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Fault ride through capability enhancement of grid connected system using ANN based DVR

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Abstract— **In order to analyze electrical interference, such as voltage dips, swells, and harmonics, this article explains the best practices of restoring electrical power during the interference. Prediction of faults and early restorer is typically the base to maintain system balanced. The rated load voltage and segmentation angle are controlled by the controller, which is purely based on dq0 conversion technology and ANN. We have performed the simulation study of a three-phase rectifier with a non-linear balanced resistor-capacitor DC load. Furthermore, using a programmable AC power supply, voltage dips and spikes on the subsequent power side were investigated. The DVR effectively reduces interference with the least amount of interference according to simulation results. The MATLAB/Simulink environment was used to analyze the DVR's overall performance. We also learned about the various devices used for this purpose and further explored the design features of a dynamic voltage restorer. It is about the principle of operation and various operating modes, which improve the quality of energy in the network of distribution and power supply. MATLAB/Simulation is used in all of this work to demonstrate how a DVR operates in real time**

Index Terms— **Power Quality issues, THD-Total Harmonic Distortion, ANN- Artificial Neural Network, DVR-Dynamic Voltage Restorer,**

INTRODUCTION

There is a higher likelihood of working with electricity given the current situation and the rising number of electronic devices that depend on it for operation. weather. In a market where competition is fierce, industrial, commercial, and residential users all depend on reliable power supplies. The dependability and consistency of the power source will cause problems with the electrical equipment's quality. Commonplace nonlinear loads of today include battery chargers, X-ray machines, and magnetic resonance imaging systems, among other medical equipment. Power outages and malfunctions could result from non-linear loads. About 80% of power outages are caused by two main power quality problems: voltage surges and sags. Most people consider the DVR to be a cheap device that protects sensitive loads from harmonics, spikes, and voltage variations by controlling voltage in accordance with power regulation [1]. DVRs use semiconductors known as insulated gate bipolar transistors (IGBTs) to inject a control voltage in order to control the voltage entering the load. Traditional PI controllers are still in use today in a variety of applications because of their ease of use, dependability, and controllability.

But balance and output control are always challenging tasks, which is why the PI controller fails in non-linear systems. Because of their adaptability, flexibility, error tolerance, and learning capabilities, artificial neural networks are used in a wide range of applications. This article presents a novel kind of artificial neural network (ANN)-based PI controller. Neural networks are trained offline for control over the internet. Create input data using a traditional PI controller so that neural networks can be trained. These results show that it functions extremely well and is a good fit for simulating experimental conditions by offering a low THD sinusoidal voltage. The monitoring and control of DVR performance using various lines and parameters has been studied by a number of researchers [2–5] in the literature.

DVR operation and control using PI control

DVR device with an IGBT inverter that runs on batteries with step-down transformer is used to lower the supply voltage from 22 KV to 415 V before it is connected to the load. This study's simulation analysis takes non-linear, non-linear, and non-precision loads into consideration. To accurately regulate the products of the rated voltage, the DVR injects power into the PWM generator, inverter, LC passive output filter, and series step-up injection transformer [6].

Under normal conditions, the dynamic voltage restorer is typically utilized in standby mode. During occurrences of noise, disturbances, or malfunctions, the nominal voltage of the system is compared to voltage variations. This evaluation allows us to figure out the additional voltage needed by the restorer to boost the output, ensuring that the supply voltage to the load remains within acceptable limits. The voltage levels that can be injected into the distribution system can be modified, enabling the regulation of the transfer of reactive and real power between the system and the DVR. A device that can store energy is attached to the DC voltage source of the DVRs end. Based on the provided source, the dynamic voltage restorer can transfer reactive power between the distribution system and itself without relying on internal reactive AC passive components. The dynamic voltage restorer receives actual power through its input DC terminal and exchanges it at the AC terminals with an external energy source or an energy storage device [7]. As mentioned earlier, the primary goal of the controller is to maintain a constant voltage magnitude when there are disturbances in the power supply affecting the sensitive load. This control approach involves comparing the source and load voltages. To accomplish this, the three-phase voltage is converted into dq0 using park transformation. Following the conversion, the voltage remains stable in both balanced and normal scenarios, with the d-voltage set at 1 per unit (p.u.) and the q-voltage set at 0 p.u. However, it tends to fluctuate more during abnormal conditions (Source: Reference [8]). Afterwards, the PI controller enhances the voltage disparity by comparing the desired voltage with the d- and q-voltages. Subsequently, it transitions from dq0 to abc, transforming into an abc component that serves as the primary signal for generating voltage switching pulses. These pulses are utilized as a power source for the PWM inverter. When voltage drop occurs within the system, one of the crucial functionalities removed from the controller is its capacity to inject voltage deviation, identify voltage sag, and shut down the inverter. The PI controller placed in the feedback path is depicted in Figure 1 [9].

