ANN Based Model Predictive Control of Inverter for Power Application

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***Abstract*—Ensuring high-quality and reliable AC power delivery from three-phase inverters with LC filters remains a significant challenge, particularly under nonlinear and dynamic load conditions. Conventional control strategies, such as proportional-integral (PI) controllers, often fail to achieve the necessary balance between low total harmonic distortion (THD), fast transient response, and computational efficiency. Although Model Predictive Control (MPC) has emerged as a robust solution due to its predictive optimization capability and superior voltage regulation, its substantial computational requirements hinder real-time implementation in high-frequency switching applications.This work proposes a hybrid control framework that integrates MPC with Artificial Neural Networks (ANN) to exploit the advantages of both approaches.**

***Index Terms*—Hybrid Control Strategy, Model Predictive Control, Artificial Neural Networks, Three-phase Inverter, LC Filter, Power Quality, Total Harmonic Distortion, Real-Time Implementation.**

1. INTRODUCTION

The growing complexity of modern power systems, driven by the increasing penetration of renewable energy sources, electrification of transportation, and the emergence of smart grids, has intensified the demand for high-quality, reliable, and efficient power conversion technologies. At the heart of these systems, power electronic converters — particularly the three-phase voltage source inverter (VSI) — play a critical role in delivering controlled alternating current (AC) from direct current (DC) sources[1]. Their ability to regulate the magnitude, frequency, and phase of the output voltage makes them indispensable in applications ranging from renewable energy integration and electric vehicle charging to Uninterruptible power supply (UPS), distributed generation, and motor drives in microgrids.

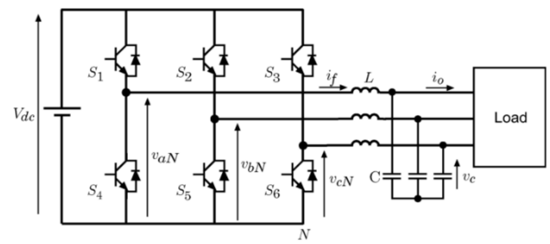

Fig 1. Schematic of a three-phase voltage source inverter with LC filter and load.

stable and efficient operation. The output of a VSI inherently contains high-frequency harmonics due to the switching action of the semiconductor devices. These harmonics degrade power quality, leading to increased losses, heating, and potential malfunction of connected loads. To mitigate these effects, an LC filter is often introduced at the inverter output to smooth the waveform by attenuating high-frequency component [2]. Although the LC filter improves output quality significantly, it also introduces resonance modes and additional dynamics, complicating the control design and potentially destabilizing the system if not properly handled.

Achieving precise control of the VSI with LC filter under varying and often unpredictable operating conditions — including nonlinear, unbalanced, and time-varying loads — presents several challenges. The controller must not only suppress harmonics effectively but also respond quickly to disturbances and changes in demand, all while maintaining stability and robustness against parameter uncertainties and external disturbances. The control objectives typically include minimizing maintaining voltage amplitude and phase accuracy, and achieving these goals with computational efficiency suitable for real-time implementation.

Traditionally, proportional-integral (PI) controllers combined with pulse-width.

2.RELATED WORK

The control of three-phase inverters has been a focal point of research in power electronics, driven by the increasing need for high-quality, reliable, and efficient AC power delivery. Achieving precise control of such systems under varying and often unpredictable operating conditions remains challenging, as the controller must minimize to maintain robustness to parameter uncertainties and load variations while remaining computationally efficient for real-time implementation. Over the years, a wide range of control strategies have been proposed to address these demands, ranging from classical linear methods to advanced model-based and data-driven approaches, each offering distinct benefits and exhibiting inherent limitations.

Conventional linear controllers, particularly under balanced linear loads. Early studies demonstrated their ability to regulate output voltage effectively and maintain acceptable power quality in steady conditions. However, these controllers often perform poorly under nonlinear, unbalanced, or rapidly changing load conditions, with noticeable degradation in transient response and reduced robustness against parameter variations. Their reliance on linearized system models limits their capacity to cope with nonlinear dynamics and complex resonance phenomena introduced by the LC filter.

