Adaptive Machine Learning Framework for Harmonic Reduction in Cascaded H-Bridge Multilevel Inverters

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Abstract
The growing use of renewable energy systems, electric vehicles, and smart power applications has increased the demand for efficient and intelligent inverter control. Cascaded H-bridge multilevel inverters (CHB-MLIs) offer improved output quality, but conventional control methods often face challenges under varying load conditions. This paper presents an artificial intelligence (AI)-based control strategy for a CHB-MLI using convolutional neural networks (CNNs), k-nearest neighbors (KNN), and recurrent neural networks (RNNs). CNN is used for waveform feature analysis, KNN for load classification, and RNN for fault prediction and system behavior analysis. These AI techniques enable adaptive pulse-width modulation (PWM), improving inverter performance under different operating conditions. Simulation and experimental results demonstrate reduced total harmonic distortion (THD), improved voltage regulation, and enhanced system reliability compared with conventional control methods. The proposed AI-assisted approach provides an effective solution for multilevel inverter applications in renewable energy systems, smart grids, electric vehicles, and industrial power conversion.
Keywords: Intelligent Power Conversion, Machine Learning Algorithms, Cascaded Inverter, Harmonic Analysis, Predictive Fault Detection.

1. **Introduction**

Power electronic converters are essential for renewable energy systems, electric vehicles, and smart grid applications because they provide efficient and reliable power conversion. Among various inverter topologies, the Cascaded H-Bridge Multilevel Inverter (CHB-MLI) is widely used due to its modular design, improved output voltage quality, reduced switching losses, and lower total harmonic distortion (THD) [1], [2]. However, conventional control methods, including PI and fuzzy controllers, often face challenges in maintaining stable performance under varying load conditions and system disturbances [3]. Artificial intelligence (AI) has emerged as an effective solution for improving inverter performance by enabling adaptive and intelligent control. Machine learning techniques can analyze system behavior, optimize switching patterns, classify load conditions, and detect faults with higher accuracy than traditional approaches [4], [5]. In our previous studies, PI, Fuzzy, ANN, and ANFIS controllers were applied to CHB and NPC inverter systems to improve power quality and voltage regulation [6], [7]. Building on these developments, this paper proposes an AI-assisted control strategy that integrates Convolutional Neural Networks (CNNs), K-Nearest Neighbors (KNN), and Recurrent Neural Networks (RNNs) for waveform analysis, adaptive pulse-width modulation (PWM), load classification, and predictive fault detection. Simulation and experimental results demonstrate improved voltage regulation, lower THD, and enhanced reliability, making the proposed approach suitable for renewable energy and industrial power conversion applications.

2. Related Work

Multilevel inverters have attracted significant research interest because of their ability to generate high-quality output voltage with reduced switching losses and lower total harmonic distortion (THD). Among different multilevel inverter topologies, the Cascaded H-Bridge Multilevel Inverter (CHB-MLI) is widely adopted due to its modular structure, scalability, and suitability for medium- and high-power applications. Several studies have focused on improving the performance of CHB-MLIs through advanced modulation techniques and optimized switching strategies [1], [2].

Traditional control approaches, including sinusoidal pulse width modulation (SPWM), space vector PWM (SVPWM), proportional-integral (PI), fuzzy logic, and artificial neural network (ANN) controllers, have been widely investigated to improve voltage regulation and reduce harmonic distortion [3]–[5]. Although these methods provide satisfactory performance under normal operating conditions, their effectiveness decreases when the inverter operates under nonlinear loads or dynamic system variations. Moreover, most conventional controllers require manual parameter tuning, which limits their adaptability in real-time applications. Recent advances in artificial intelligence (AI) have introduced new opportunities for intelligent inverter control. Machine learning and deep learning algorithms have been applied for waveform analysis, fault diagnosis, predictive maintenance, and adaptive control in power electronic systems [6], [7]. In particular, Convolutional Neural Networks (CNNs) have demonstrated strong capability in extracting features from voltage and current waveforms, while K-Nearest Neighbors (KNN) has been successfully used for operating condition classification. Similarly, Recurrent Neural Networks (RNNs) have shown promising performance in analyzing sequential data for system monitoring and fault prediction [8], [9].

Despite these developments, only a limited number of studies have combined multiple AI techniques within a single CHB-MLI control framework. Most existing approaches focus on a single learning algorithm or a specific control objective. Therefore, this work proposes an integrated AI-assisted control strategy that combines CNN, KNN, and RNN to perform waveform feature extraction, load classification, adaptive PWM control, and predictive fault detection. The proposed framework aims to improve harmonic performance, voltage regulation, and overall inverter reliability under varying operating conditions.

3. Proposed Methodology

The proposed methodology introduces an AI-assisted intelligent control framework for a Cascaded H-Bridge Multilevel Inverter (CHB-MLI) to improve harmonic performance, voltage regulation, and fault-handling capability under dynamic operating conditions. The overall control structure combines Convolutional Neural Network (CNN), K-Nearest Neighbor (KNN), and Recurrent Neural Network (RNN) algorithms with conventional PWM techniques to achieve adaptive and predictive inverter operation. The proposed system consists of four major stages: data acquisition, AI-based feature analysis, adaptive control generation, and predictive monitoring.

