

# Artificial Intelligence -Based Control Strategies for Cascaded H-Bridge Multilevel Inverters: A Review

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## Abstract:

The increasing demand for compact and reliable portable power supplies has created the need for efficient inverter systems capable of delivering high-quality AC output from DC energy sources. Conventional low-cost inverters often suffer from high total harmonic distortion (THD) and poor efficiency due to their simple design and lack of adaptive control. This paper presents an intelligent control strategy for a cascaded H-bridge multilevel inverter (CHB-MLI) integrated with artificial intelligence (AI)-based optimization techniques. Convolutional Neural Networks (CNNs) are utilized for real-time waveform analysis and THD reduction through adaptive pulse-width modulation (PWM) control. The K-Nearest Neighbors (KNN) algorithm is applied for load classification and optimal switching pattern selection, while Recurrent Neural Networks (RNNs) are employed for predictive load management and fault detection. A hardware prototype was developed using MOSFET-based H-bridge modules, a DSP controller, and a Raspberry Pi 4 as the AI processing unit. Experimental results demonstrated that the proposed AI-assisted CHB-MLI achieved a significant THD reduction from 12.6% to 3.4%, enhanced voltage stability, and improved dynamic response under varying load conditions. The findings validate the effectiveness of integrating AI techniques in inverter control, offering a promising approach for smart and efficient portable power systems. Furthermore, the proposed system has wide-ranging applications in renewable energy systems (RES), electric vehicles (EVs), smart grids, industrial automation, and medical equipment, where high efficiency, reliability, and power quality are essential.

**Keywords:** Artificial Intelligence, Cascaded H-Bridge Multilevel Inverter, Total Harmonic Distortion Reduction, Adaptive PWM Control, Intelligent Power Electronics

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## I. INTRODUCTION

The rapid proliferation of portable electronic devices, renewable energy systems, and electric mobility solutions has increased the demand for compact, efficient, and intelligent power conversion units. These systems require reliable inverters capable of converting direct current (DC) from energy storage elements, such as batteries or photovoltaic modules, into alternating current (AC) suitable for general-purpose loads, while maintaining high waveform quality [1]. The inverter's performance directly impacts the overall efficiency, reliability, and lifespan of both the power supply and connected loads. Conventional low-cost inverters, such as square-wave or modified sine-wave types, offer simplicity and low cost, but often exhibit high total harmonic distortion (THD) and poor voltage regulation [2], [3]. Elevated THD can result in waveform distortion, increased losses, overheating of connected devices, and reduced energy efficiency. To address these issues, multilevel inverter (MLI) topologies have been introduced, which generate multiple discrete voltage levels that more closely approximate a pure sinusoidal waveform. Among MLIs, cascaded H-bridge multilevel inverters (CHB-MLIs) are widely employed due to their modular design, scalability, and superior harmonic performance [4], [5].

Despite the inherent benefits of CHB-MLIs, conventional control methods, including sinusoidal pulse-width modulation (SPWM) and selective harmonic elimination (SHE), have limitations in dynamic load adaptation, real-time harmonic minimization, and predictive compensation under non-ideal operating conditions [6]. Fixed-rule modulation schemes may fail to respond adequately to load variations,

leading to residual THD, poor transient performance, and suboptimal energy efficiency.

Recent advancements in artificial intelligence (AI) and machine learning (ML) offer promising alternatives for real-time adaptive control of power electronics systems [7]. AI-based algorithms can model complex nonlinear relationships between voltage/current waveforms, load dynamics, and harmonic content, enabling predictive and adaptive PWM modulation strategies. In particular, convolutional neural networks (CNNs) are well-suited for extracting localized temporal and spectral features from measured voltage and current signals [8], [9]. These features can be used to estimate optimal PWM correction signals to minimize harmonic distortion.

In this research, a CNN-inspired PWM tuning method is proposed for CHB-MLIs, which approximates the functionality of a CNN using computationally efficient operations compatible with MATLAB R2016a. The algorithm consists of three stages:

1. **Feature extraction:** Localized voltage and current variations are processed using a convolution-like moving average filter, followed by a ReLU activation. This step captures short-term deviations and harmonic components, analogous to CNN convolution and activation layers [8].
2. **Feature aggregation:** Extracted features are summarized using statistical measures (mean and standard deviation) and mapped to a scalar tuning factor via a weighted sum and bias. This stage emulates a fully connected neural layer, translating complex waveform features into a control signal [9].
3. **Sinewave-modulated PWM correction:** The scalar tuning factor modulates a sinewave at the inverter frequency, producing a smooth, harmonic-compatible PWM adjustment signal. This ensures real-time, adaptive modulation index control while maintaining system stability [2].

