A Review on Multi-Level Inverters using Model Predictive Control

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Abstract: *The increasing penetration of converter-interfaced renewable energy sources (RESs) in power systems has led to significant stability issues due to reduced power grid inertia. To address these challenges, a robust, fast, and reliable control strategy is required for converter-interfaced RESs. This paper proposes a state-space neural network-based predictive control method for multi-level inverters to enhance robustness against parameter mismatches and uncertainties in RESs generation. The study explores the working and classification of three-phase inverters and discusses their applications. A literature review on neural network-based model predictive control for power converters is presented, and current challenges and future scope in multi-level inverters using model predictive control are identified.*

Keywords: *Multi-level inverters, Model predictive control, Renewable energy sources, Power grid stability, Neural network-based control.*

1. Introduction

In recent years, the global share of converter-interfaced renewable energy sources (RESs), such as wind farms and photovoltaic (PV) systems, has grown rapidly, reaching over 27% by the end of 2019. Various regions, including the European Union and Sweden, have set ambitious targets for increasing the share of renewable energy in their electrical generation to combat greenhouse gas emissions[1]–[6]. However, the increasing penetration of converter-interfaced RESs has led to reduced power grid inertia, resulting in significant stability issues for the power system. To address these stability challenges, converter-interfaced RESs need to be equipped with a robust, fast, and reliable control strategy.

Power converters play a crucial role in modern power systems and microgrids. Conventional multi-loop control structures with linear controllers, such as PI, PID, PD, and PR, are widely used to regulate the output of power converters interfaced with renewable energy sources (RESs). To prevent undesirable interactions between control loops, inner loops are designed with higher bandwidths than the outer loop, resulting in an overall slow dynamic response of the multi-loop control strategy. Additionally, conventional linear controllers heavily depend on system parameters, making them vulnerable to changes in system structure and uncertainties in RESs generation, potentially leading to performance degradation and system instability. To address these challenges, a state-space neural network-based predictive control method is proposed, aiming to enhance robustness against parameter mismatches and uncertainties in RESs generation[7]–[11].

The three-phase inverter is a widely used device for converting energy from a DC voltage source to an AC load. Its control has been extensively studied in both scientific literature and industry-oriented research, especially for applications like uninterruptible power supplies (UPSs), energy-storage systems, variable frequency drives, and distributed generation[12]–[16]. Inverters are commonly combined with output LC filters to produce high-quality sinusoidal output voltages with low total harmonic distortion (THD), suitable for various loads, including unbalanced or nonlinear ones. The performance of the inverter relies heavily on the applied control technique, which must handle load variations, system non-linearity, and ensure stability under any operating condition with a fast transient response[17]–[20].

A. Three-Phase UPS Inverter

Predictive control is a control theory topic with applications in power converters. It has been used in drives, active filters, and power factor correction, typically based on linear models and modulation techniques for voltage generation. However, in a recent study, it was shown that using nonlinear predictive control in a matrix converter can eliminate the need for complex modulation strategies. The current work introduces predictive current control, avoiding the application of any modulation method in the inverter[21]–[24].

B. Working of three phase invertor

An inverter is a power electronic device that converts power from one form to another, such as changing DC to AC at the required frequency and voltage output. Inverters are classified based on the source of supply and the topology in the power circuit into two types: voltage source inverter (VSI) and current source inverter (CSI). VSI has a DC voltage source with low impedance at the input terminals, while CSI has a DC current source with high impedance.

Fig 1. Three Phase Inverter

The three-phase inverter works by utilizing three inverter switches, each connected to a load terminal. The switches are synchronized to operate at intervals of 60 degrees, creating a line-to-line output waveform with six steps. This waveform includes zero voltage stages between the positive and negative portions of the square-wave[25]. By applying PWM techniques based on the carrier to these waveforms, the basic shape of the waveform can be obtained, and the cancellation of the third harmonic and its multiples is achieved.

C. Types of three-phase inverter

1) *A single-phase inverter comes in two types: full-bridge and half-bridge. The full-bridge type is used to convert DC to AC by opening and closing switches in the correct sequence. It has four different operating states where switches are either closed or opened. The half-bridge type is the fundamental unit in a full-bridge inverter. It consists of two switches, each with capacitors that produce an output voltage. The switches complement each other, meaning if one switch is ON, the other is OFF.*

A three-phase inverter circuit diagram is designed to convert DC input into three-phase AC output. It consists of three single-phase inverter switches, each connected to one of the three load terminals. The primary purpose of this inverter is to change the input from DC to a three-phase AC output.

