

Implementing artificial Neural Network Based DVR to Improve Power quality of Rumuola-Rumuomoi 11kv Distribution network

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ABSTRACT:

The most turbulent issue bedeviling Rumuomoi 11kV distribution network is voltage sag and swell reducing the power quality. No proper mitigation control has been applied. This research work is targeted at solving the power quality problem by applying artificial neural network (ANN) control with embedded dynamic voltage restorer (DVR). The artificial neural network is first of all trained with the input and desired data gotten from simulation with proportional integral (PI) controller. To minimize the set of data obtained, Levenberg-Marquardt feed forward back algorithm is used during the training and the result for each iteration is calculated in Matlab software. The desired dynamic voltage restorer system is tested with replicated model of Rumuomoi 11kV and found 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 which violated the statutory limit condition of 0.95-1.01p.u. After optimization of the network using DVR, there was no bus voltage violation, which shows that DVR is efficient in improving power quality by eliminating voltage sag and swell from the distribution network.

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

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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. Power quality problems are manifested in voltage, current or frequency [3]. Examples include: voltage swell and sag, voltage fluctuation, harmonic distortions etc. In addition to factors such as power system failures, start-stop of heavy equipment, and switch operations, nonlinear loads are considered to be the main cause of power quality problems [4]. As a global problem, power quality problems exist in the distribution systems of several countries including Nigeria, Libya, India and some developed countries. The effects of power quality problems are big; they vary from equipment failure to equipment collapse. The need to lessen power quality problems and create good quality power has brought power system engineers, equipment manufacturers, researchers and legal entities to the forefront of methodological development. Today, there are numerous ways to better power quality in order to support the ever-increasing applications of sensitive and non-linear loads in the distribution network. Traditionally, synchronous capacitor, capacitor banks, static reactive power compensators (SVCs), auto-switched reactive power compensators, etc. are used for reactive power control and power factor improvement, albeit with disadvantages such as instability issues, high transient generation during switching on and off, etc [5]. More recently, custom electrical devices

such as distributed static compensators (DSTATCOM), unified power quality conditioners (UPQCs), dynamic voltage restorers (DVRs) and more, are researched as better methods for power quality improvement, however, their performance depends on the type of controller employed. Proportional integral (PT), proportional integral differentiator (PID) etc are effective but slow in response and perform poorly under parameter variations. Artificial Mind controls (AI) such as the Artificial Neural Network (ANN), vague logic (FL) etc. Reference [6] are recommended by researchers as they provide better performance based on 'response time and operation under flexible 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 challenges which include voltage sag, voltage swell, harmonics etc. affect the performance of sensitive load utilized in the process and automation industries, homes and offices, and therefore lead to financial losses. In Rumuolai distribution system network [7], under-voltage and over-voltage are major power quality problems.

1.2 Objectives of the Study

The objectives of the research are :

- i. To simulate 11kV distribution network of RumuolaiRumuolai network using Matlab software
- ii. To improve the power quality of RumuolaiRumuolai 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 AI 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]. In distribution network, circuit breaker tripping, equipment malfunction and failure, cable and transformer heating. Data recording, metering problems, and insulation failures are common effects [3]. In more severe cases, power quality disturbances can lead to damage of any equipment [9]. Study conducted by [10] shows that quality of power supply in Nigeria is less than 10%. It was noted that power quality evaluation is difficult as data is almost completely unavailable in Nigeria. Reference[11] claim 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. Reference[12] note that in Libya, one of the fastest growing North African countries also experience 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. Reference[13] note 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 over-voltage, frequency deviation, harmonics, voltage dip, and voltage unbalance in the distribution system.

2.2. Solutions of Quality Power Challenges

Reference[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. Reference [5], in their presentation note 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.

Reference [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] present a study on DSTATCOM in controlling reactive compensation and maintaining load voltage level using P1 controller. Though excellent result was recorded. However, it was further recommended for the use of multilevel converters with dynamic loads. Reference [17] look 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. Reference [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 ishing 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. Normally, neurons can have a certain level, often called a threshold, so that a signal can only be transmitted if the total signal exceeds that level or threshold. Usually neurons are grouped in different layers. Different layers can perform different changes on related inputs. Signals move from the input layer, which happens to be layer number one, to the output or last layer after passing layers through layers many times [19].

2.4.1 Types of Artificial Neural Network

Artificial neural networks have entered a wide group of technologies that have promoted the state of the art in several domains. Types are:

- i. Static type: One of the simplest types has one or more static components. This static component includes number of layers, number of units, weight of units, and topology.
- ii. Dynamic type. Dynamic types allow one or more of them to evolve through learning. Dynamic types are quite complex, but they can make learning times shorter than before, and still produce interesting results. Some types may require learning to be monitored or supervised by the person operating it while some operate completely independently. Some neural networks run entirely on hardware, while others run entirely on software and general purpose computers [20].