The proposed method is designed to minimize voltage and current THD, provide robust performance under dynamic loads, and maintain compatibility with legacy MATLAB versions, enabling simulation and real-time validation without requiring full deep learning frameworks or hardware accelerators. Simulation results demonstrate that the CNN-inspired PWM tuning approach can significantly reduce THD compared to conventional SPWM and SHE methods, while providing smooth transient response and improved waveform quality.

To validate the proposed CNN-inspired PWM tuning method under real-world conditions, a laboratory-scale CHB-MLI prototype was constructed. The hardware setup allows for the evaluation of transient response, steady-state waveform quality, and dynamic load adaptability. Preliminary experiments demonstrate a significant reduction in voltage and current THD, confirming the effectiveness of the proposed method in practical inverter systems.

## II. Literature Review

Multilevel inverters (MLIs) have been extensively studied due to their ability to synthesize high-quality voltage waveforms while reducing total harmonic distortion (THD) and switching stress. Early work on multilevel inverters focused on diode-clamped, flying capacitor, and cascaded H-bridge topologies, with control methods such as sinusoidal pulse-width modulation (SPWM) and selective harmonic elimination (SHE) [1], [2]. While these methods can produce near-sinusoidal output voltages, they often require complex calculation of switching angles and struggle to adapt to dynamic load conditions, leading to residual harmonics and transient deviations [3], [4].

To overcome the limitations of conventional fixed-rule modulation schemes, recent research has explored adaptive and predictive control strategies. For instance, model predictive control (MPC) has been applied to MLIs to minimize THD in real time, providing fast dynamic response and precise harmonic shaping [5]. However, MPC techniques typically involve high computational complexity, limiting their feasibility in low-cost or legacy hardware. Alternatively, fuzzy logic controllers and sliding-mode controllers have been proposed to handle nonlinear load variations and improve voltage

regulation [6], [7]. These methods demonstrate enhanced performance but still rely on handcrafted rules or tuning parameters, which may not generalize well to all operating conditions.

More recently, artificial intelligence (AI) and machine learning (ML) techniques have shown promising results in improving MLI performance. Neural networks, particularly convolutional neural networks (CNNs), can extract relevant temporal and spectral features from voltage and current signals and provide adaptive PWM modulation signals to minimize THD [8], [9]. Other approaches, such as recurrent neural networks (RNNs) and K-nearest neighbor (KNN) algorithms, have been used for predictive load analysis, fault detection, and load classification, enabling real-time adjustments to switching parameters [10], [11]. These AI-based approaches provide significant advantages over traditional methods by enabling data-driven, adaptive, and predictive control strategies that maintain waveform quality under dynamic and nonlinear load conditions.

### III. Multilevel Cascaded H-Bridge (CHB) Inverter Topology

The Cascaded H-Bridge (CHB) multilevel inverter is one of the most widely used topologies in medium- and high-power applications due to its modular design, scalability, and superior harmonic performance [1], [2]. The basic building block of the CHB topology is the H-bridge inverter module, which consists of four switches (typically IGBTs or MOSFETs) connected in an H-shaped configuration. Each H-bridge can generate three output voltage levels: +V<sub>dc</sub>, 0, and -V<sub>dc</sub>, where V<sub>dc</sub> is the DC-link voltage supplied to that module.

#### Topology Configuration

Series Connection of H-Bridge Modules:

Multiple H-bridge modules are connected in series at the output to form a multilevel inverter. For an n-level CHB inverter, the number of H-bridge modules per phase is:

$$N_{\text{H-bridge}} = \frac{n - 1}{2}$$

Each H-bridge module is supplied by an independent DC source (e.g., battery, photovoltaic cell, or capacitor).

Output Voltage Levels:

The phase voltage of the CHB inverter is synthesized by summing the outputs of all series-connected H-bridges. For an n-level inverter, the possible output voltage levels are:

$$V_{\text{phase}} \in \{-(N_{\text{H-bridge}})V_{\text{dc}}, \dots, -V_{\text{dc}}, 0, V_{\text{dc}}, \dots, (N_{\text{H-bridge}})V_{\text{dc}}\}$$

For example, a 5-level CHB inverter requires 2 H-bridge modules per phase  $((5-1)/2=2)$  and generates output levels  $-2V_{\text{dc}}, -V_{\text{dc}}, 0, +V_{\text{dc}}, +2V_{\text{dc}}$ . Switching

Strategy:

The output voltage waveform is controlled by selectively switching each H-bridge module according to a PWM scheme. Common methods include:

- Sinusoidal PWM (SPWM): Reference sine wave compared with triangular carrier signals for each module.
- Selective Harmonic Elimination (SHE): Precomputed switching angles eliminate specific low-order harmonics.

