OPTIMIZED CONTROL AND PERFORMANCE ANALYSIS OF GRID-CONNECTED SMART INVERTERS FOR RENEWABLE ENERGY SYSTEMS

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ABSTRACT

This paper presents a comprehensive empirical investigation into the design, implementation, and adaptive control of grid-connected smart inverters intended for seamless integration of renewable energy sources (RES) into modern power distribution networks. With the exponential growth of distributed generation from photovoltaic (PV) systems and wind energy conversion systems (WECS), the demand for high-performance, intelligent power electronics interfaces have become critically important. The proposed smart inverter architecture incorporates a hybrid multilevel inverter (MLI) topology coupled with an Artificial Intelligence-enhanced Model Predictive Control (AI-MPC) strategy that achieves total harmonic distortion (THD) of 0.52%, considerably below the IEEE 1547-2018 standard limit of 5%. Experimental data collected over a 12-month monitoring period at a 25 kW grid-connected pilot installation in Chhattisgarh demonstrates that the proposed system achieves an average MPPT efficiency of 99.2% for solar PV and 97.8% for wind integration, with an overall power conversion efficiency of 97.4%. The system successfully demonstrated Low Voltage Ride-Through (LVRT) compliance across all simulated grid fault scenarios.

Keywords: *Smart inverter[1]; grid-connected photovoltaic[2]; renewable energy integration[3]; model predictive control[4]; total harmonic distortion[5]; low voltage ride-through[6]; multilevel inverter topology[7].*

I. INTRODUCTION

The global transition toward decarbonized electricity systems has placed distributed renewable energy sources at the forefront of power sector planning, driving unprecedented growth in solar photovoltaic and wind energy installations. India, in particular, has witnessed a dramatic expansion of its renewable energy capacity, with the Ministry of New and Renewable Energy (MNRE) reporting an installed base exceeding 180 GW as of 2023, with an ambitious target of 500 GW by 2030 [1]. A critical enabling technology in this transition is the grid-connected inverter the power electronics interface that converts the direct current (DC) output of renewable sources into alternating current (AC) compatible with grid standards. However, as penetration levels rise, the technical demands on these devices have multiplied substantially, necessitating the evolution from conventional passive inverters to intelligent, actively controlled smart inverter systems [2]. The challenges encompass power quality maintenance, grid stability under variable generation, compliance with increasingly stringent grid codes, and the provision of ancillary services such as reactive power support and frequency regulation.

Smart inverters represent a paradigm shift in the conceptualization of power conversion equipment. Unlike their passive predecessors, smart inverters are equipped with advanced sensing capabilities, bi-directional communication interfaces, and sophisticated control algorithms that allow them to respond dynamically to both local and system-level grid conditions [3]. The integration of artificial intelligence (AI) and machine learning (ML) techniques into inverter control systems has opened new possibilities for predictive optimization, fault detection, and autonomous grid support, addressing limitations of classical proportional-integral (PI) and proportional-resonant (PR) controllers that exhibit slow dynamic response under rapidly fluctuating renewable power inputs [4]. Furthermore, the adoption of multilevel inverter (MLI) topologies including neutral-point-clamped (NPC), cascaded H-bridge (CHB), and flying capacitor (FC) configurations has substantially improved output waveform quality while reducing switching stress on individual semiconductor devices [5]. The convergence of these technological strands forms the foundation of the research presented in this paper.

Despite considerable progress, empirical studies validating the integrated performance of AI-enhanced control strategies within smart inverter platforms under actual grid conditions in the Indian context remain scarce. Most existing literature relies on simulation-based validation using MATLAB/Simulink or PSCAD environments, with limited field deployment and long-term operational data. This gap motivates the present study, which reports design, laboratory characterization, and a 12-month field deployment of a 25 kW smart inverter prototype at a grid-connected renewable energy facility in Raipur, Chhattisgarh. The paper contributes original empirical evidence across five performance dimensions: (i) power quality and harmonic performance, (ii) control system dynamic response, (iii) fault ride-through capability, (iv) renewable source integration efficiency, and (v) comparative benchmarking against prior state-of-the-art systems. The results provide actionable insights for the design and deployment of next-generation smart inverter systems in India's smart grid ecosystem.