2.5. Training in Neural Networks

Reference [21], neural networks have the capacity to learn through training. The training is done on the inputs and expected to produce result called output, thereby forming a probability-weighted association between the input and the output which are stored in the data structure of the network. In the training of a neural network for a specific purpose, the training is usually done by determining what the difference between the processed output of the network which is called a prediction and a targeted output are. The difference between the targeted output and the processed output is called the error. The function of the network is to adjust its own weighted associations in line with a set of rule for learning. Repeated adjustments will make the neural network to produce an output that is increasingly similar to the targeted output. The purpose of the training is to make sure that what is expected as the targeted output is desirable. Then, with reasonable number of adjustments being made, the training can be ended based upon certain criteria. This one is called supervised learning.

2.6. Design of Artificial Neural Network

Neural architecture search makes use of machine to automate artificial neural network design. There are many approaches adopted by experts to look at neural architecture search. The approaches have networks designed to

compare with other systems. A search algorithm, known as the basic search algorithm (BSA), has to propose a candidate model, make an evaluation of the candidate model against a set of data, and the use output as feedback to teach the neural architecture search network [22]. Reference[23]talk about design issues in the design of artificial neural networks. The issues listed include making decisions as to:

- i. Number of network layers
- ii. Type of network layer
- iii. Connection of network layers
- iv. Size of the network layers
- v. Learning rate
- vi. Depth
- vii. Stride

III. MATERIALS AND METHOD

3.1 Materials Used

The materials employed in this research work are :

- i. Single line diagram of RumuolaRumuomoi 11kV distribution network
- ii. Load data of RumuolaRumuomoi 11kV distribution network
- iii. Line data of RumuolaRumuomoi 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.

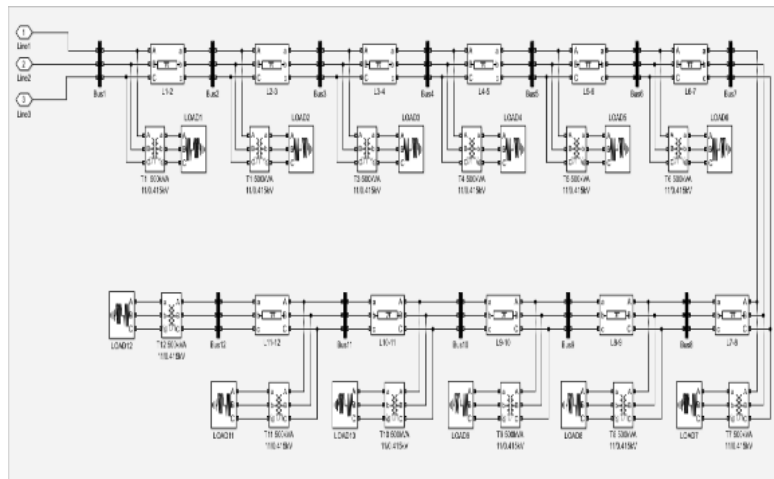


Figure 3.1 :Matlab Simulink Block of Rumuomoi 11kV Network

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

$$I_L = \frac{I_R + I_Y + I_B + I_N}{3} \quad (3.1)$$

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

$$KVA_{Load} = \sqrt{3} * I_L * V_s \quad (3.2)$$

Where

I_L is average load current

V_s is the secondary voltage of the transformer

3.3.3 Real Power (kW)

The load real power is giving by

$$kW_{Load} = PF * KVA_{Load} \quad (3.3)$$

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

$$Kvar_{Load} = \sqrt{(KVA_{Load})^2 - (kW_{Load})^2} \quad (3.4)$$

Where

KW_{Load} is the load real power

KVA_{Load} is the load apparent power

Table 3.2 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)

