Robust Fault Tolerance in MLI Systems Using Fuzzy Logic-Based Predictive Control

[1]Madhurendra Kumar [2]Mr. Deep Mala
[1]Department of Electrical Engineering, RKDF Institute of Science & Technology, Bhopal (MP)
[2]Department of Electrical Engineering, RKDF Institute of Science & Technology, Bhopal (MP)
Email [1]madhurendra11152@gmail.com, [2]deepmala.eee@gmail.com

* Corresponding Author: Madhurendra Kumar

Abstract: *This Multi-Level Inverter (MLI) systems are increasingly employed in modern power electronics due to their ability to generate high-quality voltage waveforms with reduced harmonic distortion. However, as MLI systems grow in complexity, they become more susceptible to faults, which can lead to system instability and degraded performance. This paper presents a robust fault tolerance strategy for MLI systems using Fuzzy Logic-Based Predictive Control (FLPC). The proposed method combines the predictive capabilities of model-based control with the flexibility and adaptability of fuzzy logic, offering enhanced resilience against faults and system uncertainties. The FLPC approach predicts the future states of the MLI system and adjusts control actions dynamically based on fuzzy logic rules, allowing for real-time fault detection and compensation. This ensures stable operation even in the presence of faults, while minimizing total harmonic distortion (THD) and improving overall system reliability. Simulation results demonstrate the effectiveness of the proposed FLPC strategy, showing significant improvements in fault tolerance, dynamic response, and output quality compared to conventional control methods. The proposed approach provides a viable solution for enhancing the robustness of MLI systems in critical applications such as renewable energy integration and industrial motor drives.*

Keywords: *Total Harmonic Distortion (THD), Fuzzy Logic, renewable energy sources.*

I. INTRODUCTION

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.

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. 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.

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.

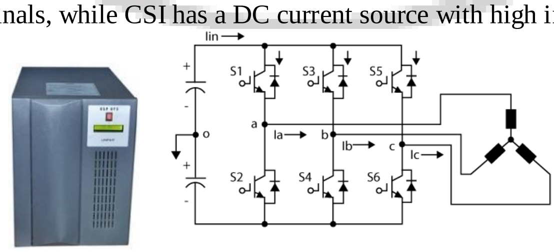


Figure 1: Three Phase Inverter

I. 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.

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.

II. 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:

A. 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.

B. 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.

C. 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 total number of levels.

III. 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.

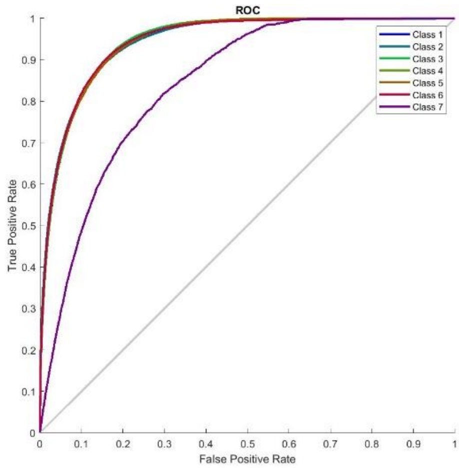


Figure 2: Learning Efficiency of Predictive Model

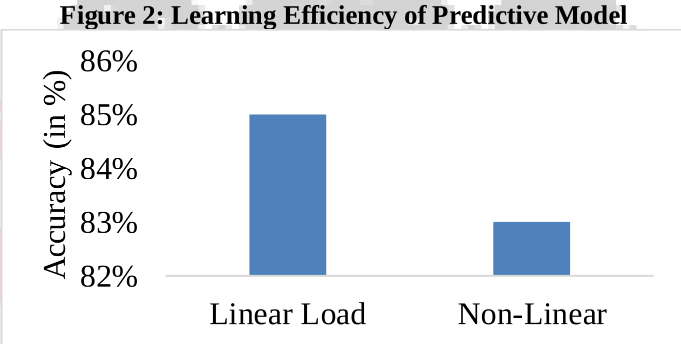


Figure 3: Learning Accuracy of Predictive Model with Linear and Non-Linear Load

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.

