Fuzzy Logic Based Fault Tolerant Model Predictive MLI Topology

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Abstract- - ***The study focuses on optimizing the performance of a three-phase voltage-source inverter using Model Predictive Control (MPC). The inverter's functioning is analyzed through Clarke Transformation, especially when the load parameters are not predefined. The research introduces an LC filter model, confirming its effectiveness in minimizing Total Harmonic Distortion (THD). By adopting fault-tolerant architectures for multilevel inverters, the system offers enhanced reliability, a crucial feature given the growing reliance on green energy. Additionally, the paper incorporates a fault management system using Fuzzy Logic, which detects and addresses faults to maintain steady inverter functionality. Extensive simulations and comparative analyses validate the approach, emphasizing its robust voltage control and fault-resilient capabilities.***

Keywords ***Heat Exchanger Technologies, Computational Thermal Fluid Dynamics, Thermal Management, Predictive Modeling, Nanofluid Applications.***

I. INTRODUCTION

Power converters serve as vital components in contemporary electrical systems and microgrids. While traditional control techniques, like PI, PID, PD, and PR controllers, are commonly employed for managing power converter outputs, they have certain limitations. One drawback is their slow dynamic response due to design constraints aimed at preventing control loop interference. Moreover, these linear controllers are highly sensitive to changes in system architecture and unpredictable fluctuations in renewable energy generation, resulting in potential performance issues and even system failure. To overcome these challenges, we propose a predictive control methodology based on state-space neural networks. This approach aims to enhance system robustness in the face of parameter variations and uncertainties in renewable energy input[1]–[4].

The three-phase inverter is a key device that changes DC power into AC energy and has received significant attention in academic and industry research. These inverters are crucial for a variety of applications, ranging from uninterruptible power supplies and energy-storage systems to variable frequency drives and decentralized power generation[5]–[9]. To ensure high-quality AC output with minimal harmonic distortion, inverters often incorporate LC filters. The inverter's performance is largely determined by the control methods utilized, which need to be versatile enough to accommodate load fluctuations, system nonlinearities, and maintain stability across diverse operating conditions[10]–[13].

In the field of power electronics, inverters are essential for converting electrical energy forms. They can be categorized into two primary types: voltage source inverters (VSIs) and current source inverters (CSIs). VSIs operate with a low-impedance DC voltage source, while CSIs function with a high-impedance DC current source. Both types are critical for various applications, yet they each come with their specific control challenges that need to be addressed for effective operation.

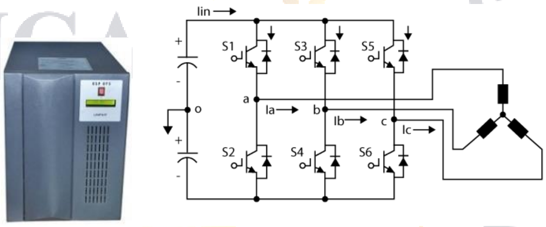


Figure 1: Three Phase Inverter

II. LITEATURE 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[10]–[16].

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[17]–[19]. 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[20]–[25].

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.

III. PROPOSED METHODOLOGY

Model Predictive Control (MPC) is an advanced control approach that determines control actions by addressing an optimization issue at each control interval. This method evaluates the system's current condition and anticipates upcoming actions across a forecasted period. The suggested procedure includes the subsequent phases:

Design of Model Predictive Control for Multi-Level Inverter

System Identification:

- Gather data and parameters of the multi-level inverter.
- Analyze the dynamic behavior of the system under different scenarios.

Formulation of the Optimization Problem:

- State the objective of the MPC, e.g., to regulate the output voltage of the inverter.
- Specify constraints of the system such as voltage, current limits, and switching frequency limits.

Modelling the Predictive Controller:

- Use state-space models or differential equations representing the multi-level inverter dynamics.
- Define a prediction horizon over which future control actions and system outputs are predicted.

Controller Implementation:

- At each control interval, solve the optimization problem to find the optimal control actions.
- Apply the first control action and reiterate the process.

THD Reduction using LC Filter

Total Harmonic Distortion (THD) represents the distortion in a waveform due to harmonics. For a multi-level inverter, this is particularly significant as the quality of the output waveform (typically a voltage) determines the performance of devices connected to it.

Harmonic Analysis:

- Use FFT (Fast Fourier Transform) or other harmonic analysis techniques to analyze the harmonics in the output waveform of the inverter.

