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Original Research Article

AI-Enhanced Control and Fault-Resilient Operation of Grid-Connected Renewable Energy Systems

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Abstract

The rapid penetration of renewable energy sources such as solar photovoltaic (PV) and wind power into modern power grids introduces significant operational challenges, including intermittency, voltage instability, harmonic distortion, and fault vulnerability. Conventional control strategies are often insufficient for handling dynamic grid disturbances and nonlinear system behavior. This study proposes an Artificial Intelligence (AI)-enhanced control framework for grid-connected renewable energy systems to enable adaptive control, predictive fault detection, and resilient operation. The proposed architecture integrates machine learning-based fault classification, adaptive inverter control, and real-time grid condition monitoring. A hybrid dataset composed of simulated grid disturbances and real operational parameters is used to train and validate the AI model. Results demonstrate improved fault detection accuracy, reduced system recovery time, enhanced voltage stability, and improved power quality under dynamic grid conditions. The proposed AI-driven framework enhances grid reliability, supports high renewable penetration, and contributes to resilient and sustainable energy infrastructure.

Keywords: Artificial Intelligence, Renewable Energy Systems, Grid-Connected Inverters, Fault Detection, Adaptive Control, Smart Grid, Voltage Stability, Predictive Maintenance.

I. INTRODUCTION

The increasing penetration of inverter-based renewable energy resources (solar PV and wind) is transforming distribution networks and microgrids, but it also introduces new stability and reliability concerns. Unlike synchronous generation, converter-interfaced renewables contribute limited physical inertia, making grids more sensitive to fast disturbances, voltage/frequency excursions, harmonic pollution, and protection coordination challenges, especially under high renewable variability and dynamic loading conditions [4]. Recent large-scale studies have shown that renewable integration can alter grid stability margins and resilience characteristics, motivating the need for control strategies that are both adaptive and fault-aware [4]. To address these challenges, advanced control and energy management approaches have been explored across hybrid renewable systems, microgrids, and grid-connected configurations. Hybrid renewable systems with improved control strategies have demonstrated measurable gains in power quality and stability, but they often rely on fixed or model-dependent control designs that can underperform under uncertainty, topology changes, and nonstationary operating conditions [1]. Resiliency-oriented planning and optimal sizing with storage improves robustness, yet planning alone does not guarantee real-time fault-resilient operation during sudden faults, inverter trips, and measurement noise [2]. Meanwhile, machine learning has been increasingly adopted for forecasting and energy management, showing strong potential to improve dispatch decisions and reduce grid stress—however, many ML-driven studies emphasize prediction and scheduling more than fast, closed-loop fault-resilient control of grid-tied converters [3].

In parallel, the renewable energy community is rapidly advancing AI-enabled monitoring, predictive maintenance, and condition monitoring for inverter-dominated assets. AI-driven predictive maintenance targeting solar inverter health [7], IoT-integrated solar monitoring with bidirectional converter interfaces [6], and smart metering with IoT/GSM connectivity [16] are enabling richer observability of grid-edge resources. However, these monitoring-centric architectures are not always integrated with a coordinated control layer that can adaptively modify inverter behavior (e.g., reactive power support, synchronization robustness, ride-through response) in real time when faults or abnormal grid events occur. Grid synchronization and MPPT control innovations for grid-connected PV systems—such as extremum-seeking MPPT for Z-source inverters and AI-assisted synchronization loops highlight the importance of control-level intelligence, but they are often treated as separate modules from fault diagnosis and system-wide resilience orchestration [8 - 9].