A. Motivation and Scope

The motivation for this research arises from the observable degradation of power quality in distribution feeders with high renewable energy penetration. Voltage fluctuations, harmonic injection, and reactive power imbalances attributable to legacy inverter technology have been documented at multiple substations in Chhattisgarh and Madhya Pradesh, creating technical barriers to further capacity addition [6]. The scope of this study encompasses hardware design, closed-loop control development, real-time digital simulation (RTDS) pre-validation, laboratory testing under programmed grid conditions using a grid simulator, and field deployment under monitored operational conditions. The research explicitly addresses THD compliance, LVRT performance, MPPT optimization, and ancillary service delivery, corresponding to key performance indicators specified in the Central Electricity Regulatory Commission (CERC) Grid Code and IEEE 1547-2018 standard [7].

B. Research Objectives

The specific objectives of this research are fourfold. First, to design and fabricate a hybrid multilevel smart inverter architecture optimized for dual-source (PV and wind) renewable integration with embedded communication capability. Second, to develop and implement an AI-MPC control algorithm that simultaneously minimizes current tracking error, reduces harmonic content, and provides real-time reactive power compensation. Third, to characterize the inverter's performance empirically under laboratory-controlled fault and transient conditions corresponding to LVRT requirements of IEC 61727 and IEEE 1547. Fourth, to validate the system's energy yield and power quality performance over an extended 12-month field deployment, providing statistically robust performance metrics for comparison with published prior work.

C. Paper Organization

The remainder of this paper is organized as follows. Section II presents a critical review of related literature on smart inverter topologies and control strategies. Section III describes the methodology, including hardware design, control implementation, and experimental protocol. Section IV presents and analyzes the empirical data collected across five performance categories, supported by tabular results. Section V provides a critical discussion comparing the present findings with prior published work. Section VI draws conclusions and outlines directions for future research.

II. LITERATURE SURVEY

The evolution of grid-connected inverter technology from simple single-phase, single-stage systems to sophisticated multifunctional smart devices reflects decades of incremental innovation driven by both academic research and industry deployment. Early grid-connected inverters, as reviewed by Teodorescu et al. [8], employed simple PI current control in the synchronous reference frame (d-q frame), providing adequate steady-state performance but exhibiting substantial transient response limitations and poor harmonic rejection under distorted grid conditions. The introduction of proportional-resonant (PR) controllers by Zmood and Holmes [9] addressed the zero steady-state error requirement for sinusoidal current tracking in the stationary reference frame, significantly improving low-order harmonic suppression. However, these linear controllers are inherently model-dependent and degrade in performance when system parameters deviate from design conditions a common occurrence in real-world renewable energy installations subject to temperature and aging effects.

The development of multilevel inverter topologies represented a transformational advance in power quality. Nabae et al. [10] introduced the three-level diode-clamped (NPC) topology, demonstrating that increasing the number of output voltage levels reduces harmonic content and allows higher power ratings with standard-rated semiconductor devices. Subsequent refinements by Rodriguez et al. [11] catalogued and compared NPC, Flying Capacitor (FC), and Cascaded H-Bridge (CHB) configurations, establishing the fundamental trade-offs between component count, voltage balancing complexity, and harmonic performance. The CHB topology gained particular favor for high-power PV applications due to its modularity and the natural isolation provided by separate DC sources at each H-bridge cell [12]. Recent literature has further explored T-type and ANPC variants that combine reduced conduction losses with the harmonic benefits of three-level operation, as systematically reviewed by Stala [13].

Model Predictive Control (MPC) emerged as a compelling alternative to conventional linear controllers for power electronics applications in the mid-2000s. Kouro et al. [14] demonstrated finite control set MPC (FCS-MPC) for multilevel inverter current control, showing superior dynamic response and inherent incorporation of multi-objective optimization without requiring modulation blocks. The direct discretization of converter models within the MPC framework allows simultaneous optimization of current tracking, switching frequency, and common-mode voltage, representing a qualitative improvement over classical cascaded linear control structures [15]. However, conventional MPC requires accurate system models and is sensitive to parameter uncertainty and computational burden, limitations that have driven integration of machine learning techniques to create adaptive, self-tuning MPC variants [16]. Deep reinforcement learning-based inverter control proposed by Duan et al. [17] demonstrated online adaptation to grid impedance variations, while neural network-augmented MPC by Zhang et al. [18] achieved stable operation under 30% parameter uncertainty.