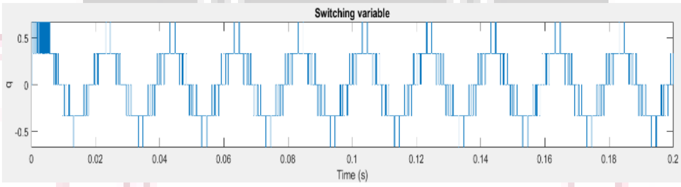


Figure 4: Switching Variable to generate 7 level output

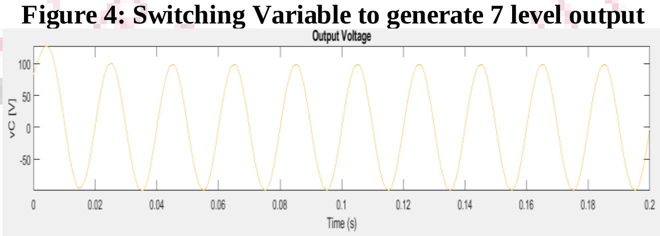
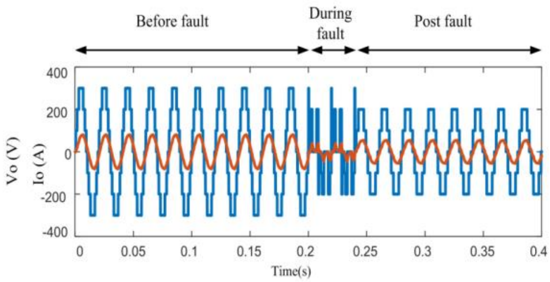
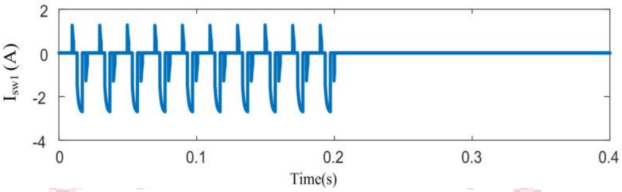


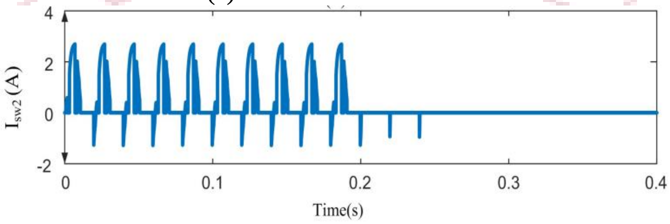
Figure 5: Output voltage generated for 7-level MLI



(a) Output Voltage and Current Graph



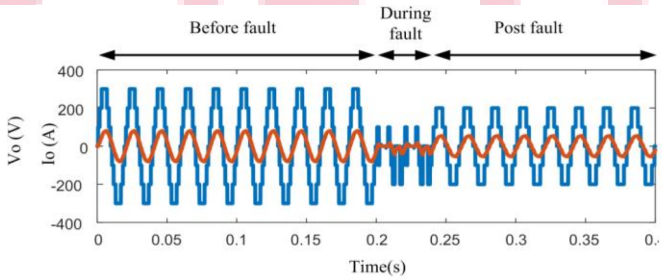
(a) Current at Switch S1



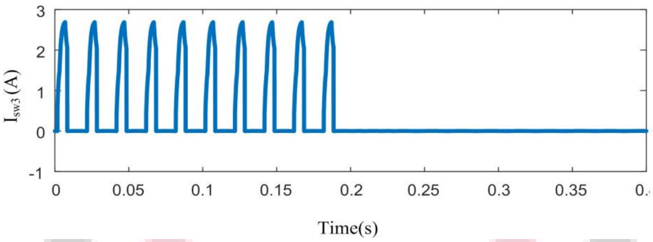
(b) Current at Switch S2

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

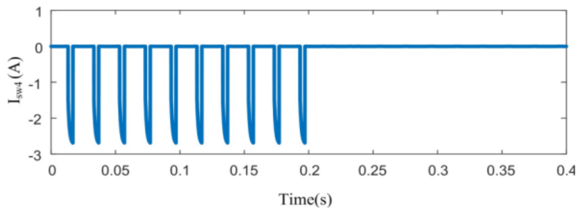
In Figure 6, there's a noticeable change in the output voltage levels. Specifically, when switches S1 and S2 experience faults, the voltage levels drop from seven to five. This demonstrates the impact of these switch faults on the overall voltage output.