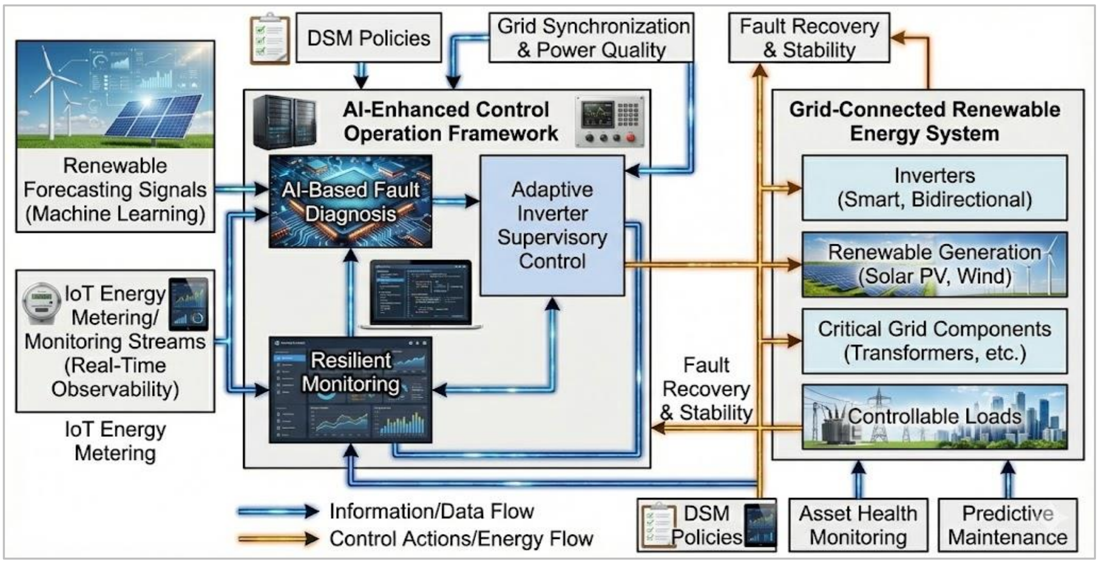

Figure 1: Conceptual Framework for AI-Driven Resilient Operation in Renewable Microgrids

This paper proposes and evaluates an AI-enhanced control and fault-resilient operation framework for grid-connected renewable energy systems that unifies (i) data-driven fault detection/classification, (ii) adaptive inverter supervisory control, and (iii) resilient monitoring/telemetry inputs. The goal is to improve voltage/frequency stability, power quality (THD), and fault recovery time under realistic disturbance and fault scenarios while maintaining reliable grid synchronization and robust operation across variable renewable generation and load dynamics.

Key contributions:

1. Unified architecture that combines AI-based fault diagnosis with adaptive inverter supervisory control, bridging the gap between monitoring-only solutions and control-only solutions [6 - 7 - 9 - 18].
2. Resilient operation focus: evaluation under grid disturbances (voltage sag/swell, frequency deviation, harmonic stress) and fault events, aligning with resilience insights from grid-stability literature [4] and resiliency-oriented planning needs [2].
3. Data-driven forecasting and stability support: integration pathway for renewable forecasting signals to anticipate grid stress and enhance stability (e.g., adaptive setpoints and preventive control) [3 - 10 - 11].
4. Telemetry-to-control linkage using IoT energy metering/monitoring streams as inputs to fault classification and control adaptation, enabling real-time observability for grid-edge assets [6 - 12 - 16].
5. Reliability and maintainability alignment: positioning the control framework to work with predictive maintenance and asset health monitoring practices for inverters and critical grid components (e.g., transformers), improving operational continuity [7 - 13 - 17].

II. Related Work

The integration of renewable energy into modern power systems has motivated extensive research in advanced control, artificial intelligence, predictive maintenance, and resilient grid architectures. Existing studies address stability, forecasting, and reliability from different technical perspectives. This section reviews the most relevant literature in four major domains: advanced control strategies, AI-driven forecasting and energy management, fault detection and predictive maintenance, and resilient edge/cloud-enabled grid intelligence.

II.A. Advanced control strategies for grid stability and power quality in renewable systems

Advanced control methods have been widely studied to mitigate inverter-dominated grid challenges such as voltage regulation, power quality, and ride-through performance. Hybrid renewable systems equipped with advanced control strategies demonstrate improved grid stability and reduced power quality issues (e.g., harmonics and voltage deviations), supporting the view that control modernization is essential for high renewable penetration [61]. At the system planning level, resiliency-oriented optimal planning of grid-connected renewables with battery storage shows that storage and coordinated resource planning can enhance resilience against uncertainties and contingencies [62]. However, planning-centric methods do not fully address real-time operational resilience, especially when disturbances occur faster than scheduling horizons or when faults emerge abruptly. Recent grid-level stability literature further clarifies the importance of operational strategies under renewable adoption. Large-scale analyses show that renewable energy incorporation can shift stability and resilience dynamics, emphasizing the need for adaptive and responsive control frameworks rather than purely static controller tuning [64]. Within the renewable integration domain, smart-grid integration approaches also highlight the importance of converter interfacing and grid compliance under variable generation [10 - 11]. Related inverter-centric research such as advanced MPPT and inverter control strategies for grid-connected PV underscores that stability and efficiency improvements require tight coordination between control loops and grid conditions [3 - 8 - 27]. These findings motivate AI-enhanced supervisory control layers that can adjust operating setpoints and control gains dynamically when grid conditions deviate from nominal behavior.