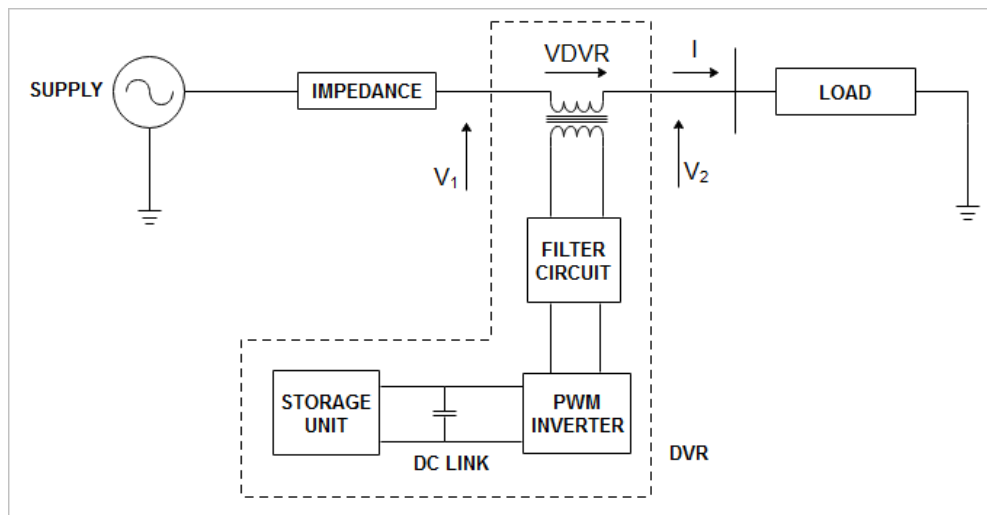


Figure 3.2: Block Diagram of DVR

Figure 3.2 shows the block diagram of Dynamic Voltage Restorer (DVR) adopted for this study. The above custom device is a series-shunt compensator composed of converter, filter, series transformer, controller etc. The converter transforms the ac source voltage to dc voltage. Also, it controls the gate turn off (GTO) thyristor in a pulse width modulation (PWM) structure then reconvert it to ac voltage in an event of power quality disturbances. The ac outputting of the converter is filtered to produce a pure voltage waveform that is sent into the power system via the coupling series transformer. The amplitude and phase angle of the injected voltage allows the control of real 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

$$V_{dc} = a\sqrt{2}V_{rms}V_{si(pu)} \quad (3.5)$$

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

$$S_{series} = V_{series} * I_L \quad (3.6)$$

Where

V_{series} is the injected voltage

I_L is the load current

3.5.3 Determination of Modulation Index

$$k = \frac{\sqrt{2}V_0}{V_{dc}} \quad (3.7)$$

Where

V_0 is nominal load voltage

V_{dc} 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

f_r is fundamental frequency

f_s is switching frequency

I_0 is the load current

3.5.6 Determination of Capacitor

The capacitance is given by

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

Where

V_{dc} is the dc link voltage

FF is the filter factor

L is the inductance

f_s 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. Artificial Neural Network are the biologically inspired computer simulation performed to confirm the basic connection in a set of data similar to the human brain. The neural network helps to modify the input so that the network gives the best result without redesigning the output. The modified dynamic voltage restorer (DVR) proportional integrator (PI) for ANN data collection is shown in figure 3.3 below.

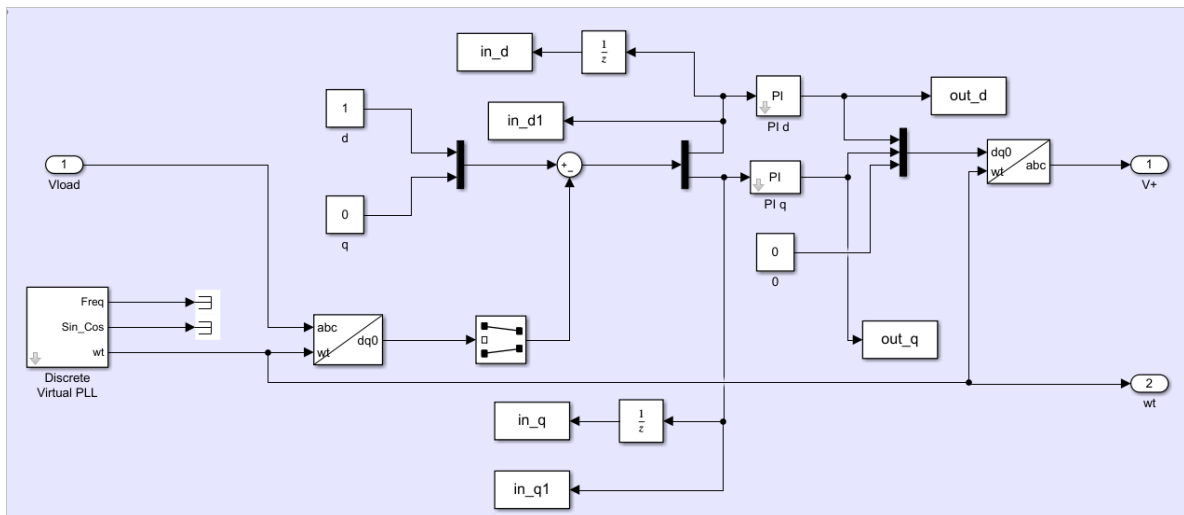


Figure 3.3 : Modified DVR PI Controller for ANN Data Collection

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 2x15MVA 33/11kV injection substation at Rumuolais given in figure 4.1.