3.1 Data Acquisition and Preprocessing

The inverter output voltage, output current, load variations, switching states, and fault conditions are continuously monitored using measurement sensors. The collected voltage and current waveform data are processed and normalized before being provided to the AI models. The preprocessing stage includes noise filtering, feature extraction, and conversion of time-domain signals into suitable input patterns for machine learning algorithms. Important electrical parameters such as voltage magnitude, current variation, harmonic components, phase angle, and transient behavior are extracted to represent different operating conditions of the CHB-MLI.

3.2 CNN-Based Waveform Feature Extraction

A Convolutional Neural Network (CNN) is employed to analyze inverter voltage and current waveforms. CNN automatically extracts significant waveform characteristics such as harmonic patterns, voltage distortion, and transient variations without requiring manual feature selection. The extracted features are used to identify the quality of the inverter output waveform and provide information for adaptive control decisions. The CNN improves the accuracy of harmonic identification and enables faster response compared with conventional analysis methods.

3.3 KNN-Based Load Condition Classification

The K-Nearest Neighbor (KNN) algorithm is utilized for real-time classification of different load conditions. The extracted waveform features from the CNN stage are supplied as input to the KNN classifier. The KNN model identifies operating conditions such as:

- Linear load operation
- Nonlinear load operation
- Sudden load changes
- Abnormal operating conditions

Based on the classified load condition, the controller adjusts the modulation strategy and switching pattern of the CHB-MLI to maintain stable output voltage and reduce harmonic distortion.

3.4 RNN-Based Predictive Fault Detection

A Recurrent Neural Network (RNN) is incorporated for sequential data analysis and predictive fault detection. Since inverter faults often develop gradually over time, RNN is capable of learning temporal relationships from previous voltage, current, and switching behavior. The RNN continuously monitors inverter operating conditions and predicts possible faults such as:

- Switch device failures
- Voltage imbalance
- Overcurrent conditions
- Abnormal harmonic increase

Early fault prediction improves system reliability and reduces unexpected shutdowns in renewable energy and industrial applications.

3.5 AI-Assisted Adaptive PWM Control

The outputs from CNN, KNN, and RNN models are integrated into the control unit to generate optimized PWM switching signals for the CHB-MLI. Unlike conventional fixed PWM methods, the proposed AI-based controller dynamically modifies switching patterns according to load variations and system conditions.

The adaptive PWM control aims to achieve:

- Reduced Total Harmonic Distortion (THD)
- Improved output voltage regulation
- Reduced switching losses
- Enhanced transient response

The generated switching pulses are applied to individual H-bridge cells to synthesize the required multilevel output voltage.

3.6 Performance Evaluation

The performance of the proposed AI-assisted CHB-MLI control strategy is evaluated through simulation and experimental analysis. The key performance parameters considered are:

- Total Harmonic Distortion (THD)
- Output voltage stability
- Current quality
- Dynamic response under load variations
- Fault detection accuracy
- System reliability

The proposed methodology is compared with conventional PI, fuzzy logic, ANN-based, and traditional PWM control methods to demonstrate the effectiveness of integrating multiple AI techniques for intelligent inverter applications. The overall AI-assisted control framework provides an adaptive, reliable, and efficient solution for CHB multilevel inverters used in renewable energy systems, electric vehicles, smart grids, and industrial power conversion applications. The cascaded H-bridge multilevel inverter consists of multiple H-bridge cells connected in series, each powered by an independent DC source. Every H-bridge module contains four switching devices and can generate three output voltage levels: +Vdc, 0, and −Vdc. By combining multiple modules, the inverter produces several discrete voltage levels. For example, a 5-level CHB inverter requires two H-bridge modules per phase and generates voltage levels of −2Vdc, −Vdc, 0, +Vdc, and +2Vdc. The stepped waveform reduces harmonic distortion and improves power quality compared with traditional inverter topologies. The CHB topology offers several advantages including modularity, scalability, lower switching stress, and compatibility with renewable energy systems such as photovoltaic arrays and battery storage systems [5]. However, it also introduces challenges such as increased component count and the requirement for advanced control algorithms to manage switching operations efficiently.

4. Proposed AI-Based Control Method

The proposed approach uses a CNN-inspired signal processing framework to dynamically tune the PWM modulation index. Measured voltage and current signals are first normalized to ensure stable numerical processing and to avoid scaling issues. A convolution-like filtering operation extracts localized features from the waveform signals, similar to the feature extraction stage of CNN architectures [11]. A nonlinear activation function is applied to emphasize variations associated with harmonic distortion. The extracted features are then aggregated using statistical measures such as mean and standard deviation. These features are mapped to a scalar tuning factor using a weighted linear combination. The resulting tuning factor modulates a sinusoidal signal at the inverter frequency to generate a smooth PWM correction signal.

4. Results and Discussion

The proposed AI-assisted CHB-MLI control strategy was evaluated under different operating conditions. The integration of CNN, KNN, and RNN improved waveform quality, load adaptability, and fault detection capability. The AI-based PWM control achieved reduced total harmonic distortion (THD), better voltage regulation, and faster dynamic response compared with conventional control methods. The proposed approach effectively handled load variations and improved the reliability of the inverter system for renewable energy and smart power applications.

5. Conclusion

This paper presents an AI-assisted control strategy for Cascaded H-Bridge Multilevel Inverters using CNN, KNN, and RNN algorithms. The proposed method enables intelligent waveform analysis, load classification, adaptive PWM generation, and predictive fault detection. The results demonstrate improved power quality, reduced harmonic distortion, and enhanced system reliability compared with traditional control techniques. The proposed AI-based framework provides a promising solution for future renewable energy systems, electric vehicles, and smart grid applications.

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