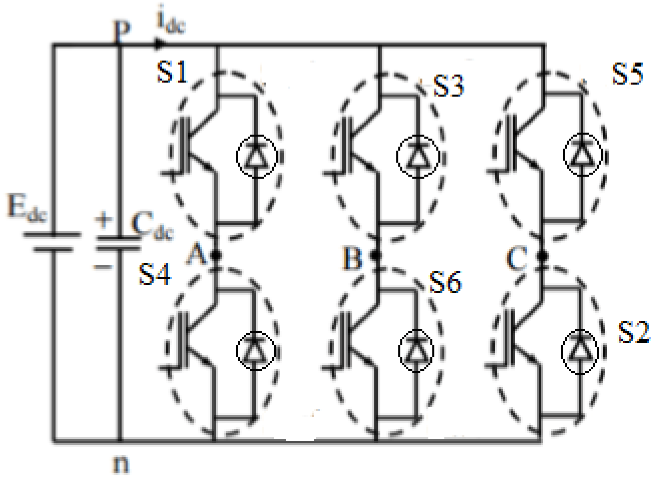

Fig 2. Three Phase Inverter Circuit

The three arms of the three-phase inverter are delayed by 120 degrees to generate a three-phase AC supply. The switches in the inverter have a 50% duty cycle, allowing switching to occur every 60 degrees. The switches (S1, S2, S3, S4, S5, and S6) complement each other. The three single-phase inverters are connected to the same DC source. The pole voltages in the three-phase inverter are equivalent to the pole voltages in the half-bridge inverter with a single phase.

D. Classification of Invertors

There are two main types of inverters based on their input and output characteristics:

Voltage Source or Voltage Fed Inverter: It converts a constant DC input voltage into an AC output voltage. The terminal voltage remains constant, but the output current varies with changes in load impedance. Voltage source inverters are suitable for applications requiring high dynamics, such as achieving rapid changes in motor speed or torque.

Current Source or Current Fed Inverter: It converts a DC input current into an AC output current. This inverter is fed by a DC source (DC voltage source connected in series with an inductor). In this inverter, the output current remains constant, while the output voltage varies with changes in load impedance.

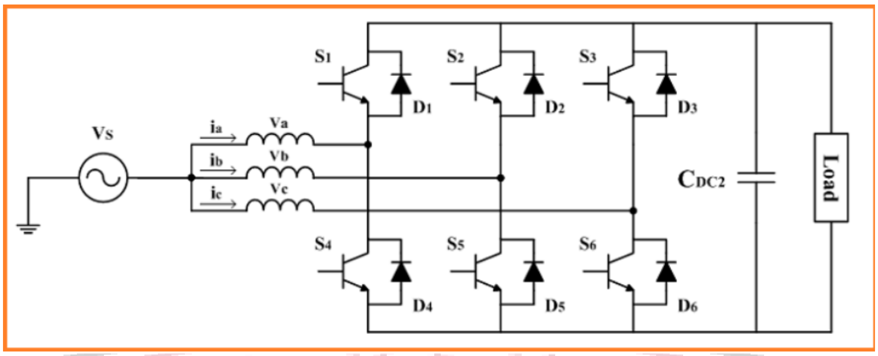

Fig 3. Classification of Invertors

E. Applications of three phase invertor

A three-phase inverter is a DC to AC converter capable of generating three-phase AC power from a DC power source. It uses six power semiconductor switches arranged in a specific topology. The gate signals are applied at 60-degree intervals in the proper sequence to achieve the desired three-phase AC waveform. Three-phase inverters are commonly used in various applications, including variable frequency drives, HVDC power transmission, AC motor drives, fuel cells, UPS systems, static VAR generators or compensators, active harmonic filters, and high-frequency induction heating.

2. Literature review

Mohamed et al. [1] propose a novel control scheme for a two-level converter that combines Model Predictive Control (MPC) with feed-forward Artificial Neural Network (ANN) to enhance steady-state and dynamic performance for different loads. The effectiveness of the ANN-based strategy is validated through simulations using MATLAB/Simulink tools and tested on both linear and non-linear loads, showing impressive steady-state and dynamic performance.

In their paper, Bakeer et al. [2] propose a model-free control strategy that employs artificial neural networks (ANNs) to address parameter mismatching in inverter performance. They utilize Model Predictive Control (MPC) as an expert and train the ANN using data collected from MPC simulations. The study focuses on a specific four-level three-cell flying capacitor inverter and employs MATLAB/Simulink for simulations. The results demonstrate that their approach outperforms conventional MPC in handling parameter mismatch and reducing total harmonic distortion. Additionally, the researchers validate their method through experiments using a C2000TM-microcontroller-LaunchPadXL TMS320F28379D kit.