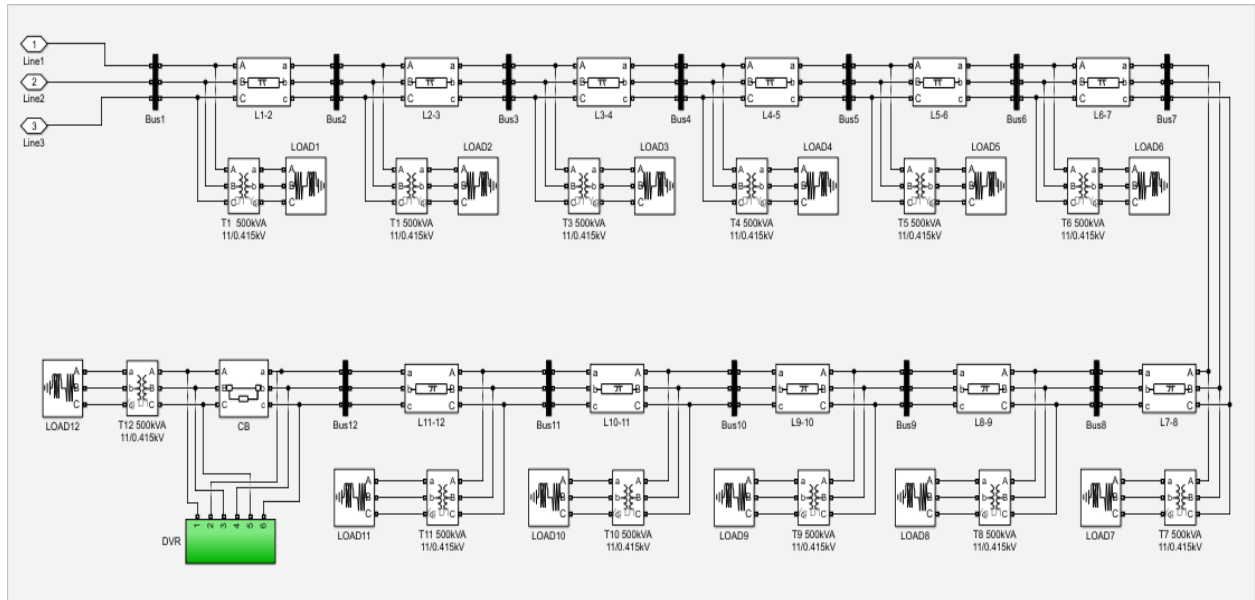


Figure 4.1 : Simulation Result of 11kV Distribution Network of Rumumoi with ANN Based DVR Controller