Grid code compliance, particularly Low Voltage Ride-Through (LVRT), has emerged as a central design requirement following high-profile incidents of mass disconnection of distributed generators during grid faults in Germany (2006) and India (2012) [19]. The IEC 61400-21 and IEEE 1547-2018 standards mandate that grid-connected inverters remain connected during specified voltage sag profiles and inject reactive current proportional to the voltage deviation. Research by Marinopoulos et al. [20] characterized the reactive current injection requirements of different LVRT strategies and their impact on grid voltage recovery, while Bae et al. [21] demonstrated an enhanced LVRT controller for grid-connected PV systems under German grid code compliance. For PV-specific LVRT, Bollen and Hassan [22] highlighted the importance of DC-link voltage regulation during fault conditions to prevent controller saturation and hardware damage. Recent work on smart inverter communication capabilities by Seal and Forner [23] demonstrated the role of IEEE 2030.5 and SunSpec Modbus protocols in enabling utility-interactive voltage and frequency ride-through adjustment, a feature incorporated in the proposed system.

MPPT algorithm optimization for PV and wind systems continues to attract research attention due to its direct impact on energy yield under partial shading and variable wind speed conditions. The perturb-and-observe (P&O) algorithm, while widely implemented, exhibits oscillation near the maximum power point (MPP) and fails under rapidly changing irradiance [24]. The incremental conductance (INC) method offers improved tracking under dynamic conditions but requires accurate derivative computation. Artificial intelligence-based MPPT approaches, including fuzzy logic controllers and artificial neural network (ANN) models trained on irradiance and temperature data, have demonstrated tracking efficiencies exceeding 99% under field conditions as reported by Karami et al. [25]. Reinforcement learning MPPT by Yin et al. [26] achieved sub-cycle adaptation to irradiance step changes, providing a benchmark for the AI-enhanced MPPT incorporated in the proposed system. Collectively, this body of literature establishes that the integration of multilevel topologies, AI-enhanced MPC, robust LVRT strategies, and intelligent MPPT represents the current frontier for smart inverter design.

III. METHODOLOGY

The hardware platform developed for this research consists of a three-phase hybrid multilevel inverter (HM-MLI) combining a three-level T-type NPC stage with cascaded half-bridge cells to achieve an effective five-level output waveform. The main switching devices employ 1200 V, 100 A SiC MOSFETs (Wolfspeed C3M0016120K) for the NPC stage and 650 V, 60 A Si IGBTs (Infineon IKW40T120) for the cascaded cells, selected to balance switching speed, conduction loss, and cost. The DC bus interfaces with a 5 kW monocrystalline PV array (25 x 200 W panels) and a 10 kW permanent magnet synchronous generator (PMSG) wind turbine through isolated DC-DC boost converters incorporating individual MPPT controllers. The grid interface is realized through an LCL filter (L1 = 1.2 mH, Cf = 20 uF, L2 = 0.6 mH) designed for 97% attenuation of switching harmonics at 20 kHz, with active damping implemented in firmware to suppress LCL resonance. The control platform employs a Texas Instruments TMS320F28379D dual-core DSP interfaced with a Xilinx Artix-7 FPGA for parallel execution of MPC optimization and PWM generation, achieving a control loop execution time of 25 us corresponding to a 40 kHz sampling rate.

The AI-enhanced Model Predictive Control (AI-MPC) algorithm developed in this work operates in two layers. The inner control layer executes a finite control set MPC (FCS-MPC) with a prediction horizon of N = 3 steps over a discretized three-phase current model, minimizing a composite cost function J = lambda1||i*-i_pred||^2 + lambda2*DeltaS + lambda3*Q_ref, where the three terms penalize current tracking error, switching state transitions, and reactive power deviation respectively. The weighting coefficients are dynamically updated by an outer AI layer a Long Short-Term Memory (LSTM) neural network trained offline on 6 months of grid condition data collected from the CSPDCL distribution network in Raipur and updated online using an adaptive gradient algorithm. The LSTM network receives as inputs the grid voltage harmonic spectrum (up to 50th harmonic), frequency deviation, and DC bus voltage ripple, and outputs optimal weighting vectors that adapt the MPC cost function to prevailing grid conditions. This two-layer architecture enables the inverter to autonomously adapt its control priority between harmonic suppression, reactive power support, and power maximization based on real-time grid state without operator intervention. The MPPT stage employs an ANN-based predictor that uses historical irradiance and temperature patterns combined with real-time sensor data to anticipate MPP location, reducing tracking oscillation to less than +/-0.3% of rated power under field conditions.

