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Intelligent Voltage Sag Compensation Using an Artificial Neural Network (ANN)-Based Dynamic Voltage Restorer in MATLAB Simulink

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Abstract: An innovative Dynamic Voltage Restorer (DVR) system based on Artificial Neural Network (ANN) technology, implemented in MATLAB Simulink, accurately detects, and dynamically restores voltage sags, significantly improving power quality and ensuring a reliable supply to critical loads, contributing to the advancement of power quality enhancement techniques. Voltage sags are a prevalent power quality concern that can have a significant impact on sensitive electrical equipment. An innovative approach to address voltage sags through the operation of a Dynamic Voltage Restorer (DVR) based on Artificial Neural Network (ANN) technology. The proposed system, developed using MATLAB Simulink, leverages the ANN's capabilities to accurately detect voltage sags and dynamically restore the voltage to the affected load. The ANN is trained using a comprehensive dataset comprising voltage sag events, enabling it to learn the intricate relationships between sag characteristics and optimal compensation techniques. By integrating the trained ANN into the DVR control scheme, real-time compensation for voltage sags is achieved. The effectiveness of the proposed system is rigorously evaluated through extensive simulations and performance analysis. The results demonstrate the superior performance of the ANN-based DVR in terms of voltage sag detection accuracy and restoration precision. Consequently, the proposed system presents an intelligent and adaptive solution for voltage sag compensation, ensuring a reliable and high-quality power supply to critical loads. This research contributes to the advancement of power quality enhancement techniques, facilitating the implementation of intelligent power system.

Keywords: Artificial Neural Network (ANN), critical loads, cascade h-bridge, multilevel inverter, Dynamic Voltage Restorer (DVR), intelligent power systems, MATLAB Simulink, power quality, restoration precision, voltage sags

1. Introduction

The reliability and quality of electric power supply are vital for the efficient operation of various industrial and commercial sectors. However, power systems are susceptible to various disturbances [1], such as voltage sags, which can disrupt the operation of sensitive electrical equipment and cause significant economic losses. Voltage sags, also renowned as voltage dips or short-duration voltage variations, refer to a sudden decrease in the magnitude of voltage for a short period, typically ranging from a few milliseconds to a few seconds. These disturbances can result from various factors, including faults in the power grid [2], the starting of large motors, or the switching of heavy loads.

Voltage sags have become a prevalent power quality issue in modern power systems [3] due to the increased utilization of power electronics-based equipment and the sensitivity of critical loads to voltage variations. Critical loads, such as data centers, industrial processes, and medical equipment, require a constant and high-quality power

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supply to ensure uninterrupted operations. Therefore, the effective mitigation of voltage sags is crucial to maintain a reliable and stable power supply for these applications. Traditional methods for voltage sag compensation, such as static voltage compensators or energy storage devices, have limitations in terms of their response time, accuracy, and adaptability. In recent years, the use of intelligent and adaptive techniques, such as Artificial Neural Networks (ANNs) [4-6], has gained significant consideration in the field of power quality enhancement. Artificial neural networks (ANNs) are computerized models that draw inspiration from the neural structure of the human brain, enabling them to acquire intricate patterns and connections from data [7]. By utilizing ANNs [8], it becomes possible to develop dynamic voltage compensation techniques that adapt to varying system conditions [9] [10] and provide precise and rapid voltage restoration. This research paper aims to propose and evaluate an innovative approach for voltage sag compensation using an ANN-based Dynamic Voltage Restorer (DVR) implemented in MATLAB Simulink. The DVR, as a power electronic device [11], is specifically engineered to identify voltage dips and introduce corrective voltage adjustments to return the load voltage to its intended standard level. By incorporating an ANN [12-14] within the control scheme of the DVR, the system can intelligently and accurately detect voltage sags [15] and determine the optimal compensation strategy based on the sag characteristics.

The integration of the ANN into the DVR control scheme offers several advantages over conventional techniques [16-18]. Firstly, the ANN can learn from a vast dataset of voltage sag events, enabling it to identify complex patterns and correlations between sag characteristics and the required compensation actions [19-21]. This learning capability enhances the accuracy of voltage sag detection and enables the system to respond effectively to different sag scenarios. Additionally, the ANN-based DVR [22] [23] can adapt to changes in the power system and load conditions, ensuring optimal compensation performance in dynamic environments. The development of the proposed ANN-based DVR involves several key steps. Firstly, a comprehensive dataset of voltage sag events is collected, encompassing various sag magnitudes, durations, and waveforms. This dataset is used to train the ANN model [24], allowing it to learn the nonlinear mappings between the input sag characteristics and the desired compensating voltages. The training procedure entails fine-tuning the neural network's weights and biases using iterative optimization methods to minimize prediction errors. Following the completion of training, the ANN is incorporated into the MATLAB Simulink control system for the DVR. In real-time, voltage sag detection occurs by inputting the measured voltage signal into the ANN, which subsequently produces the necessary compensation voltage signals for the restoration of load voltage. The performance of the ANN-based DVR is evaluated through extensive simulations and compared against conventional voltage sag compensation techniques.

The contributions of this research include the development of an intelligent and adaptive solution for voltage sag compensation using ANNs, as well as the analysis and validation of the proposed system's performance. The results of the simulations provide insights into the effectiveness and superiority of the ANN-based approach in terms of voltage sag detection accuracy and restoration precision. In conclusion, this research paper addresses the significant issue of voltage sags in power systems and presents a novel solution utilizing an ANN-based DVR implemented in MATLAB Simulink. The integration of ANNs into the control scheme enables intelligent and adaptive compensation for voltage sags [5], ensuring reliable and high-quality power supply to critical loads. The subsequent sections of this paper will delve into the methodology, implementation details, simulation results, and performance analysis of the proposed ANN-based DVR system.

2. Literature Review

The utilization of a Dynamic Voltage Restorer (DVR) [25] with an Artificial Neural Network (ANN) controller has been investigated in the context of power system studies [26]. Various studies [27-33] have focused on modeling and simulating the DVR in the MATLAB environment to evaluate its performance under different load conditions. Researchers have examined the DVR's ability to maintain a balanced voltage during varying load scenarios and under unbalanced system conditions [34]. Additionally, investigations have been carried out to assess the DVR's effectiveness in reducing Total Harmonic Distortion (THD) for different charging types, particularly in the Single Line-to-Ground (SLG) fault state. The findings consistently demonstrate the significant harmonic reduction achieved by the DVR, simplifying the charging voltage. The literature highlights the ANN-based DVR [35] as a promising solution for power quality enhancement in diverse applications, showcasing its effectiveness in mitigating voltage-related issues and improving overall system performance [36]. Furthermore, the studies indicate that the DVR holds substantial potential to enhance power system efficiency and reliability by effectively compensating for voltage disturbances [37] In the field of Dynamic Voltage Restorers (DVRs), researchers have proposed an artificial intelligence-integrated control approach. One such approach involves the development of a Levenberg Marquardt back-propagation (LMBP) algorithm, which utilizes intelligent computational systems for supervised learning. By optimizing an Artificial Neural Network (ANN) model [38], the proposed algorithm facilitates the computation of load voltage components in the training process. However, a common challenge with ANN models is slow learning and the tendency to get trapped in local optima. To overcome this issue, a hybrid learning system called LMBP is introduced, which combines the advantages of the LMBP algorithm with an adaptive neuro-fuzzy inference system (ANFIS) [6] controller to regulate DC and AC link voltage errors.