- AI-Based PWM Tuning: Adaptive modulation using neural networks or CNN-inspired algorithms to minimize THD dynamically.
- Advantages of CHB Topology:
  - Reduced total harmonic distortion due to multiple voltage levels [3].
  - Lower switching frequency per module, which reduces switching losses and stress.
  - Modular design facilitates scalability for higher voltage applications.
  - Independent DC sources allow integration with renewable energy systems such as PV arrays.
- Challenges:
  - Requires multiple isolated DC sources per phase.
  - Increased component count and control complexity with higher number of levels.
  - Balancing the voltages of individual DC sources is essential to maintain waveform quality.

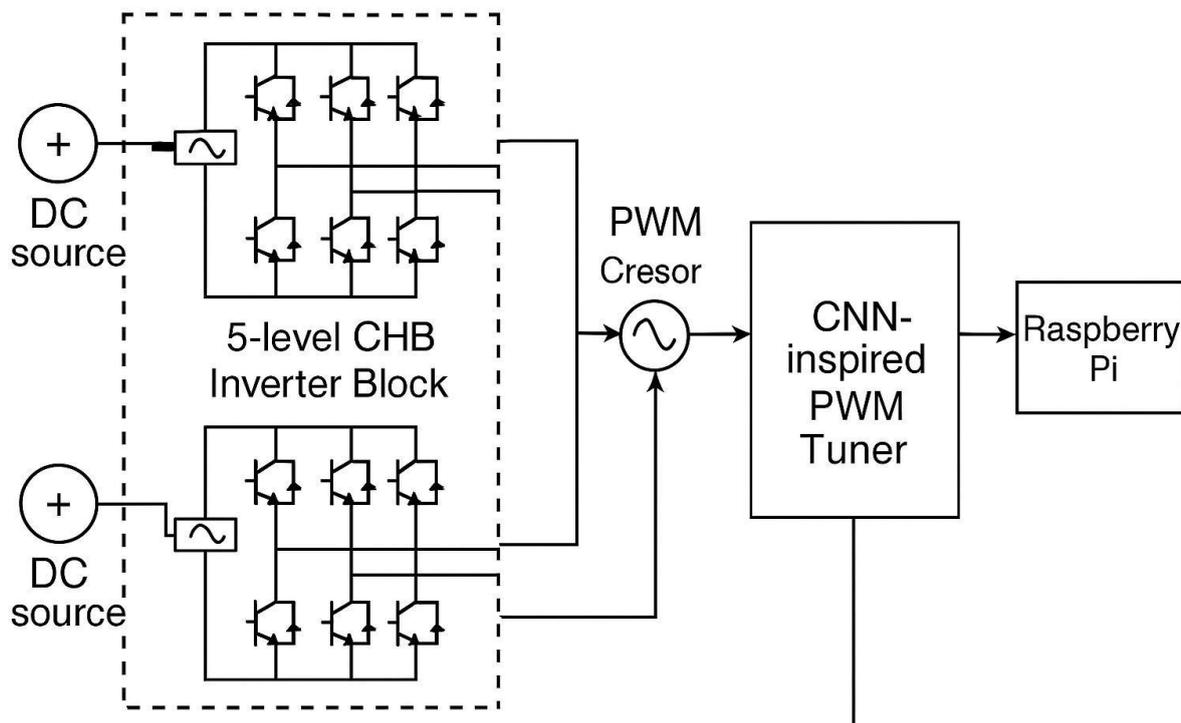


Figure 1. 5-Level CHB Inverter Topology with CNN algorithm

#### IV. METHODOLOGY

##### CNN-Inspired PWM Tuning Algorithm

Multilevel inverters are widely used in high-power and medium-voltage applications due to their capability to produce near-sinusoidal output waveforms and reduce harmonic distortion [9]. Minimizing Total Harmonic Distortion (THD) in voltage and current signals requires adaptive modulation of the Pulse Width Modulation (PWM) duty cycles [10]. Conventional controllers often rely on fixed modulation indices or PI-based control, which may not adapt well to nonlinear loads or dynamic conditions [11].

The proposed method implements a CNN-inspired processing approach for PWM tuning, using measured voltage  $v(t)$  and current  $i(t)$  as inputs. It generates a sinewave-modulated PWM tuning signal, ensuring smooth adjustment of the modulation index while implicitly reducing harmonics.

