iJRASET
International Journal For Research in
Applied Science and Engineering Technology

INTERNATIONAL JOURNAL FOR RESEARCH
IN APPLIED SCIENCE & ENGINEERING TECHNOLOGY

Volume: 14 Issue: II Month of publication: February 2026

DOI: https://doi.org/10.22214/ijraset.2026.77485

Advanced Power Quality Control through Artificial Neural Networks Controller and Fuzzy Logic Controller Based Dynamic Voltage Restorer Systems

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Abstract: Power quality is a major concern in modern power systems because it directly affects both consumers and utility operations. Issues like voltage harmonics, sags, and swells can cause significant damage to sensitive equipment, which is increasingly prevalent in modern electrical systems. As more sensitive devices are used, ensuring high power quality becomes critical for the reliable and secure operation of these systems. To manage these power quality issues, a device known as a Dynamic Voltage Restorer (DVR)is widely used in distribution systems. The DVR is a type of Distribution Flexible AC Transmission System device is used to correct non- standard voltage conditions by injecting voltages that help maintain the desired voltage profile. This ensures a continuous and stable voltage supply to loads, protecting them from voltage fluctuations. Artificial neural networks control based DVR do not give sufficient Total harmonic distortion (THD), voltage balance, efficiency. This paper focuses on reducing voltage sags, voltage swells, and total harmonic distortion (THD) by employing a Dynamic Voltage Restorer (DVR). A hybrid control scheme that combines an Artificial Neural Network (ANN) with a Fuzzy Logic Controller is adopted to improve the effectiveness of voltage compensation. The integrated control strategy addresses the drawbacks of conventional ANN-controlled DVR systems and enhances overall power quality performance. The performance and the control strategy of the DVR by the combine of Artificial neural network (ANN) & Fuzzy logic controller is simulated using MATLAB SIMULINK software.
Keywords: Dynamic voltage restorer (DVR), Artificial neural network (ANN), fuzzy logic controller.

I. INTRODUCTION

Advancements in modern electrical and electronic technologies have increased the susceptibility of power systems to disturbances such as voltage sags, swells, harmonics, and flicker. These power quality problems typically arise from faults in distribution systems, sudden fluctuations in load demand, the operation of large inductive equipment, and the widespread use of nonlinear devices. Poor power quality can result in malfunctioning, accelerated wear, or even damage to sensitive equipment, making the improvement of power quality a critical requirement in contemporary electrical networks [1]–[3].

To address voltage-related power quality challenges, several custom power devices have been introduced, with the Dynamic Voltage Restorer (DVR) emerging as a dependable and efficient solution [4]–[12]. A DVR functions by injecting an appropriate compensating voltage in series with the supply to ensure that the load voltage remains within permissible limits during abnormal operating conditions [13], [14]. The effectiveness of a DVR largely depends on its control methodology, especially when dealing with nonlinear loads and rapidly changing system conditions [5], [6].

Traditional control techniques, including Proportional–Integral (PI) and Proportional–Integral– Derivative (PID) controllers, are commonly employed in DVR systems due to their simplicity and ease of implementation [7], [12]. However, under nonlinear operating conditions and sudden disturbances, these controllers often suffer from reduced performance, resulting in slower transient responses and increased harmonic distortion [6], [14]. To overcome these drawbacks, intelligent control approaches such as Fuzzy Logic Control (FLC) and Artificial Neural Networks (ANN) have gained attention for improving DVR performance [15].

Fuzzy logic controllers utilize rule-based decision- making and expert knowledge to handle system nonlinearities and uncertainties without relying on exact mathematical models [11]. Although FLC offers improved robustness compared to conventional controllers, its effectiveness heavily depends on the appropriate selection of membership functions and rule sets [10]. On the other hand, ANN-based controllers exhibit adaptive learning and self-adjusting characteristics, enabling them to manage complex and time-varying system behaviors more effectively [15]. Through training with historical data, ANN controllers can deliver faster dynamic responses, superior voltage regulation, and lower harmonic distortion [15].

This study emphasizes the application of Fuzzy Logic and ANN-based control strategies in DVR systems to improve power quality in distribution networks. The proposed intelligent controllers aim to provide efficient voltage compensation during sag and swell conditions while reducing total harmonic distortion. Comparative evaluations demonstrate that ANN-based control techniques surpass conventional and fuzzy logic methods in terms of precision, adaptability, and overall system performance [15].

II. PROPOSED SYSTEM

A. Existing ANN-Based Controller

Artificial Neural Network (ANN)–based control approaches have been widely explored for improving power quality due to their effectiveness in handling the nonlinear and time-varying nature of power systems. In conventional Dynamic Voltage Restorer (DVR) systems employing Artificial Neural Network (ANN) control, the neural model is trained to estimate the required compensating voltage by utilizing inputs such as the source voltage, reference voltage, voltage deviation, and the rate of change of the error signal. Feedforward neural networks trained using the backpropagation learning algorithm are commonly employed for this application.

One of the major advantages of ANN controllers is their learning capability, which enables them to adapt to varying operating conditions. Once adequately trained, the ANN can provide fast and accurate voltage compensation during power quality disturbances, including voltage sag and swell events. Moreover, ANN-based controllers possess strong generalization abilities, allowing them to maintain satisfactory performance under unseen operating conditions, thereby enhancing robustness against system parameter variations.

