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A Review: Deep Learning-Based Intelligent Control for DC–AC Power Converters Loss Minimization and Power Quality Enhancement

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ABSTRACT

The rapid expansion of renewable energy and electric vehicles has increased the need for intelligent, high-performance DC–AC converters. Conventional control methods such as PI, PID, and MPC struggle under nonlinear and grid-interactive conditions, leading to higher THD and reduced stability. This paper reviews deep learning-based control strategies for DC–AC converters, emphasizing loss reduction, power quality enhancement, and real-time adaptability. Real neural networks can be classified into specific architectures such as convolutional neural networks (CNNs,) Long Short-Term Memory (LSTMs), and Deep Reinforcement Learning (DRLs), and Physics-Informed Neural Networks (PINNs). are treated in detail. The results demonstrate that DL-based inverter controllers outperform classical control algorithms not only for THD attenuation and dynamic stability, but also for efficiency, under a digital control platform configuration, particularly when multi-point-injected energy grid-forming inverter topologies are considered. The paper concludes with directions for future research on real-time application feasibility, computational burden, and hybrid intelligent control systems. Finally, we present future research directions towards self-adaptive, sustainable, and cyber-resilient inverter control strategies for smart grids.

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1. INTRODUCTION

The rapid deployment of renewable energy sources (RES), e.g., photovoltaic (PV) systems and wind turbines, has led to a drastic shift in the contemporary power system, resulting in a distributed, inverter-dominant architecture. In this context, DC-AC power converters (inverters) serve as the central interface between stochastic energy sources and the utility grid. They must maintain not only synchronization but also voltage stability and optimal power transmission [1]. With the advancement of smart grids, more advanced control strategies are required to improve energy efficiency and reduce Total Harmonic Distortion (THD) and voltage flicker[2]. To overcome the challenges in modern grids and interconnections, a new generation of intelligent optimization technology must be incorporated into power electronics. In recent years, several works have demonstrated that Artificial Intelligence (AI) can play a significant role in improving the behavior of power converters, providing robustness to parameter deviations and dynamic loads [3]. Renewable energy systems have received significant attention for the application of artificial intelligence technologies to make them more reliable and efficient, showing great potential for solving complex control problems that classical linear controllers often cannot handle [4]. In addition, designing power electronics systems for smart grid applications is a paramount research challenge that contributes to achieving higher efficiencies and improved grid stability. There has been an increased effort to apply artificial intelligence-based optimization methods to improve switching strategies and controller settings, yielding significant enhancements in system performance[5]. Besides control optimization, Digital Twin technology integrated with AI is becoming a strong tool for monitoring and prognostics of power converters, such as those used in transportation systems and critical infrastructure [6]. Deep Reinforcement Learning Among a diversity of AI methods, one type that has elicited great interest is Deep Reinforcement Learning (DRL), which can learn optimal control policies through interaction with the environment. DRL proposes a model-free method that is well-suited to power converter control under uncertain conditions and dynamic scenarios [7]. A thorough survey of DRL applications indicates its capability to accommodate various control objectives, such as voltage regulation and current set-point tracking; moreover, it has been shown to have superior performance over traditional Model Predictive Control (MPC) in automated learning and actuation time[8]. On the hardware side, the inverter topology is an important factor in overall system efficiency and power quality. Single-phase differential-mode inverters are widely studied for low-power applications, and trade-offs between component count and performance are well documented [9]. Multilevel Inverters (MLIs), a preferred solution for providing higher-quality power, are widely used and produce ladder voltage waveforms with reduced harmonic content. Latest developments in MLI topologies aim to reduce the number of switching devices, without compromising the quality of output[10].Hybrid topologies for multilevel inverters are also under investigation, combining the advantages of various circuit structures to propose small-sized, cost-effective, yet high-performance designs[11]. Furthermore, research on reduced-switch-count MLI highlights the need to continue reducing converter structures, thereby leading to lower DC power losses and enhanced reliability through a dynamic recurrent fuzzy neural network (DRFNN) [12]. As for the control schemes, Model Predictive Control (MPC) remains a promising technique for grid-connected inverters, thanks to its excellent dynamic performance and explicit constraint handling[13]. Nonetheless, the trend away from synchronous generation to inverter-dominated grids has subsequently given rise to Grid-Forming (GFM) inverters that can regulate grid voltage and frequency autonomously. The control paradigms of GFM inverters must also be evaluated in light of their contribution to grid inertia and stability [14]. A taxonomy-based classification of emerging control strategies to enhance stability under weak-grid conditions is also presented in [15]. The change of control type from classical to intelligent means a shift in the power electronics paradigm, as illustrated in Figure 1, shows that control design has moved from linear PI controllers (which were widely accepted in the past due to their simplicity) to intelligent , which provides advanced dynamic handling but imposes heavy computational demands. The current frontier, as depicted, is shifting to Data-Driven Deep Learning (DL). These contemporary approaches do not require a complex mathematical model, as they can learn from operational data themselves and thereby avoid the parameter sensitivity of traditional methods. Optimal and Advanced Control of Power Electronic Converters

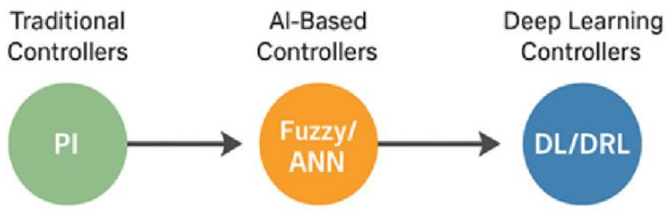

Figure 1: The development of control strategies

Lastly, coordination control strategies must be implemented to address voltage control in the presence of active distribution networks with high photovoltaic penetration. Multi-agent Deep RL has demonstrated its ability to control distributed resources, ensuring that voltage profiles remain within an acceptable range, further highlighting the scalability of AI-based solutions in complex network settings**.** This paper aims to fill the gap between advanced deep learning algorithms and their application in DC–AC power converters. We review recent advances in Deep Learning-based control, loss functions for deep learning-based control, and automatic differentiation approaches such as differentiable programming.The contribution of this review is to give the comprehensive synthesis of recent advances in DC–AC power conversion and intelligent control strategies, highlighting both technical progress and research gaps.The layout of this review is organized as follows: Section 2 presents background on DC–AC power converters, Section 3 discusses control strategies for DC–AC inverters, Section 4 examines recent deep learning–based intelligent control approaches, Section 5 provides a comparative evaluation and discussion, Section 6 outlines future research directions and Section 7 concludes the review.

2. Background on DC–AC Power Converters

This section develops the theory of DC–AC power conversion and outlines advanced inverter topologies and modulation techniques. It then dives into the crucial power quality concerns, particularly Total Harmonic Distortion (THD), and presents the shift toward intelligent optimization to minimize losses.

2.1. Fundamentals of DC–AC Conversion

The DC–AC power conversion stage is the cornerstone of contemporary renewable energy systems, which is responsible for converting stochastic Direct Current (DC) generated by sources such as PV arrays or batteries into grid-compatible Alternating Current (AC). The selected inverter topology determines the system's efficiency, power density, and harmonic response.

2.1.1. Voltage Source Inverter (VSI): The VSI topology is the most commercially popular at low-to-moderate power levels because of its simplicity of control and high degree of maturity of technology. In a VSI, the input is a rigid DC voltage source and a capacitor bank. The basic output voltage ($\mathbf{V_{out,1}}$) of a simple two-level VSI in the linear region is defined by the DC link voltage ($\mathbf{V_{dc}}$) and the modulation index ($\mathbf{m_a}$). It is given by eq. (1).

$$V_{out,1} = m_a \frac{V_{dc}}{2} \qquad \text{Where } 0 < m_a \leq 1. \tag{1}$$

Although conventional VSIs suffer from switching losses, recent developments have to do with the quality of the waveform. Developed a high-quality true sine wave VSI, in which the achieved optimal switching patterns can guarantee minimized THD and strong voltage regulation under dynamic conditions. The VSI architecture is considered among the popular PV inverters [13] and UPSs, given its simple structure and great ease of control[17].On this basis, fractional multivariable grey models have been used for VSI control to improve tracking performance during non-linear operating conditions. Topology of the three-phase, two-level VSI connected through an LC filter to an isolated RL load. Despite its well-known reliability and ease of control, this type of transformer is extremely sensitive to various forms of stress, which often cause it to break [19].