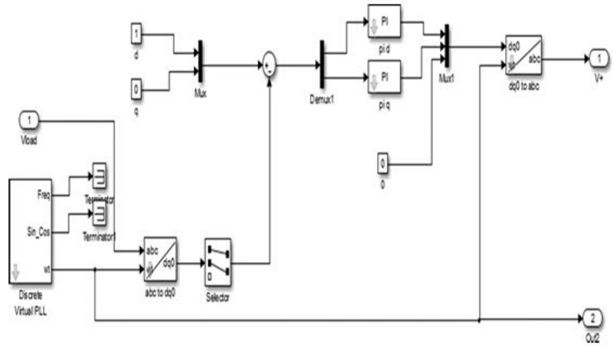

Figure: 1 Proportional Integral controller with d-q transformation

The input for the controller is the voltage of the sensitive load. The VSI (Voltage Source Inverter) level is gauged at the delicate load by taking three-phase V-I (Voltage-Current) measurements. is subsequently converted into a specific term. A PI controller is used to handle voltage drop, which is the difference between the reference value and the dq-voltage, by measuring it. The q reference is zero, and the d reference is set to the rated voltage of unity in per unit.

DVR with ANN controller approach

Figure 2 presents the DVR device equipped with a battery-operated IGBT inverter. Prior to being connected to the load, a step-down transformer is utilized to lower the voltage from 22 KV to 415 V. The simulation tests employed in this study encompass both non-precision and non-linear elements. In order to precisely regulate the rated voltage products, the DVR effectively introduces power from the PWM generator, inverter, LC passive output filter, and series step-up injection transformer [10].

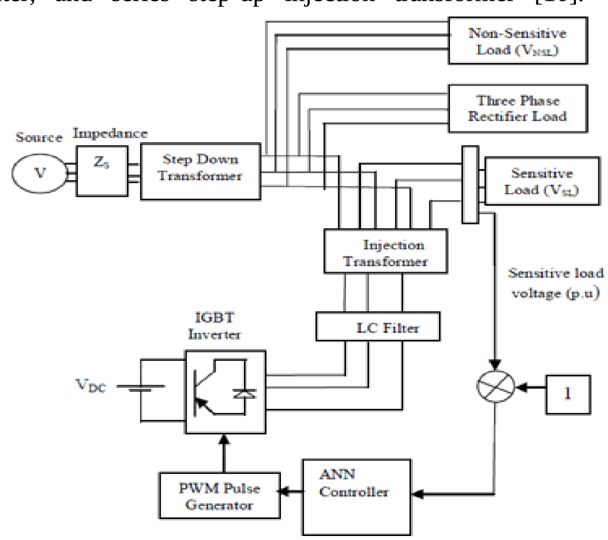

Figure 2: block diagram of DVR with ANN controller

ANN Training

It has been found that artificial neural networks (ANNs) consist of interconnected nodes or units referred to as artificial neurons, which bear a resemblance to the neurons found in biological brains. Similar to synapses in the human brain, each connection transmits a signal to numerous other neurons. Upon receiving a signal, an artificial neuron processes both the signal itself and the connected neurons. Each neuron's output is computed using a non-linear function applied to the sum of its inputs, and the signal transmitted through each connection is a real number. These connections are known as edges. Similar to neurons, the weights of the edges also change as the learning process progresses.