In response to these shortcomings, various nonlinear and optimal control strategies have been investigated. Methods and deadbeat control have shown improvements in dynamic performance and robustness to disturbances. HVC, for instance, offers rapid transient response but introduces variable switching frequency, which increases switching losses and complicates filter design. SMC enhances robustness against parameter uncertainties and external perturbations but suffers from the well-known chattering phenomenon, which can degrade power quality and shorten component lifespan. Deadbeat control theoretically achieves minimal tracking error in the shortest possible time; however, it is highly sensitive to modeling inaccuracies and measurement noise, making it challenging to implement in practical systems. Optimal control techniques, including linear quadratic regulators and controllers, have also been applied to improve performance under constraints, yet their high computational complexity and tuning difficulty hinder real-time applicability.

To its predictive optimization capability and ability to handle multivariable interactions and constraints naturally. MPC predicts the system's future behavior over a finite horizon and computes control actions that minimize a predefined cost function at each sampling instant, thereby directly generating optimal switching signals without relying on modulation stages. Several studies have demonstrated that MPC achieves superior voltage tracking, lower THD, and faster transient response compared to classical and nonlinear methods, while effectively managing the dynamics introduced by the LC filter. Nevertheless, the main drawback of MPC is its substantial computational burden, as solving an optimization problem at every sampling interval demands significant processing power, which limits its implementation at high switching frequencies or on cost-constrained hardware platforms.

In parallel with advancements in model-based control, the rise of avenues in the control of power electronic systems. ANNs can approximate complex nonlinear mappings between inputs and outputs without requiring an explicit mathematical model, offering significant advantages in systems with parameter uncertainties and unmodeled dynamics. Once trained, ANNs can generate control actions almost instantaneously, making them well suited for real-time applications where conventional model-based methods are infeasible. Prior research has demonstrated that ANNs are effective for tasks such as fault detection, parameter estimation, and direct control of converters, achieving fast inference and robustness to disturbances. However, their performance strongly depends on the quality and diversity of the training data, and careful design of the network architecture is essential to avoid over fitting and ensure generalization to unseen operating conditions.

To leverage the complementary strengths of MPC and ANN, hybrid strategies have been proposed wherein MPC is employed offline to generate optimal control actions over a range of operating scenarios, creating a dataset that captures the desired control policy. This dataset is then used to train an ANN to approximate the MPC policy. Once trained, the ANN can replace MPC in real-time operation, providing near-optimal control performance with significantly reduced computational requirements. Such hybrid approaches retain the predictive accuracy of MPC while offering the computational efficiency of ANN, making them attractive for embedded applications. Although promising results have been reported in simplified systems, their efficacy in realistic configurations—such as three-phase VSIs with LC filters operating under nonlinear and unbalanced loads—remains less explored.

Building upon this body of work, the present study proposes and evaluates a hybrid MPC–ANN control methodology tailored for a three-phase VSI with an LC output filter supplying both linear and nonlinear loads. This work systematically designs and validates the hybrid strategy in a realistic inverter system, explicitly addressing the challenges posed by the LC filter dynamics and load variability. The proposed method is assessed through detailed MATLAB/Simulink simulations, demonstrating that the ANN-based controller effectively replicates the performance of MPC, achieving high-quality output voltage, low THD, fast transient response, and robust operation while significantly reducing computational complexity, thereby facilitating real-time implementation.

3. METHODOLOGY

The methodology adopted in this study aims to develop, train, and validate a hybrid control with the computational efficiency of Artificial Neural Networks (ANN) for controlling a three-phase voltage source inverter (VSI) with an output LC filter supplying both linear and nonlinear loads. The approach integrates mathematical modeling of the system, design and implementation of the MPC controller, generation of training data through MPC, training of an ANN to approximate the MPC control law, and validation of the proposed hybrid strategy through extensive simulations.