2.1.2. Current Source Inverter (CSI): Unlike VSI, the CSI is supplied from a stiff DC source, which can be formed using a bulk DC-link inductor. This structure inherently provides short-circuit protection and step-up operation (output voltage higher than the input voltage), making it suitable for certain medium-voltage drives or grid-connected systems that require galvanic isolation. But its dynamic characteristics are slower than VSI in most cases due to the high inductances, and it also requires reverse-blocking switches [9], [11].

At the DC link side, the inductor current i_{dc} dynamics is expressed as follows:

$$L_{dc} = \frac{di_{dc}}{dt} = v_A - v_{dci} \tag{2}$$

L_{dc} is the inductance of the DC choke, is the CSI's DC-side voltage, and is the switched voltage across the buck converter: eq. (3)can also be discretized as: [20].

$$i_{dc}^{p}(k+1) = i_{dc}(k) + \frac{D\,T_s}{L_{dc}}[\,V_{dc} - v_{dci}(k)] + \frac{(1-D)T_s}{L_{dc}} = i_{dc}(k) - \frac{T_s}{L_{dc}} v_{dci}(k) - \frac{T_s V_{dc}}{L_{dc}} D \tag{3}$$

Here, D is the duty ratio of S_{dc}. Using eq. (3), the DC in the next sampling can be predicted and controlled through adjusting the duty ratio [20].

2.1.3. Multilevel Inverter (MLI): The recent growth of power electronics technology has led to large-scale integration of renewable energy sources. But these sources are sensitive to many factors that can cause failure of their parts, leading to failure of the device itself. To overcome this problem, interest in multilevel inverters is increasing due to their imperative benefits, such as reduced harmonic distortion, lower power loss, and reduced voltage stress on semiconductor switches, making them better alternatives for lower-, medium-, and higher-rated applications[19]. To alleviate the high dv/dt stress and harmonic problems of two-level inverters, Multilevel Inverters (MLIs) are developed to synthesize staircase voltage waveforms with multiple DC levels. This structure can greatly reduce the requirement for heavyweight passive filters. (K) Level CHB Inverter with DC Sources. The output voltage levels ($\boldsymbol{N_{level}}$) are determined by eq. (3)

$$N_{level} = 2k + 1 \tag{4}$$

Current research is now focused on Reduced Switch Count topologies to reduce both cost and complexity. Hosseinkhani et al. presented a five-level inverter with an optimized structure, specifically suitable for transformer-less PV systems, that only reduced leakage current and improved efficiency [21]. In order to overcome the limitations of voltage boosting in MLIs, Panda et al. proposed a self-balanced switched-capacitor boost-based MLI with the added advantage of not employing complicated auxiliary balancing circuitry [22]. Also, asymmetric topologies enable
more voltage levels with fewer devices. Radhakrishnan et al. reported the so-called Asymmetric H-6 structure, which maximizes the number of levels with the minimum number of switches [23].
Additionally, Lei et al. integrated Quasi-Z-Source networks with the MLIs to achieve single-stage buck-boost gain operation with enhanced reliability [24]. Both models generate three-phase step-down sine-wave output; however, one is focused on safety and harmonic reduction, while the other is designed to be compact with higher voltage capacity.

2.1.4. Modular Multilevel Converter (MMC): The Modular Multilevel Converter (MMC) has emerged as the leading candidate for grid connections at high voltage and power levels due to its modular structure and scalable capacity. The device is composed of cascaded sub-modules (SMs). Resutík et al. verified a 100-kVA multiphase multilevel traction inverter with high fault tolerance and excellent thermal distribution. The arm current of the MMC leg and its corresponding arm voltage can be expressed as eq. (5) and eq. (6) respectively.

$$\mathrm{i_{arm}(t)} = \frac{\mathrm{i_{dc}}}{2} \pm \mathrm{i_{dc}(t)} \tag{5}$$

$$\mathrm{v_{arm}(t)} \sum_{\mathrm{j=1}}^{\mathrm{N}} \mathrm{S_j(t)\, v_{cj}(t)} \tag{6}$$

N is the number of sub modules, i indicates the switching status, and represents the capacitor voltage of each sub module [25]. Passive components of the MMCs are also important for volume reduction; Das et al. introduced a cascaded structure with reduced capacitor size [26]. Furthermore, capacitor voltage balancing must be carefully handled in the control scheme of MMCs; an enhanced control system for MMC-based PV plants that can maintain continuous operation under grid faults was proposed by Xie [27] .Table 1: Comparative overview of DC–AC Converters Topologies: Topological comparison of inverters with advantages and drawbacks.

Table 1: Comparative overview of DC–AC Converters Topologies

Topology	Key Feature	Advantages	Limitations	Ref.
VSI	Stiff DC Voltage	Simple control, mature tech	High dv/dt, limited voltage boost	[17]
CSI	Stiff DC Current	Inherent boost, short-circuit proof	Slow dynamic, bulky inductor	[9]
MLI	Staircase Waveform	Low THD, low switch stress	Component count, balancing	[21]
MMC	Modular Sub-modules	Scalable to HV, fault tolerant	Complex balancing control	[25], [26].

2.2. Modulation Methods and Efficiency Linkage

The performance of the DC–AC converter basically depends on the modulation strategy used. The switching sequence of the power semiconductor devices is determined by the modulation and has a direct impact on the harmonic content, working stress conditions, and the utilized DC-link voltage. The output voltage quality imposed by the modulation strategy.

2.2.1. SPWM:(Sinusoidal Pulse Width Modulation): (SPWM) is still considered as the base method for inverter control dueto its ease of implementation. It consists of the comparison of a sinusoidal reference signal with a high-frequency triangular carrier. But the conventional SPWM may result in unsatisfactory harmonic performance. To mitigate this, Zhang et al. introduce an upgraded SPWM method for selecting the optimal phase of the carrier signal, which shifts considerable harmonics to higher frequencies to facilitate their elimination by filtering, thereby minimizing THD in the output current [28]. It is worth noting that the symmetric sampling method for generating control signals for power electronics converters includes optimization strategies, thereby ensuring enhanced efficiency and lower HL distortion. This method is known for its time accuracy. It can be done using the precise sampling technique with consideration of the symmetry at peak points of the triangular carrier wave. In this approach, sampling occurs only at the apex of the triangular carrier wave,

2.2.2. Space Vector Pulse Width Modulation: (SVPWM) using a single unit of the inverter, selects a switching vector to track the rotation of the reference voltage vector in the complex plane. This technique often results in a 15% increase in DC bus usage over SPWM, and the THD can be reduced, leading to an increase in the power converter efficiency, especially for three-phase systems [25]. Advantages of Three-Level Neutral-Point-Clamped (NPC) inverters include high efficiency and good harmonic performance , Three different voltage levels (0) are obtained at the inverter output. The space vector pulsewidth modulation (SVPWM) method was used to control the rectifier. A method of switching for obtaining a desired waveform and high efficiency. The synthesis of the reference voltage vector $\vec{V}_{ref}$ is as:

$$\vec{V}_{ref} T_s = V_1 T_1 + V_2 T_2 + V_0 T_0 \tag{7}$$

$$T_s = T_1 + T_2 + T_0 \tag{8}$$

Where is the sampling time, and T_1, T_2, T_0 are the dwelling times of non-active and zero vectors, respectively[29]. In addition, reducing the efficiency of hybrid topologies is important. Kim et al. implemented a new generation hybrid SVPWM with dynamic zero-vector distribution. This method improves harmonic performance while minimizing the voltage utilization ratio, achieving a suitable compromise between power quality and switch efficiency. [30].

2.2.3. Selective Harmonic Elimination (SHE-PWM): In high power applications, it is desirable to minimize the switching frequency to reduce losses. Selection Harmonic Elimination (SHE-PWM) is the method of choice. It comprises pre-calculating certain switching angles $(\alpha_1, \alpha_2, \ldots, \alpha_N)$ to eliminate low-order harmonics (e.g., 5th, 7th, 11th) and retain the fundamental. For this, we have to solve an n non-linear transcendental equation. (9)

$$\begin{cases} \sum_{i=1}^{N}(-1)^{i+1}\cos(n\,\alpha_i) = m_{a,} & \text{for } n = 1 \\ \sum_{i=1}^{N}(-1)^{i+1}\cos(n\,\alpha_i) = 0, & \text{for } n = 5,7,11,\dots \end{cases} \quad (9)$$

Who has Ayala applied SHE-PWM to Multilevel Inverters (MLIs) to reduce the THDv and shown it to be an effective way to achieve high-quality waveform synthesis at low switching frequency , [31]. The international and national standards specify that the maximum THDv limit for low-voltage systems is < 8%.