The controllers' primary objectives are to respond quickly and accurately to the intended DVR compensation and detect disruptive signals. The conventional controller struggles to work well when there are changes in parameters, disturbances, or non-linearity. However, a recent survey found that an ANN-based controller can keep the DVR stable in different situations and respond quickly to changes. A network of artificial neurons, which are not linear, forms the artificial neural network (ANN). Usually, it represents a group of simple, nonlinear components that can change and learn. A multi-layered neural network-based control system was developed to enhance the DVRs performance characteristics. the ANN-based controller is composed of three layers: an input layer with a single neuron, a hidden layer with twenty neurons, and an output layer with a single neuron. The MATLAB workspace stores the PI controller data, which are used to train the neural network controller offline. The input layer and hidden layers are activated using Trained LM, and the output layer is activated using a linear function. This research employs Levenberg Marquardt back propagation (LMBP) as its method of training. The weight influences the signal strength of the link when it rises or falls. Neurons possess a threshold, wherein a signal is transmitted solely when the total signal surpasses the threshold. Layers are formed by the accumulation of neurons, and each layer has the purpose of transforming inputs in a different way. The signal goes through the layer's multiple times, beginning at the input layer (first layer) and ending at the output layer (final layer). Training or learning neural networks involves processing instances, where each one has a known "outcome" and "input" to help build probability-weighted correlations between the two. The network's data structure then contains these associations. As seen in Figure 2[11–14], the neural network from the previously described example is trained by calculating the difference between the desired output and the network's processed output.

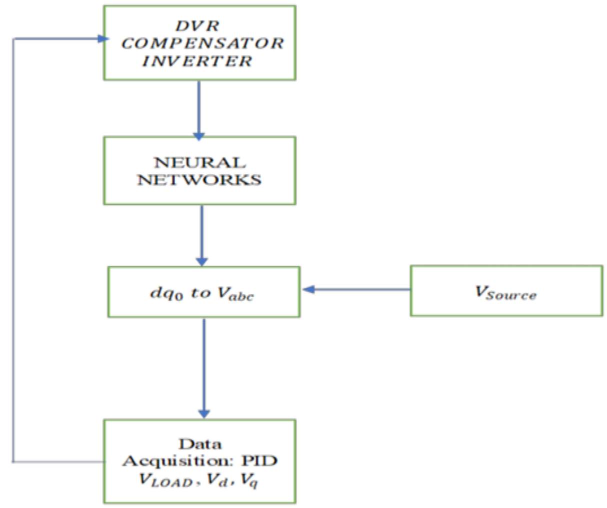

Figure 3: Representation of Artificial Neural Network (ANN) System

This is an error. The network uses this error value and modifies its weighted associations in accordance with the learning rule. The result of the gradual modifications is a neural network output that closely resembles the intended output. Following numerous modifications, the training is deemed to be over in accordance with specific standards. Two input nodes make up the input layer: the base voltage and the DC voltage of the capacitor. Twenty nodes comprise a hidden layer that is activated and has a sigmoid function. The output layer was built of a single node, which is the best gate control possible. [15-17]

Simulink representation of DVR using ANN

Vdref and Vsd are different from each other because of the input of neural network function 1, which is acquired by converting abc to dq0. Similarly, neural network 2 uses the difference between Vqref and Vsq as input during the fitting process; this can also be obtained by replacing abc with dq0. The output controllers Vd* and Vq* provide the modulation signal, which is then used to generate IGBT pulses. This is the output signal that results from translating dq0 to ABC. Three layers are created in a feedforward network: one processing layer, ten layers, and one output controller layer. This improves DVR performance. Whereas output neurons have a linear activation function, secretory neurons have a tangential sigmoid activation function as show in figure 3.

$$V_{sd} = V_{dDC} + V_{dAC} \tag{1}$$

$$V_{sq} = V_{qDC} + V_{qAC} \tag{2}$$

The input and output data from the PI controller are regularly captured and stored in the MATLAB office [18–20]. Utilize this information to train a neural network. The pre-generated training data is used to conduct offline neural network training. Levenberg-Marquardt backpropagation is the training algorithm that is being used (LMBP). The squared error is used to evaluate the neural network model's performance over the course of repeated training.

$$Vd^* = V_{dDC} - V_{loss} \quad (3)$$

$$Vq^* = V_{qDC} - V_{Qr} \quad (4)$$

Simulation Results

Results of the Simulation MATLAB/Simulink simulation results validate the claim. Sensitive products are protected from voltage outages during fault conditioning by DVRs controlled by artificial neural networks. This project investigates three separate scenarios. Initially system is simulated with no DVR as well as a three-phase fault to analyze power quality issues.