LC Filter Design:

- Choose suitable values for the inductor (L) and capacitor (C) based on the predominant harmonics and desired cut-off frequency.

- The LC filter will act as a low-pass filter, allowing the fundamental frequency to pass while attenuating higher-frequency harmonics.

Integration and Testing:

- Connect the LC filter to the output of the inverter.
- Re-analyze the output waveform and calculate the new THD to confirm the improvement.

Fault Tolerant MLI using Fuzzy Logic

Fault tolerance ensures the system operates correctly even in the presence of faults. Fuzzy logic, with its capability to handle imprecise data and make decisions, is apt for this.

Fault Detection:

- Define possible faults that can occur in a multi-level inverter, e.g., short-circuit, over-voltage, etc.
- Monitor key parameters that indicate these faults.

Fuzzy Logic Controller Design:

- Define fuzzy sets for input and output variables.
- Formulate fuzzy rules based on expert knowledge or simulation results to determine the control actions during fault conditions.
- Defuzzify the output of the fuzzy system to obtain a crisp value for the control action.

Sample of fuzzy rules are presented below:

IF SwitchStatus(S1) IS Failed AND SwitchStatus(S2) IS Failed THEN VoltageLevel IS NOT +3VDC

IF SwitchStatus(S3) IS Failed AND SwitchStatus(S4) IS Failed THEN VoltageLevel IS NOT +3VDC

IF SwitchStatus(S3) IS Working OR AlternateConfiguration IS Working THEN VoltageLevel IS 2VDC

IF SwitchStatus(S5) IS Failed AND SwitchStatus(S6) IS Failed THEN VoltageLevel IS +3VDC

... and so on.

Fault Handling:

There are several methods to manage an MLI through the PWM strategy. The most prevalent techniques include Sinusoidal Pulse Width Modulation (SPWM), space vector modulation (SVM), and Selective Harmonic Elimination (SHE-PWM). Furthermore, determining the switching angles in SHE can be challenging with an increasing number of levels. In this study, we employ the Nearest Level Control (NLC) or rounding approach. This method boasts of a low switching frequency and also minimizes switching losses. The essence of the NLC method is to generate a large number of voltage levels by equating the amplified voltage reference (K*Vref) to the nearest producible voltage level by the converter, as illustrated in the provided figure. The gain, denoted as K, can be expressed as: $K = (n-1)/2$. Here, n signifies the total number of levels.

Simulation Setup

Table 1 shows the parameters description with their values including resistance, Inductance, Capacitance, DC voltage, Frequency, Load type and levels.

Table 1: Parameters Description

Input Parameters	Values
Resistance	1 ohm
Inductance	2e-3 H
Capacitance	1e-3 F
DC voltage	220 volt
Frequency	50Hz
Load Type	Resistance
Levels	7

IV. RESULT ANALYSIS

Figure 2 presents the voltage prediction efficiency of the model after it's trained using ANN. The training model incorporates filter current, output voltage, output current, and reference voltage as input parameters. Its primary objective is to forecast the desired switching state, viewed as the voltage vector for inverters. The results of testing seven different switching states are showcased. In the subsequent figure, 2, the learning accuracy for both linear and non-linear data samples is displayed.