SHE-PWM Technique This technique allows the desired harmonics to be canceled on the voltage output by choosing the appropriate switching angles of the (PWM), as demonstrated, for example, in Figure 2, two levels of a voltage signal.

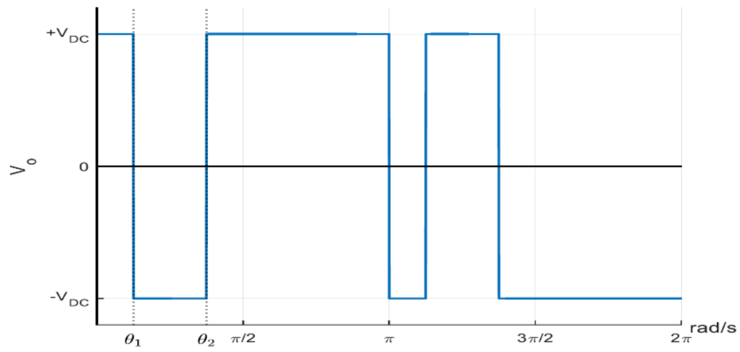

Figure 2: Trigger signal of SHE-PWM [31].

These equations are not easily solved analytically; hence, Lopez et al. used the Taguchi approach to obtain optimal switching angles that converged well even when the modulation indices were unequal, in which case the harmonic content of the output voltage is given by eq. (10)

$$V_n = \frac{4V_{dc}}{n\pi}\sum_{k=1}^{N} cos(n\,\theta_k) \quad (10)$$

Vn is the *nth* harmonic amplitude, and *n* is the number of harmonic components to be removed.

N is the switching angle number defining the stepped waveform in in the first quarter.

Vdc is the DC source voltage, $\frac{4V_{dc}}{n\pi}$ is the global amplitude, and θ_k are the unit-time switching angles corresponding to the number of inverter levels (m). Limited to the first quarter of the signal:

$$0 \le \theta_1 < \theta_2 < \theta_3 < \pi/2$$

SHE-PWM deduces calculated values of 2N relative to specific n, thus SHE-PWM eliminates selective harmonics for better power quality [32]. **Error! Reference source not found.**: depicts the output voltage waveform for a seven-level CHBMLI topology. In this latter context, the angles to be computed are *θ1, θ2,* and *θ3.*

2.3 Quality of power and efficiency concerns

Power quality and conversion efficiency are the most significant challenges in today's inverter systems. Deficits in waveform synthesis and nonlinear loads can cause Total Harmonic Distortion (THD), reactive power imbalance, and voltage imbalance, which, in turn, affect the reliability and service life of loaded equipment. The THD is a good measure of inverter waveform quality and is defined by the following equation: (11). The quality of the signal has been evaluated by THD [31], which consists of the total harmonic distortion.

$$THD\% = 100\sqrt{\left(\frac{V_{rms}}{V1_{rms}}\right) - 1} \quad (11)$$

The RMS of the signal and the RMS of its fundamental component follow from (12) and (13), respectively.

$$V_{rms} = \sqrt{n^2 - \frac{\pi}{2}\left(\sum_{i=1}^{n}(2i-1)\theta i\right)} \quad (12)$$

$$V1_{rms} = \frac{4}{\pi\sqrt{2}}(\cos(\theta_1) + \cdots . + \cos(\theta_n)) \quad (13)$$

The objective to minimize (11) is the optimization goal derived in subsequent sections [32].Table 2. Shaw the abstract of the modulation topologies that are applied in the power converter.

Table 2: Modulation and topology summary comparison.

Technique	Advantage	Application	Ref.
SPWM	Low Complexity	General VSI	[28]

SVPWM	+15% DC Utilization	AC Drives	[29], [30]
SHE-PWM	Zero Low-Order Harmonics	High Power MLI	[31], [32]

2.3.1. Optimization and Harmonic Reduction Techniques

The integration of the stage's load with the power grid (e.g., IEEE 519) has been strict, and many conventional analytical methods never achieve minimal eq. (11) effectively. The DRFNNISMC algorithm can enhance the quality of grid-connected current by reducing THD and low-order harmonics, which are difficult to eliminate. First, a dynamic model that accounts for the uncertainty of the grid-connected inverter system is presented to design the GISMC. As illustrated in. [12]. As a result, various meta-heuristic optimization algorithms have been applied to search for the global optima of switching angles. Lopez et al. demonstrated the performance of the MFO (Moth–Flame Optimization) algorithm, based on a new metaphoric search inspired by moth navigation, to minimize THD in multilevel inverters more effectively than conventional techniques [33]. Regarding nonlinear load situations, Sánchez-Vargas et al. suggested a hybrid ANFIS-PSO model. The modulation parameters of this Neuro-fuzzy system are updated online to keep the THD minimized against load changes [34]. In grid's power system, e.g., parallel-connected inverters, has a serious problem with circulating current. Alghamdi et al. studied the reduction of voltage harmonics in parallel inverters interfaced to a common Point of Common Coupling (PCC), highlighting the need for synchronized control to suppress zero-sequence circulating currents [35]. Additionally, Tennyson et al. employed the Sparrow Search Algorithm (SSA), a bio-inspired algorithm inspired by the foraging behavior of sparrows to reduce the harmonics in cascaded H-bridge Inverter's, and Genetic Algorithms (GAs) have been used for SHE and parameter tuning of multi-level inverter topologies, and these algorithms search iteratively for the best switching angles that annul prominent low-order harmonics while preserving the desired fundamental amplitude, as described by .by eq.(14) [36].

$$\frac{V_n}{V_{dc}} = \frac{4}{n\pi}\sum_{i=1}^{N} cos(n\,\theta_i) \tag{14}$$

Here, V_n is the amplitude of the nth harmonic V_{dc}, is the DC input voltage and θ_i Best switching angle [35]. A high THDv value may lead to a series of problems that affect power quality and device operation. Table 3. Show a comparison of inverter topologies for PWM.

Table 3: Summary of DC–AC Converter Topologies and Their Comparisons.

Topology / Technique	Key Advantage	Primary Challenge	Target Application	Ref.
True Sine VSI	Simple Control	High Switching Loss	Low Power PV	[17]
5-Level MLI	Low THD, Low EMI	Capacitor Balancing	Transformer less PV	[19]
MMC	Modular, Scalable	Complex Control	High Voltage Grid	[23]
SHE-PWM	Low fsw, Zero Low-Order Harmonics	Solving Eq. (3)	High Power Drives	[29]
AI-Based SVPWM	Fast Computation	Training Data Required	Real-Time Control	[27]

Figure 3: shows a comparison of Control Techniques by THD Performance (Worst to Best). The extracted minimum THD (Total Harmonic Distortion) values for each control technique are presented in the graph. The lower the THD value, the better the performance for SVM, PWM, PS-PWM, and ANN. The imitation of FCS-MPC shows an extracted level of 20.12% at the top (i.e., worst performance). The method Dynamic Weighting 1D-CNN-based MPC (Deep Learning) has the smallest THD of 0.50%, which is the optimal among all these options.