In the domain of distribution systems, this literature review focuses on addressing the issue of sag voltage mitigation. Sag voltage, often a consequence of single-phase-to-ground short circuit faults, exerts a significant impact on the integrity of load distribution along the feeder line. To effectively address voltage sag issues, the utilization of a Dynamic Voltage Restorer (DVR) is recommended [39]. Within the domain of power quality assessment, voltage sags and swells are acknowledged as critical factors affecting sensitive loads in distributed systems. To tackle this concern, a control system has been developed, incorporating a model that combines fuzzy logic and particle swarm optimization (PSO) [10]. The article explores two distinct approaches for fine-tuning the PI controller parameters: a trial-and-error method and an intelligent optimization method [2]. Furthermore, it investigates the utilization of an Artificial Neural Network (ANN), Machine Learning techniques [7], and the Hysteresis-based voltage control method in the design and analysis of a Dynamic Voltage Restorer (DVR) integrated with a photovoltaic source [4] [40]. In the realm of distributed systems, voltage sag and swell are acknowledged as influential factors impacting power quality for sensitive loads [41]. To address this issue, a controller system is developed, utilizing a combination of linear and non-linear fuzzy logic [27], particle swarm optimization (PSO) [12], ant lion optimizer-optimized artificial neural network (ALO-ANN) [24] and Grasshopper Optimization Algorithm models [29]. This literature review [11] [41] provides a concise overview [23] of the configurations and control strategies of the Dynamic Voltage Restorer (DVR) as described in previous research [34] [39]. The DVR provides a remedy for a range of power quality concerns, including addressing problems related to voltage harmonics as well as compensating for voltage sags and swells [4]. To improve the DVR's effectiveness, significant areas of emphasis encompass achieving energy efficiency, minimizing components and losses, minimizing power injection, reducing the rating, and implementing selective harmonics mitigation.

The examination conducted in reference [11] underscores the suitability of the DVR in mitigating voltage sags and swells via various control methods. Linear control approaches are especially favored for their relatively straightforward implementation and reduced computational demands when compared to alternative methods. The comprehensive literature review explores the diverse DVR configurations, fundamental architecture, operational modes, control strategies, compensation methods, and control algorithms in-depth. This literature review provides an overview of the Dynamic Voltage Restorer (DVR) and explores different control strategies [39] for its implementation. The DVR can inject a controlled three-phase voltage to maintain the load voltage at its nominal value. Among the various control methods, the space vector Pulse Width Modulation (SVPWM) technique [15] stands out as a highly effective approach for the inverter in the DVR. The main advantages of the DVR include its cost-effectiveness, simplicity of implementation, minimal computational demands, and ease of control compared to alternative methods. The findings from this study provide valuable insights for researchers seeking to develop new DVR designs for addressing voltage disturbances in electrical systems. Based on the literature survey of DVR applications, this review concludes that the field of DVR research remains a robust area of study.

3. Methodology

The data for the DVR ANN-based controller is collected from the distribution line voltage measurements and inverter amplitude modulation. A dataset consisting of 1000 observations is obtained for both the predictors (distribution line voltage) and responses (inverter amplitude modulation). The distribution line voltage data includes a single feature, while the inverter amplitude modulation data also consists of a single feature. An Artificial Neural Network (ANN) architecture is designed to address the problem of predicting inverter amplitude modulation based on RMS Line Voltage as shown in Fig 1. The neural network we propose is a feedforward architecture that comprises one input layer, ten hidden layers, and one output layer. The input layer represents the RMS Line Voltage, while the output layer predicts the amplitude modulation. Each layer of the network utilizes an activation function to process the incoming data. During training, we employ a backpropagation algorithm to update the weights (w) and biases (b) of the network, allowing it to learn and adapt to the task at hand. The collected data is preprocessed to ensure its suitability for training the ANN-based controller.

The data is checked for any missing values or outliers, and appropriate handling techniques are applied if necessary. Feature scaling or normalization is employed to bring the predictor and response variables to a similar scale, ensuring efficient training of the ANN. The Levenberg-Marquardt (LM) algorithm is selected as the training algorithm for the ANN-based controller. The LM algorithm is an optimization technique commonly used for training neural networks. It combines the advantages of the Gauss-Newton and steepest descent methods to efficiently minimize the error between predicted and actual responses.

The Levenberg-Marquardt algorithm is a second-order optimization algorithm that can be used to train feedforward neural networks. It does not require the computation of the Hessian matrix, which can be computationally expensive. Instead, the Hessian matrix is approximated as a sum of squares as in equation 1.

$$H = J^T J \tag{1}$$

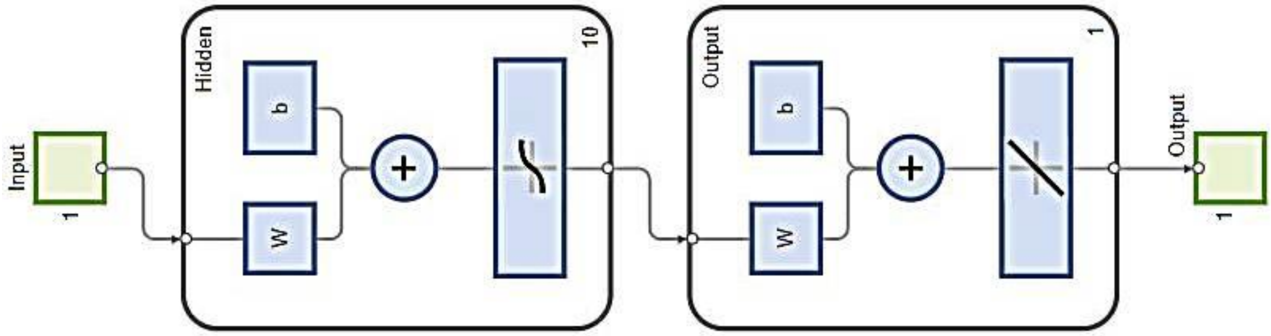

Fig. 1 - ANN architecture

This approximation is typically accurate enough to achieve good training results. the gradient can be computed as

$$g = J^T e \tag{2}$$

Here, J represents the Jacobian matrix, which encompasses the initial derivatives of the network errors in relation to the weights and biases, while e is a vector containing the network errors. The Jacobian matrix can be calculated utilizing a conventional backpropagation method. The Levenberg-Marquardt algorithm applies this approximation to the Hessian matrix in the subsequent Newton-like update as depicted in equation 3.