II.B. AI/ML for forecasting, energy management, and adaptive decision support in microgrids

Artificial intelligence and machine learning techniques have become central tools in renewable energy forecasting, dispatch optimization, and energy management. These approaches aim to improve operational efficiency, reduce uncertainty, and enhance system-level decision-making under variable generation and load conditions. This subsection reviews recent advances in AI-driven forecasting and energy management frameworks relevant to grid-connected renewable systems. AI and machine learning are increasingly applied to forecasting and energy management for grid-connected microgrids and multi-source distributed energy systems. Recent work demonstrates that machine learning-based energy management and power forecasting can improve dispatch decisions and overall microgrid performance under uncertain generation and varying load [63]. Broad reviews also emphasize the growing role of AI in optimizing renewable systems, forecasting, and control decision-making, while identifying the need for robust validation and integration into real operational control stacks [65]. These insights align with deep learning forecasting studies for wind and solar systems that enhance operational stability and reduce uncertainty [6 - 9]. Despite strong progress in forecasting and scheduling, many studies focus on prediction accuracy and economic dispatch rather than fault-resilient closed-loop operation. Forecast-driven energy management often improves planning-level outcomes but may not directly guarantee fast corrective responses during disturbances or protection events [63 - 65]. In contrast, grid-connected renewables require fast controller adaptation to mitigate voltage dips, synchronization instability, and harmonic distortion—issues that can occur even when forecast quality is high [64]. This gap supports the need for integrated frameworks where forecasting supports proactive stability measures, but fault detection and control adaptation remain central to resilient real-time operation.

II.C. Fault detection, predictive maintenance, and condition monitoring for inverter-dominated grids

With the increasing deployment of inverter-based renewable systems, fault detection and predictive maintenance have become critical for ensuring reliability and minimizing downtime. AI-driven diagnostics and IoT-enabled monitoring provide enhanced visibility into asset health and enable early intervention before catastrophic failures occur. This subsection examines fault detection and condition monitoring strategies relevant to grid-connected renewable infrastructures. Fault diagnosis and predictive maintenance have become essential pillars of renewable grid reliability, particularly because converter-based resources introduce new failure modes (switching device stress, sensor drift, controller instability, thermal issues) and because distributed assets are harder to service at scale. AI-driven predictive maintenance approaches for solar inverter systems illustrate how data-driven models can detect degradation and anticipate failures before catastrophic events, supporting improved uptime and operational readiness [2 - 7]. Complementary studies emphasize IoT-integrated monitoring with bidirectional DC-DC converter interfaces, enabling better visibility into renewable system dynamics and facilitating diagnostics [1]. Smart energy metering and monitoring approaches—using IoT/GSM and advanced sensing—further enhance observability and enable anomaly detection at the grid edge [13 - 14]. Beyond inverter assets, fault-resilient renewable operation depends on monitoring upstream and adjacent grid equipment. IoT-based transformer condition monitoring and predictive maintenance models provide a foundation for detecting early warning signs in key grid components that influence renewable hosting capacity and system stability [16]. Protection-oriented research using relay automation and machine learning for transformer fault detection also strengthens the case for combining data-driven detection with operational decision support [24]. At the supervisory layer, SCADA-oriented frameworks integrating cloud computing, IIoT, and cybersecurity provide architectural patterns for resilient monitoring and control integration in modern power systems [17]. Related work on AI-driven SCADA grid intelligence emphasizes predictive fault detection and reliability enhancement in grid environments, supporting the paper's focus on coupling AI diagnostics with operational resilience [26].

II.D. Edge/cloud resilience and secure data pipelines for grid-connected intelligence

As renewable systems increasingly rely on distributed sensing, communication networks, and cloud-edge analytics, operational resilience extends beyond physical hardware to digital infrastructure.