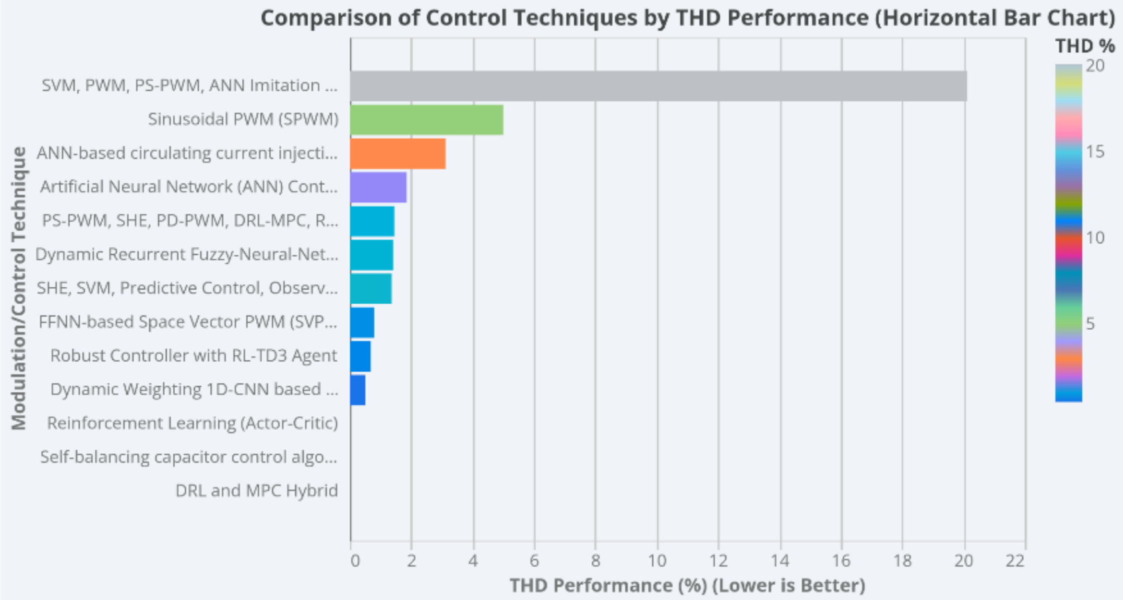

Figure 3: THD Comparison for different Control Techniques

2.3.2.PWM and LEARN-Enhanced Efficiency advancements

In addition to the suppression of harmonics, recent work now emphasizes energy efficiency, thereby aiming to reduce conduction and switching losses. Deep Learning (DL) has shown great efficacy in this field. Al-Zubaidi et al. discussed sustainable DNN techniques for power converter efficiency, where their data-driven model can be used to predict and reduce loss components in a real-time operation fashion [15]. Similarly, Patel et al. introduced advanced DL-based power-processing units for energy optimization. They demonstrated that NNs can be deployed to learn optimal switching trajectories, sacrificing a slightly higher THD to achieve significant thermal efficiency improvements and prolonged device life time's [16].

From a harmonic perspective, minimizing switching losses is important. El Gadari et al. proposed a sensor-less balancing method to reduce the number of voltage sensors and improve reliability and efficiency [37]. Valderrabano et al. employed a NN surrogate model for real-time harmonic optimization to avoid the computational lag of conventional solvers [38].

3. Control Strategies for DC–AC Inverters

The control structure of DC–AC inverters has changed dramatically, from traditional linear controllers to intelligent and hybrid schemes. This evolution is motivated by the need to achieve greater stability and robustness in modern power systems, which are highly nonlinear and subject to stochastic penetration of renewable generation.

3.1. Traditional Control Methods

Classical control techniques, such as Proportional-Integral (PI), Proportional-Integral-Derivative (PID), Proportional-Resonance (PR), and Model Predictive Control (MPC), have been the standard approach for inverter regulation. use MPC to control these quantities to reduce the complexity of controller implementation and thus improve their performance. Advances in model predictive control (MPC) for grid-connected power inverters of renewable resources. It specifically addresses the interconnected PV systems based on MPC.

Traditional control techniques mainly target the grid-following (GFL) and grid-forming (GFM) modes. GFL inverters are, in general, current-source oriented with a Phase-Locked Loop (PLL) for grid synchronization [39]. Another work presented a full numerical state-space description for GFL resources, focusing on the influence of PLL dynamics over system stability. The small-signal state-space model for a grid-connected inverter is given by:

$$\dot{x} = \mathbf{A}\mathbf{x} + \boldsymbol{Bu} + \boldsymbol{Evg} \tag{15}$$

Where

$\dot{x}$ is the vector of the state (currents and voltages),u is the input, and denotes the grid voltage disturbance.

Another work also used the small-signal model to investigate the relationships between these modes and grid impedance [40]. Due to the relatively low mechanical inertia of the modernized grid, the GFM inverter has been proposed and operated as a dynamic frequency regulator, without relying on voltage regulation in saturation mode, and a dual-mode control structure has been proposed that smoothly switches between DM and D modes [41]. At its engine, GFM control systems may work by simulating the swing equation of the synchronous machine to produce artificial inertia:

$$Jw_m \frac{dw_m}{dt} = P_m - P_e - D(w_m - w_0) \tag{16}$$

Here, J is the inertia, D is the damping factor, and they are the mechanical and electrical powers. Garzon et al. analyzed RoCoF in GFM-dominated networks and confirmed that RoCoF can outperform DFIGs in weak grids [42]. Yet, under fault conditions, the performance of GFM converters is reduced, especially in frequency regulation in their comparison framework, under a distorted grid. However, when a fault occurs, GFM converters suffer from Tina et al.'s comparison of frequency regulation performance under distorted conditions [43]. Liu et al. and Zhang et al. proposed dynamic overcurrent limitation and current-limited operation schemes for protecting power devices during transient protection events [44]**,** [45]. Additionally, Ward et al. confirmed these procedures for microgrid islanding based on stability measures during the transition from grid-connected to isolated operation mode [46] **.**

3.2. Intelligent and Hybrid Control Techniques

The conventional PI and PR controllers are limited to consider uncertainties of the parameters as well as non-linearities, thus motivating the adoption of Artificial Neural Networks (ANN) with hybrid schemes, which showed good performance for current compensation in a four-leg inverter under an unbalanced load is also successfully handled by nneUTal neutral-current forces, elaborating the proposed approach for compensating grid current under an unbalanced load situation. At first, an ANN was designed to obtain the reference current to eliminate unbalanced power. Synchronous coordinate values of the AC were used as inputs to train the ANN. Furthermore, three incremental ANNs were constructed to regulate the phase current. The inverter was controlled using a classical pulse-width modulation (PWM) carrier-based method, with the ANN output used for training. **Error! Reference source not found.**: Schematic representations of the simulation and experimental setups. [47].

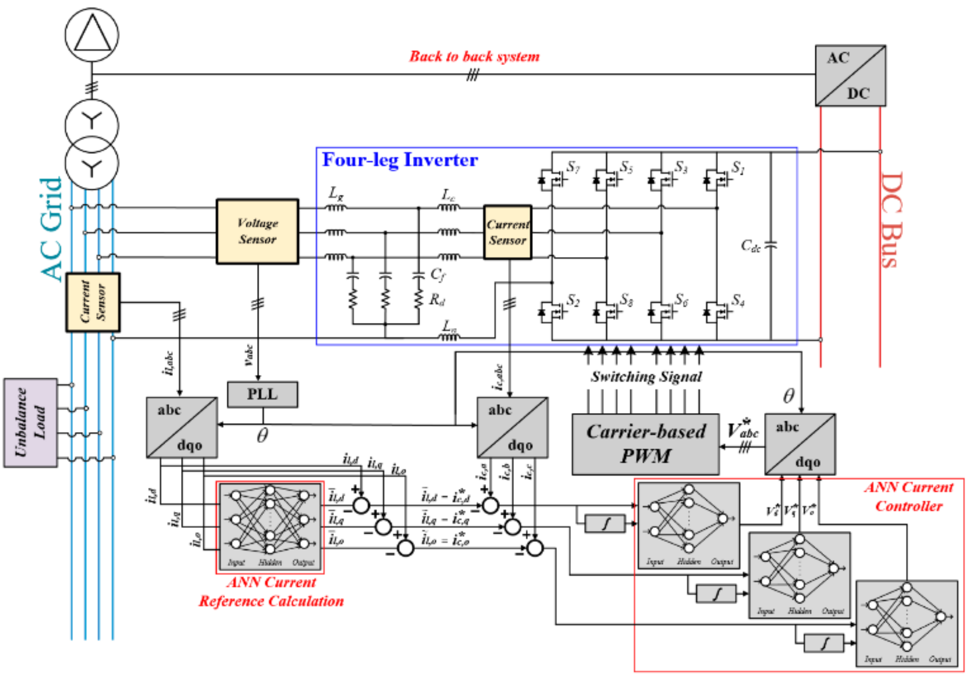

Figure 4: The setting of the simulation and measurement setups.