$$X_{k+1} = X_k - [J^T J + \mu I]^{-1} J^T e \tag{3}$$

When the scalar μ is set to zero, it essentially represents Newton's method, employing an approximate Hessian matrix. Conversely, when μ takes on a large value, it transforms into gradient descent with a small step size. Given that Newton's method demonstrates higher speed and accuracy in proximity to an error minimum, the objective is to transition toward Newton's method as rapidly as feasible. As a result, μ is reduced following each successful step (resulting in a performance function decrease) and is only increased when a potential step would lead to an increase in the performance function. Through this approach, the performance function continually experiences reduction at each iteration of the algorithm. The algorithm adjusts the weights and biases of the ANN by iteratively updating them based on the calculated gradients and the damping factor. In each iteration, the algorithm estimates the Hessian matrix, which determines the direction and step size for weight and bias updates.

The damping factor helps control the balance between the Gauss-Newton and the steepest descent steps, improving convergence and stability of the training process. The ANN architecture is designed based on the problem requirements and complexity of the task as shown in Fig 1. The number of input neurons is set to match the dimension of the predictor variables, and the number of output neurons corresponds to the response variables. Hidden layers are 10 and the number of neurons in each layer are determined through experimentation and consideration of the problem's complexity. The activation functions, such as sigmoid, are selected for the neurons in the hidden and output layers. The training dataset is divided into 75% training and 15% validation sets to monitor the model's performance and prevent overfitting. The Levenberg-Marquardt (LM) algorithm is employed to train the artificial neural network (ANN) through an iterative process, wherein weights and biases are adjusted until the specified convergence conditions are satisfied. The training process is tracked by monitoring metrics like loss function values and validation performance. The performance of the trained ANN model is assessed using suitable metrics, such as mean squared error. To evaluate the model's ability to generalize, it is tested on an independent test dataset, comprising 15% of the data, which was not utilized during the training phase.

In a regression plot with a regression line, the X-axis represents the independent variable (predictor variable) which is distribution line voltage, and the Y-axis represents the dependent variable (response variable) which is amplitude modulation of inverter. The regression line in Fig 2 represents the best-fit line that minimizes the distance between the observed data points and the predicted values based on the regression equation 4.

$$Y = \beta_0 + \beta_1 X \tag{4}$$

Where:

Y represents the dependent variable (amplitude modulation)

X represents the independent variable (distribution line voltage)
β0 represents the y-intercept (the value of Y when X is zero)
β1 represents the slope (the change in Y for a unit change in X)

In Fig 3, the Performance Plot indicates the best validation performance is achieved at an MSE of 4.407e-15 at epoch 133. This means that after 133 epochs of training, the model has achieved an extremely low MSE, indicating excellent accuracy in predicting the target variable. The evaluation results provide insights into the effectiveness and performance of the DVR ANN-based controller.

