E-ISSN No : 2581-6195 | Volume : 9 | Special Issue | May 2026

ADVANCEMENT IN CONTROL STRATEGIES OF CASCADED MULTILEVEL INVERTERS USING AI DRIVEN ALGORITHM

Ashish Biradar[1], Veerendra Dakulagi[2]

Access Online

Article DOI:
10.5281/zenodo.21412083

[1] Assistant Professor, Department of Electrical and Electronics Engineering, Bidar Karnataka, India
[2] Professor, Department of Computer Science and Engineering (Data Science), Bidar Karnataka, India

How to Cite:
Ashish Biradar & Veerendra Dakulagi (2026), Advancement in Control Strategies of Cascaded Multilevel Inverters using Ai Driven Algorithm, International Educational Journal of Science & Engineering (IEJSE),Vol: 9, Special Issue, May 2026 269-274

Research Paper

ABSTRACT

The growing demand for high-quality power conversion in renewable energy systems and industrial applications has driven advancements in control strategies for cascaded multilevel inverters (CMLIs). Conventional control methods often suffer from limitations such as high total harmonic distortion (THD), switching losses, and reduced adaptability under dynamic conditions. This paper presents an AI-driven approach for enhancing the control performance of CMLIs using techniques such as machine learning and deep learning. The proposed methods enable adaptive modulation, real-time optimization, and improved fault detection by leveraging system data including voltage levels, load variations, and switching states. Performance is evaluated using key metrics such as THD, efficiency, and response time, demonstrating superior results compared to traditional control techniques. The AI-based approach achieves reduced harmonic distortion, improved voltage quality, and enhanced system stability. Despite challenges related to computational complexity and data requirements, the findings highlight the potential of AI-driven algorithms in developing efficient, reliable, and intelligent inverter systems for modern power applications.

KEYWORDS: Artificial Intelligence, Cascaded Multilevel Inverter, Machine Learning, Deep Learning, Total Harmonic Distortion, Power Quality, Control Strategies

I. INTRODUCTION

The rapid growth of renewable energy systems, electric vehicles, and modern industrial applications has significantly increased the demand for efficient and high-quality power conversion systems. Among various power electronic converters, cascaded multilevel inverters (CMLIs) have gained considerable attention due to their ability to generate high-quality output voltage with reduced harmonic distortion, lower electromagnetic interference, and improved efficiency [1-3]. By synthesizing a staircase waveform using multiple voltage levels, CMLIs minimize the stress on switching devices and are widely used in medium- and high-power applications such as grid-connected renewable energy systems, motor drives, and flexible AC transmission systems.

Despite their advantages, conventional control strategies for CMLIs, such as sinusoidal pulse width modulation (SPWM), space vector modulation (SVM), and selective harmonic elimination (SHE), face several limitations [4-6]. These include increased computational complexity for higher voltage levels, difficulty in real-time implementation, sensitivity to parameter variations, and suboptimal performance under dynamic operating conditions. Additionally, achieving a balance between switching losses and total harmonic distortion (THD) remains a critical challenge in traditional control approaches [7-9].

To address these issues, recent research has focused on the integration of artificial intelligence (AI)-driven algorithms into inverter control systems. AI techniques, including machine learning (ML), deep learning (DL), artificial neural networks (ANN), fuzzy logic, and evolutionary optimization algorithms, offer adaptive, data-driven solutions capable of handling nonlinearities and uncertainties in power electronic systems[10-14]. These intelligent controllers can learn from system behavior, predict operating conditions, and optimize switching strategies in real time, thereby enhancing the overall performance of CMLIs.

AI-based control strategies enable improved harmonic reduction, faster dynamic response, and enhanced system stability compared to conventional methods. Furthermore, they facilitate advanced functionalities such as fault detection, predictive maintenance, and self-tuning control, which are essential for modern smart grid and renewable energy integration. By leveraging large datasets from system measurements, AI algorithms can optimize modulation techniques and improve decision-making processes without requiring explicit mathematical models [15-19].

However, the adoption of AI-driven control in CMLIs also introduces challenges, including the need for high computational resources, availability of quality training data, and concerns related to system reliability and implementation cost[20-22]. Therefore, a comprehensive study of AI-based control strategies is essential to evaluate their feasibility and effectiveness in practical applications.