Belgana et al. presented an NN-based droop control for parallel DG inverters to optimize power sharing. Thus, there is a need for communication, but with the delay of the centralized controller [48]. For a particular application, the authors of applied ANNs to bidirectional inverters in Vehicle-to-Grid (V2G) systems, replacing conventional PI loops for improved settling times under load steps [49]. It can also be noted that the intelligence gives added value for the modeling: For example, there is a paper of Li et al where an aggregated neural model was used to follow up the external behavior of PV cells; this simplified thereafter the design process for the subsequent DC/AC conversion stage [50]. To address disturbances caused by hardware removal, Alharbi developed a smart control scheme for PV inverters under double-frequency DC-link oscillations, thereby extending the life of DC capacitors [51]. Hybridization also includes that in (a robust disturbance rejection for weak power systems), such that this design has better performance in terms of underdeveloped a GFM-based controller with improved disturbance rejection capability, stability improvement, and dynamic LFC (left-rank forced commutated) transformers. Mensah Akwasi integrating MPC with RL proposed a learning-based adaptive hybrid control structure (HALC). Punctual prediction of parameters determined by inverter dynamics, such as switching effects, filter dynamics, load changes, and grid perturbations, is combined with a modelling approach that incorporates power balance constraints. MPC is based on, for each sample index, calculating and solving a constrained optimization problem to find the best control action. Optimization Goal: The goal of the objective function is to reduce voltage deviation and minimize power losses in a prediction horizon.

$$J = \sum_{k=1}^{N}\left(V_{ref} - V_k\right)^2 + \lambda P_{loss} \tag{17}$$

Where J: total cost function minimized by MPC, V_{ref} Reference voltage, V_kPredicted output voltage at the k step,: P_{loss}Total power losses (switching + conduction), λ: Weighting factor balancing voltage regulation vs. efficiency, N: Prediction horizon.

$$Vmin \leq Vk \leq Vmax, fmin \leq fk \leq fmax \tag{18}$$

Power balance:

$$Pinverter + Pload = Pgrid \tag{19}$$

Control action limits:

$$umin \leq uk \leq umax \tag{20}$$

Where

uk is the control signal to the inverter at time step.

The proposed HALC framework unifies self-learning with real-time predictive optimization to achieve better grid performance. The model-predictive controller (MPC)-based reinforcement learning scheme enhances the system's robustness in terms of grid-connected resilience, reactive power dispatch, and voltage stability. Performance Comparison: HALC has several advantages over conventional PID and the droop-based control methods:

•Faster voltage stabilization to reduce response time to 20ms.

•Upper accuracy in short-term voltage control, where MPC reached 97% regulation accuracy using the prediction of disturbances.

•Enhanced fault tolerance and adaptivity, because the reinforcement-learning part iteratively updates control solutions at different grid environments. Such robustness is especially important in the context of massive integration of renewable energy resources (such as PV arrays or wind farms), which naturally exhibit intermittency and dynamic disturbances.

Component Reinforcement-Learning agent is a neural network-based actor–critic using the Deep Deterministic Policy Gradient (DDPG) algorithm• Actor Network: Three hidden layers with 128, 64, and 32 neurons respectively with Rectified Linear Unit (ReLU) activations. The output layer uses a tanh activation function, constrained by the maximum and minimum values of the MPC gain, to operate in a continuous space for tuning control gains. • Critic net: a second 128-64 hidden-layer structure for approximating the action-value function [52].

Finally, we stressed the need to validate these smart models using experimental frequency restoration data to ensure their reliability in real grid conditions [53]. In, Table **4** a comparison of traditional vs intelligent controllers is given. Traditional controllers (PI, PR, droop) are simple and easy to implement, making them hardware-friendly, but suffer from parameter sensitivity and an inability to handle nonlinearities. However, intelligent algorithms (Artificial Neural Network (ANN), fuzzy-neural, and AI-droop) enhance flexibility and robustness but require significant computation and a training set.

Table 4: Traditional vs Intelligent Control Strategy for DC–AC Inverters.

Control Category	Representative Methods	Key Advantages	Main Limitations	Ref.
Traditional (GFL/GFM)	PI, PR, Droop, Virtual Synchronous Machine	Well-established, can be implemented in hardware easily	Susceptible to parameter modifications, undesirable non-linearity handling	[41] [42]
Intelligent (NN/Hybrid)	ANN Compensators, Fuzzy-Neural, AI-Droop	Model-free, nonlinear, insensitive to grid changes	Computationaly expensive, need to be trained	[49] [52]

4-Deep Learning-Based Intelligent Control

Deep learning has recently been proposed as a breakthrough paradigm for power electronics, providing model-free solutions to challenging control and estimator design problems. In contrast to conventional control, DL architectures such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTMs), and Deep Reinforcement Learning (DRL) can capture high-level features directly from raw sensor data, enabling adaptive and robust operation of an inverter.

4.1. CNN and 4.2. LSTM (Classification and Prediction)

Spatial feature extraction and control mode classification are the main tasks for CNNs. Kim et al. presented a CNN-based model for selecting an appropriate modulation mode for grid-connected inverters under different network conditions, with smooth dynamic transitions and stability. The equation for the convolutional layer is as follows.

$$\boldsymbol{y} = \boldsymbol{f}\left(\sum_{j=1}^{m} \sum_{i=1}^{n} (\boldsymbol{x_{ij}} * \boldsymbol{w_{ij}}) + \boldsymbol{b}\right) \tag{21}$$

Where (x) are the input, (w) and(b) are the filter weights and bias that adapt as the network trains over data, and (∗) denotes a convolution operation. To extract complex patterns, the output of a convolutional network is passed through an activation function, which also helps in their recognition. Most of the pooling layers (that support the convolutional network) down-sample the feature map. Max pooling: by partitioning a map into regions and representing each region with its maximum value, it retains salient features and reduces the number of nodes in the blueprint. Learning with the maximum number of clustering layers is not trainable because these layers don’t have weights to be trained via back propagation. Some extra layers are included in some cases (such as normalization and reshaping layers) to enhance the network's performance and to reshape data into multiple sizes [54]. The proposed CNN model for classifying the two control models, GFM and GFL, is shown in **Error! Reference source not found.** illustrates the structure of the proposed CNN, designed to classify the two control modes GFM. This model is implemented using Python and Tensor Flow libraries. The proposed architecture is two-part, i.e., the convolutional part and the dense layers part. The CNN architecture has two inputs, so the AM sample is split into two outputs: magnitudes and phases of *Ydd* on input 1, and magnitudes and phases of *Yqq* on input 2.

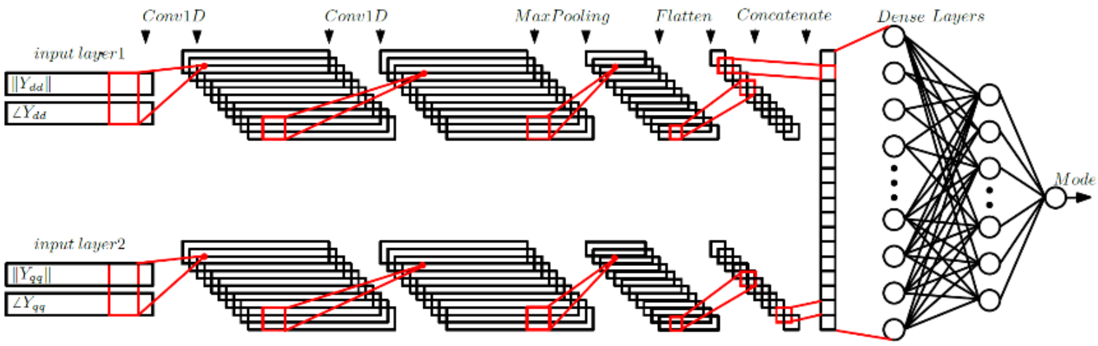

Figure 5: The architecture of the proposed CNN [54].

LSTM networks are the most popular choice. Xue et al. applied LSTM for predicting voltage compensation in DVR: With the network determining the next grid voltage state where compensation is to be applied before a sag fully occurring, this approach becomes especially interesting when it comes to tasks like power grid voltage trend prediction (sudden voltage changes as well as long-term patterns are important here). Through iterations and by minimizing mistakes during training, LSTM models can make time-variant data very predictable. [55]. Furthermore, Lim et al. used an LSTM to analyze the lifetime of efficiency degradation in PV inverters using historical power-loss data [56]. To improve grid stability, Renhai et al. proposed a Deep RNN-based droop control to stabilize frequency in low-inertia systems [57].