(a) Output Voltage and Current Graph



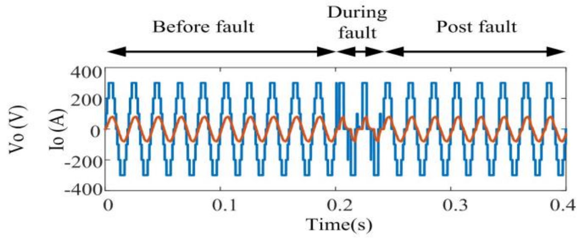
(b) Current at Switch S3



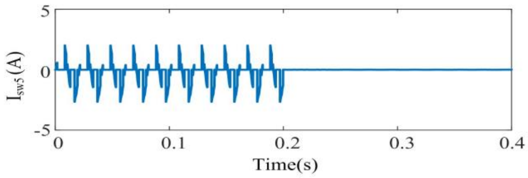
(c) Current at Switch S4

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

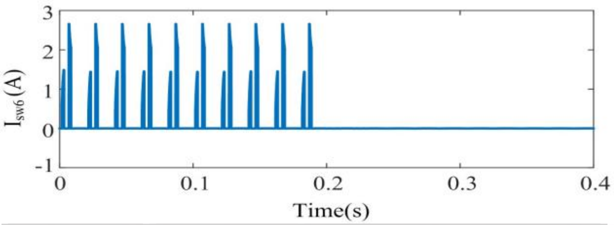
Figure 7 illustrates the output voltage and current waveforms resulting from faults in switches S3 and S4. These disruptions cause the Multilevel Inverter to function as a five-level inverter after the fault. Conversely, Figure 4.7 indicates that even when faults arise in bidirectional switches S5 and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

References

[1] I. S. Mohamed, S. Rovetta, T. D. Do, T. Dragicević, and A. A. Z. Diab, “A Neural-Network-Based Model Predictive Control of Three-Phase Inverter With an Output LC Filter,” *IEEE Access*, vol. 7, pp. 124737–124749, 2019, doi: 10.1109/ACCESS.2019.2938220.

[2] A. Bakeer, I. S. Mohamed, P. B. Malidarreh, I. Hattabi, and L. Liu, “An Artificial Neural Network-Based Model Predictive Control for Three-Phase Flying Capacitor Multilevel Inverter,” *IEEE Access*, vol. 10, pp. 70305–70316, 2022, doi: 10.1109/ACCESS.2022.3187996.

[3] S. Wang, T. Dragicevic, Y. Gao, and R. Teodorescu, “Neural Network Based Model Predictive Controllers for Modular Multilevel Converters,” *IEEE Trans. Energy Convers.*, vol. 36, no. 2, pp. 1562–1571, 2021, doi: 10.1109/TEC.2020.3021022.

[4] D. S. Sarali, V. Agnes Idhaya Selvi, and K. Pandiyan, “An Improved Design for Neural-Network-Based Model Predictive Control of Three-Phase Inverters,” in *2019 IEEE International Conference on Clean Energy and Energy Efficient Electronics Circuit for Sustainable Development (INCCES)*, 2019, pp. 1–5. doi: 10.1109/INCCES47820.2019.9167697.

[5] D. Zhao *et al.*, “Improved Active Damping Stabilization of DAB Converter Interfaced Aircraft DC Microgrids Using Neural Network-Based Model Predictive Control,” *IEEE Trans. Transp. Electrif.*, vol. 8, no. 2, pp. 1541–1552, 2022, doi: 10.1109/TTE.2021.3094757.

[6] G. Abbas, U. Farooq, and M. U. Asad, “Application of neural network based model predictive controller to power switching converters,” in *The 2011 International Conference and Workshop on Current Trends in Information Technology (CTIT 11)*, 2011, pp. 132–136. doi: 10.1109/CTIT.2011.6107948.

[7] J. Chen, Y. Chen, L. Tong, L. Peng, and Y. Kang, “A Backpropagation Neural Network-Based Explicit Model Predictive Control for DC–DC Converters With High Switching Frequency,” *IEEE J. Emerg. Sel. Top. Power Electron.*, vol. 8, no. 3, pp. 2124–2142, 2020, doi: 10.1109/JESTPE.2020.2968475.

[8] B. B. Pho, M. H. Tran, T. M. Tran, and P. Vu, “An Artificial Neural Network-Based Model Predictive Control Of Cascaded H-Bridge Multilevel Inverter,” *Int. J. Renew. Energy Res.*, vol. 12, no. 3, pp. 1279–1288, 2022, doi: 10.20508/ijrer.v12i3.13145.g8513.