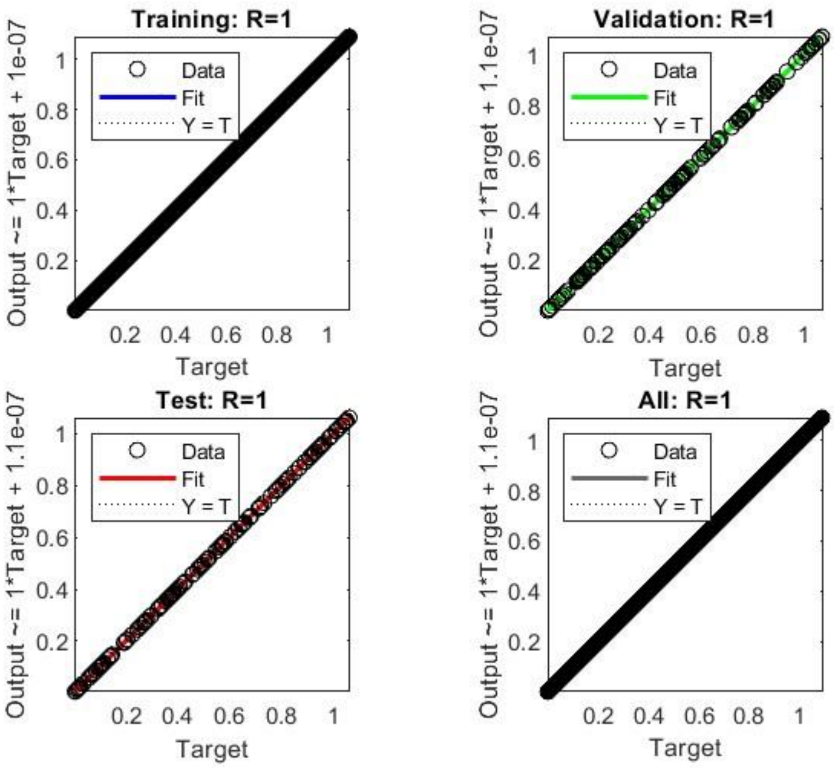

Fig. 2 - ANN regression plot

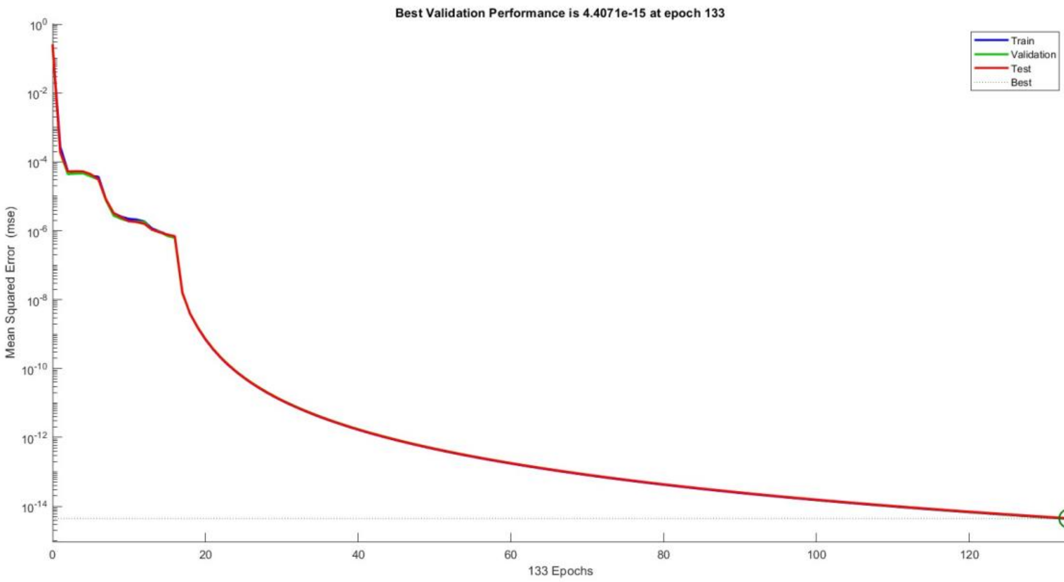

Fig. 3 - ANN performance plot

4. Simulation Results

The MATLAB Simulink model in Fig 4 represents a realistic simulation of a 400V distribution system. The system includes a linear load, which is commonly found in various electrical applications. The purpose of the model is to analyze the performance and effectiveness of a DVR in mitigating voltage disturbances within the distribution system. The DVR is connected in series to the distribution system through a bypass breaker, allowing for seamless integration and operation. This arrangement ensures that the DVR can inject controlled voltages into the system when needed to compensate for voltage sags or swells caused by external factors or system faults. The Simulink model captures the dynamics and interactions of the components in the system, including the linear load, DVR, and the bypass breaker. It accurately represents the behavior of the distribution system under various operating conditions and disturbances. Within the Simulink model, different control strategies and algorithms can be implemented to regulate the DVR's operation. These controls ensure that the DVR responds swiftly and accurately to voltage disturbances, maintaining the desired voltage levels at the linear load. The model can be used to study and evaluate the performance of the distribution system with the DVR in real-time scenarios. By analyzing the simulation results, researchers and engineers can assess the effectiveness of the DVR in compensating for voltage sags or swells, improving the power quality, and ensuring reliable operation of the linear load. It is important to note that the specific details of the MATLAB Simulink model, such as the components' parameters, control strategies, and simulation setup, may vary based on the requirements and objectives of the study. The model can be customized and expanded to incorporate additional features and complexities as needed to accurately represent the behavior of the distribution system and the performance of the DVR.

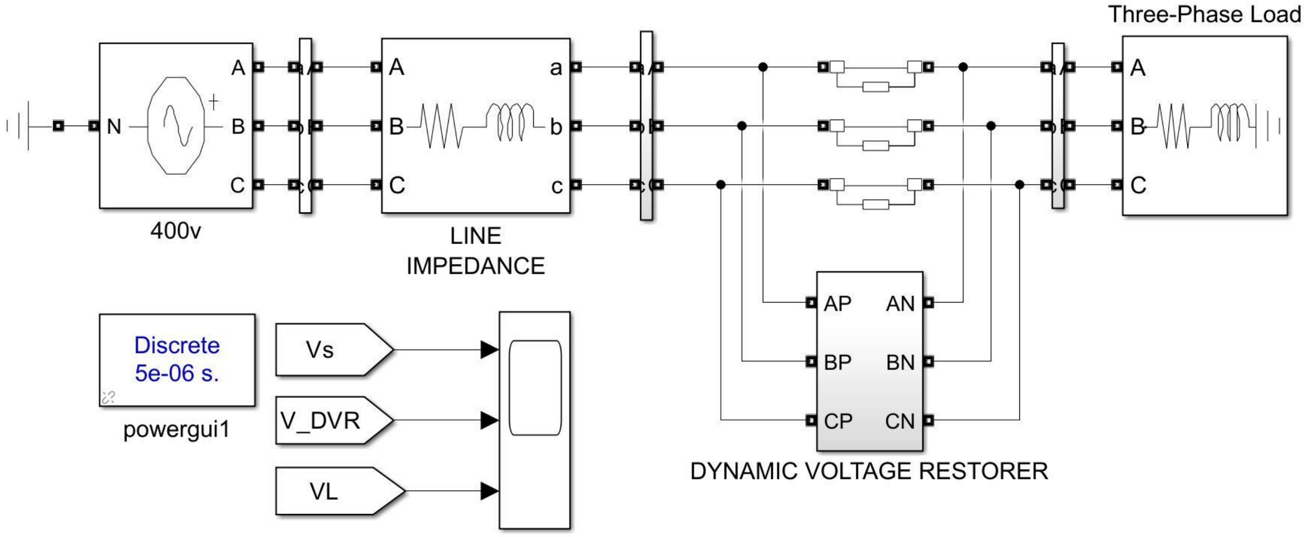

Fig. 4 - 400V distribution system with dynamic voltage restorer MATLAB Simulink model

A Dynamic Voltage Restorer (DVR) with a 9-level Cascade H-Bridge Multilevel Inverter, an inductor filter, and an injecting transformer is developed in MATLAB Simulink as shown in Fig 5. This model aims to provide an accurate representation of the DVR system and analyze its performance in mitigating voltage disturbances in power distribution networks. The 9-level Cascade H-Bridge Multilevel Inverter serves as the main component of the DVR. It is designed to generate the required voltage to compensate for voltage sags disturbances in the power system. The multilevel inverter operates by combining several H-bridge modules in a cascaded manner, allowing for the generation of voltage levels beyond the traditional two-level inverter.

To ensure the smooth operation of the DVR and minimize harmonic distortions, an inductor filter is included in the model. The filter helps attenuate high-frequency harmonics, improving the overall quality of the injected voltage. By reducing harmonics, the inductor filter enhances the performance of the DVR in compensating for voltage disturbances while maintaining the integrity of the power system. The injecting transformer connects the DVR system to the distribution network, facilitating the injection of controlled voltages into the system when voltage disturbances occur. The transformer allows for impedance matching and ensures that the injected voltages align with the distribution network's requirements. An Artificial Neural Network (ANN) function-fitting neural network shown in Fig 6 that takes line voltage as input and generates amplitude modulation for a Cascaded H-Bridge Multilevel Inverter (CHBMLI) as output is designed. The purpose of this model is to accurately predict the required amplitude modulation signals for the CHBMLI based on the provided line voltage values. The line voltage measurements serve as input to the ANN, which is trained to learn the relationship between the input voltage and the corresponding amplitude modulation required by the CHBMLI. The ANN's hidden layers and activation functions are designed to capture the complex nonlinear mapping between the input and output variables. During the training phase, a suitable dataset is used to train the ANN.

This dataset consists of pairs of line voltage values and their corresponding amplitude modulation signals for the CHBMLI. The ANN is trained using a suitable training algorithm, such as backpropagation, which adjusts the network weights and biases to minimize the difference between the predicted and actual output values. Once the ANN is trained, it is integrated into the Simulink model to provide real-time predictions of the amplitude modulation for a given line voltage input. The predicted amplitude modulation values are then fed into the CHBMLI component, which generates the corresponding output waveform based on the received modulation signals.