4.3. Hybrid CNN–DRL Architectures

Hybrid structures integrate the feature-extraction capabilities of CNNs and the decision-making capabilities of DRL. Shanmugam, Introduced the smart control of multiport converters in a renewable system according to hybrid distribution; it is possible to provide multi-port support simultaneously with synchronous optimization of power flow by Dual-Port Power Converter. The diagram shown in Figure 20 interconnects both the PV system and the pumped-storage battery system with the grid, integrating with a powerful control strategy. In the optimization, energy management approach to maximize the electric power output of the PV system is used **.**Combinations of Convolutional Neural Networks (CNNs) and Deep Reinforcement Learning (DRL), known as hybrid architectures, provide promising results. CNNs are used for feature identification and extraction from high-dimensional inputs, and DRL enables the agent to make adaptive, real-time, intelligent decisions. In **Error! Reference source not found.**, an implementation of a Dual-Port Power Converter is presented as an example. This inverter interconnects the PV system, a battery storage, and the grid via a well-designed control structure. The control algorithm is falling into place, which could improve the utilization of power generated by the PV system and, hence, the effective integration of renewable energy [58]. Similarly, Rahman et al. presented a model-based, control-synergy approach for analyzing an integrated power system with GFMs. They discussed the underlying stability and power quality of such a system by using voltage-source active filters to suppress harmonic distortion [59].

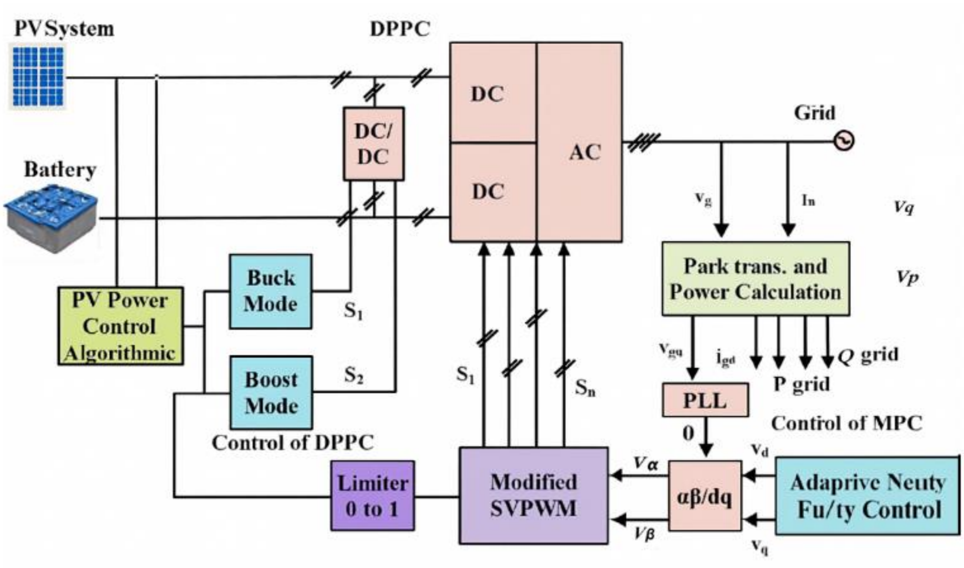

Figure 6: A system-based control strategy of a hybrid intelligent DC–AC converter control.

4.4. Deep Reinforcement Learning (DRL)

DRL is the most powerful DL tool for inverter control, as it can learn an optimal policy through interactions with the electrical environment. Li et al. designed a grid configuration inverter control strategy with compensation for the loss of moment of inertia and damping based on a new deep reinforcement learning algorithm, the SD3 (Softmax Deep Double Deterministic policy gradients) algorithm. In this paper, the stability of grid operation was improved under complex operating conditions by damping fluctuations in VSG (Virtual Synchronous Generator) frequency and power output using the SD3 algorithm in combination with VSG grid control. The reward the agent receives for some action depends on how efficiently he ends up in a desirable state. Voltage and current dynamics within the environment are feedback to a learning agent through a closed loop. The agent, consisting of a neural network and a learned policy, receives observations from the environment and chooses actions that best suit them. These actions are performed on the environment and affect the system's response. In exchange, the environment will provide a reward signal indicating how good the agent's decision was, guiding its learning. Such a feedback loop allows the agent to learn control policies online, to react robustly to changing conditions, and, by optimizing standard test reward measures, to achieve improved performance without requiring system models. DRL usually formulates the control problem as a Markov Decision Process (MDP) presented by the tuple

Where: S → Set of possible states (e.g., voltage, current, system maintenance) A → Set of possible actions (e.g., control inputs applied by the agent) P → State transition probability function R, reward function → Discount factor (0 ≤ γ ≤ 1) mapping immediate versus future rewards. The agent aims for a policy π(a|s) that maximizes the expected discounted return:

$$J(\pi) = E[\sum_{t=0}^{\infty} \gamma^t R(s_t, a_t)] \tag{23}$$

Eq. (23) defines the RL objective. Here, E[.] indicates expectation over trajectories $\tau = (s_0, a_0, r_0, ..)$ generated by the closed-loop system under the policy π and plant dynamics with measurement noise and disturbance. The policy π is a parameterized feedback controller mapping the observed state s_t to a probability distribution over control actions a_t, which are either continuous setpoints or discrete switchable commands.

Translating DRL Concepts to Power Converter Control Irrespective of the application area, the use of DRL in power electronics requires an efficient mapping between reinforcement learning components and converter control attributes. This requires the control problem to be cast as a sequential decision-making process in which the agent learns through interaction and feedback.

•The system vector (system observations): The system vector corresponds to the converter's operating status. Here, typical state variables for feedback control (Output Voltage, output current, Input voltage, Converter temperature, Duty cycle, etc.) and Grid voltage/current with respect to inverters.

•Action Space (control variables): control variables are varied by the agent to adjust the operation of the converter. ((PWM) duty cycle (DC-DC converters), Phase shift (DAB converters), Modulation index (inverters), Reference signals (in hierarchical control))

• Reward Function (performance objective) The reward function is designed to drive the agent towards efficient and stable operation: Potential reward functions are: (Negative absolute or squared tracking errors, Penalties for overshoot, settling time, or oscillations, Loss-related metrics in (e.g., switching/conduction losses), Soft-switching performance characteristic such as ZVS/ZCS jumping, Constraint violations like overcurrent/overvoltage.

•Environment and Simulation: The environment is the dynamic system of the converter with which an agent interacts. Typical modeling tools are :(the real-time digital simulator (RTDS), Opal-RT, or Typhoon HIL for Hardware-in-the-loop testing, FPGA or DSP test benches to avoid using a HIL platform, etc.), dynamic model from the Open AI Gym platform.

• Temporal Structure: Training is organized in episodes, i.e., limited time lengths which mimic converter operations to various settings (e.g., start-up and load transients). The length of these time steps has to be determined based on the dynamics of the converter and in consideration of short-term control accuracy and the longer-term performance of the reward horizon.

•Integration: DRL is able to be integrated with existing control hierarchies through: • Direct control: replacing the traditional controller with a DRL agent, and • Supervisory control: applying DRL to derive references for lower-level controllers, and • Hybrid control: application of DRL in specific fashions (e.g., fault recovery or MPPT) along with classical control during normal operation [60]. Beyer developed an adaptive online-learning Volt-Var control method based on the Deep Deterministic Policy Gradient (DDPG) algorithm that enables smart inverters to operate in real time without relying on a grid model [61]**.** In dynamic environments, a DRL-based optimal PV smart inverter control for rapid solar changes [62]. For weak grids, Yang et al. proposed a hybrid adaptive GFM strategy combining real-time voltage regulation and short-term MPC optimization with long-term self-improvement via DRL for instantaneous response to grid disturbances. The MPC model, which predicts and adjusts short-term control actions to counter voltage fluctuations, is integrated with the RL, enabling continuous optimization of the response and learning from the grid's past behavior (improved system resiliency) [63]. Another main advantage is resilience. Beikbabaei et al. proposed the first model-free resilient controller against cyber-attacks based on RL [64], and Alfred et al. provided a general framework for RL-based converter control [65]**.** In case of faults, Askarov et al. applied DRL for overcurrent protection in VSG-based inverters [66]. Seo and Kwon et al. developed a label-free fault-detection methodology by training the RL agent to learn dynamic thresholds for recognizing inverter faults. Proposed in this work is a novel method for identifying uncategorized faults in DR based on the RL method, which dynamically adjusts the threshold within reasonable confidence intervals, accounting for varied environmental conditions during PV power generation [67]. When intelligent control is incorporated into the power conversion stage. The process between the physical power stage (PV array, DC-link, and Inverter Bridge) and the knowledge agent is depicted in **Error! Reference source not found.**. In contrast to conventional control loops that use constant gains, "the AI agent learns continuously about the system state (St) at time t - e.g., grid voltage and current - and takes optimal actions (At) to maximize long-term reward (Rt) by robustly synchronizing with a utility glider.