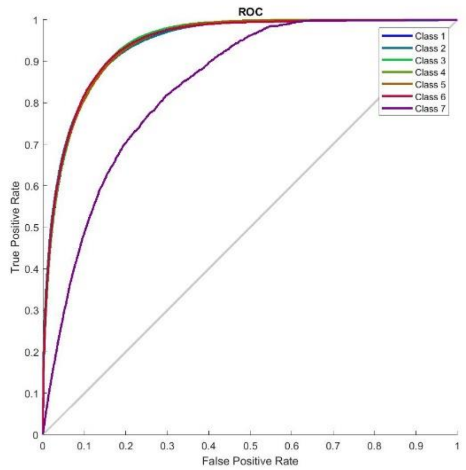


Figure 2: Learning Efficiency of Predictive Model

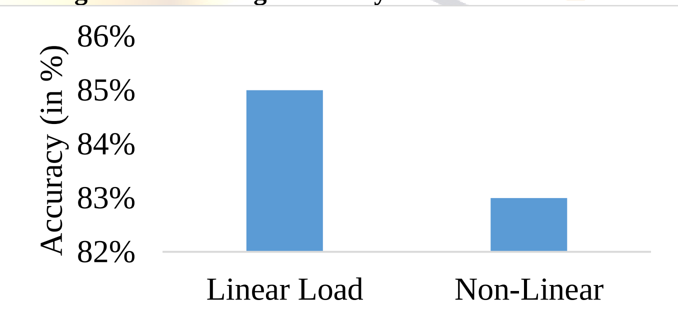


Figure 3: Learning Accuracy of Predictive Model with Linear and Non-Linear Load

Figure 3 and 4 depict the output variable paired with the switching variable to produce a 7-level output, as well as the output voltage for a 7-level MLI. When contrasted with the current approach, the proposed technique yields a more accurate sinusoidal output within the time frame of 0-0.2 seconds.

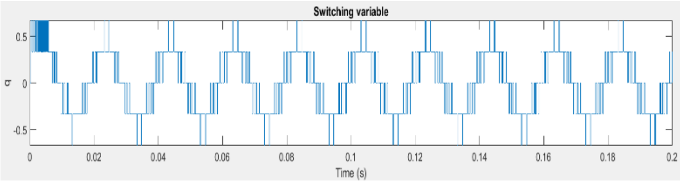


Figure 4: Switching Variable to generate 7 level output

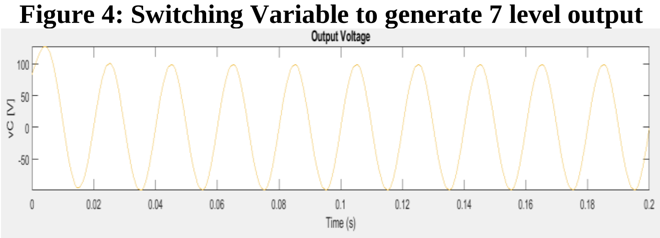
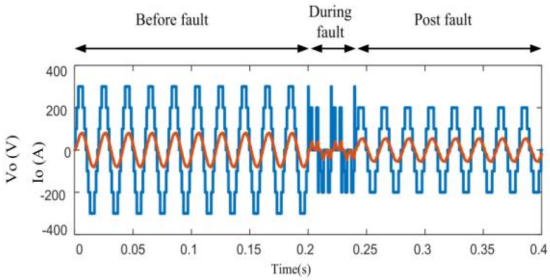
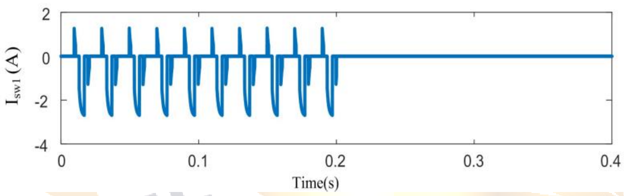


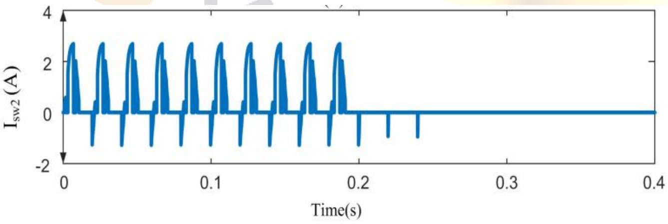
Figure 5: Output voltage generated for 7-level MLI