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

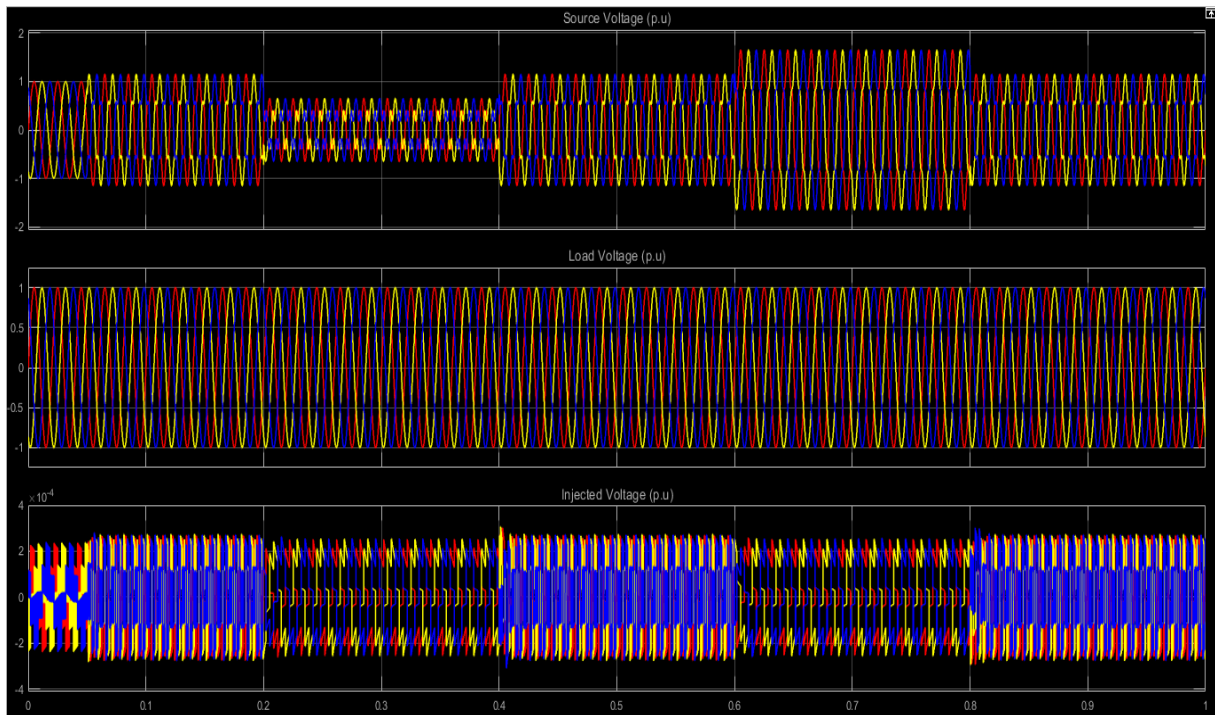


Figure 4.2: plot of Source voltage, Load voltage and Injected voltage signal waveforms

Figure 4.2 shows Source voltage, Load voltages and Injected voltage for Sag and swell in power system. It tells that Sag is observed in source voltage within 0.2 sec to 0.4 sec and swell is seen within 0.4 sec to 0.6 sec. DVR sends corresponding voltage compensating signals to power system and thus the load voltage is maintained at fixed amplitude compensating sag and swell in power system.

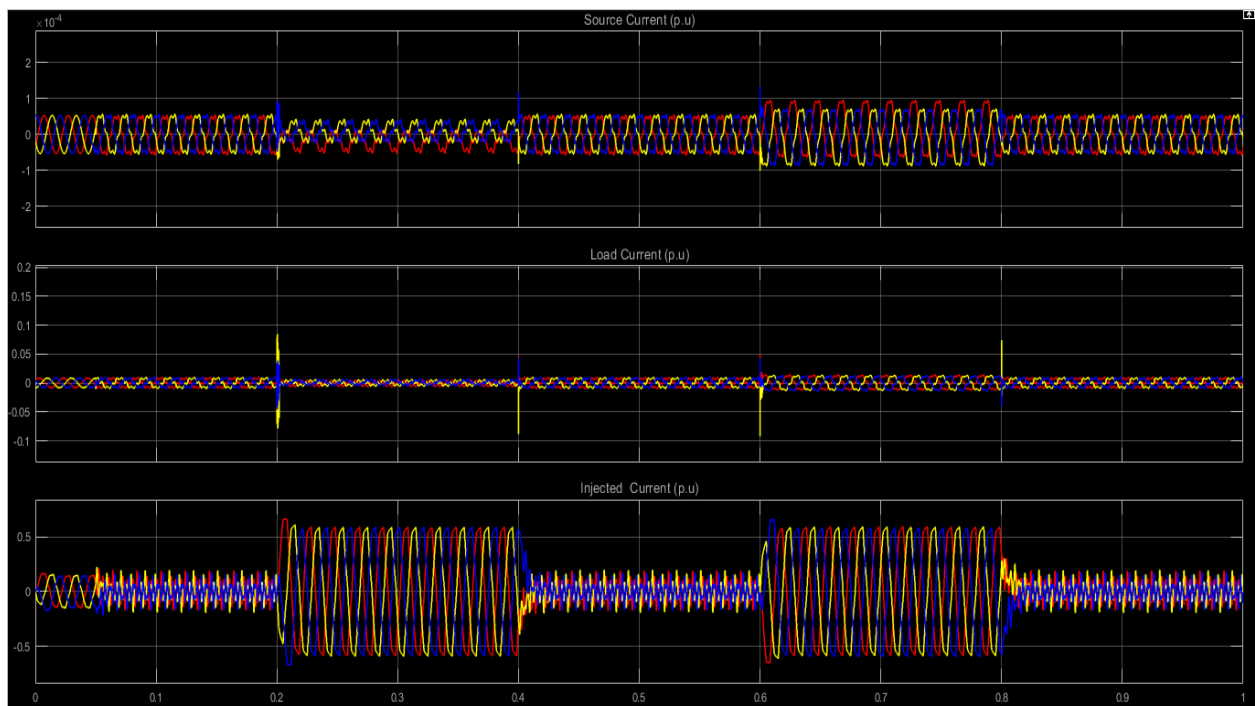


Figure 4.3: plot of Source Current, Load Current and Injected Current signal waveforms

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.

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