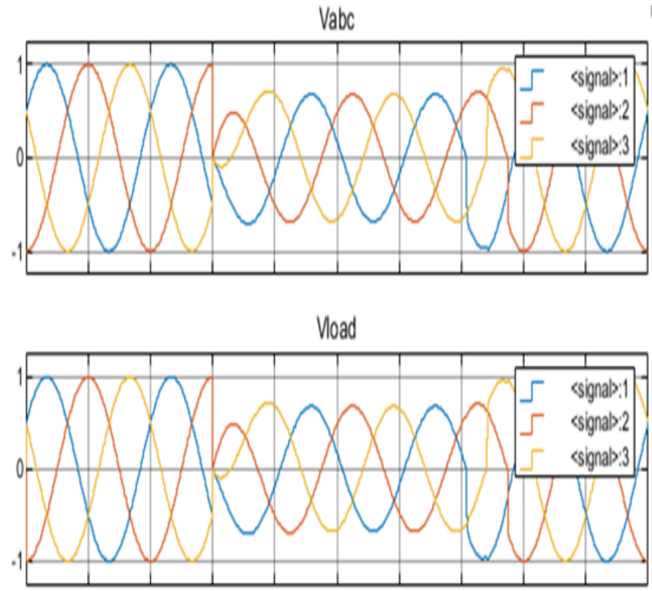

Figure 4: Supply voltage and load voltage under fault condition

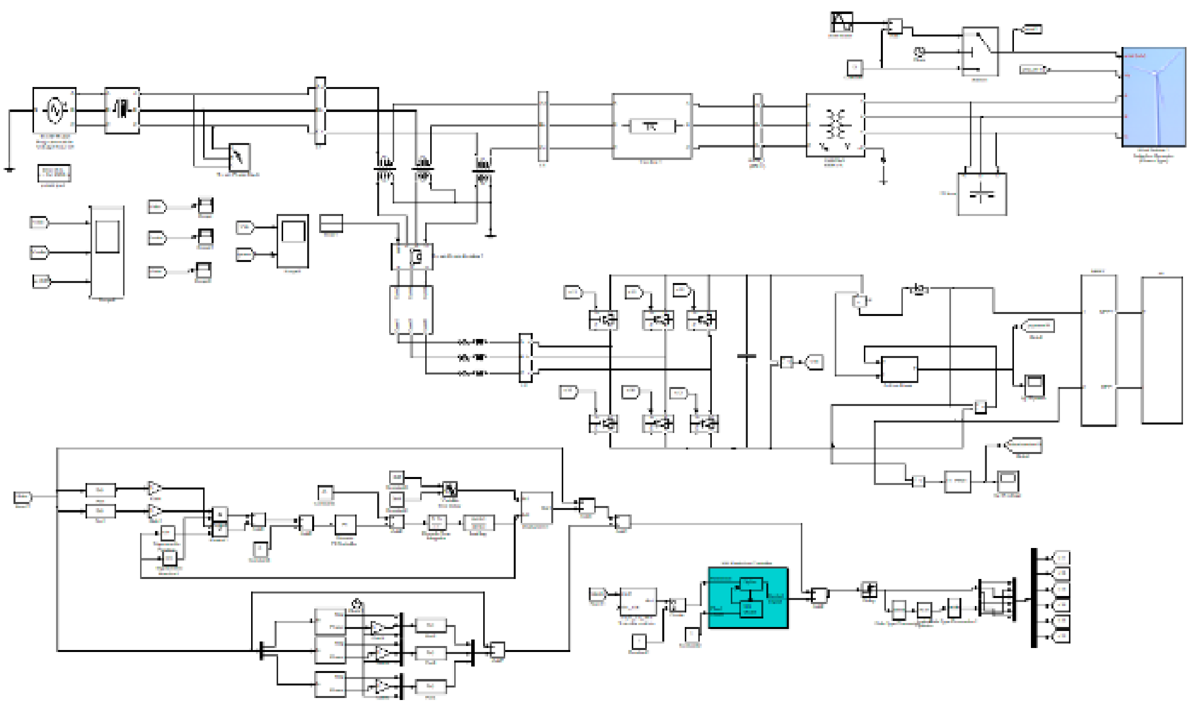

Figure 5: Simulink implementation of DVR using ANN

Case 1. In Figure 4, the simulation time diagram, a three-phase rectifier connected to a balanced electronic/capacitive DC load is used as a nonlinear component for the DVR to drive the electronic neural network controller. This is done to demonstrate the DVR's behavior in non-linear scenarios and to bolster the effects of position. In this instance, the rectifier load must be connected to a three-phase circuit breaker in order to change the supply voltage. At 0.2 seconds, the circuit breaker closes and stays that way for 0.2 and 0.3 seconds. The supply voltage waveform becomes erratic and departs from a sinusoidal shape during this time. Since the DVR protects and makes up for them, the addition of non-linear components to the system has no effect on sensitive loads. THD values of roughly 52.48% respectively, were revealed by a fast Fourier transform (FFT) analysis of the sensitive load voltage and source voltage. Figure 5 displays the voltages of the base, injection, and sensitive load (in volts). DVR simulation model, an ANN controller is employed to handle non-linear load conditions. Time in seconds Figure 5: With the ANN controller in place, DVR performance under non-linear load conditions

Under Swell condition

Then the system is conducted with three-phase fault and swell conditioning is shown in wave forms and THD of the system are analyzed

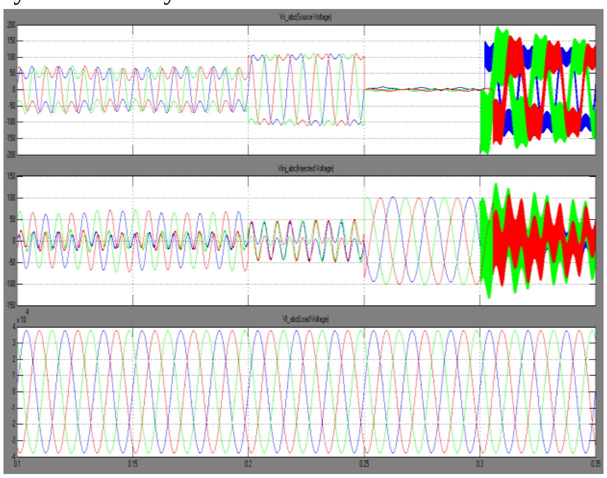