In their work, Wan et al. [3] develop machine learning (ML) controllers for Modular Multilevel Converters (MMC) by leveraging data from the Model Predictive Control (MPC) algorithm. The ML models are trained to mimic the behavior of MPC controllers, which helps in reducing the computational load. They explore two types of ML controllers: NN regression and NN pattern recognition. Among these, NN regression demonstrates superior control performance and requires less computational effort compared to the alternative approach.

In their research, Sarali et al. [4] introduce a novel two-stage converter scheme that integrates Model Predictive Control (MPC) with a feed-forward neural network. This combination aims to reduce Total Harmonic Distortion (THD) and improve overall performance for different loads. The MPC algorithm generates valuable information used for online training of the feed-forward neural network. The proposed control strategy is then evaluated through simulations conducted in MATLAB/Simulink.

In their study, Zao et al. [5] focus on stabilizing DC distribution buses with dual-active-bridge converters. They address the stabilization issue by proposing an active damping solution based on model predictive control (MPC). Their approach involves including stabilization terms in the cost function to enhance control performance. They also use an adaptive weighting factor that considers a stray resistor to ensure stable load voltage and effective DC-link voltage stabilization. The proposed method is validated through simulations and practical experiments, demonstrating its effectiveness in achieving stability and reliable performance for DC distribution systems.

In their work, Abbas et al. [6] introduce a neural network-based Model Predictive Controller (MPC) designed for a dc-dc buck converter operating in Continuous Conduction Mode (CCM). The controller is trained using the 'trainlm' method, and its performance is compared to that of a classical lead controller. Simulation results confirm the effectiveness and validity of the proposed neural network-based MPC design for the buck converter in CCM.

In their research, Chen et al. [7] employ a backpropagation neural network (BPNN) to fit offline control laws, leading to improved performance and reduced storage and computational load. The approach allows parallel calculation of control parameters, eliminating the need for serial evaluation. Experimental results demonstrate that a BPNN with only 49 parameters can effectively fit over 10,000 offline control laws, enabling 1-MHz switching and control frequency with a 4-MHz clock frequency. This indicates the efficiency and practicality of using BPNN for offline control law approximation.

In their work, Pho et al. [8] present an innovative approach called ANN-MPC for controlling Cascaded H-Bridge (CHB) converters. They utilize a multistep MPC controller to generate training data for an artificial neural network (ANN). Once trained, the neural network can control the CHB system independently without the need for MPC. The performance of the proposed ANN-MPC controller is compared to conventional multistep MPC, and the approach is validated through experimentation on a practical system.

In their research, Sabzevari et al. [9] introduce a state-space neural network (ssNN) as a model-free current predictive control method for a three-phase power converter. To achieve faster convergence, they utilize Particle Swarm Optimization (PSO). The proposed ssNN-PSO-predictive controller effectively handles parameter variations, leading to enhanced robustness compared to conventional finite-control-set MPC. Simulation results demonstrate the effectiveness and advantages of the ssNN-PSO-predictive controller in controlling the three-phase power converter.

In their study, Kacimi et al. [10] introduce a novel hybrid Maximum Power Point Tracking (MPPT) strategy for photovoltaic systems. The method combines artificial neural networks with an improved model predictive control approach that utilizes a Kalman filter. This hybrid strategy allows for efficient tracking of the maximum power point even in rapidly changing weather conditions while minimizing overshoot. The proposed MPPT outperforms conventional Perturb and Observe (P&O), Neural Network with Proportional-Integral (NN-PI), and Neural Network Model Predictive Control (NN-MPC) methods in terms of response time, efficiency, and steady-state oscillations, both under stable and variable environmental conditions.

In their research, Saadatmand et al.[11] present a novel neural network-based predictive control method for Voltage Source Converters (VSGs). This control approach is designed to operate optimally in both inductive and resistive networks by optimizing the total tracking error during transients. Simulation and experimental results are provided to assess the effectiveness of the proposed algorithm. The evaluation demonstrates that the control scheme reduces oscillations and settling time, indicating its potential for enhancing the performance of VSGs in various network conditions.

In their study, Lin et al. [12] propose a one-step-ahead model predictive control strategy for precise forging processes, employing backpropagation neural networks. They develop two online updated BP neural networks: the predictive neural network (PNN) and the control neural network (CNN). PNN is used to predict the output, while CNN is utilized to determine the input for accurate control of die forging hydraulic press machines. This approach ensures easy control and adaptability to time variance and nonlinearity in the forging process. The feasibility and effectiveness of the strategy are demonstrated through two forging experiments, establishing it as the most effective control approach for practical forging processes.