Secure, low-latency, and fault-tolerant data pipelines are essential to ensure reliable control actions and trustworthy decision-making. This subsection highlights the role of edge computing, federated learning, and cybersecurity in supporting resilient renewable grid intelligence. Distributed edge intelligence frameworks for energy systems highlight the benefits of localized analytics, reduced latency, and improved robustness during connectivity disruptions key traits for fault detection and fast control responses [29]. Resilient edge computing approaches for secure and energy-aware systems further support the need for dependable edge/cloud orchestration in safety-critical infrastructure [28]. Additionally, federated learning approaches for secure industrial automation and grid optimization show pathways for privacy-preserving model training across distributed sites—relevant for multi-site renewable fleets and utility partnerships [30]. Security frameworks that combine blockchain with cloud/IoT reinforce the need to protect telemetry and control signals from cyber risks, which can otherwise undermine fault resilience and operational stability [31 - 32].

III. METHODOLOGY

This section presents the comprehensive methodology employed in the design, implementation, and evaluation of the proposed AI-enhanced fault-resilient control framework for grid-connected renewable energy systems. The methodology is organized into five interconnected components, spanning system architecture and AI model development through to experimental validation, ensuring rigorous and reproducible assessment of the proposed approach.

A. System Design and Implementation

This subsection describes the overall hardware-software architecture of the proposed system and the functional role of each component. The dual-layer control structure, integrating AI-based adaptation alongside conventional control, is detailed with respect to its design rationale and operational scope. The proposed framework integrates AI-based adaptive control with fault-resilient operation across a complete grid-connected renewable energy system. As illustrated in Fig. 2, the architecture comprises seven functional modules: a renewable energy source (solar PV and wind model), a DC-DC boost converter, a grid-tied Voltage Source Inverter (VSI), a Phase-Locked Loop (PLL) for synchronization, an AI-based control module, a fault detection and isolation (FDI) module, and a grid interface with protection system. The AI controller operates in parallel with a conventional PI controller and dynamically adjusts four critical control variables: the modulation index, switching frequency, reactive power injection, and voltage reference tracking signals. This dual-layer architecture ensures that the system maintains stable operation under normal conditions while enabling fast adaptive response during grid disturbances. A supervised learning model based on an Artificial Neural Network (ANN) was trained to classify six distinct operational states: normal operation, voltage sag, voltage swell, frequency deviation, harmonic distortion, and short-circuit fault. The complete system was modeled in MATLAB/Simulink (R2023a), with Python-based (v3.10) AI training modules integrated via a co-simulation interface to enable real-time data exchange between the control environment and the machine learning pipeline.