VSI powered by a constant DC voltage source, an output LC filter that smooths the inverter output by attenuating switching harmonics, and a load that can vary between linear and nonlinear types. The inverter is modeled as a bridge of six controllable semiconductor switches, capable of producing stepped AC output voltages by switching between discrete states. The LC filter, comprising series-connected inductors and shunt-connected capacitors in each phase introduces resonant dynamics that complicate the control task. The primary control objective is to regulate the output voltage of the inverter such that it follows a sinusoidal reference waveform with minimal total harmonic distortion (THD), fast transient response, and robust performance under varying load conditions, while ensuring that the control strategy is computationally feasible for real-time implementation.

To effectively model the inverter system, the state-space equations representing the dynamics of the VSI, LC filter, and load are derived. The mathematical model is formulated which converts the three-phase variables into two orthogonal components. This transformation simplifies the mathematical representation of the system without loss of dynamic information, making it more suitable for control design. The equations of the system are discretized to align with the digital implementation of the controller. The state variables, such as the filter currents and capacitor voltages, are expressed as functions of the inverter switching states and the system parameters, providing the basis for predictive control.

In the first stage of the proposed methodology, a finite-control-set MPC is implemented. At each sampling instant, the MPC predicts the future states of the system for all feasible switching vectors over a single-step prediction horizon. Using the discretized model, it evaluates a cost function for each switching vector, which quantifies the deviation of the predicted output voltage from the desired reference. The switching vector that minimizes the cost function is then applied to the inverter. This procedure enables the MPC to achieve excellent tracking performance and low THD while inherently respecting the system's constraints and multivariable interactions. However, MPC's reliance on solving an optimization problem at each sampling instant imposes a significant computational burden, particularly at high switching frequencies, which limits its real-time applicability in practical systems.

To mitigate this limitation, an ANN is trained to approximate the control policy of the MPC. A comprehensive dataset is generated by executing MPC offline over a wide range of operating scenarios, including different load types, magnitudes, and system parameter variations. For each scenario, the current system states — such as capacitor are recorded as inputs, and the optimal switching vector determined by the MPC is recorded as the corresponding output. This dataset captures the expert knowledge of the MPC and forms the foundation for training the ANN.

The ANN is designed as corresponding to the system states, one or more hidden layers equipped with nonlinear activation functions to capture the underlying nonlinear relationships, and an output layer representing the predicted optimal switching vector. The specific number of neurons and layers is determined empirically through experimentation to achieve an optimal trade-off between prediction accuracy and computational efficiency. The ANN is trained using supervised learning, where the weights and biases the mean squared error between its output and the MPC-generated optimal control actions.

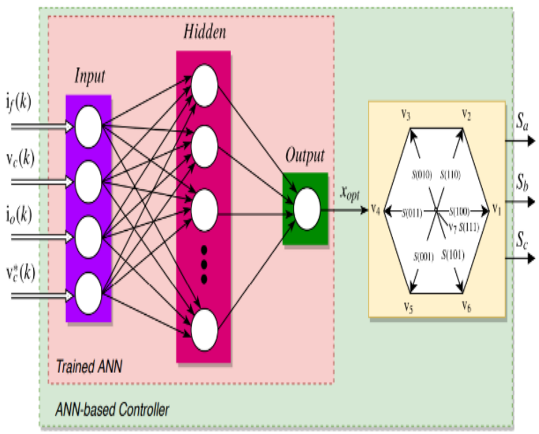

Fig 2. ANN Architecture

The architecture of the ANN which depicts the flow of information from the input layer through the hidden layers to the output layer.

Once trained, the ANN replaces the MPC in the real-time control loop. At each sampling instant, the ANN infers the optimal switching vector directly from the current system states, effectively replicating the MPC's control policy while eliminating the need to solve an optimization problem online. This hybrid strategy leverages the predictive optimality of MPC during the offline phase and the fast inference capability of ANN during the online phase, thereby achieving high control performance with significantly reduced computational complexity.

The overall hybrid control strategy which shows the block diagram of the proposed approach. In the offline stage, MPC generates optimal control actions for various system conditions, and the resulting dataset is used to train the ANN.