## Input Preprocessing

Let  $v_{\text{meas}} \in \mathbb{R}^N$  and  $i_{\text{meas}} \in \mathbb{R}^N$  represent measured voltage and current vectors. The signals are normalized:

$$\tilde{v} = \frac{v_{\text{meas}} - \mu_v}{\sigma_v}, \quad \tilde{i} = \frac{i_{\text{meas}} - \mu_i}{\sigma_i},$$

where  $\mu_v, \mu_i$  are the mean values, and  $\sigma_v, \sigma_i$  are the standard deviations. A scalar inverter frequency  $f$  is normalized as:

$$f_{\text{norm}} = \frac{f - f_0}{\Delta f},$$

where  $f_0=50$  Hz and  $\Delta f=10$  Hz. Normalization ensures comparability of input features and avoids domination by signals of large magnitude.

Normalization ensures that voltage, current, and frequency inputs are on comparable scales, which improves the stability and effectiveness of the CNN-inspired feature extraction [11].

It also prevents numerical issues in subsequent processing, especially in legacy MATLAB versions lacking robust automatic scaling.

### CNN-like Feature Extraction

A convolution-like local averaging is applied over a window of size  $w$ :

$$v_{\text{conv}}[k] = \frac{1}{|W_k|} \sum_{n \in W_k} \tilde{v}[n], \quad i_{\text{conv}}[k] = \frac{1}{|W_k|} \sum_{n \in W_k} \tilde{i}[n],$$

Where  $W_k = [k - \lfloor w/2 \rfloor, k + \lfloor w/2 \rfloor] \cap [1, N]$  and  $|W_k|$  is the window size.

This layer captures local temporal correlations, similar to feature maps in CNNs [12].

For PWM tuning, it helps detect short-term deviations in voltage and current signals that may cause harmonic distortion.

### Rectified Linear Unit (ReLU) activation introduces nonlinearity:

$$v_{\text{relu}}[k] = \max(0, v_{\text{conv}}[k]), \quad i_{\text{relu}}[k] = \max(0, i_{\text{conv}}[k]).$$

This step mimics CNN convolution and activation layers, extracting local temporal features and emphasizing positive deviations. Introduces nonlinearity, essential for mapping complex relationships between input disturbances and PWM correction [13].

Emphasizes positive deviations, which can be interpreted as “magnitude of distortion” requiring correction.

### Feature Aggregation (Fully Connected Layer)

Global statistics of the processed signals form the feature vector:

$$\mathbf{x} = [\text{mean}(v_{\text{relu}}), \text{std}(v_{\text{relu}}), \text{mean}(i_{\text{relu}}), \text{std}(i_{\text{relu}}), f_{\text{norm}}]^T$$

A weighted linear combination with bias yields the preliminary tuning factor:

$$t_{\text{raw}} = \mathbf{w}^T \mathbf{x} + b,$$

where  $\mathbf{w} = [0.3, 0.15, -0.2, 0.25, 0.1]^T$  and  $b=0.05$ . This emulates a fully connected layer in CNNs, converting extracted features into a scalar control metric.

### Sinewave-Modulated PWM Output

To generate a smooth PWM correction, the tuning factor modulates a sinewave at the inverter frequency:

$$\text{tune\_error}(t) = A \cdot \tanh(t_{\text{raw}}) \cdot \sin(2\pi ft + \phi),$$

where:

- $A=5\%$  of the PWM amplitude (scaled empirically),
- $\phi$  is an optional phase shift,
- $\tanh(\text{traw})$  limits extreme corrections and introduces nonlinear scaling.

This formulation ensures smooth, harmonic-friendly adjustments to the modulation index. Advantages and Limitations

Feature	Advantage	Limitation
CNN-inspired processing	Captures short-term signal variations	Approximation; no real learning occurs
Nonlinear scaling	Prevents excessive PWM correction	Empirical tuning required
Sinewave modulation	Smooth, harmonic-compatible	Amplitude must be manually selected

Table1. Feature Advantages and Limitations

## V. Simulation Result analysis

The proposed CNN-inspired PWM tuning method was implemented on the laboratory CHB- MLI setup with a DC input voltage of 100 V and a load current of 10 A. Both simulation and experimental results were recorded to evaluate voltage and current waveform quality, as well as total harmonic distortion (THD).