[9] S. Sabzevari, R. Heydari, M. Mohiti, M. Savaghebi, and J. Rodriguez, “Model-Free Neural Network-Based Predictive Control for Robust Operation of Power Converters,” *Energies 2021, Vol. 14, Page 2325*, vol. 14, no. 8, p. 2325, Apr. 2021, doi: 10.3390/EN14082325.

[10] N. Kacimi, S. Grouni, A. Idir, and M. S. Boucherit, “New improved hybrid MPPT based on neural network-model predictive control-Kalman filter for photovoltaic system,” *Indones. J. Electr. Eng. Comput. Sci.*, vol. 20, no. 3, pp. 1230–1241, 2020, doi: 10.11591/ijeecs.v20.i3.pp1230-1241.

[11] S. Saadatmand, P. Shamsi, and M. Ferdowsi, “Power and Frequency Regulation of Synchronverters Using a Model Free Neural Network-Based Predictive Controller,” *IEEE Trans. Ind. Electron.*, vol. 68, no. 5, pp. 3662–3671, 2021, doi: 10.1109/TIE.2020.2984419.

[12] Y. C. Lin, D.-D. Chen, M.-S. Chen, X.-M. Chen, and J. Li, “A precise BP neural network-based online model predictive control strategy for die forging hydraulic press machine,” *Neural Comput. Appl.*, vol. 29, no. 9, pp. 585–596, 2018, doi: 10.1007/s00521-016-2556-5.

[13] N. L. Jian, H. Zabiri, and M. Ramasamy, “Control of the Multi-Timescale Process Using Multiple Timescale Recurrent Neural Network-Based Model Predictive Control,” *Ind. Eng. Chem. Res.*, 2022, doi: 10.1021/ACS.IECR.2C04114/ASSET/IMAGES/MEDIUM/IE2C04114_0021.GIF.

[14] O. Machado, P. Martín, F. J. Rodríguez, and E. J. Bueno, “A Neural Network-Based Dynamic Cost Function for the Implementation of a Predictive Current Controller,” *IEEE Trans. Ind. Informatics*, vol. 13, no. 6, pp. 2946–2955, 2017, doi: 10.1109/TII.2017.2691461.

[15] D. Wang *et al.*, “Model Predictive Control Using Artificial Neural Network for Power Converters,” *IEEE Trans. Ind. Electron.*, vol. 69, no. 4, pp. 3689–3699, 2022, doi: 10.1109/TIE.2021.3076721.

[16] H. S. Khan, I. S. Mohamed, K. Kauhaniemi, and L. Liu, “Artificial Neural Network-Based Voltage Control of DC/DC Converter for DC Microgrid Applications,” in *2021 6th IEEE Workshop on the Electronic Grid (eGRID)*, 2021, pp. 1–6. doi: 10.1109/eGRID52793.2021.9662132.

[17] O. Han, T. Ding, C. Mu, Y. Huang, X. Zhang, and Z. Ma, “Multi-time Scale Optimal Dispatch for the Wind Power Integrated System with Demand Response of Data Centers Based on Neural Network-based Model Predictive Control,” *IEEE Trans. Ind. Appl.*, pp. 1–11, 2023, doi: 10.1109/TIA.2023.3296065.

[18] C. Li, L. Feng, Q. Wang, Z. Wang, L. Liao, and J. Lin, “Parameter optimization for three-level inverter model Predictive control based on artificial neural network,” in *2022 IEEE Vehicle Power and Propulsion Conference (VPPC)*, 2022, pp. 1–4. doi: 10.1109/VPPC55846.2022.10003303.

[19] H. Wang, Y. Yue, B. Sun, and H. Zhao, “Neural Network-based Model Predictive Control Approach for Modular Multilevel Converters,” in *2023 4th International Conference on Electronic Communication and Artificial Intelligence (ICECAI)*, 2023, pp. 324–330. doi: 10.1109/ICECAI58670.2023.10176482.

[20] X. Yang, K. Wang, J. Kim, and K.-B. Park, “Artificial neural network-based FCS-MPC for three-level inverters,” *J. Power Electron.*, vol. 22, no. 12, pp. 2158–2165, 2022, doi: 10.1007/s43236-022-00535-6.