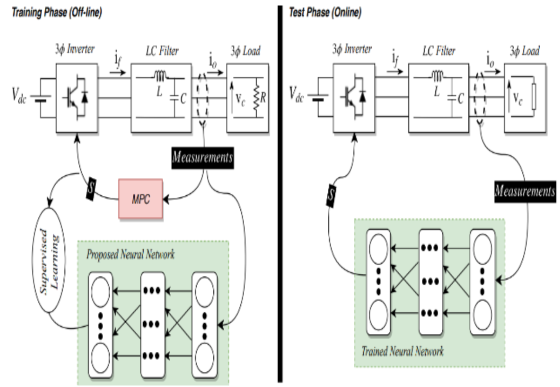

Fig 3. Hybrid MPC-ANN Diagram

In the online stage, the trained ANN is deployed in the control loop, where it provides near-optimal control actions in real time.

The proposed hybrid control strategy is implemented and validated through detailed simulations in MATLAB/Simulink. The full system — including the inverter, LC filter, load, and controllers — is modeled accurately to capture the relevant dynamics. The hybrid controller's performance is evaluated under both linear and nonlinear load conditions and compared with that of the conventional MPC controller. Key performance metrics, such as output voltage quality, THD, transient response, and computational effort, are analyzed to demonstrate the effectiveness of the proposed method.The switching vector that minimizes the cost function is then applied to the inverter. This procedure enables the MPC.

4.SIMULATION SETUP

Control algorithms while allowing comprehensive evaluation under realistic operating scenarios. The goal of the simulation was to assess the controller's ability to deliver high-quality voltage output, minimize total harmonic distortion (THD), and maintain performance across both linear and nonlinear load conditions.

The system under study includes a three-phase voltage source inverter (VSI) supplied by a fixed DC voltage source. The inverter is modeled as a bridge of six ideal semiconductor switches capable of generating three-phase AC output through discrete switching states. An LC filter is connected at the inverter output to suppress high-frequency switching harmonics and ensure a clean sinusoidal waveform reaches the load. The system is tested under two load types: a balanced resistive (linear) load and the control strategy is implemented in two phases. In the offline phase, a finite-control-set MPC is used to generate optimal switching actions for a wide range of system conditions. The MPC predicts system behavior over a one-step horizon and evaluates a cost function based on voltage tracking error. These optimal control decisions, along with corresponding system states (filter currents and capacitor voltages in α–β reference frame), form the training dataset for the ANN. In the online phase, the trained ANN is deployed as the main controller, replacing MPC and inferring the optimal switching states in real time based on current system inputs.

The ANN is constructed The inputs include real-time measurements of the system states; the output is the selected switching vector. The network is trained using supervised learning to minimize prediction error with respect to MPC-labeled outputs.

Parameter	Value
DC link voltage	400 V
Filter inductance (per phase)	2 mH
Filter capacitance (per phase)	10 µF
Reference output frequency	50 Hz
Switching frequency	10 kHz
Sampling time	50 µs
Load types	Resistive and Diode bridge
Simulation platform	MATLAB/Sim ulink

Table 1. Simulation Parameters

These values were selected based on standard inverter design principles and ensure practical system performance. The switching frequency, filter values, and sampling time were chosen to ensure dynamic stability and acceptable harmonic performance while maintaining realistic computational load.

The system was modeled using Simscape Power Systems blocks and Simulink control components. The inverter, filter, and load were implemented using electrical component blocks, while the MPC and ANN controllers were implemented using Embedded MATLAB Function blocks and neural network blocks. The simulation was discretized according to the selected sampling time, and control decisions were updated at each time step.