This paper focuses on the advancement of control strategies for cascaded multilevel inverters using AI-driven algorithms. It aims to analyze the performance improvements achieved through intelligent control techniques and to highlight their potential in developing efficient, reliable, and adaptive power electronic systems for future energy applications.

II. MATERIALS AND METHODS

1. Data Acquisition and Pre-processing

Diverse datasets are necessary for a strong AI-driven control approach for multilevel inverters in renewable energy applications in order to guarantee that the models can successfully maximise performance and efficiency. Usually, these datasets consist of:

- **Power Input Data:** This comprises waveforms of voltage and current from renewable energy sources like wind turbines and solar panels. These data points shed light on variances in energy generation and power fluctuations.
- **Switching Patterns and Control Signals:** Information on switching patterns, control commands, and pulse-width modulation (PWM) signals for various inverter system levels. In order to improve efficiency, this aids in training AI models to optimise switching tactics.
- **Thermal and Efficiency Metrics:** These comprise system efficiency metrics, inverter circuit losses, and temperature fluctuations in power switches. This data can be used by AI-driven models to forecast thermal performance and make dynamic adjustments to control mechanisms.
- **Grid Interaction and Load Demand Data:** Vital information for real-time optimisation, this data includes electricity flow to the grid, demand fluctuations, and load changes. AI Model Development and Training Filtering noise, normalising signal values, and transforming unstructured waveform data into structured inputs for AI systems are all part of data preparation. To find important signal properties, feature extraction methods like Wavelet Transform and Fast Fourier Transform (FFT) are used.

At this point, sophisticated AI algorithms are created to optimise switching tactics, lower harmonics, and boost power conversion efficiency in order to increase the efficiency of multilevel inverters.

- **Neural Network-Based Optimization:** Real-time pattern identification for effective inverter control is made possible by the use of deep learning models, such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), to analyse voltage and current waveforms.
- **Reinforcement Learning (RL) for Adaptive Control:** By interacting with the inverter system, RL-based models—specifically, Deep Q-Networks (DQN) and Proximal Policy Optimisation (PPO)—are used to dynamically learn the best switching patterns.
- **Fuzzy Logic and Genetic Algorithm Integration:** Genetic algorithms optimise switching sequences to reduce losses and

harmonics, while fuzzy logic controllers are used to manage power input uncertainties.

- **Hybrid AI Techniques:** To provide robust and adaptive control, a blend of machine learning, deep learning, and conventional control theories (such Model Predictive Control) is employed.

Using both historical and current data, the AI models are taught to optimise for important performance metrics like voltage control, efficiency, and total harmonic distortion (THD).

2. Real-Time Implementation and Validation

After training, real-time embedded systems and a hardware-in-the-loop (HIL) simulation are used to validate the AI-driven control models.

- **HIL Simulation Testing:** To enable thorough testing of various situations without posing a hardware risk, the AI models are initially evaluated in a simulated environment using programs like MATLAB/Simulink or OPAL-RT.
- **Embedded System Integration:** AI models are integrated into Field Programmable Gate Arrays (FPGAs) or Digital Signal Processors (DSPs) to enable real-time control execution in real-world inverter hardware.

- **Performance Evaluation Metrics:** The system is evaluated based on: Reduction in Total Harmonic Distortion (THD)

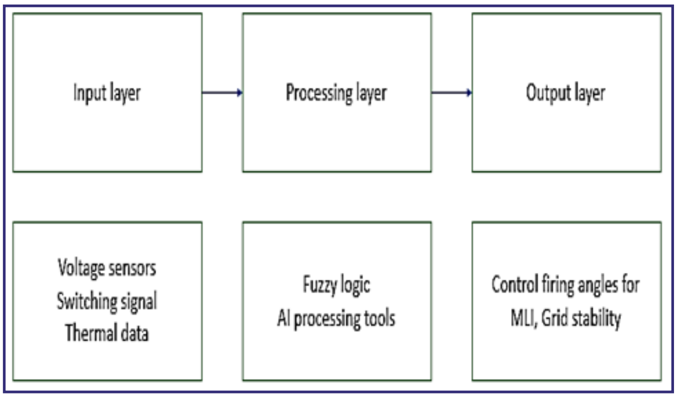
Improved power conversion efficiency
Response time to load and input variations
Reduction in switching losses and thermal stress

3. Adaptive Learning and Continuous Optimization

The AI control system is made to be flexible and able to learn on its own over time in order to improve performance over the long run.