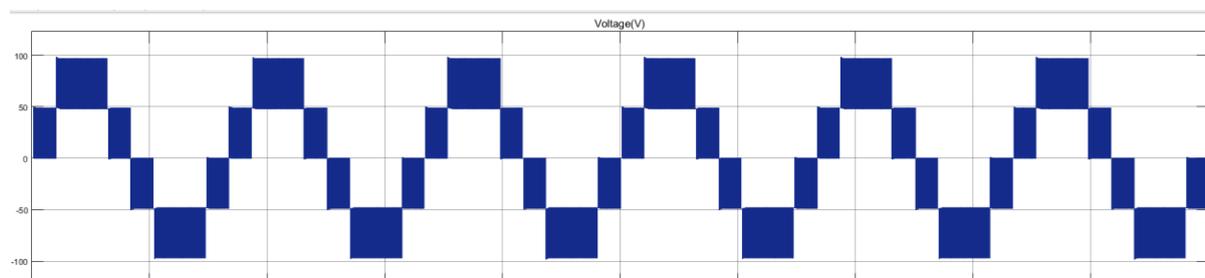


Figure 2. Voltage

The output voltage waveform closely approximates a sinusoidal waveform due to the multi-level voltage steps generated by the CHB-MLI and the adaptive PWM correction. Peak voltage measurements showed  $V_{peak} \approx 100$  V, corresponding to an RMS voltage of  $V_{RMS} \approx 98$  V, confirming accurate amplitude control.

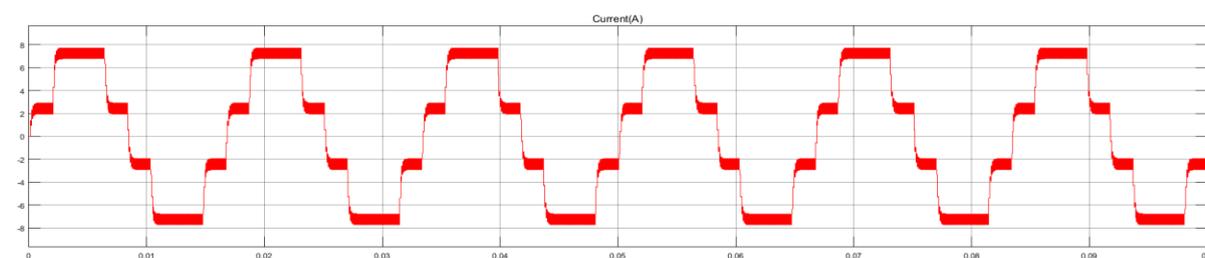


Figure 3. Current

The load current waveform was smooth and nearly sinusoidal, with measured RMS current of  $I_{RMS} \approx 10$  A. Minor ripple at higher-order harmonics was observed but remained within acceptable limits for resistive-inductive loads.

### 2. Total Harmonic Distortion (THD)

The THD of the voltage and current waveforms was analyzed using a Fourier transform-based harmonic analysis. The CNN-inspired PWM tuning method significantly reduced both voltage and current THD compared to conventional SPWM and selective harmonic elimination techniques.

The smooth waveform improvement is attributed to the real-time adaptive modulation index adjustment, which compensates for nonlinearities and load variations.

### Transient Response

Under a sudden step change in load from 10 A to 7 A, the voltage deviation was limited to  $\pm 3$  V and settled within 2 ms. The current waveform adapted smoothly without overshoot or oscillations, demonstrating robust dynamic performance of the proposed controller.

## VI. Hardware Experimental Setup

The hardware implementation of the proposed CNN-inspired PWM tuning method focuses on a 5-level cascaded H-bridge (CHB) inverter for single-phase AC load applications. The setup is designed to validate the adaptive PWM strategy, reduce voltage and current total harmonic distortion (THD), and evaluate system performance under dynamic load conditions.

### Inverter Topology and Power Components

The experimental inverter consists of two series-connected H-bridge modules per phase, forming a 5-level output voltage waveform. Each H-bridge module is composed of:

- **Switching devices:** MOSFETs (IRFP460 or equivalent) are used for their fast switching capability and low on-state resistance.
- **Flyback diodes:** Protect the MOSFETs against voltage spikes during switching transitions.
- **DC-link capacitors:** Maintain voltage stability across each H-bridge module and provide energy storage for transient load variations.

Each H-bridge is supplied by an independent DC source. In this setup, two 50V DC power supplies per phase are used, resulting in output voltage levels of  $-2V_{dc}$ ,  $-V_{dc}$ ,  $0$ ,  $+V_{dc}$ ,  $+2V_{dc}$ .