However, ANN-based control methods also have several limitations when used independently. Their performance is strongly influenced by the quality, quantity, and representativeness of the training data. Inadequate or poorly diversified datasets can lead to incorrect compensation, especially during uncommon or severe disturbance conditions. In addition, ANN models operate as black-box systems, offering limited interpretability and making online adjustment and performance evaluation difficult. The computational effort required for ANN training and real-time execution further adds to system complexity and cost. As a result, standalone ANN-based controllers may not always deliver optimal performance in highly dynamic or uncertain operating environments.

B. Proposed ANN–Fuzzy Logic Controller

To overcome the drawbacks of conventional ANN- based control techniques, a hybrid Artificial Neural Network–Fuzzy Logic Controller is developed for the Dynamic Voltage Restorer. The proposed control approach integrates the adaptive learning features of ANN with the rule-based decision-making capabilities of Fuzzy Logic Control (FLC), thereby providing a more robust and flexible control architecture. In the proposed framework, the fuzzy logic controller addresses system nonlinearities and uncertainties by producing preliminary control actions based on linguistic rules formulated from expert knowledge. Fundamental inputs, including the voltage deviation and the time derivative of the error signal, are evaluated using fuzzy membership functions and a predefined rule set to generate the control output. This fuzzy-derived signal is subsequently utilized either as a reference signal or as supervisory training data for the ANN module.

The ANN component is trained using a combination of real-time system operating data and the outputs provided by the fuzzy controller, enabling it to learn the optimal mapping between disturbance scenarios and the corresponding compensating voltage. Through continuous adaptive learning, the ANN refines the control signal, leading to improved transient response characteristics and minimized steady-state error. This integrated control approach enhances overall system stability and significantly reduces harmonic distortion during voltage sag and swell conditions.

Compared to traditional ANN-only controllers, the proposed ANN–Fuzzy Logic control scheme exhibits greater adaptability, reduced dependence on extensive training datasets, and improved robustness against system uncertainties. By merging knowledge-based inference with data-driven learning, the hybrid controller delivers superior voltage compensation performance and more effective suppression of total harmonic distortion (THD).Consequently, the proposed control scheme presents a robust and efficient solution for enhancing power quality in modern distribution systems.

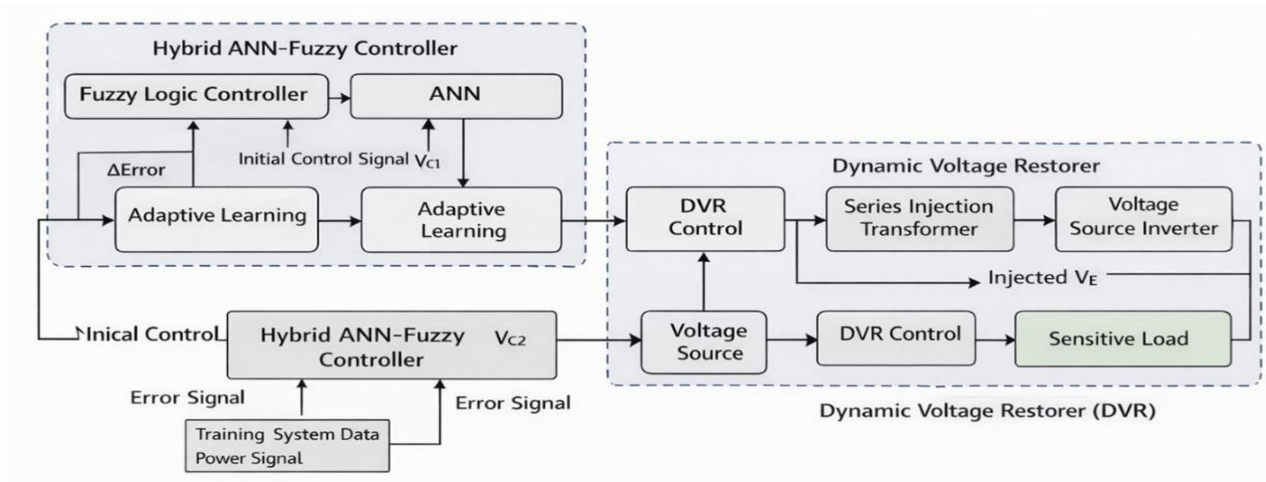

Fig :1 Proposed system of ANN and fuzzy of DVR systems

III. MATHEMATICAL MODELLING

Power quality is a critical factor in ensuring the dependable operation of modern electrical power systems, as disturbances such as voltage sags, voltage swells, and harmonic distortion can significantly affect sensitive industrial and commercial equipment. To address these challenges, various compensation devices have been introduced, among which the Dynamic Voltage Restorer (DVR) has emerged as an effective and commonly adopted solution. By injecting a suitable compensating voltage in series with the distribution feeder, the DVR maintains the load voltage at its rated value during fault events or temporary voltage reductions..

Accurate mathematical modeling of the DVR system and its associated control strategies is essential for effective system design and implementation. These models enable engineers and researchers to study system performance under different operating scenarios, optimize control parameters, and assess the effectiveness of the DVR through simulation studies prior to real-world deployment.