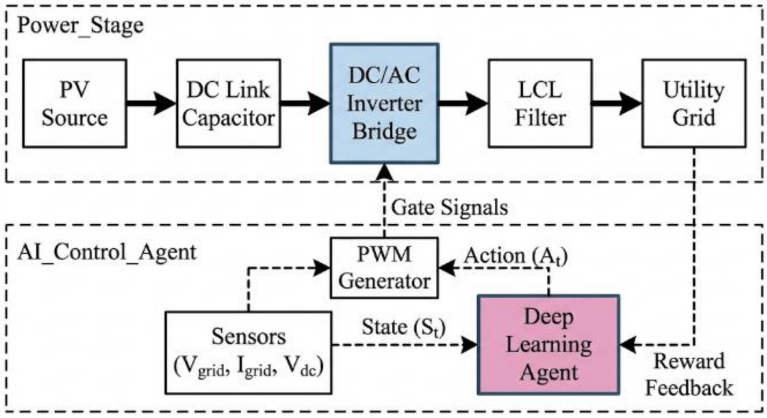

Figure 7: Block Diagram of a DC–AC converter (Inverter Bridge) driven from a deep learning agent.

4.5. Physics-Informed Neural Networks (PINN)

PINNs are a new frontier where physical laws (such as KVL and KCL) are integrated into the neural network's loss function. Our work has demonstrated PINN-based modelling for quasi-VSC back-to-back systems, ensuring that the predicted states satisfy the underlying circuit differential equations. **Error! Reference source not found.**: shows the final model PINN architectures for each VSC control to train the grid stability estimation model.

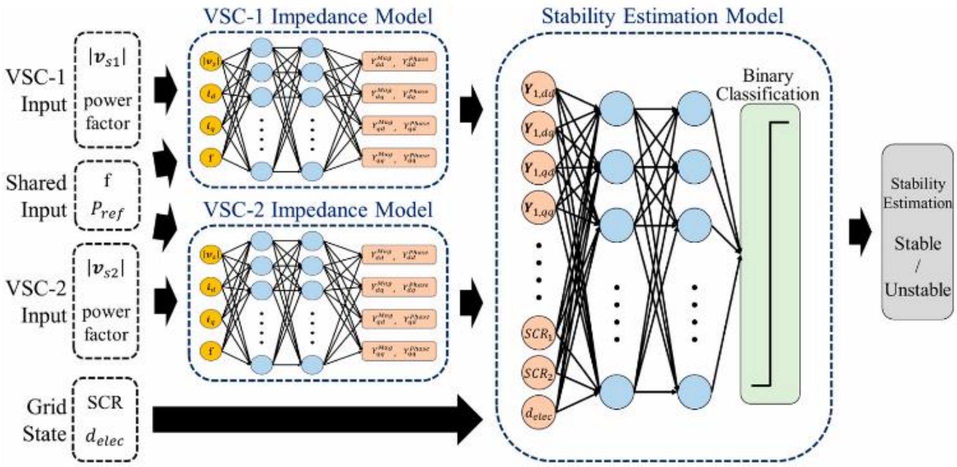

Figure 8: Conceptual Structure of (PINN) in DC–AC Converter Control [68].

The Advantages of PINN

PINNs exhibit strong generalization even with very few training data, due to the strong physical constraints imposed on the problem.

The learning process is physically interpretable, and control engineers can trace model behavior to system dynamics.

PINNs are well-suited for hybrid digital twin architectures that can run on embedded devices such as STM32 microcontrollers to create efficient, real-time controllers.

Table 5: shows summary CNN excels in fault detection, LSTM predicts voltage, DRL adapts grid support, and PINN ensures physical consistency—Advancing reliable, adaptive physics-informed power systems.

Table 5: Comparison Summary of Deep Learning Architectures in DC–AC Inverter Control.

Architecture	Core Function	Key Strength	Ref.
CNN	Classification / Fault Detection	Excellent spatial feature extraction	[54]
LSTM	Predictive Voltage Control	Handles long-term temporal dependencies	[55]
DRL	Adaptive Volt-Var / Grid Support	Model-free adaptive decision making	[58], [61]
PINN	Hybrid Data-Physical Modeling	Guaranteed physical consistency	[68]

5- Comparative Evaluation and Discussion

This part evaluates the efficiency and robustness of the discussed control and topology schemes. To that end, the harmonicas suppression, dynamic response, and system-level stability must all be carefully considered when advanced power electronics and smart control need to be integrated.

5.1. Performance Comparison and Power Quality

Power quality remains the primary indicator of an inverter's performance. Lowczowski et al. studied the influence of (Volt/VAR) control on harmonics within Distribution Networks, where a VVC can be used to control harmonic content if its parameter tuning is appropriate [69]. Furthermore, Safarishaal et al. showed that the nonlinear effect of topological configuration in inverter-based resources cannot be neglected, as it has a significant influence on harmonic flow in distribution networks, indicating that hardware is as important as control software selection [70]. Pragathi et al. The authors also compared the performance of customized hardware for power-quality control, such as the Hybrid MLI. They demonstrated that reducing the number of switches does not necessarily decrease power quality; however, it enables the use of optimized switching techniques [71]. One of the representative metrics for such comparison is the Efficiency Improvement Factor (EIF) [72], which could be expressed as:

$$\boldsymbol{EIF} = \frac{\boldsymbol{P_{out}}}{\boldsymbol{P_{out}+P_{sw}+P_{cond}+P_{filter}}} \times \mathbf{100}\% \tag{23}$$

Where

(P_{sw}),(P_{cond}), and (P_{filter}) are the switching, conduction, and filter losses.

A comparison of conventional control and AI-based control, where the THD, efficiency, response time, stability, as well as adaptability are progressively improved with advanced methods, such as DRL and PINN , providing better adaptive nature; b consistent response; and c self-learning capability over power systems shows in Table 6.

Table 6: Comparison of performance indices of DC-AC converter control methods

Control Method	THD (%)	Efficiency (%)	Response Time (ms)	Dynamic Stability	Adaptability	Key Ref.
PI / PID	4.8–6.5	91–93	40–60	Moderate	Low	[2]
(FLC) / ANN	2.5–3.5	95–97	20–35	High	Medium–High	[47]
ANFIS	1.8–2.5	96–98	15–25	Very High	High	[58]
CNN	1.5–2.0	97–98	12–18	Very High	High	[54]
LSTM	1.3–1.8	97–99	10–15	Excellent	High	[55]
DRL	1.2–1.5	98–99	8–12	Excellent	Adaptive	[60],[67],[68]
PINN	1.0–1.4	98–99	10–14	Physically Consistent	Self-Learning	[68]

5.2. Stability and Validation

Dynamic stability is critical to GFM applications. Zubiaga et al. verified the effectiveness of GFM inverters against low-frequency oscillations by experimental tests, demonstrating that intelligent GFM controllers yield improved damping compared to traditional synchronous generator emulators [72]. Similarly, [24] examined system-wide stability for solar-PV systems and noted that damping Sub Synchronous Resonance (SSR) and oscillations in turbo-generator plants require high-bandwidth AI-based converters to maintain the steady-state operating frequency during transient faults [73].Table 7: Display of evaluated parameters for power systems: ↑ Improved voltage profile, damping of oscillations, inverter cost reduction, SSR mitigation ↓ , THD increase, impedance sensitivity, balancing complexity, as well as high-speed data required.

Table 7: Comparative Evaluations between Control and Hardware Architectures.