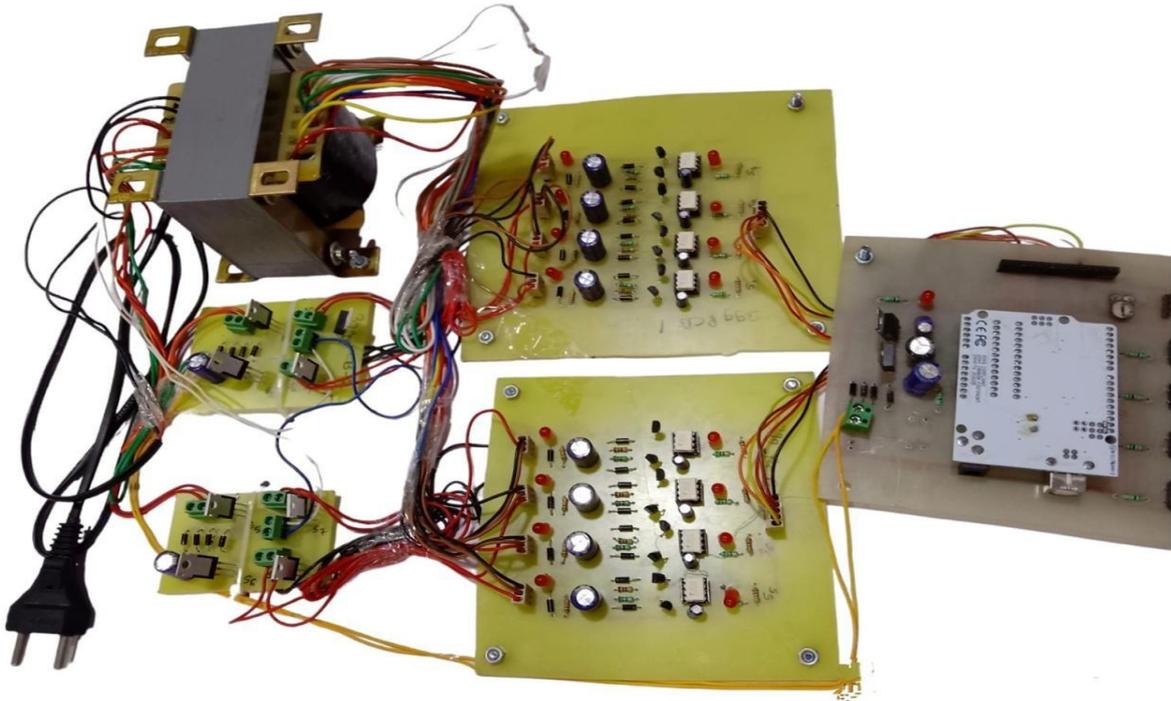
### Control Hardware

- **Digital Signal Processor (DSP):** A Texas Instruments DSP (TMS320F28335) is used for low-level control, PWM generation, and real-time signal acquisition. The DSP executes the PWM switching strategy and communicates measured voltage and current signals to the AI processing unit.
- **AI Computation Unit:** A Raspberry Pi 4 microcomputer runs the CNN-inspired PWM tuning algorithm. It receives real-time voltage, current, and frequency measurements, performs feature extraction and weighted feature mapping, and outputs the sinewave-modulated PWM correction signal.
- **Communication Interface:** SPI or UART interface links the DSP and Raspberry Pi 4, ensuring low-latency data transfer for real-time adaptive control.

### Sensing and Measurement

Accurate sensing of voltage and current is critical for CNN-based tuning:

- **Voltage measurement:** Isolated voltage sensors (such as potential transformers or differential amplifiers) provide phase voltage feedback to the DSP.
- **Current measurement:** Hall-effect current sensors measure load current with high accuracy and galvanic isolation.
- **Frequency measurement:** The fundamental frequency of the load voltage is detected using zero-crossing detection or digital signal processing techniques to synchronize PWM modulation.