$V_{sag/swell} = Z_f + Z_S$ (1)

Where,

Z_f =The impedance between the PCC and the fault including fault and line impedances;

Z_S = The source impedance including the transformer impedance;

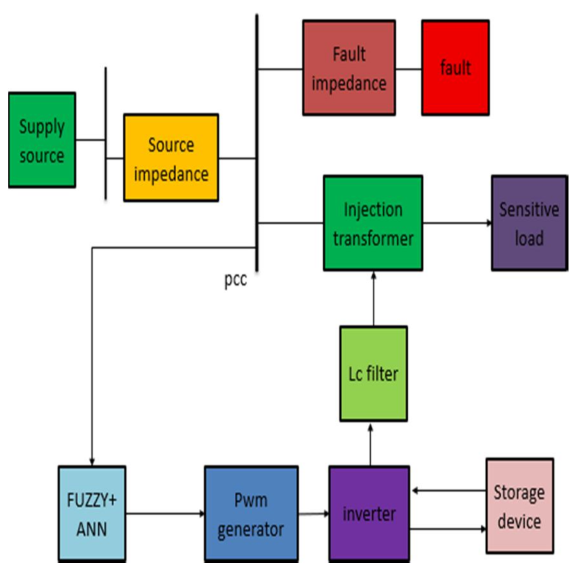

Fig:2 Block diagram of DVR system with ANN&FUZZY

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

Table: 1 Parameters For The Power System Used In Simulation

Component	Details
Source	33 kV, 50 Hz
Transformer T1	5 MVA, 33/11 kV DYn11
T2	750 MVA, 11/4 kV DYn11
Line	0.675+j0.372 Ohm /km, 2 km
Load	4.75 kW, 3.25 KVAR

Dynamic Voltage Restorers (DVRs) are advanced power electronic devices designed to enhance voltage stability in distribution systems by injecting a suitable compensating voltage during voltage sag events. The primary function of a DVR is to offset reductions in supply voltage by adding the required voltage component, ensuring that the load continues to receive the rated voltage level. This voltage compensation is implemented through a power electronic switching converter coupled with a series injection transformer.

Depending on their energy configuration, DVR systems are generally classified into DVRs are broadly classified into two categories: those with energy storage and those without energy storage. In storage- based DVRs, the compensating energy is supplied from an onboard energy storage unit, while non- storage DVRs draw the required compensation current directly from the power source to mitigate voltage sag conditions.

To reduce the impact of voltage sags and maintain acceptable power quality levels, Dynamic Voltage Restorers typically operate using three compensation techniques: pre-sag compensation, in-phase compensation, and phase-advanced compensation. In each method, the reduced voltage at the point of common coupling (PCC), represented as V_{sag}, is compared with the pre-disturbance voltage $V_{\text{pre-sag}}$to determine the magnitude of the voltage that must be injected by the DVR.

A major difference between a DVR with energy storage and an Uninterruptible Power Supply (UPS) lies in their functional operation. A DVR compensates only for the missing portion of the voltage waveform caused by a sag, whereas a UPS is designed to supply the full load power during a complete interruption. The main elements of a DVR system include a voltage source converter (VSC), a series injection (booster) transformer, a harmonic filter, and a control unit. DVRs are known for their rapid dynamic response and high efficiency. Moreover, DVR configurations without energy storage avoid the challenges associated with energy storage management.

In addition to mitigating voltage sags, DVRs enhance overall power quality by reducing harmonic distortion, limiting fault current levels, improving power factor, and suppressing transient disturbances.

$$V_{inj} = V_{pre\,sag} - V_{sag} \qquad (2)$$

$$\theta_{inj} = \frac{V_{pre-sag} \sin \theta_{pre-sag}}{V_{presag} \cos \theta_{pre-sag} - V_{sag} \cos \theta_{sag}} \qquad (3)$$

The voltage injected by DVR for in-phase compensation is given by

$$V_{dvr} = V_{inj} \qquad (4)$$

$$V_{inj} = V_{presag} - V_{sag} \qquad (5)$$

$$\angle\theta = \theta_{inj} = \theta_{sag} \qquad (6)$$

The phase-advanced compensation technique restores the voltage level by utilizing only reactive power support. In this approach, the Dynamic Voltage Restorer injects a compensating voltage that is phase- The compensating voltage is shifted by 90 degrees relative to the load current. As a result, the voltage injection is purely reactive, and no active power is transferred during the compensation. Consequently, voltage sag mitigation is accomplished solely through reactive power injection. This method is particularly well suited for DVR systems without energy storage, where reducing active power demand is a critical design consideration.