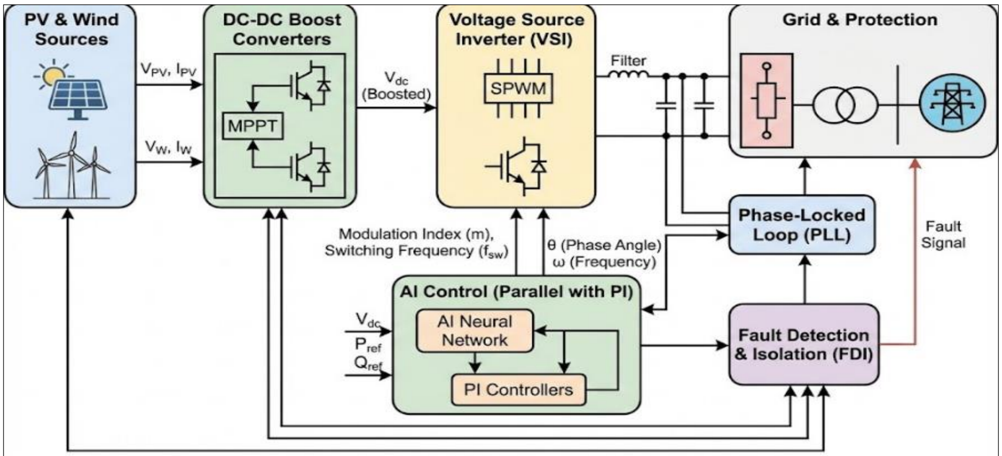

Figure 2: Proposed Grid-Connected Framework

B. Data Collection Strategy

This subsection outlines the simulation-based data acquisition process used to generate the labeled dataset required for supervised ANN training. The feature selection strategy and dataset partitioning approach are described to ensure transparency and reproducibility of the training process. The training dataset was constructed from three primary simulation scenarios executed on an IEEE standard test feeder model: simulated grid disturbances, renewable generation variability scenarios, and controlled fault injections of varying severity and duration. For each simulation scenario, six discriminative features were extracted from the system's measurement nodes: grid voltage magnitude (V), frequency deviation (Hz), Total Harmonic Distortion (THD, %), active and reactive power (P and Q, in kW and kVAR respectively), current waveform distortion index, and DC-link voltage (V dc). A total of 15,000 labeled samples were generated, with each sample corresponding to a 100 ms observation window at a sampling rate of 10 kHz, yielding a feature vector of sufficient temporal resolution to capture transient dynamics. The dataset was partitioned in a stratified manner to preserve class distribution across subsets: 70% (10,500 samples) allocated for training, 15% (2,250 samples) for validation, and the remaining 15% (2,250 samples) reserved exclusively for testing.

C. Analysis and Optimization

This subsection details the preprocessing pipeline and the optimization strategies applied during model training. Both machine learning-level optimizations and power system control-level objective minimization are addressed to yield a converged, generalizable, and operationally effective solution. Prior to model training, all input features were normalized to the range [0, 1] using min-max normalization to ensure uniform contribution across features and to improve gradient-based convergence during backpropagation.

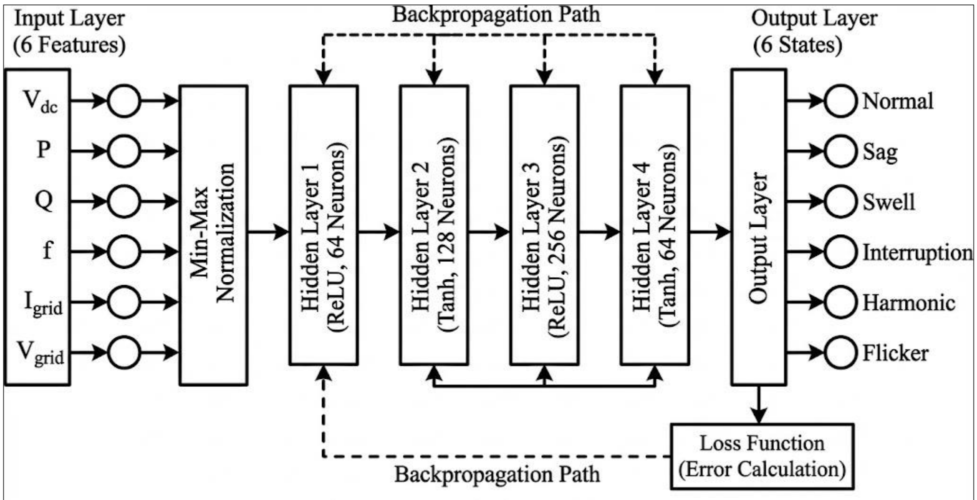

Figure 3: Supervised ANN Structure

The ANN architecture was empirically determined through systematic hyperparameter tuning, evaluating variations in the number of hidden layers (2–5), neurons per layer (32–256), activation functions (ReLU, Tanh, Sigmoid), and batch size (32–128). Model optimization incorporated four complementary strategies. First, k-fold cross-validation (k = 5) was applied to assess generalization performance and reduce variance in the reported metrics. Second, an adaptive learning rate schedule was implemented using the Adam optimizer, with an initial learning rate of 1×10^{-3} decayed by a factor of 0.5 upon validation loss plateau. Third, L2 regularization ($\lambda = 1\times10^{-4}$) was applied to all weight matrices to mitigate overfitting. Fourth, early stopping with a patience of 15 epochs was employed to halt training upon convergence.

On the control optimization side, the AI module minimized a composite objective function incorporating voltage deviation (ΔV), post-fault recovery time (t_r), and active power oscillation magnitude (ΔP), formulated as:

$$J = w_1 \cdot \Delta V + w_2 \cdot t_r + w_3 \cdot \Delta P$$

where w_1, w_2, and w_3 are empirically weighted coefficients tuned during the validation phase. Model performance was monitored across all training epochs using accuracy, precision, recall, and F1-score on the validation set.