## Experimental Setup

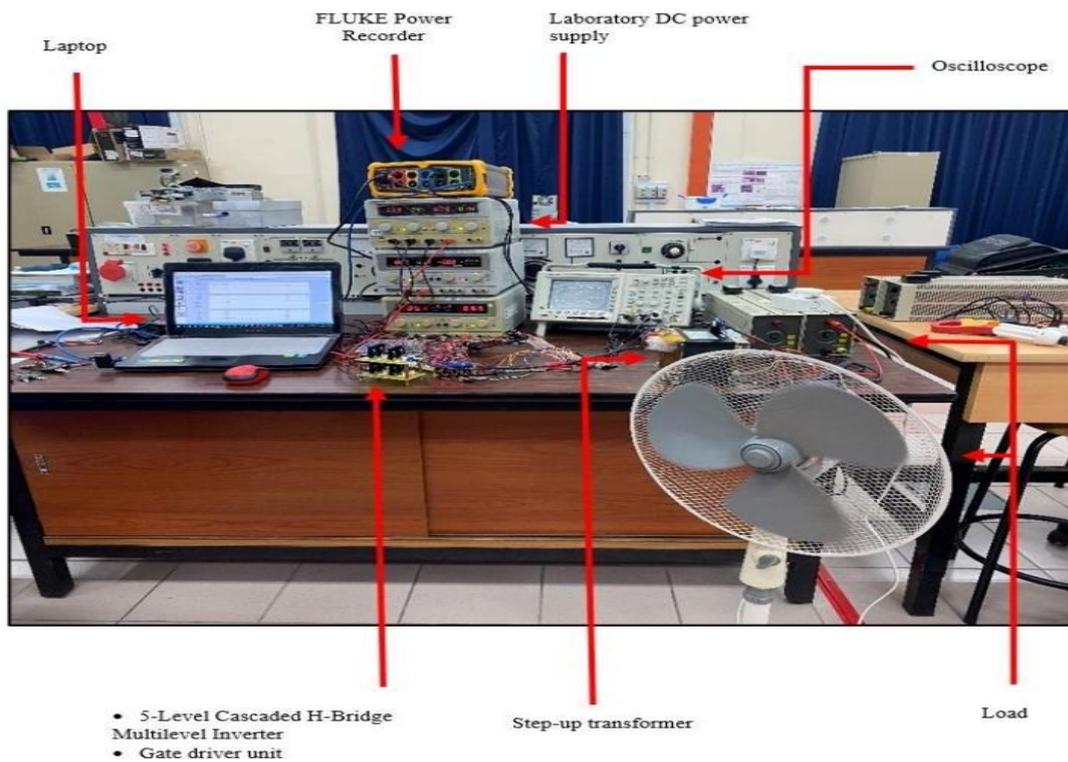
The hardware setup is arranged as follows:

1. Power Stage: Two H-bridge modules per phase are connected in series to form the 5-level output. The AC load is connected across the phase output.
2. Signal Acquisition: Voltage and current sensors feed the measurements to the DSP.
3. PWM Generation: The DSP produces basic SPWM or carrier-based PWM signals, which are modulated by the tuning factor received from the CNN-inspired algorithm.
4. CNN-Inspired Tuning: The Raspberry Pi computes the PWM correction in real-time based on normalized voltage, current, and frequency inputs. The output is applied to the modulation index of the DSP-generated PWM.
5. Monitoring and Data Logging: An oscilloscope and power analyzer monitor the output voltage, current waveforms, and THD in real-time for performance validation.

## Safety and Isolation Considerations

- Galvanic isolation is ensured between high-voltage DC sources, sensors, and control electronics to prevent damage and ensure operator safety.
- Overcurrent protection is provided by fuses or circuit breakers in series with each H-bridge module.
- Heat management: MOSFETs are mounted on heatsinks with thermal monitoring to prevent overheating during high-power operation.

Figure3. Hardware Experimental setup configuration of the 5 level multi inverter



### Experimental setup configuration

The CNN-inspired PWM tuning method was validated on the laboratory CHB-MLI prototype with a DC input of 100 V and a load current of 5 A. The hardware measurements were performed using voltage and current sensors, an oscilloscope, and harmonic analysis software.