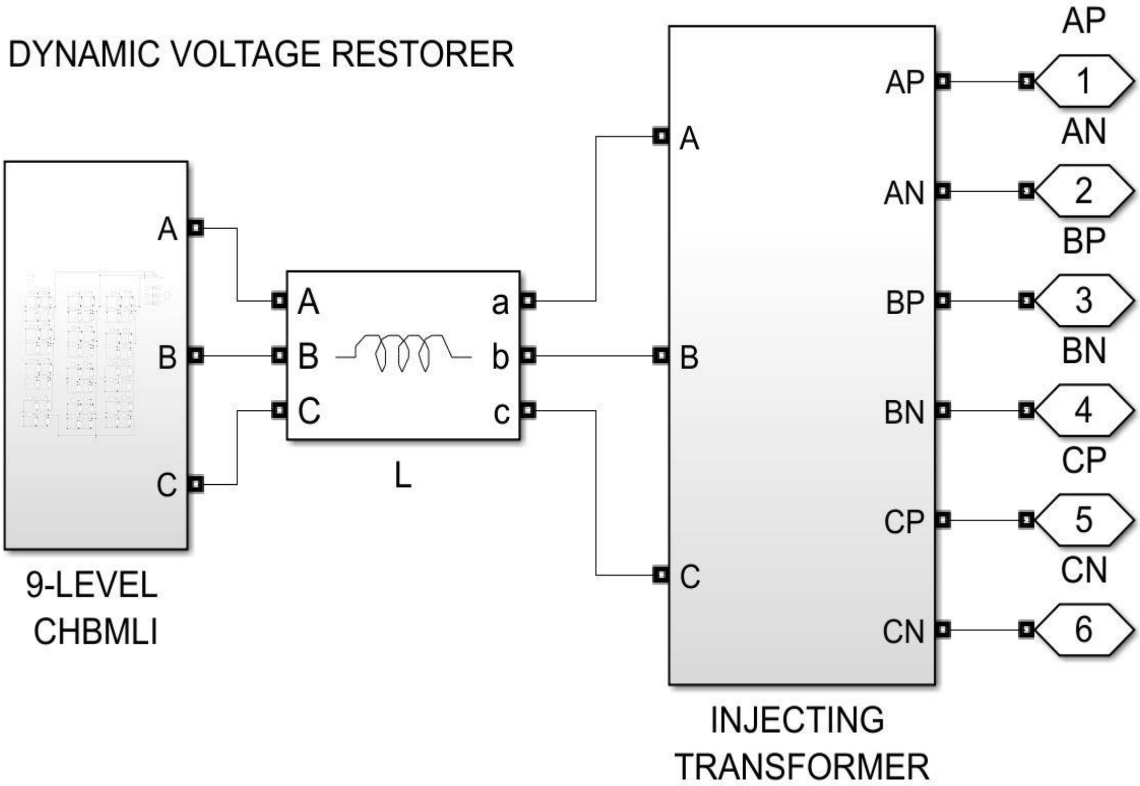

Fig. 5 - Dynamic voltage restorer MATLAB Simulink model

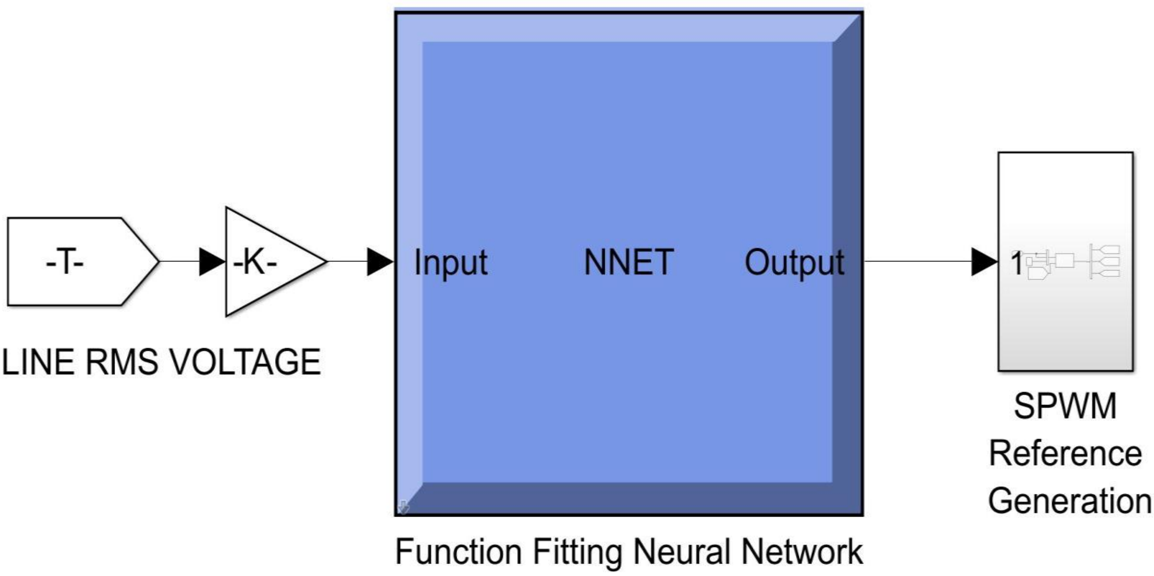

Fig. 6 - Artificial neural network controller

Under a voltage sag condition, the supply phase voltage waveform experiences a temporary reduction in magnitude, leading to a significant impact on the load connected to the distribution system as illustrated in Fig 7. The supply phase voltage waveform during a voltage sag condition typically exhibits a noticeable decrease in amplitude and may deviate from its regular sinusoidal shape. This sag in the voltage waveform can be observed as a downward shift from the nominal voltage level in Load Phase Voltage as well. To mitigate the adverse effects of voltage sags on the load, the DVR is utilized. The DVR acts as a custom device that injects controlled voltage into the distribution system, ensuring that the load receives a steady and constant voltage, even during sag events as shown in Fig 8. This voltage injection is precisely regulated by the DVR to compensate for the reduced supply voltage magnitude.