IV. CONTROL SRATEGY

The control strategy employed in a Dynamic Voltage Restorer plays a crucial role in ensuring effective compensation of voltage sags and swells while maintaining acceptable power quality at the load terminals. Since the DVR operates using a voltage source inverter (VSI) with high-frequency switching, its control system must accurately regulate the inverter output to ensure proper voltage compensation must be both precise and robust to generate accurate compensating signals under nonlinear and rapidly varying operating conditions. In this study, a hybrid control approach combining By combining Artificial Neural Networks and Fuzzy Logic, the system achieves enhanced performance in voltage restoration and improved power quality. The primary aim of the proposed control scheme is to maintain the load voltage at a desired reference level, regardless of fluctuations or disturbances in the supply. This is achieved by continuously monitoring the load voltage and comparing it with the reference value. The resulting voltage deviation and its rate of change serve as key inputs for calculating the he precise magnitude and phase of the voltage that the DVR must supply to achieve effective compensation. Initially, the voltage error is processed by the Fuzzy Logic Controller for decision-making and its derivative using linguistic variables and a rule-based inference system. By doing so, the fuzzy controller effectively handles system nonlinearities and uncertainties without requiring an exact mathematical model. Based on the defined membership functions and rule set, the FLC generates an initial control signal representing the required compensating voltage. To improve the system's adaptability and dynamic performance, an Artificial Neural Network is integrated with fuzzy controller. The ANN is trained using both the operational data of the system and the output provided by the fuzzy controller, allowing it to learn the nonlinear relationship between input disturbances and the optimal control action. Leveraging its learning and generalization abilities, the ANN refines the initial fuzzy control signal to produce an optimized control output. This hybrid control strategy effectively combines the interpretability and robustness of fuzzy logic with the adaptive learning capability of the ANN.

The optimized signal generated by the ANN–Fuzzy controller is subsequently used to produce switching pulses for the voltage source inverter (VSI) through a suitable modulation method, such as pulse width modulation (PWM). The VSI then generates the compensating voltage, which is injected in series into the distribution line via the injection transformer. As a result, the load voltage is maintained at its nominal value, with improved transient response and reduced harmonic distortion.

Overall, the proposed hybrid control approach offers fast dynamic response, accurate voltage compensation, and robust performance under system uncertainties. In comparison with conventional linear controllers, the ANN–Fuzzy-based scheme achieves superior voltage regulation and significantly improves power quality across diverse disturbance scenarios.

A. Voltage Sag/Swell Modelling

The voltage supplied at the point of common coupling (PCC) during a disturbance can be expressed as:

$$V_{PCC} = V_S - Z_S I_L \qquad (7)$$

Where,

V_S = source voltage

Z_S=source impedance

I_L= load current

Under voltage sag or swell conditions, the voltage at the load can be expressed as:

$$V_L = V_{\mathrm{PCC}} + V_{\mathrm{inj}} \qquad (8)$$

To ensure the load voltage remains at the specified value, the DVR injects a compensating voltage, which can be expressed as:

$$V_{\mathrm{inj}} = V_{\mathrm{ref}} - V_{\mathrm{PCC}} \qquad (9)$$

Here, V_{ref} represents the reference (nominal) load voltage, $V_{\mathrm{PCC}}$is the voltage at the point of common coupling, and V_{inj} is the voltage supplied by the DVR to restore the load voltage to its rated value.

B. Voltage Error Calculation

The voltage deviation signal is defined by the difference between the reference and load voltages:

$$(t) = V_{\mathrm{ref}}(t) - V_L(t) \qquad (10)$$

The change in the voltage error is expressed

$$\Delta(t) = e(t) - e(t-1) \qquad (11)$$

Both (t) and $\Delta e(t)$serve as key inputs to the Fuzzy Logic Controller and the ANN-based controller, providing the critical data needed to calculate the compensating voltage.

C. Fuzzy Logic Controller (FLC) Equations

1) Fuzzification

The crisp input signals, $(t)$and $\Delta e(t)$, are transformed into fuzzy variables through the use of membership functions. A commonly used form for the membership function is the triangular a membership function, representing the degree to which a given input value is associated with a fuzzy set in a simple and computationally efficient manner.

$$\mu(x) = \begin{cases} 0, & x \le a \\ \frac{x-a}{b-a}, & a < x \le b \\ \frac{c-x}{c-b}, & b < x \le c \\ 0, & x > c \end{cases} \qquad (12)$$

2) Fuzzy Rule Base

Fuzzy rules are expressed as:

IF e is A_i AND Δe is B_j THEN u_f is C_k (13)

3) Defuzzification

The centroid (center-of-gravity) method is used to obtain the crisp output:

$$u_f = \frac{\sum_{i=1}^{N} \mu_i u_i}{\sum_{i=1}^{N} \mu_i} \qquad (14)$$

where $u_f$is the initial control signal V_{c1}.

D. Artificial Neural Network (ANN) Model

A feedforward ANN with one hidden layer is commonly used.

1) Hidden Layer Output

$h_j = (\sum_{i=1} w_{ij}\, x_i + b_j)$ (15)

where:

w_{ij}= weights between input and hidden layer

b_j=bias

f= activation function (tansig)

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \qquad (16)$$

2) Output Layer Equation

$$y = g\left(\sum_{j=1}^{m} v_j h_j + b_o\right) \qquad (17)$$

where $g$is a linear activation function.

The ANN output provides a refined control signal:

$V_{c2} = y$ (18)

E. ANN Training (Error Minimization)

The training error is defined as:

$$E = \frac{1}{2}\sum(t-y)^2 \qquad (19)$$

Weight update using gradient descent:

$$w^{new} = w^{old} - \eta \frac{\partial E}{\partial w} \qquad (20)$$

where $\eta$is the learning rate.