Figure 6: waveforms of supply voltage, injected voltage and load voltage

Because of the significantly greater THD (27.21%) in the system (input 1), which required to be lowered, we built the PI controller and the THD of PI was lowered to 2.77%. We employed a neural network to further minimize the THD, and the outcomes were superior to those of a PI controller. With the same 50 Hz frequency, the system's THD is now only 0.49%. Figure 6 below illustrates the same [21]

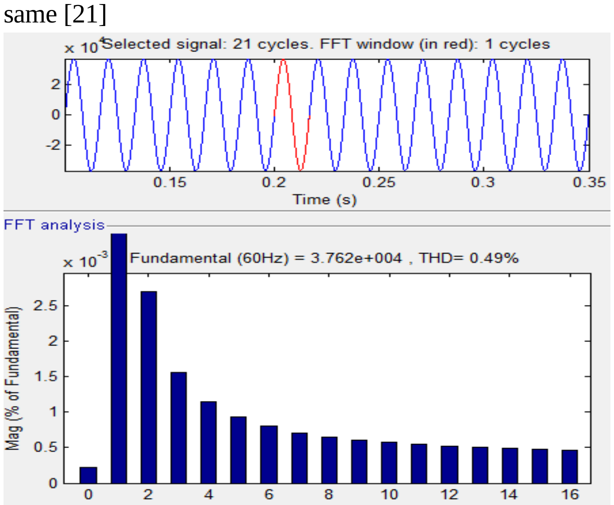

Figure 7: waveforms of supply voltage, injected voltage and load voltage with THD values under

Case 2: The ANN controller used to measure voltage sags and swells is depicted in Figure 6 with THD values uses a three-phase programmable AC power supply to display the DVR simulation diagram. For sag condition, these effects happen between 0.2 and 0.3 seconds, and for impacts, they happen between 0.2 and 0.3 seconds. In specifics, 0.1 seconds. The results unequivocally demonstrate that the DVR's efficient operation regulates the measured levels' energy consumption. The DVR will immediately respond to voltage dips and spikes by injecting both positive and negative voltages to safeguard delicate loads. In this example, the DVR's functionality is tested after the three-phase rectifier load is removed. The source voltage, injection voltage, and sensitive load voltage (per unit volt) are shown in Figure 6. The ANN controller improves DVR performance by adjusting for voltage dips and s in the impacted area. The THD of the load voltage has now been reduced to 0.49% for the same 50 Hz frequency.