Evaluated Parameter	Core Finding	Key Limitation Identified	Ref.
Volt/VAR Harmonics	Improved voltage profile	Increased high-frequency THD	[69]
GFM Resilience	Effective oscillation damping	High sensitivity to line impedance	[69]
Hybrid MLI	Reduced switch count/cost	Complex balancing requirements	[72]
System Stability	SSR mitigation in PV grids	Requires high-speed data acquisition	[71]

5.3 Enhancing Efficiency and Minimizing Energy Loss

Loss reduction in advanced DC–AC converters increasingly relies on loss estimation for prediction-based control strategies and adaptive modulation methods. DL-based systems employ instantaneous feature extraction and reinforcement learning reward functions to suppress both conduction and switching losses during converter operation. In experimental studies, DRL-based inverters have shown an efficiency boost of 1.5-2% higher than ANN-based controllers [77]. losses (*P* conduction and *Psw* con, the total parasitic losses can be expressed as: [74]

$$P_{loss} = P_{cond} + P_{sw} \tag{24}$$

Total loss P_{loss} equal the sum of P_{cond} and P_{sw} (conduction losses plus switching losses) is called the total loss. For DRL-based control, the reward function is designed to penalize power loss and voltage deviation to stimulate the best switching:

$$P_{loss} = P_{cond} + P_{sw} \tag{25}$$

In DRL-based control, the reward function corrects energy losses and voltage deviation to promote optimal switching:

$$\mathrm{r_t} = -(\alpha \mathrm{P_{loss}} + \beta|\mathrm{V_{ref}} + \mathrm{V_{out}}|) \tag{26}$$

Where α and β are weighting factors that balance minimizing energy loss with preserving voltage accuracy[58]. Moreover, PINN models maintain the physical consistency through accounting for the power balance: The input power is equal to the output power plus losses [74] [75].

$$P_{in} = P_{out} + P_{loss} \tag{27}$$

Finally, MPC, when combined with deep learning in Hybrid MPC–DRL frameworks, is promising for realizing near-optimal switching trajectories. This provides a unified control solution for steady-state regulation and dynamic response optimization, filling the gap between classical control theory and real-time AI-based adaptation.

6-Future Research Directions :

The development of intelligent control based on deep learning (DL) has provided a solid foundation for improving power converter performance. Yet, there are a few research gaps and opportunities to enhance adaptability, interpretability, and energy optimization in DC–AC inverter systems. The intelligent control based on deep learning has revolutionized inverter optimization, but there is still room to enhance adaptability, interpretability, and real-time performance.

6.1. Hybrid MPC and Multi-Agent Systems

For real-time applications, Villalón et al. highlighted the importance of choosing optimal switching frequencies for MPC to accommodate the computational burden [19]. There is much research being done in the fusion of MPC with Deep Learning (DL) (MPC–DL). Amoura et al. and Shen et al. designed robust sensor-less OT-neural-network-based MPC schemes to eliminate the need for sensors while ensuring prediction accuracy [76]**,** [77] Scalability in the context of large networks is being investigated using Multi-Agent Deep Reinforcement Learning (MADRL). Ikram et al. and Jung proposed grid-synchronous systems in which several inverters can work together to control the grid voltage and reactive power [74]**,** [78]**.** The N—MADRL method proposed herein aims to ensure frequency stability by optimal scheduling of active power, thereby minimizing frequency deviations, improving effective reserve scheduling, and ensuring good power sharing. Remarked that in comparison to the PPO and DDPG, proposed N—MADRL scheme has shown a significant 42.10% and 61.40% increased efficiency when it comes to collective dispatch; as well as a high efficiency of 68.30%,74.48% improvement in frequency neglecting respectively . Finally numerical effectiveness of the N—MADRL scheme is demonstrated by considering communication breakdown with dynamic topologies, in the HPP space

6.2. Digital Twin, Optimization, and the Realities of Hardware

Optimized grid-connected voltage support has increasingly focused on enhancing energy flow strategies via Deep Learning, as highlighted by Lv et al. for smart cities [79]. Also, establish MPC and DRL convergence in energy-efficient eco-driving applications for electric driving, and this could be extended to industrial microgrid energy management [80]. “Digital Twin” is also an interesting buzzword in predictive maintenance. Ahmed et al. analyzed fault self-diagnosis for systems using a Digital Twin, enabling action before hardware failure occurs. As powerful computing technology and various simulation technologies have developed rapidly, artificial intelligence (AI) and digital twins can support control design, reflecting the strength of the algorithm and model quality, thereby improving overall performance. [81]. Ultimately, for the future of inverter control, HIL & real-time constraints should be considered so that complex AI models can run within the might-as-well-be-a-MCU time frame of microseconds when we are dealing with power electronic switches. The roadmap of inverter control research is presented in **Error! Reference source not found.**: According to the trends which are spotted from the roadmap, it transitions from Solo intelligent control towards Edge-Cloud collaborative optimization, Digital Twin-assisted maintenance, and physics-informed cooperative multi-agent networks."

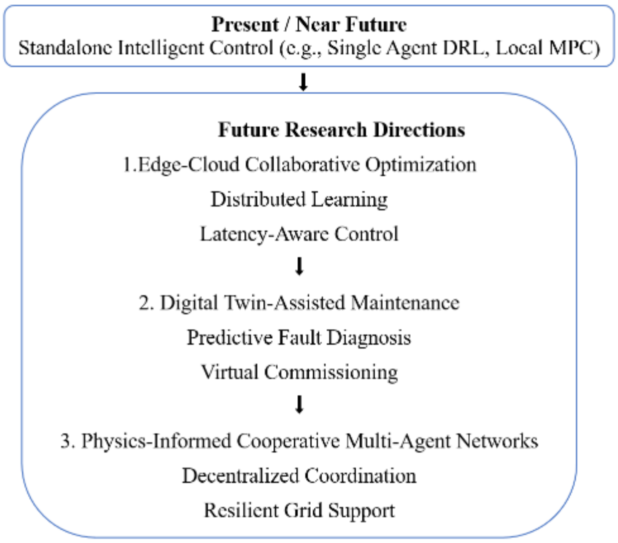

Figure 9: future work in inverter control

7-Conclusion

This comprehensive work has investigated the development, topologies, and control methods of DC–AC power converters. Consequently, a focus on the revolutionary application of Deep Learning (DL) to improve efficiency, power quality, and dynamic stability was presented. Starting with a thorough overview of existing approaches—including Proportional-Integral (PI), Proportional-Integrative-Derivative (PID), and Model Predictive Control (MPC)—the research recognized the basic nature of build-up and reliability. Still, it emphasized the limitations of nonlinear, transient grid-connected systems. The shift towards intelligent control strategies, namely Fuzzy Logic, ANNs, and ANFIS, has led to significant improvements in lower THD and excellent dynamic response. However, the integration of state-of-the-art Deep Learning (DL) architectures, such as convolutional neural networks (CNNs), long short-term memory (LSTM) networks, and deep reinforcement learning with Physics-Informed Neural Networks (PINNs), has revolutionized control by enhancing adaptability, predictability, accuracy, and real-time learning. Using these models, converters themselves optimize switching patterns, predict voltage instabilities, and respond to variations in the grid without explicit identification. Comparing the results, it is clear that with the use of DL, control applications have achieved THD levels below 2%, efficiencies above 98%, and response times below 15 milliseconds – values not achievable with classical or prior conventional AI-based solutions. In particular, DRL approaches lead to a new spirit of control autonomy, with agents that interact continuously with the environment and improve their strategies through learning from rewards. Contrary to these results, PINNs link data-driven learning with power electronics theory by enforcing physics-based constraints and ensuring interpretability and physical consistency. In the near future, the formation of hybrid DL structures, the development of edge intelligence, and the incorporation of digital twins will mark a new era for intelligent power electronics. In the future, CNN–LSTM–DRL hybrid controllers are expected to be implemented on an STM32-based embedded platform for low-latency adaptive learning at the edge. The advent of multi-agent DRL architectures and physics-informed models will be paramount to the development of fully autonomous, interpretable, and energy-aware converter networks. In conclusion, this paper demonstrates that deep learning–assisted intelligent control represents an entirely new design paradigm for DC-AC converters in bringing closed-loop adaptive thinking and self-optimization to the traditional power electronics. Combining deep neural architectures with embedded hardware has enabled fully autonomous, highly efficient energy conversion for next-generation smart grids and electric vehicles.

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