International Journal for Research in Applied Science & Engineering Technology (IJRASET)
ISSN: 2321-9653; IC Value: 45.98; SJ Impact Factor: 7.538
Volume 14 Issue II Feb 2026- Available at www.ijraset.com

F. PWM Generation

The modulation index is calculated as:

$$m = \frac{V_{c2}}{V_{dc}} \quad (21)$$

The PWM gating signals are generated by comparing modulating signal with carrier signal:

$$V_{PWM} = \begin{cases} 1, & V_{ref} > V_{carrier} \\ 0, & V_{ref} \le V_{carrier} \end{cases} \quad (22)$$

G. Injected Voltage by DVR

The injected voltage through the transformer is:

$$V_{inj} = m \times V_{dc} \quad (23)$$

Final load voltage becomes:

$$V_L = V_S + V_{inj} \quad (24)$$

Power quality disturbances, such as voltage sags and swells, can significantly affect the reliable operation of sensitive electrical equipment. The Dynamic Voltage Restorer (DVR) provides an effective custom power solution to mitigate these disturbances by injecting an appropriate compensating voltage in series with the distribution system. However, conventional control methods often face limitations in handling nonlinear system behavior and rapidly varying operating conditions.

To overcome these challenges, control approaches based on Artificial Neural Networks (ANN) and Fuzzy Logic have been increasingly employed in DVR applications. ANN-based controllers provide adaptive learning and self-tuning capabilities, whereas fuzzy logic controllers offer robust decision-making under uncertain conditions. The integration of ANN with fuzzy logic enhances the DVR's response speed, accuracy, and overall robustness, enabling effective regulation of load voltage during power quality disturbances.

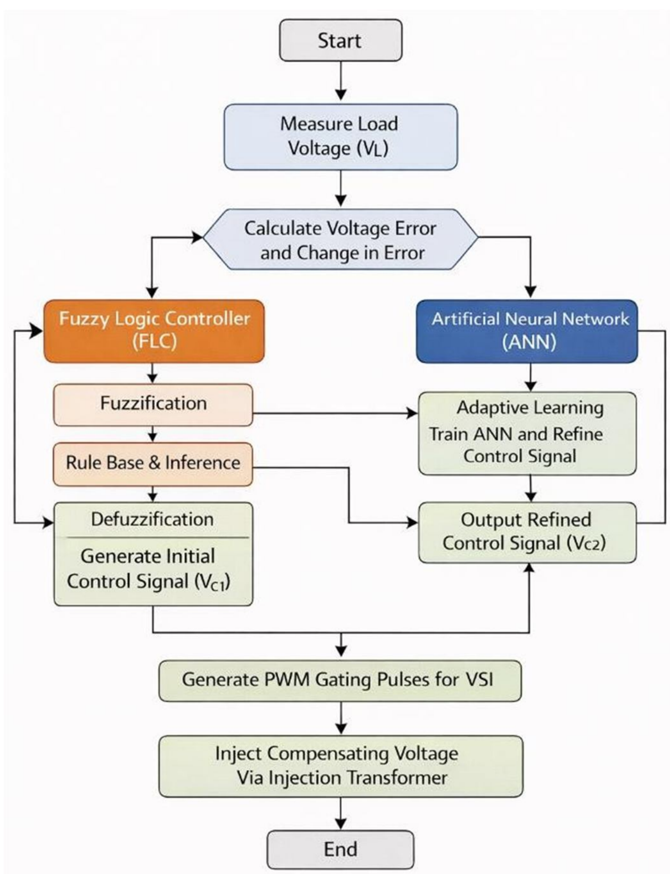

Fig: 3 Flowchart of Artificial neural network and fuzzy controller

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V. PROPOSED ANFIS CONTROLLER

The proposed control strategy delivers fast dynamic response, accurate voltage compensation, and enhanced robustness against system uncertainties. The hybrid ANN–Fuzzy control framework outperforms conventional linear controllers by providing superior voltage regulation and improved overall power quality across a broad range of disturbance conditions.

Artificial Neural Networks (ANN) and Fuzzy Logic (FL) are complementary computational intelligence techniques commonly used for modeling complex and uncertain systems. While ANN excels at learning nonlinear relationships from data, it generally functions as a black-box model with limited interpretability. Fuzzy logic, on the other hand, provides transparent, rule-based reasoning but lacks intrinsic learning capabilities. By combining these two approaches, Neuro-Fuzzy systems are formed, leveraging the adaptive learning ability of ANN alongside the interpretability and robustness of fuzzy logic.

One of the most commonly implemented neuro-fuzzy architectures is the Adaptive Neuro-Fuzzy Inference System (ANFIS). ANFIS utilizes a layered structure to perform fuzzy inference while simultaneously adapting membership functions and rule parameters through neural network learning algorithms, thereby improving both precision and flexibility. Other hybrid approaches include neural-network-based tuning of fuzzy controllers, embedding fuzzy logic elements within neural networks, and cascaded ANN–fuzzy control arrangements. Among the various ANN training methods, the feedforward backpropagation algorithm is widely used, where input signals propagate forward through the network and errors are back-propagated to iteratively update weights and biases using gradient descent optimization.

VI. SIMULATION RESULTS

A. *Existing Results*

While controllers based on Artificial Neural Networks (ANN) and PID strategies provide several advantages, they present significant challenges in real-world applications. Their performance is highly dependent on the presence of comprehensive and representative training data, and inadequate or poor-quality datasets can lead to errors and reduced control accuracy.