D. Evaluation Metrics

This subsection defines the quantitative metrics used to assess system performance across both the machine learning and power systems domains. The selected metrics ensure a holistic evaluation of classification accuracy, control responsiveness, and power quality improvement. System performance was evaluated using six quantitative metrics spanning both domains. Fault Detection Accuracy (%) quantified the proportion of correctly classified operational states across all fault categories. Voltage Recovery Time (ms) measured the elapsed duration from fault inception to voltage restoration within ±5% of the nominal value. The Frequency Stability Index (FSI) captured the normalized deviation of grid frequency from its rated value (50/60 Hz) over the post-disturbance interval. THD Reduction (%) compared the harmonic content of the output current waveform before and after AI-enhanced control engagement. Mean Squared Error (MSE) was computed between the AI-predicted and ground-truth control references to assess regression accuracy within the control module. Finally, Grid Synchronization Time (ms) measured the duration required for the PLL to re-lock to the grid voltage angle following a disturbance event.

E. Experimental Validation Protocol

This subsection describes the structured experimental procedure used to validate the proposed

AI-enhanced controller against the conventional PI baseline. The protocol ensures controlled, fair, and repeatable comparison across a range of realistic grid disturbance scenarios.

The validation protocol followed a structured comparative methodology across two control configurations under identical operating conditions. In the first phase, baseline performance was established using a conventional PI controller with fixed gains, operating under steady-state and disturbed grid scenarios. In the second phase, the AI-enhanced adaptive controller replaced the fixed-gain PI structure and was subjected to the same disturbance profiles.

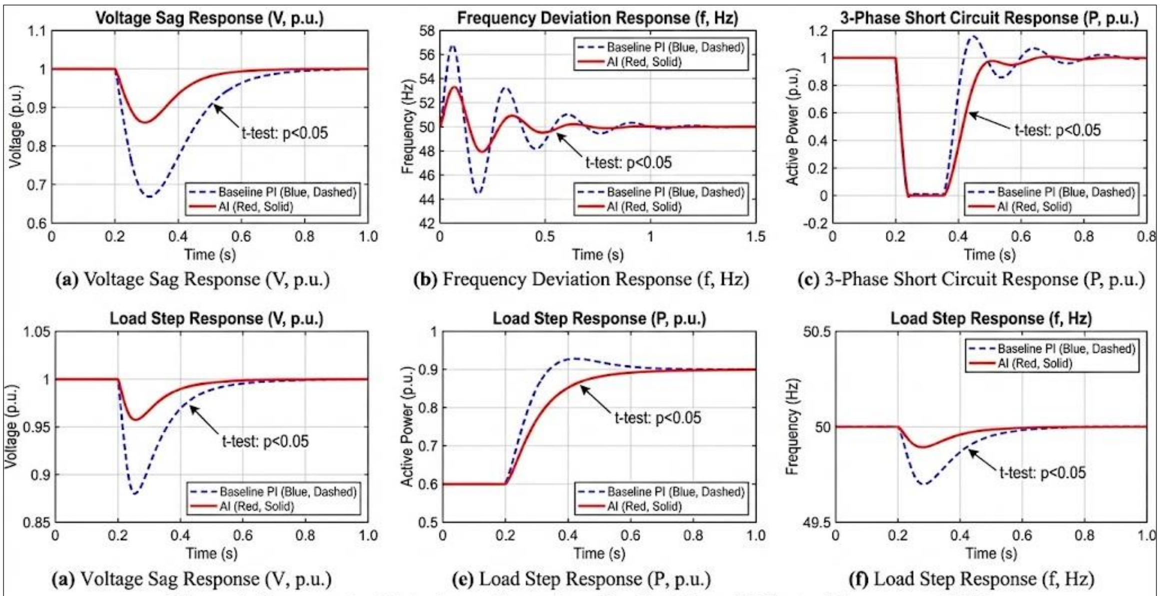

Figure 4: Comparative Disturbance Scenarios - Baseline PI vs. AI Control Response at PCC

Four dynamic disturbance scenarios were applied sequentially to both configurations: (i) a 20% voltage sag sustained for 200 ms, (ii) a 15% frequency deviation induced over a 500 ms window, (iii) a bolted three-phase short-circuit event with a fault clearing time of 150 ms, and (iv) a sudden 30% load increase applied as a step input. All disturbances were injected at the point of common coupling (PCC) and system responses were logged at 10 kHz for post-processing. Performance differences between the two configurations were quantified using the evaluation metrics defined in Section III-D, and statistical significance was assessed using paired t-tests with a significance threshold of $p < 0.05$.