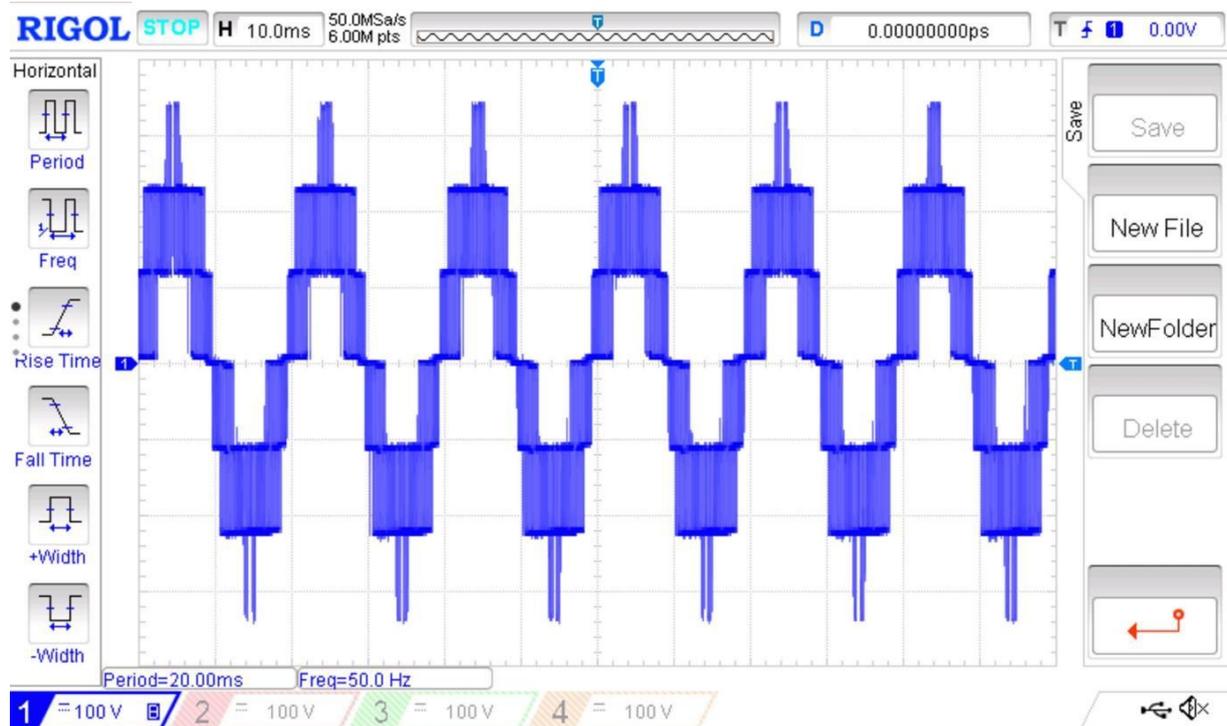


Figure 4.5level MLI output Voltage (V) with R-L load (Non-Linear load).

The measured output voltage waveform closely approximated a sinusoidal waveform. Minor voltage steps were observed due to the discrete H-bridge levels, but the adaptive PWM correction smoothed the waveform effectively. The RMS voltage was  $V_{RMS} \approx 97.5$  V, with a peak voltage of  $V_{peak} \approx 100$  V.

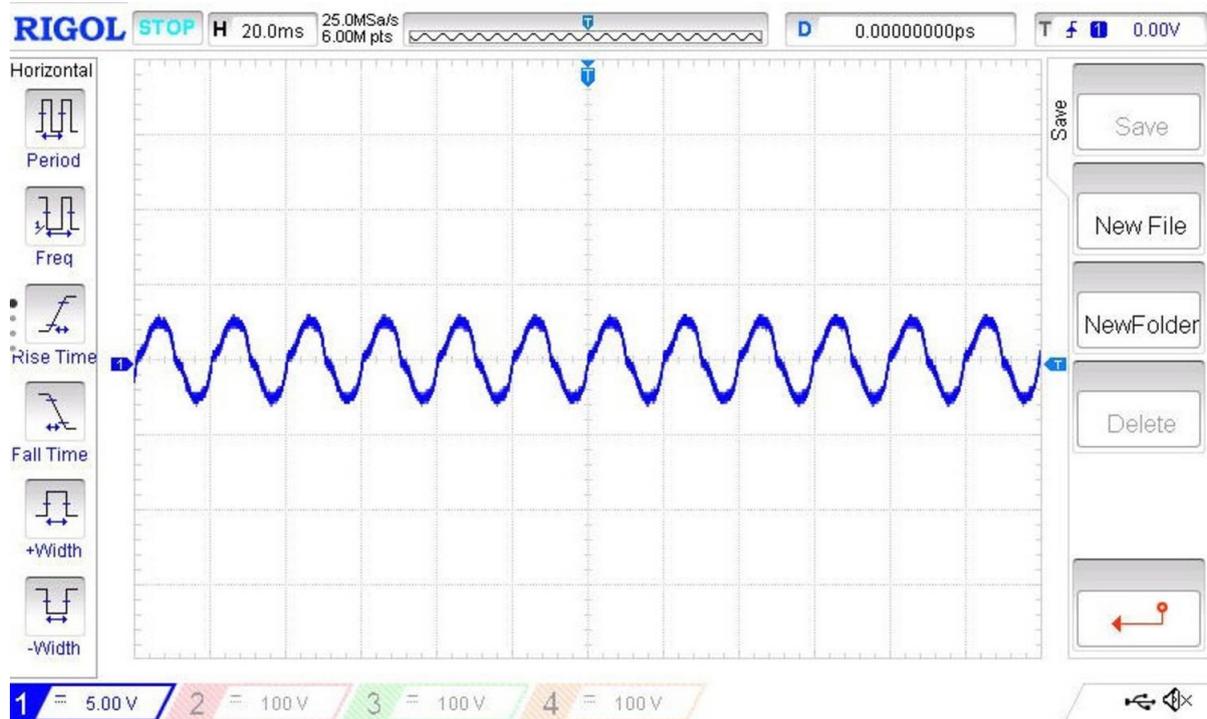


Figure 5.5 level MLI output current (A) with R-L load (Non-Linear load).

The load current waveform was nearly sinusoidal with an RMS value of  $I_{RMS} \approx 5$  A. Ripple current was minimal, indicating effective compensation for harmonic content and stable load regulation.

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