Under sag condition

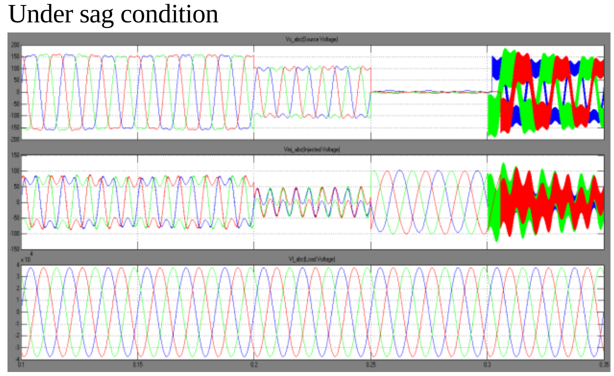

Figure 8: waveforms of supply voltage, injected voltage and load voltage

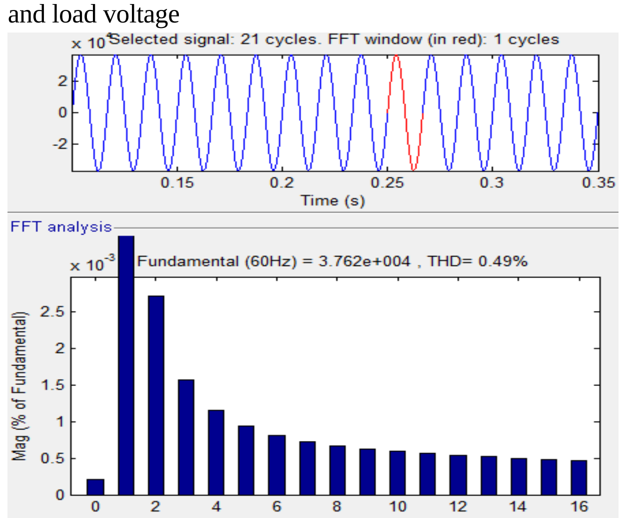

Figure 9: waveforms of load voltage with THD values under sag condition

Case 3. Examine the DVR's efficacy in relation to the single-phase influence of the three-phase supply voltage. A mismatch causes a voltage rise between 0.2 and 0.3s and a swell in three phase when using a three-phase programmable AC power supply. In order to maintain a steady and balanced voltage on delicate components, the DVR modifies the voltage. The controller's ability to supply the necessary voltage was proven by the simulation results. Figure 7 displays the input voltage, injection voltage, and output load voltage (in volts). Time (in seconds) under Sag

The claim is verified by simulation results using MATLAB/Simulink. When there is a voltage outage, sensitive products are safeguarded by ANN-controlled DVRs. Three distinct scenarios are investigated in this project. The simulation time diagram uses a three-phase rectifier as a nonlinear component to allow the DVR to drive the electronic neural network controller. The rectifier is connected to a balanced electronic/capacitive DC load. This is done to demonstrate the DVR's behavior in non-linear scenarios and to bolster the effects of position. In this instance, the rectifier load must be connected to a three-phase circuit breaker in order to change the supply voltage. At 0.2 seconds, the circuit breaker closes and stays that way for 0.1 seconds. At this point, the supply voltage waveform stops being sinusoidal and starts to become erratic. Since the DVR protects and makes up for them, the addition of non-linear components to the system has no effect on sensitive loads. THD values of roughly 52.48%, without DVR respectively, were revealed by a fast Fourier transform (FFT) analysis of the sensitive load voltage and source voltage. DVR simulation model that uses an ANN controller to non-linear load circumstances Time in seconds with the ANN controller in place, DVR performance under non-linear load conditions. In results the THD has improved to 0.49% between 0.2 to 0.3 s for both swell and sag condition.

CONCLUSION

A MATLAB/Simulink simulation unequivocally demonstrates how well the DVR controlled by the ANN can control the voltage with faulty conditioning. The DVR functions flawlessly when downloading and upgrading, responding with stability and speed. There are no disruptions while the DVR is in use. The DVR design's performance and response are evaluated using these three tests. Values of THD and unit load voltage are consistently maintained below standard limits through the use of suitable control strategies. Thus, ANN-based DVR controllers offer an additional means of mitigating power quality impacts like voltage dips, spikes, and harmonics.

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