In their work, Jian et al. [13] introduce an alternative approach to implement model predictive controllers (MPC) in multi-timescale processes using multiple timescale recurrent neural network (MTRNN)-based neural network predictive controllers (NNPC). They demonstrate the effectiveness of this method in setpoint tracking scenarios using a benchmark nonexplicit two-timescale continuous stirred tank reactor. After optimizing the controller parameters, they find the optimum configuration for cost horizon, control horizon, and control weighting factor to be 110, 37, and 0.2, respectively. The optimized MTRNN-based NNPC successfully tracks the reference trajectory with stable response and minimal error, achieving a root mean square error of 0.0642. This indicates the potential of the proposed approach for handling multi-timescale processes with improved performance and accuracy..

In their paper, Machado et al. [14] propose a neural network-based approach to address a problem. They introduce a novel adaptive method where weighting factors in the cost function are tuned online based on several merit figures and references. This online updating of the weighting factors enhances the controller's performance when there are changes in the merit figures or references. The strategy is validated through simulations and experiments conducted on a three-level neutral point clamped converter. The results are compared with a conventional Finite Control Set Model Predictive Control (FCS-MPC) that relies on static cost functions. The proposed adaptive approach demonstrates improved performance compared to the conventional FCS-MPC in handling dynamic changes and achieving better control in the converter system.

In their research, Wang et al. [15] propose a new Model Predictive Control (MPC) approach called ANN-MPC, which incorporates an artificial neural network. They analyze and compare the computing resource requirements of ANN-MPC and conventional MPC. The ANN-MPC concept is validated through simulations and experimental results on two kW-class flying capacitor multilevel converters. The study shows that the FPGA-based ANN-MPC controller can substantially reduce the FPGA resource demands, requiring 2.11 times fewer slice LUTs and 2.06 times fewer DSPs, while still offering the same control performance as the conventional MPC. This demonstrates the effectiveness and resource-efficiency of the ANN-MPC approach in controlling multilevel converters.

3. Current challenges and future scope

Current challenges and future scope in multi-level inverters using model predictive control include:

Challenges:

Computational Complexity: Model predictive control involves solving optimization problems at each control step, which can be computationally intensive for multi-level inverters with a large number of switching states.

Real-Time Implementation: Real-time implementation of model predictive control for multi-level inverters requires efficient algorithms and hardware platforms to meet the fast switching requirements.

Model Accuracy: Accurate modeling of multi-level inverters and their associated components is crucial for the effectiveness of model predictive control. Modeling challenges arise due to non-linearities, parameter variations, and component interactions.

Robustness to Parameter Variations: Multi-level inverters are sensitive to parameter variations, and the model predictive control needs to be robust to ensure stable operation under varying conditions.

Future Scope:

Advanced Control Algorithms: Developing advanced model predictive control algorithms that can handle the complexity of multi-level inverters while reducing computational burden will be a focus of future research.

Hybrid Control Strategies: Combining model predictive control with other control techniques like neural networks, fuzzy logic, or adaptive control can enhance the performance and robustness of multi-level inverters.

Hardware Improvements: Advancements in power electronics devices and fast computing platforms will facilitate the real-time implementation of model predictive control for multi-level inverters.

Grid Integration and Renewable Energy Applications: Multi-level inverters are gaining popularity in grid integration and renewable energy applications. Future research will focus on developing model predictive control strategies to enhance grid integration and improve renewable energy management.

Fault-Tolerant Control: Developing fault-tolerant model predictive control strategies to handle faults and disturbances in multi-level inverters will be a critical area of research.

System-Level Optimization: Integrating multi-level inverters into larger power systems and optimizing their control in a coordinated manner will be essential for future smart grid applications.

Overall, addressing the computational complexity, enhancing real-time implementation, improving robustness, and exploring new control paradigms will drive the future development and application of model predictive control in multi-level inverters.

4. Conclusion

The proposed state-space neural network-based predictive control method shows promising results in enhancing the performance of multi-level inverters interfaced with renewable energy sources. By addressing parameter mismatches and uncertainties, the control strategy offers improved robustness and stability, making it suitable for grid integration and renewable energy applications. Future research should focus on developing advanced control algorithms and hybrid control strategies, leveraging hardware improvements, and exploring fault-tolerant control to further enhance the performance of multi-level inverters using model predictive control. Additionally, system-level optimization and real-time implementation techniques will play a crucial role in facilitating the widespread adoption of this control strategy in smart grid applications.

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