The experimental protocol comprised three distinct phases. Phase 1 involved laboratory characterization of the fabricated prototype using a Chroma 61845 programmable AC grid simulator to apply standardized voltage sag, swell, and harmonic profiles corresponding to IEC 61727 and IEEE 1547-2018 test sequences. Power quality measurements were conducted with a Yokogawa WT5000 precision power analyser with 0.02% basic accuracy. Phase 2 involved Real-Time Digital Simulation (RTDS) hardware-in-the-loop (HIL) testing using an OPAL-RT OP5700 system to validate controller performance under simulated large-scale grid scenarios including high renewable penetration (60% of feeder load). Phase 3 consisted of the 12-month field deployment at a 25 kW grid-tied installation at the NIT Raipur campus microgrid, where power quality, energy yield, fault event logging, and communication performance were continuously monitored through a SCADA system interfacing with the inverter's SunSpec Modbus communication stack. Data integrity was ensured through redundant logging with 1-minute interval averaging and 10 ms event-triggered recording for fault analysis, yielding a dataset of 524,160 1-minute records and 47 recorded fault/transient events over the monitoring period.

IV. DATA COLLECTION AND ANALYSIS

This section presents the empirical findings organized across five analytical dimensions corresponding to the research objectives. All quantitative data are derived from the laboratory and field experimental protocols described in Section III, with statistical significance tested at the 95% confidence level where applicable. The tables below summarize key performance metrics for each dimension, with results compared against industry standards and prior published benchmarks.

A. Harmonic Performance and Power Quality

Table 1 compares THD values across inverter topologies with different filter configurations. The proposed smart inverter achieves a THD of 0.52% with the LCL filter, which is 89.6% lower than the IEEE 1547-2018 limit of 5% and substantially better than all benchmark topologies under identical filter conditions. The improvement is attributable to the combined effect of the five-level hybrid MLI topology and the AI-MPC harmonic suppression strategy.

Table 1: THD Comparison Across Inverter Topologies and Filter Configurations

Inverter Type	**THD (%) No Filter**	**THD (%) L-Filter**	**THD (%) LCL-Filter**	**IEEE 1547 Compliance**
Single-Phase H-Bridge	12.4	5.8	2.1	Compliant
Three-Phase VSI	9.7	4.2	1.6	Compliant
NPC Multilevel	7.1	2.9	0.9	Compliant
CHB Multilevel	5.3	2.1	0.7	Compliant
Proposed Smart Inverter	4.1	1.7	0.52	Fully Compliant

B. Control System Dynamic Performance

Table 2 presents the transient response characteristics of five control strategies applied to the same inverter hardware. The proposed AI-MPC achieves a settling time of 14.7 ms 65.4% faster than conventional PI control with steady-state error reduced to 0.18%, confirming the superior dynamic performance attributable to predictive optimization and LSTM-based adaptive weighting under real grid distortion conditions.

Table 2: Control Strategy Performance Comparison

Control Strategy	Rise Time (ms)	Settling Time (ms)	Overshoot (%)	Steady-State Error (%)
PI Controller	18.2	42.5	8.3	1.4
PR Controller	14.6	35.8	6.1	0.9
Deadbeat Controller	11.3	28.4	4.7	0.6
MPC	8.9	21.2	3.2	0.4
Proposed AI-MPC	5.4	14.7	1.8	0.18

C. Low Voltage Ride-Through (LVRT) Performance

Table 3 documents LVRT performance across five fault scenarios applied during laboratory testing. The inverter successfully remained connected in all scenarios, injecting reactive current in compliance with the IEC 61727 requirement of 1.0 pu during balanced three-phase faults, with voltage recovery times well within the 250 ms grid code requirement, demonstrating the robustness of the AI-MPC DC-link clamp function.

Table 3: Grid Fault Ride-Through Performance Metrics

Fault Scenario	Voltage Sag (%)	Recovery Time (ms)	Reactive Current Inj. (pu)	LVRT Compliance
Single-Phase	85	120	0.62	Yes

Fault				
Two-Phase Fault	70	165	0.81	Yes
Three-Phase Fault	55	210	1.00	Yes
Voltage Swell	115	98	0.45	Yes
Frequency Deviation	N/A	85	0.30	Yes

D. Renewable Integration Efficiency

Table 4 summarizes energy yield and conversion efficiency data collected over the 12-month field deployment. The PV subsystem achieved an MPPT efficiency of 99.2%, validating the ANN-based MPPT predictor, while the hybrid PV-wind configuration delivered an annual energy yield of 24.73 MWh against a modelled reference yield of 24.98 MWh a performance ratio of 99.0%, demonstrating effective multi-source power flow coordination.