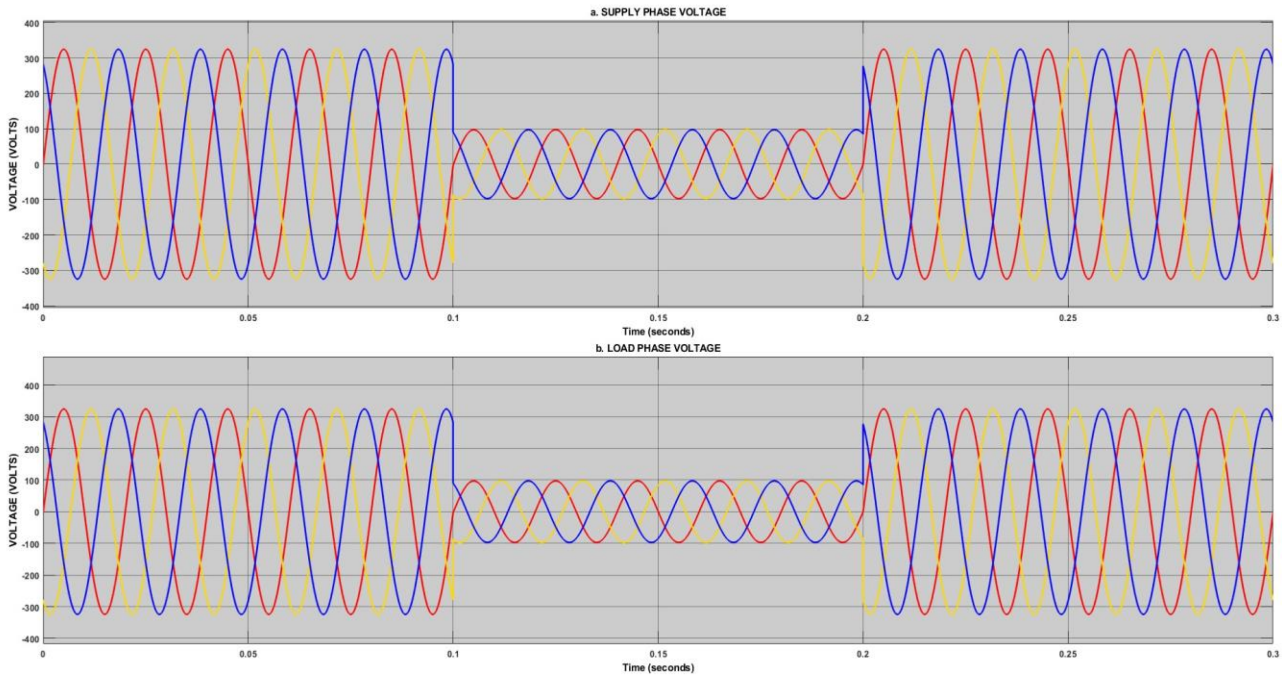

Fig. 7 - Voltage waveforms without DVR (a) supply phase voltage; (b) load phase voltage

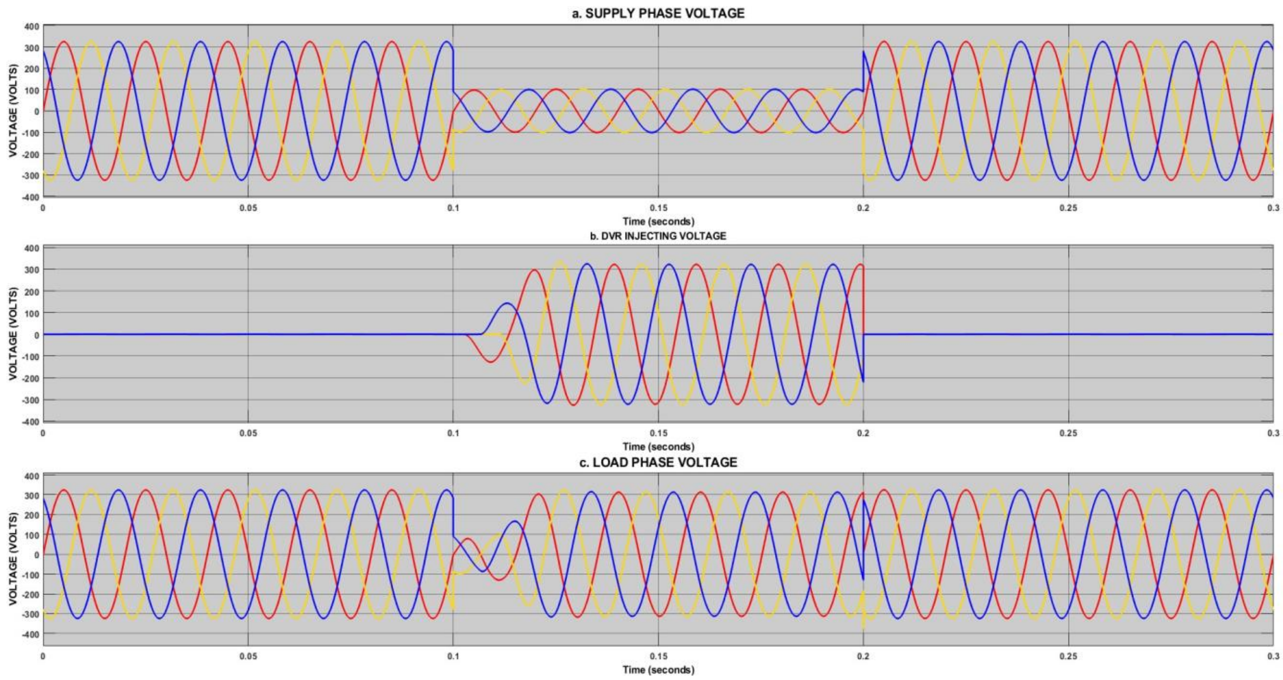

Fig. 8 - Voltage waveforms with DVR (a) supply phase voltage; (b) DVR injecting voltage; (c) load phase voltage

The DVR plays a critical role in mitigating voltage disturbances in power distribution systems. It injects controlled voltage into the system to compensate for voltage sags from the desired voltage levels. The CHBMLI serves as the main component responsible for generating the required compensating voltage waveform as shown in Fig 9.

To generate the compensating voltage, the CHBMLI utilizes the multi carrier phase disposition Sinusoidal Pulse Width Modulation (SPWM) technique as shown in Fig 10. SPWM is a widely used modulation technique that efficiently generates multilevel output waveforms with reduced harmonic content. By using the phase disposition SPWM technique, the DVR ensures that the compensating voltage injected into the power distribution system closely follows the desired voltage waveform, thereby mitigating voltage disturbances. This technique minimizes harmonics and allows for precise control over the injected voltage, enabling the DVR to maintain high-quality power supply to sensitive loads.