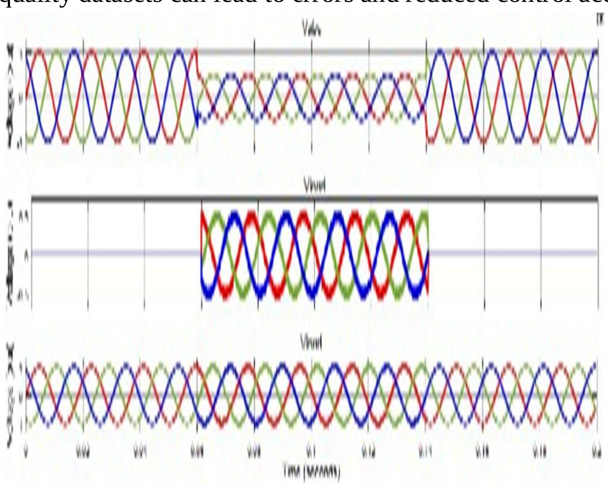

Fig:4 Output waveforms of ANN controller

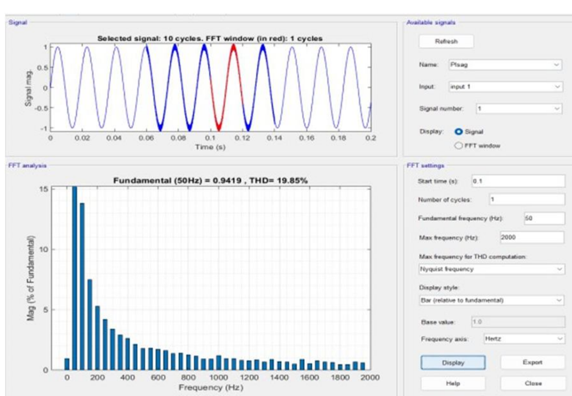

Fig:5 THD of PID controller

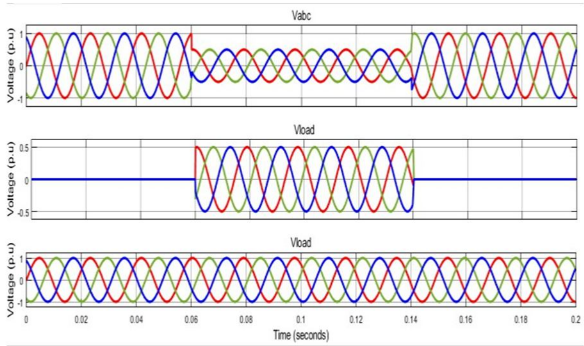

Fig:6 Output waveforms of ANN controller

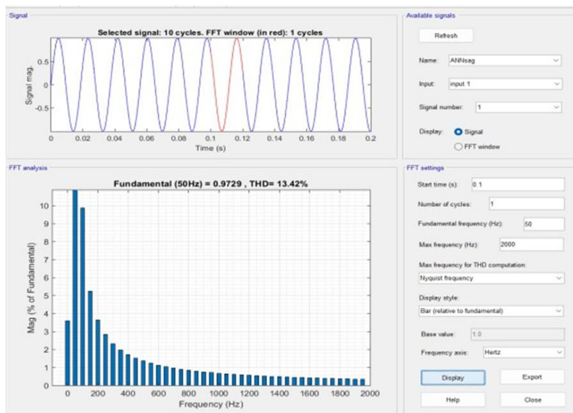

Fig:7 THD of ANN controller

B. Extension Results

ANFIS demonstrates a strong ability to manage system nonlinearities and uncertainties, ensuring stable and reliable performance during voltage sag and swell events. In contrast to conventional control methods, which often rely on precise mathematical models and may have difficulty coping with dynamic variations, ANFIS adjusts in real time, providing faster transient response and lower steady-state error. Its self-learning and adaptive characteristics improve overall system stability, enabling efficient operation under fluctuating loads and frequent disturbances. Consequently, ANFIS-based DVR control enhances voltage regulation, robustness, and reliability, making it a highly suitable solution in applications where traditional controllers may fail to maintain optimal performance.

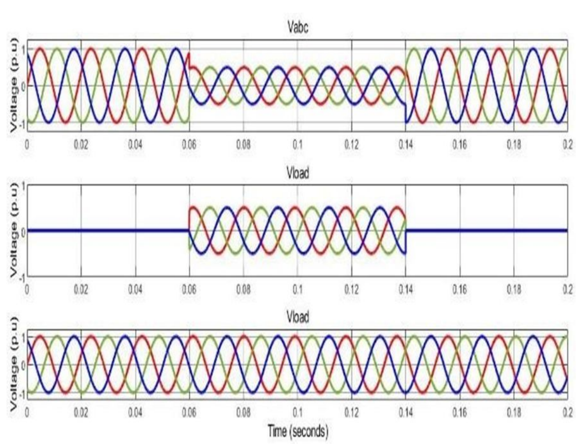

Fig:8 Output waveforms of ANFIS controller

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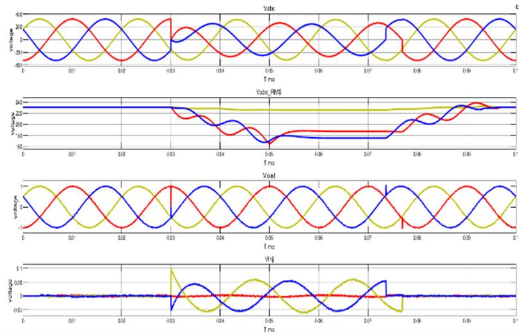
Fig:9 Output waveforms when three phase RLC series load applied

