 8(11), 1183-1193.

[20] Zissis D. (2015). A Cloud Based Architecture Capable of Perceiving and Predicting Multiple Behavior, Applied soft Computing. 35, 652-661.

[21] Mallaparap K., Nalini P., Vishnu T.R., and Lakshmi D. (2011). Non-blind Adaptive Beamforming Algorithms, *International Journal of Applied Engineering Research* 6(3), 491-496.

[22] Zoph B. and Le Q.V – (2016). Neural Architecture Search with Reinforcement Learning. Arxiv: 1611.01578.

[23] Beatriz A. Garro[1] and Roberto A. Vázquez (2015). Designing Artificial Neural Networks Using Particle Swarm Optimization Algorithms *Computational Intelligence and Neuroscience* / *2015* / *Article* 3, 2-7.