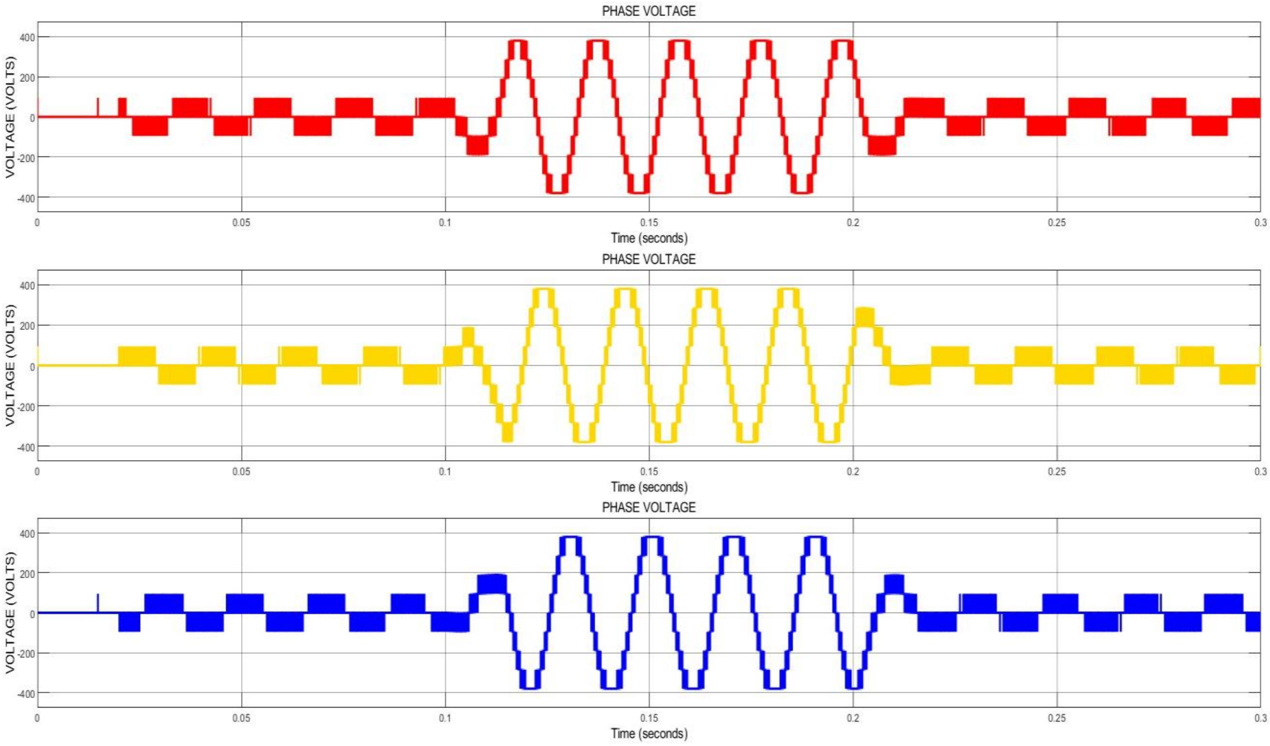

Fig. 9 - Cascade H-Bridge multilevel inverter 9-Level voltage waveforms

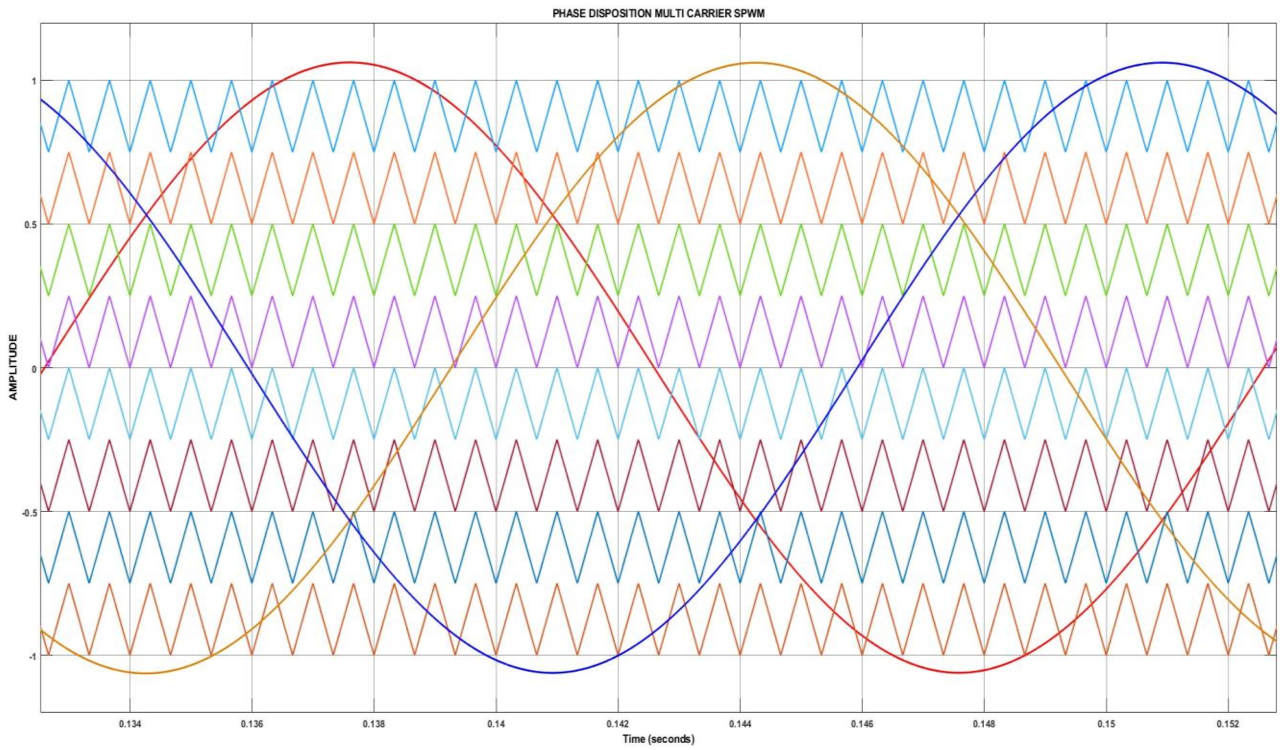

Fig. 10 - Cascade H-Bridge multilevel inverter phase disposition multi carrier SPWM

To assess the quality of the load phase voltage signal and quantify the presence of harmonic components, an FFT analysis is performed as shown in Fig 11. In the case of analyzing THD, a specific portion of the load phase voltage signal is selected for the FFT analysis. This portion is typically chosen to represent a stable and representative segment of the signal, ensuring accurate assessment of the harmonic content. In the given scenario, the THD obtained from the analysis of the load phase voltage signal is determined to be 0.45% as illustrated in Fig 12. This means that the harmonic components in the signal contribute to approximately 0.45% of the total voltage magnitude. A lower THD value indicates a cleaner and more sinusoidal waveform.