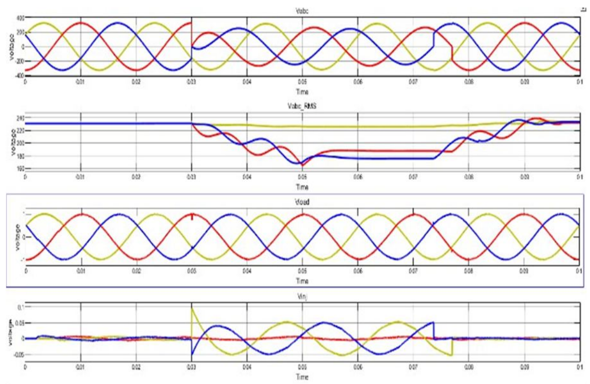

Fig:10 Output waveforms when three phase parallel RLC load is applied

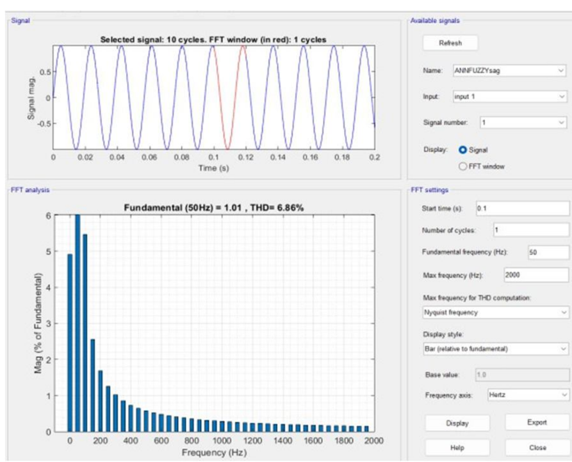

Fig:11 THD of ANFIS controller

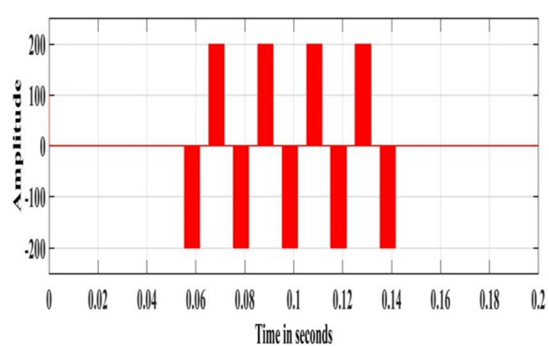

Fig:12 Output voltage of the inverter circuit

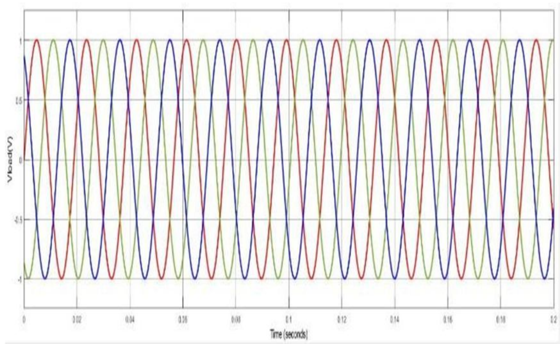

Fig:13 Load voltage waveform using ANFIS

The performance of the three control strategies was carefully assessed by analyzing their Total Harmonic Distortion (THD), a critical measure of power quality. The conventional PID controller showed the highest THD at 19.7%, indicating limited capability in mitigating harmonics and maintaining stable voltage under dynamic conditions. The ANN-based controller demonstrated notable improvement, reducing THD to 13.5% by adapting to system nonlinearities through its learning mechanism. The ANFIS controller, however, achieved the best performance, attaining a significantly lower THD of 6.86%, highlighting its superior harmonic suppression and adaptive control capability. This substantial reduction in THD underscores ANFIS's effectiveness in managing nonlinearities and system uncertainties, thereby enhancing overall power quality and stability. Collectively, these results confirm that ANFIS-based control surpasses both PID and ANN methods, offering a highly reliable and efficient solution for modern distribution networks subject to frequent disturbances and variable load conditions.

Table:2Comparision of Artificial neural network (ANN), PID controller, ANFIS

Type of controller	% of Total Harmonic Distortion (THD)
PID	19.7 %
ANN	13.5 %
ANFIS	6.86 %

As shown in Table 4.1, the conventional PID controller records the highest THD at 19.7%, underscoring its limitations under nonlinear and rapidly changing conditions such as voltage sags and harmonic disturbances. The fixed nature of its parameters limits adaptability, resulting in comparatively higher distortion levels.