Table 4: Renewable Source Integration Efficiency and Energy Yield

Source Type	MPPT Efficiency (%)	Power Factor	Conversion Efficiency (%)	Annual Energy Yield (MWh)
Solar PV (5 kW)	99.2	0.998	97.4	7.82
Wind Turbine (10 kW)	97.8	0.995	95.1	18.64
Battery Storage (8 kWh)	99.6	0.999	96.8	N/A
Hybrid PV-Wind	98.9	0.997	96.3	24.73
Grid Ancillary Services	N/A	0.999	N/A	2.41 (savings)

E. Comparative Benchmarking Against Prior Work

Table 5 positions the proposed system against four representative peer-reviewed publications selected to represent the progression of smart inverter technology from 2003 to 2022. The proposed system demonstrates the lowest THD (0.52%), competitive conversion efficiency (97.4%), full LVRT compliance, and the only field-validated implementation combining full AI-MPC with a hybrid MLI topology.

Table 5: Comparative Benchmarking with Prior Published Work

Reference	Year	THD (%)	Efficiency (%)	LVRT	AI/ML	Topology
[4] Zhang et al.	2019	2.8	95.2	Partial	No	2-Level VSI
[9] Zmood & Holmes	2003	3.1	94.8	No	No	Standard VSI
[14] Kouro et al.	2009	1.9	96.9	Yes	Partial	CHB
[21] Bae et al.	2013	1.4	97.3	Yes	Yes	T-Type NPC
Proposed Work	2024	0.52	97.4	Full	Full AI-MPC	Hybrid MLI

V. DISCUSSION

The empirical results presented in Section IV collectively validate the design hypothesis that integrating an AI-MPC control strategy with a hybrid multilevel inverter topology yields measurable and statistically significant improvements across all key performance dimensions relevant to grid-connected smart inverters. The THD value of 0.52% achieved by the proposed system under LCL-filtered conditions (Table 1) merits particular attention. This figure represents an improvement of 26% over the CHB topology with LCL filter (0.7%) and a 68% reduction compared to the three-phase VSI with LCL filter (1.6%). The improvement is attributable to two concurrent mechanisms: the additional voltage levels afforded by the hybrid MLI topology reduce the harmonic content of the fundamental switching waveform before filter processing, while the AI-MPC controller actively monitors harmonic content through the LSTM input layer and adjusts the switching pattern to suppress dominant harmonic orders in real time. Comparing these results with the seminal multilevel inverter review by Rodriguez et al. [11], who reported THD values of 1.5–3.5% for five-level CHB topologies under comparable filter conditions, the present system demonstrates that AI-enhanced control can extract an additional 30–55% reduction in THD beyond what topology selection alone achieves.

The control dynamic performance data (Table 2) reveals a consistent hierarchy of improvement from PI through PR, Deadbeat, standard MPC, to the proposed AI-MPC, with settling time decreasing from 42.5 ms to 14.7 ms across this progression. The 30.6% improvement in settling time of the proposed AI-MPC over standard MPC (21.2 ms) is particularly significant because it demonstrates the incremental benefit of the LSTM-based adaptive weighting beyond the predictive optimization that both strategies share. This finding aligns with and extends Zhang et al.'s [18] report that neural network-augmented MPC reduced current tracking error by 22% compared to fixed-weight MPC in a simulation study; the present work quantifies a larger improvement under actual grid conditions, suggesting that the adaptive response to real grid harmonic distortion which cannot be fully replicated in simulation contributes additional performance gains in field conditions. The steady-state error of 0.18% achieved by AI-MPC compares favorably with the 0.4% reported by Kouro et al. [14] for FCS-MPC and the 0.6% of Deadbeat control, confirming that predictive control with adaptive cost function weighting achieves the best balance between tracking accuracy and computational tractability at the current hardware platform.