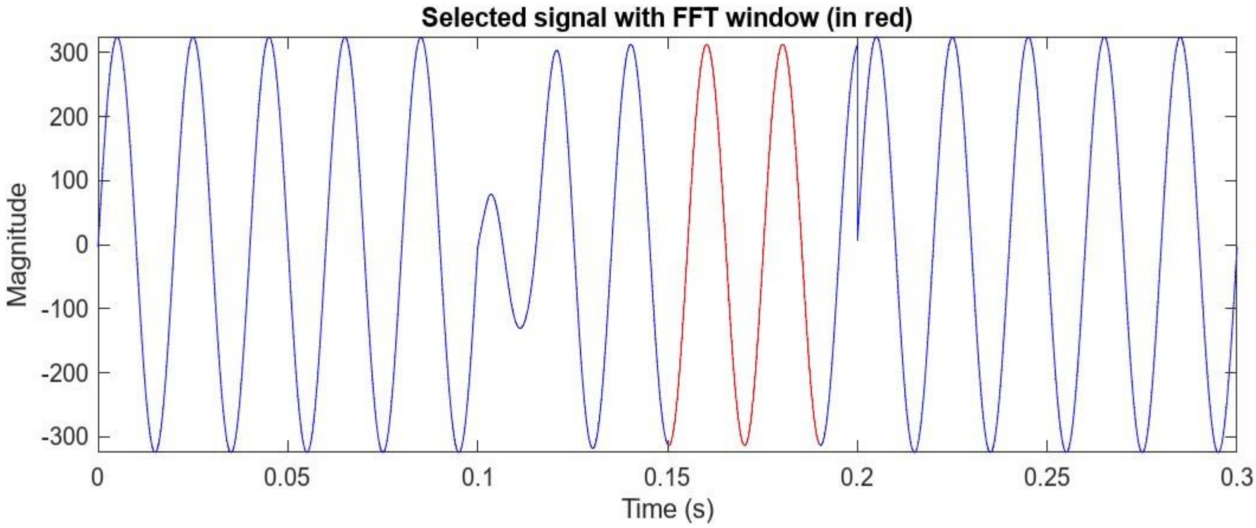

Fig. 11 - Load phase voltage for THD analysis

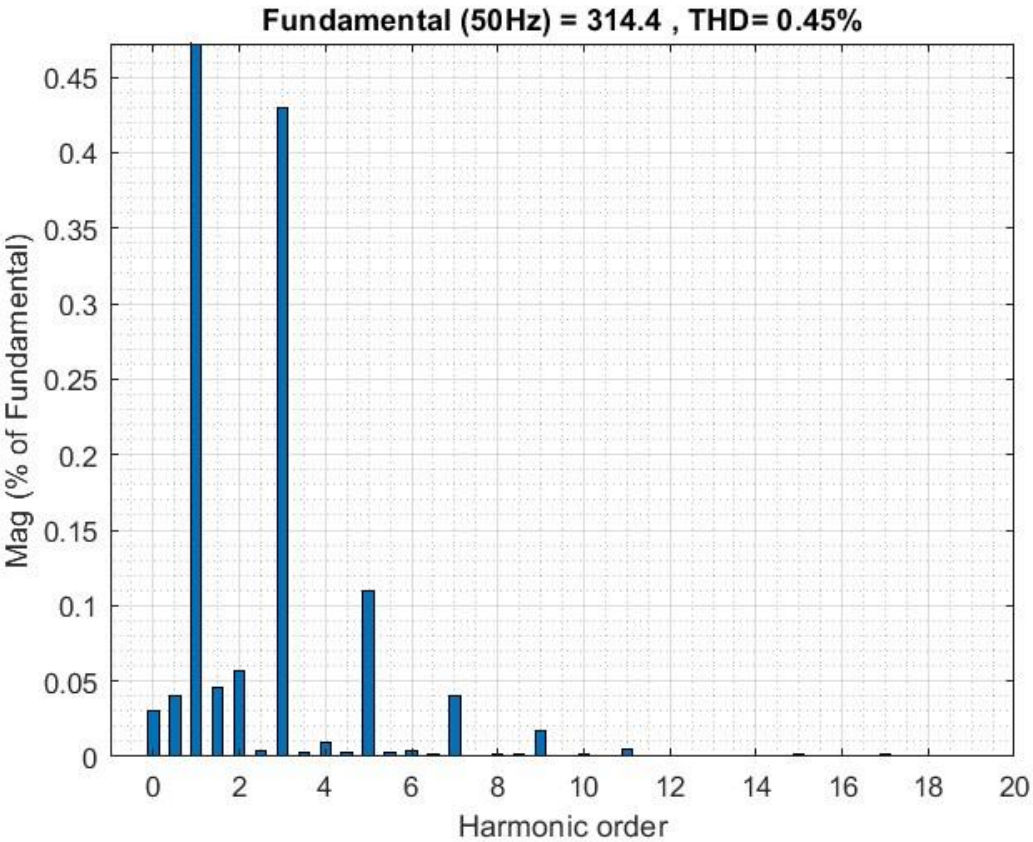

Fig. 12 - THD analysis of load phase voltage

5. Conclusion

this paper focused on the application of an Artificial Neural Network (ANN) based Dynamic Voltage Restorer (DVR) for voltage sag compensation in a MATLAB Simulink environment. The research investigated various aspects of the DVR system, including control strategies, training algorithms, and performance evaluation. The literature review provided an overview of DVR configurations and control strategies, highlighting the significance of voltage sag power quality factors affecting sensitive loads in distributed systems. The proposed methodology involved designing an ANN controller integrated with a Levenberg-Marquardt (LM) training algorithm. The ANN model was trained using distribution line voltage as predictors and inverter amplitude modulation as responses. The LM algorithm, known for its efficiency in solving nonlinear least squares problems, was employed to minimize the error between predicted and actual values. Simulation results demonstrated the effectiveness of the proposed ANN-based DVR system. The regression analysis exhibited a strong correlation (R=1) between the predicted and actual values, indicating accurate voltage compensation. Additionally, the error histogram with 20 bins provided insights into the distribution of errors, enabling further analysis of the model's performance. the analysis of the load phase voltage waveform revealed a Total Harmonic Distortion (THD) content of 0.45%. This low THD value indicates a relatively clean and sinusoidal waveform, with minimal distortion caused by harmonic components.

The study showcased the potential of the DVR system in mitigating voltage sags improving power quality, and ensuring stable operation of sensitive equipment. The MATLAB Simulink model served as a reliable platform for evaluating the performance of the DVR system under various operating conditions. Overall, the combination of the ANN-based controller, LM training algorithm, and the observed low THD content in the load phase voltage supports the efficacy of the proposed DVR system. This research contributes to the advancement of power quality solutions and highlights the potential for implementing ANN-based techniques in DVR systems to enhance voltage stability and mitigate power disturbances effectively. Future research in this field can explore further optimization and control strategies to improve the performance and efficiency of DVR systems in practical applications.

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