The Artificial Neural Network (ANN) controller offers improved performance, reducing THD to 13.5%. This improvement highlights the ANN's capacity to learn system dynamics and adjust control actions accordingly. Through training-based parameter tuning, the ANN responds more effectively to disturbances, achieving better harmonic suppression than the PID controller.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) achieves the lowest THD at 6.86%, delivering the best overall performance among the three controllers. By combining neural network learning with fuzzy logic's rule-based reasoning, ANFIS provides adaptive and precise control. These results demonstrate that ANFIS is the most effective in mitigating harmonics and enhancing power quality, making it highly suitable for DVR-based voltage compensation applications.

VII. CONCLUSION

Enhancing power quality with a The Dynamic Voltage Restorer, controlled using a combination of Artificial Neural Networks and Fuzzy Logic, presents an effective method for mitigating voltage sags, swells, and harmonics, in modern distribution systems. By integrating these intelligent control strategies, the DVR can respond dynamically and accurately to voltage variations, achieving performance levels far superior to conventional controllers. The ANN controller adjusts to changing operating conditions by learning the nonlinear behavior of the system, while the Fuzzy Logic controller strengthens decision- making under uncertain or rapidly changing load conditions. Simulation results indicate that this hybrid control approach maintains the load voltage close to its nominal value, minimizes interruptions, and enhances overall power quality. Consequently, the intelligent DVR design delivers a reliable, efficient, and adaptive means of voltage regulation, ensuring stable operation and uninterrupted power supply in smart distribution networks subject to frequent disturbances and load variations.

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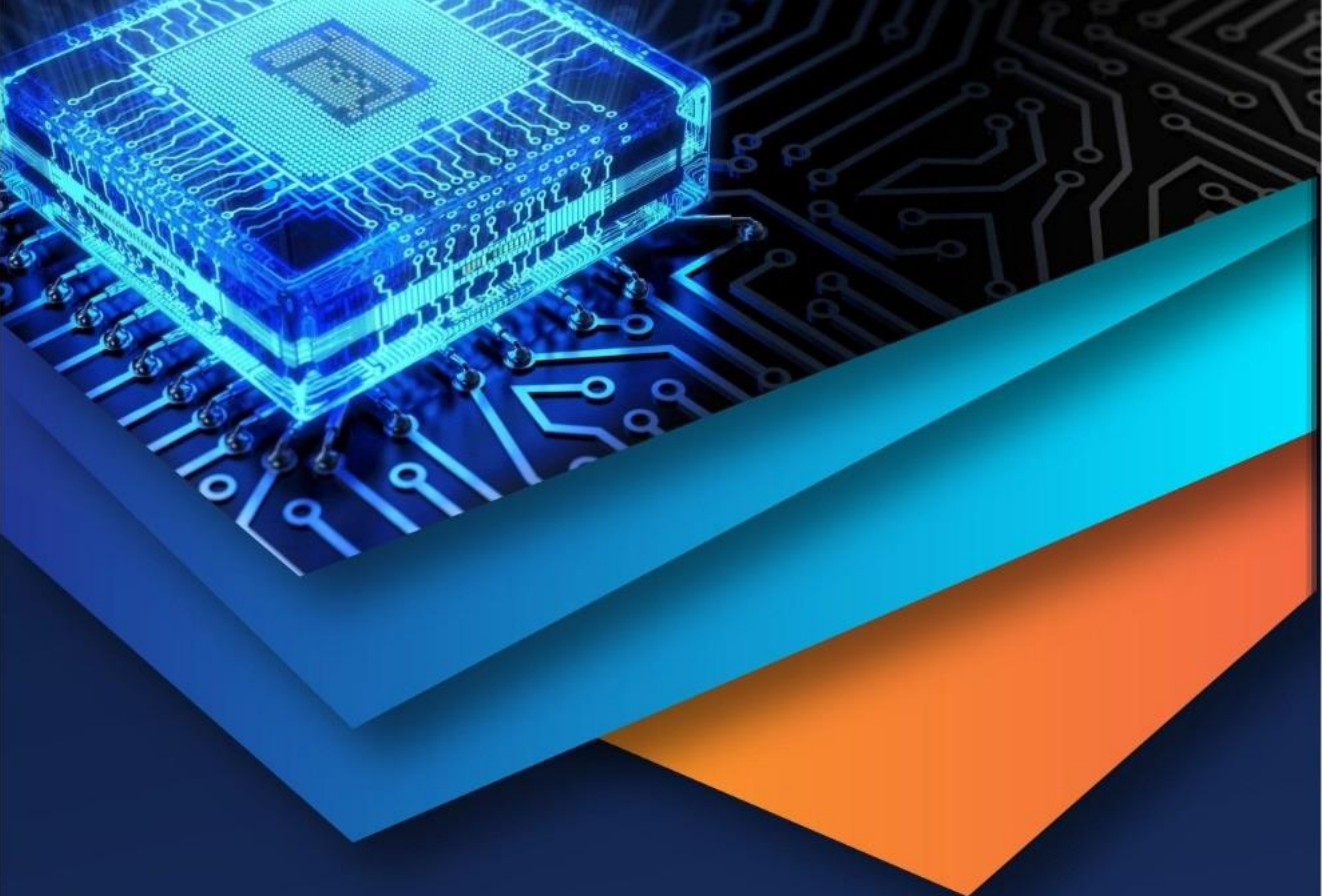

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