The LVRT performance documented in Table 3 demonstrates full compliance with IEEE 1547-2018 and IEC 61727 requirements across all five tested fault scenarios. The three-phase fault recovery time of 210 ms is particularly noteworthy given that the standard allows up to 250 ms; the 16% margin provides confidence in compliance even under degraded operating conditions. Comparison with Bae et al.'s [21] LVRT results for grid-connected PV systems, which reported recovery times of 230–280 ms for comparable fault depths, suggests that the proposed inverter's faster DC-link voltage regulation enabled by the predictive DC-link clamp function in the AI-MPC algorithm contributes meaningfully to faster voltage recovery. The reactive current injection levels recorded during single-phase (0.62 pu), two-phase (0.81 pu), and three-phase (1.00 pu) faults demonstrate graduated, fault-severity-proportional response, consistent with the k-factor injection characteristic specified in VDE-AR-N 4105 and adopted in the proposed control. Marinopoulos et al. [20] emphasized the importance of precisely graduated reactive current injection to prevent over-voltage at unfaulted phases; the present results confirm that the AI-MPC controller achieves this graduation within the +-5% accuracy required by the standard across all tested fault scenarios.

The renewable integration efficiency data (Table 4) validates the ANN-based MPPT predictor's contribution to energy yield. The PV MPPT efficiency of 99.2% exceeds the 98.1–98.7% range reported in the literature for advanced incremental conductance MPPT [24] by 0.5–1.1 percentage points. While this margin appears modest in percentage terms, its practical significance is substantial: over the 12-month field period, this efficiency differential translates to approximately 62 additional kWh of energy harvest from the 5 kW PV array, equivalent to 0.8% additional annual yield. At national scale, across India's 67 GW of installed PV capacity, a 1% MPPT efficiency improvement would correspond to approximately 850 GWh of additional annual generation, sufficient to serve the electricity needs of approximately 700,000 Indian households [1]. The wind MPPT efficiency of 97.8% reflects the greater difficulty of maximum power extraction from variable-speed wind turbines compared to PV, consistent with Yin et al.'s [26] observation that ANN-based wind MPPT achieves 97–98% efficiency under realistic turbulence intensity conditions. The hybrid PV-wind performance ratio of 99.0% demonstrates effective power flow management between the two sources, with the AI-MPC seamlessly coordinating DC bus voltage across the PV boost converter, wind rectifier, and battery storage subsystems.

The comparative analysis in Table 5 places the proposed work in the context of the broader literature trajectory. A clear progression is evident from Zhang et al.'s [4] 2019 baseline (THD 2.8%, no LVRT) through Kouro et al.'s [14] NPC implementation (THD 1.9%, full LVRT, partial AI) to Bae et al.'s [21] T-type NPC with LVRT and partial AI integration (THD 1.4%, 97.3% efficiency). The proposed system achieves the lowest THD (0.52%) across all benchmarks while matching the highest efficiency (97.4%) and adding the only full AI-MPC implementation with 12-month field validation. The critical differentiator is not any single metric but the demonstration that all performance dimensions harmonic quality, dynamic response, fault compliance, and energy yield can be simultaneously optimized within a single integrated architecture deployed under real grid conditions. Prior studies achieving sub-1% THD relied exclusively on simulation or short-duration laboratory tests, while field-validated studies reported higher THD values. The present study bridges this validation gap, establishing empirical benchmarks for smart inverter systems applicable to India's distribution grid modernization programs under the National Smart Grid Mission and PM Surya Ghar Yojana initiatives.

VI. CONCLUSION

This paper has presented the design, implementation, and empirical validation of a grid-connected smart inverter system for renewable energy integration, combining a hybrid multilevel inverter topology with an AI-enhanced Model Predictive Control strategy and field-validating its performance over a 12-month deployment. The key findings are: (i) a THD of 0.52% was achieved under LCL-filtered conditions, representing an 89.6% improvement over the IEEE 1547-2018 limit and a 26% improvement over the best comparative topology; (ii) the AI-MPC controller achieved a settling time of 14.7 ms and steady-state error of 0.18%, outperforming all benchmark control strategies by substantial margins; (iii) full LVRT compliance was demonstrated across all IEC 61727 fault scenarios with recovery times within grid code requirements; (iv) MPPT efficiencies of 99.2% (PV) and 97.8% (wind) delivered an annual hybrid energy yield of 24.73 MWh with a performance ratio of 99.0%; and (v) comprehensive benchmarking confirmed the proposed system achieves the best multi-dimensional performance profile among published works while providing the only 12-month field-validated evidence at this scale. These results establish a robust technical foundation for AI-enhanced smart inverter deployment in India's smart grid modernization programs and provide a reproducible empirical benchmark for future research. Future work will investigate the extension of the AI-MPC framework to active participation in grid frequency regulation markets and scaling of the platform to 100 kW for industrial microgrid applications in Chhattisgarh's industrial corridors.

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