(a) Output Voltage and Current Graph



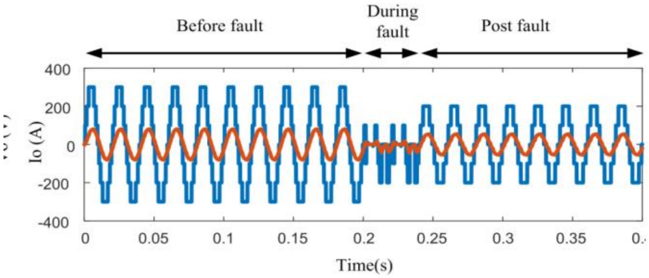
(a) Current at Switch S1



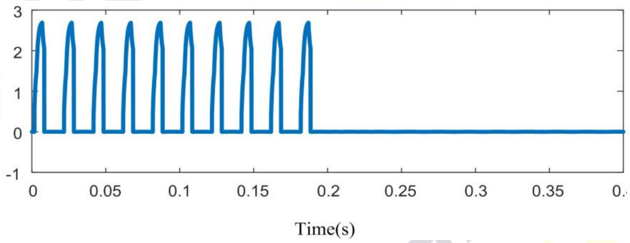
(b) Current at Switch S2

Figure 6: Voltage and Current Graph at Fault Occurrence at Switch S1 and S2

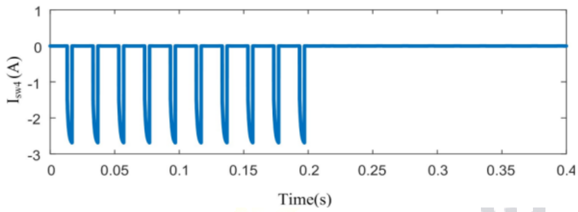
In Figure 6, there's a noticeable change in the output voltage levels. Specifically, when switches S1 and S2 experience faults, the voltage levels drop from seven to five. This demonstrates the impact of these switch faults on the overall voltage output.



(a) Output Voltage and Current Graph



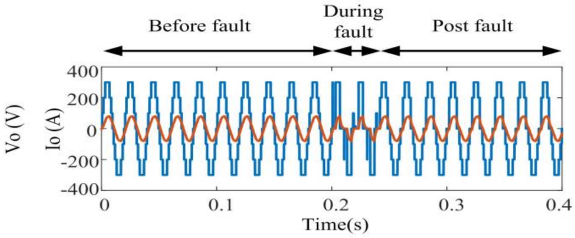
(b) Current at Switch S3



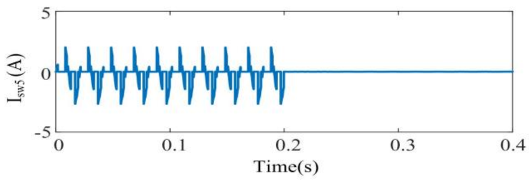
(c) Current at Switch S4

Figure 7: Voltage and Current Graph at Fault Occurrence at Switch S3 and S4

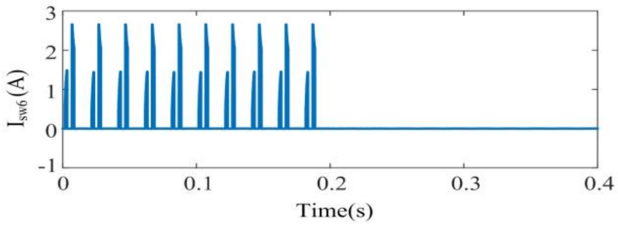
Figure 7 illustrates the output voltage and current waveforms resulting from faults in switches S3 and S4. These disruptions cause the Multilevel Inverter to function as a five-level inverter after the fault. Conversely, Figure 4.7 indicates that even when faults arise in bidirectional switches S5 and S6, the Multilevel Inverter's output remains consistent at seven levels.



(a) Output Voltage and Current Graph



(b) Current at Switch S5



(c) Current at Switch S6

Figure 8: Voltage and Current Graph at Fault Occurrence at Switch S5 and S6

V. CONCLUSION

The research has effectively exhibited the merits of integrating Model Predictive Control (MPC) with a three-phase voltage-source inverter, emphasizing its role in output voltage regulation. The inclusion of the LC filter has unequivocally proven beneficial in mitigating THD, enhancing the quality of the output voltage waveform. Through fault-tolerant multilevel inverter topologies, the study underscores the necessity for uninterrupted power supply systems, especially in renewable energy setups. The Fuzzy Logic-based system has also demonstrated significant potential in identifying and counteracting faults, ensuring a steadfast performance of the inverter. The simulation results affirm the robustness of the proposed methodology. When pitted against existing models, the proposed system exhibits superior voltage output, especially between 0-0.2 seconds, and maintains its efficiency even when faced with faults in its bidirectional switches. This study underscores the potential of leveraging modern control strategies and fault-tolerant topologies in building efficient and resilient power electronic systems. The exploration of Model Predictive Control (MPC) combined with neural networks for multilevel inverters, as presented in this study, opens a myriad of opportunities for further research. Future endeavors can focus on enhancing the real-time execution speed of the combined MPC-ANN model, expanding its applicability to other power electronic configurations, and incorporating additional fault diagnosis techniques. Moreover, the integration of more advanced machine learning algorithms might lead to even better prediction and control accuracy. The adaptability of the proposed approach to emerging power electronic applications, particularly in renewable energy domains such as solar and wind energy systems, can also be a promising avenue for future research.

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