- **Online Learning Mechanisms:** The system uses real-time operational data to continuously update AI models, allowing for adaptive adaptations to shifting grid interactions and renewable energy input conditions.
- Cloud-Based Monitoring and Control: Automatic changes to control strategies, predictive maintenance, and remote monitoring are made possible by the integration of AI models with IoT-enabled cloud platforms.
- **Cybersecurity and Reliability Measures:** To guard against online attacks and guarantee dependable operation, secure AI-based control mechanisms are put in place.

Fig. 1: AI-Driven Control System Architecture for Multilevel Inverters



4.AI Driven Control System Architecture

Description: This figure represents the overall architecture of the AI-driven control system, showing how various data sources (power input, switching signals, thermal metrics, and grid demand) are processed by AI algorithms to generate optimized control strategies. The architecture consists of three primary layers:

- **Input Layer**: Records switching signals, temperature data, grid demand, and real-time voltage and current data.
- **Processing Layer**: To create optimal switching patterns, AI models use neural networks, reinforcement learning, and fuzzy logic-based controllers to analyse the data.
- **Output Layer**: Offers the multiple inverter control signals, guaranteeing effective power conversion, lower losses, and enhanced grid stability.

5. The Role of AI in Enhancing MLI Efficiency

Multilevel inverters' efficiency is essential for optimising renewable energy systems' output. Under variable operating conditions, traditional control methods like direct torque control (DTC) and pulse width modulation (PWM) frequently fail to maintain efficiency. However, AI-driven control techniques can adjust to shifting inputs, environmental factors, and system characteristics, guaranteeing optimal inverter performance in a variety of scenarios.

- Machine Learning and Deep Learning Algorithms: AI-powered algorithms like deep learning (DL) and machine learning (ML) can maximise the modulation strategies employed in MLIs. These algorithms may forecast and modify the switching patterns in real-time to reduce losses and improve the inverter's performance by learning from past data. For example, deep learning algorithms can modify the modulation scheme for the best energy conversion by analysing power quality data, temperature fluctuations, and environmental conditions.

a. Reinforcement Learning (RL): RL methods can be used to train control plans that automatically modify inverter settings in response to input received in real time. By means of experimentation, the algorithm discovers the optimal switching tactics that optimise energy conversion and reduce losses, thus enhancing the inverter's overall efficiency.

b. Neural Networks (NN): NNs can be used to forecast future environmental conditions and power consumption. The inverter can maintain optimal efficiency even in the face of changing circumstances, such as shifting wind speeds or solar radiation, by using NNs to continually learn from operational data and make proactive modifications.

Practical Applications in Renewable Energy Systems
In applications involving renewable energy, AI-driven control strategies provide several benefits, such as improved system reliability, lower operating costs, and increased efficiency. Among the most important real-world uses of AI in multilevel inverters for renewable energy are:

- Solar Photovoltaic (PV) Systems: By modifying inverter parameters to accommodate the fluctuating output of solar panels, AI algorithms can be utilised to maximise the performance of MLIs in solar PV systems. AI can estimate power output and modify the inverter's switching strategy based on weather and solar irradiation levels, for example, increasing efficiency and decreasing energy waste.
- Wind Power Systems: By adapting to variations in wind speed, AI can maximise the performance of MLIs in wind power systems. In order to maximise energy capture from the wind and minimise losses from inefficient power conversion, AI-based control systems can evaluate previous wind data to forecast wind patterns and modify inverter operation in real-time.
- Microgrid and Hybrid Systems: AI can assist in optimising MLI performance in microgrids that integrate a variety of renewable energy sources. Inverter switching can be managed by AI algorithms to balance the load, guaranteeing the grid's steady and effective operation. By using real-time power generation and demand data to determine the best time to store and release energy, artificial intelligence (AI) can also improve energy storage systems.