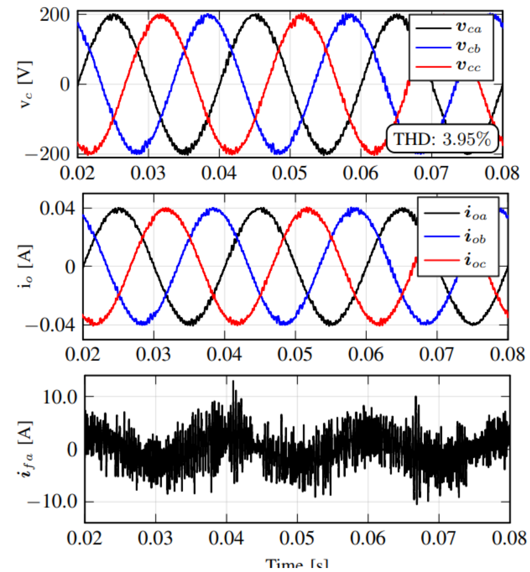

Fig 4. Simulink model of VSI.

An overview of the complete simulation model illustrates the integrated system including the inverter, LC filter, load, and the hybrid controller. The model layout demonstrates how real-time system variables are fed into the controller and how switching actions are applied to the inverter bridge.

This simulation framework enables thorough validation of the control strategy under both steady-state and dynamic operating conditions. Key performance indicators, including voltage waveform quality, THD, settling time, and control computation time, are recorded to support the comparison between the ANN-based controller and conventional MPC.

5. RESULT

The performance of the proposed hybrid ANN-based controller was evaluated through detailed simulations conducted in MATLAB/Simulink. The primary objective was to assess the controller's capability to produce a sinusoidal output voltage with minimal distortion and stable dynamic response under various loading conditions.

Initially, the system was tested with a linear resistive load. The ANN controller effectively tracked the reference sinusoidal waveform, producing a clean and stable output with minimal deviation. The results confirmed that the neural network was able to approximate the optimal switching strategy learned from the MPC without any noticeable degradation in performance. The output voltage remained well-regulated even under steady-state and transient conditions.

Further analysis was performed under nonlinear loading, specifically using a diode-bridge rectifier with a capacitive filter to introduce distortion into the system. Despite these nonlinear effects, the ANN controller-maintained voltage stability and quickly responded to changes in load dynamics. The transient behavior exhibited low overshoot and rapid settling, indicating that the controller effectively compensated for abrupt load variations.

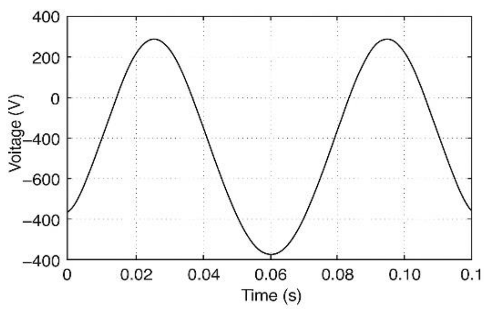

Fig 5. Inverter output under nonlinear load.

The waveform presented illustrates ANN-based controller under nonlinear loading. As observed, the waveform remains symmetrical and closely follows the desired reference profile, demonstrating the controller's effectiveness in preserving waveform quality. The low level of ripple and distortion confirms that the ANN accurately emulates the control behavior of the original MPC strategy.

6. CONCLUSION

This study presented an Artificial Neural Network inverter system. The proposed hybrid approach utilized offline MPC-generated data to train a neural network capable of producing optimal switching decisions in real-time. By replacing the computationally intensive MPC algorithm with a trained ANN, the system achieved substantial reductions in execution time without compromising control quality.

Simulation results demonstrated that the ANN controller effectively tracked reference waveforms and maintained low total harmonic distortion (THD) under both linear and nonlinear loading conditions. The inverter output remained stable, sinusoidal, and symmetric, validating the controller's robustness and adaptability to varying operational scenarios. Moreover, the ANN achieved these outcomes with significantly lower computational overhead compared to conventional MPC, making it suitable for real-time embedded applications.

Overall, the proposed control scheme successfully combines the predictive intelligence of MPC with the real-time efficiency of neural networks. It offers a promising solution for advanced power electronic systems requiring fast, accurate, and low-complexity control strategies.

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