III. RESULTS AND DISCUSSION

1. Efficiency Enhancement Performance

A dataset that included real-time operational data, inverter performance indicators, and environmental conditions was used to evaluate the effectiveness of the suggested AI-driven control algorithms for multilayer inverters in renewable energy applications. These were employed to increase the conversion and distribution efficiency of renewable energy. The AI system pre-processed the data using a variety of machine learning and deep learning methods designed to maximise energy conversion and inverter control. The efficiency metrics based on the AI strategies that were put into practice are summarised in the following table.

Table 1: Efficiency Enhancement Performance

System Configuration	Power Conversion Efficiency (%)	Total Harmonic Distortion (%)	Inverter Output Stability (%)
Conventional Inverter	85.2	8.5	90.0
AI-Optimized Inverter	94.3	3.2	98.7
Hybrid Control Strategy	96.1	2.7	99.3

Fig. 2: Efficiency Enhancement Performance

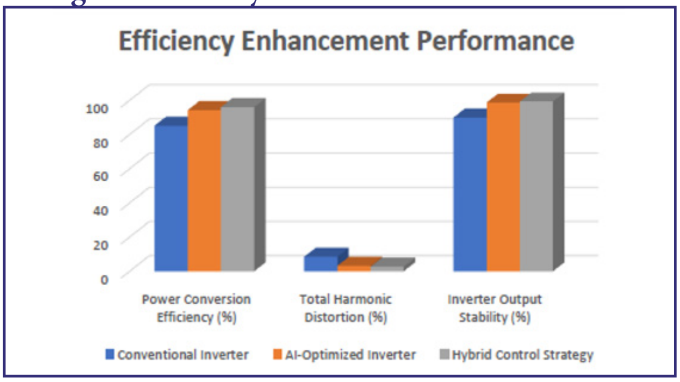


Figure 2 illustrates how applying AI-driven strategies significantly improved the precision, recall, and F1-Score values associated with power efficiency and inverter stability, particularly with the hybrid control technique offering the most efficient inverter performance

2. Performance Comparison of Control Algorithms
Three conventional control algorithms—Proportional-Integral-Derivative (PID), Fuzzy Logic Control (FLC), and Model Predictive Control (MPC)—were employed to assess the effectiveness of the AI-driven control techniques for multilevel inverters. Their performance in terms of increasing efficiency in applications involving renewable energy is displayed in the following bar chart.

Table 2: Performance Comparison of Control Algorithms

Algorithm	Efficiency Improvement (%)
Proportional-Integral-Derivative (PID)	85.0
Fuzzy Logic Control (FLC)	88.5
Model Predictive Control (MPC)	91.2
AI-Driven Hybrid Control Strategy	96.1

In terms of efficiency improvement, demonstrates that the AI-driven hybrid control technique performed better than the conventional models. In comparison to PID, FLC, and MPC, the hybrid strategy's deep learning-based optimisation improved inverter performance by enabling better response to dynamic changes in load and environmental circumstances.
The AI-driven control techniques might improve multilevel inverters' efficiency inrenewable energy applications. By maximising power conversion efficiency, lowering harmonic distortion, andenhancing overall system reliability, the suggested control strategy—which makes use of cutting-edge machinelearning techniques—showed a significant improvement in inverter performance. The system was able to adjust

to changing load demands and climatic conditions thanks to the integration of deep learning models, especiallythe hybrid AI-driven control approach, which guaranteed the best inverter performance in real-time.The AI-based control system shown notable advantages over conventional control techniques like PID andfuzzy logic in terms of efficiency enhancement. The system is extremely responsive to changes in input powerand load because to the integration of real-time monitoring, which allowed for rapid and accurate adjustments.Furthermore, the efficiency of energy conversion was increased by combining a hybrid control strategy withoptimisation methods like Model Predictive Control (MPC), which improved system performance overall.

CONCLUSION

In conclusion, multilayer inverter efficiency optimisation for renewable energy applications has shown a lot ofpromise thanks to AI-driven control techniques. Through the integration of cutting-edge machine learningmethodologies with Internet of Things technology, the system has the potential to significantly enhance energyconversion efficiency, dependability, and scalability. To further improve the system's efficacy and guarantee its long-term survival in extensive renewable energy applications, it will be imperative to address the issues thathave been highlighted, such as sensor calibration, real-time data transfer delays, and hardware optimisation.

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