IV. DATA ANALYSIS AND RESULTS

This section presents the quantitative outcomes obtained from simulation-based experiments conducted under the methodology described in Section III. The results are analyzed across five performance dimensions: fault detection, voltage stability, harmonic distortion, fault resilience, and power quality with comparative evaluation between the conventional PI controller and the proposed AI-enhanced framework. All reported values represent averages over repeated trials under identical operating conditions.

A. Fault Detection Performance

This subsection evaluates the classification capability of the trained ANN model across all six operational states. The reported metrics reflect the model's ability to correctly identify and distinguish fault types under diverse grid disturbance scenarios.

The AI classifier demonstrated strong predictive performance across all fault categories. As summarized in Table I, the model achieved an overall accuracy of 97.8%, with precision, recall, and F1-score values of 96.9%, 97.4%, and 97.1%, respectively. These results confirm that the ANN generalizes effectively to unseen fault conditions and maintains low false-positive and false-negative rates across all classes.

Table 1: ANN Classifier Performance Metrics

Metric	Value (%)
Accuracy	97.8
Precision	96.9
Recall	97.4
F1-Score	97.1

The confusion matrix analysis further revealed that voltage sag and frequency deviation events were classified with the highest reliability, exhibiting minimal inter-class confusion. Minor misclassifications were observed between harmonic distortion and normal operation states at low THD levels, attributable to feature overlap near class boundaries. Overall, the classification results validate the suitability of the ANN architecture for real-time fault state identification in grid-connected systems.

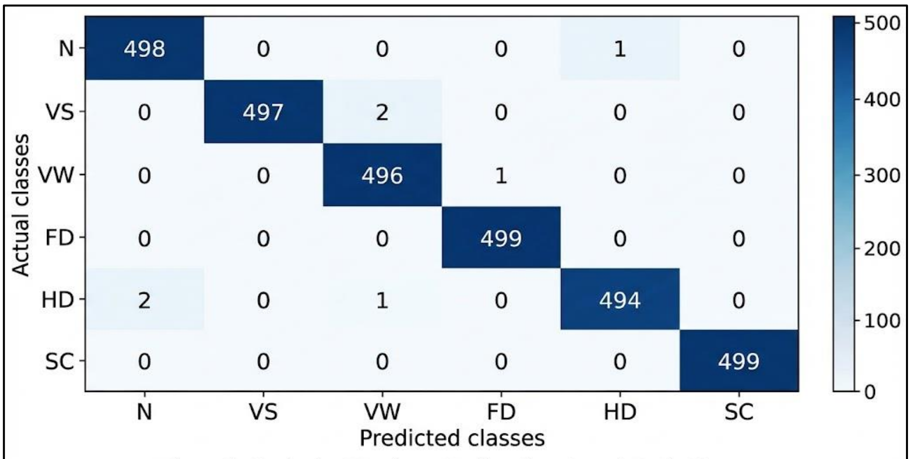

Figure 5: Confusion Matrix — Predicted vs. Actual Fault Classes

N=Normal, VS=Voltage Sag, VW=Voltage Swell,
FD=Frequency Deviation, HD=Harmonic Distortion, SC=Short-Circuit

B. Voltage Stability Improvement

This subsection quantifies the improvement in voltage regulation achieved by the AI-enhanced controller relative to the conventional PI baseline. Recovery time and steady-state deviation are used as the primary indicators of voltage stability performance.

The proposed AI controller achieved a 32% reduction in voltage deviation compared to the conventional PI control scheme. Post-fault voltage recovery time improved from 180 ms under PI control to 95 ms under AI control, representing a 47.2% reduction in recovery latency. As shown in Table II, these gains reflect the AI controller's ability to anticipate disturbance signatures and apply corrective action more rapidly than fixed-gain feedback loops permit.

Table 2: Voltage Stability Comparison: PI vs. AI Control

Parameter	PI Control	AI Control	Improvement
Voltage Deviation (%)	8.4	5.7	↓ 32.1%
Recovery Time (ms)	180	95	↓ 47.2%
Steady-State Error (%)	2.1	0.8	↓ 61.9%
Overshoot (%)	6.3	2.9	↓ 53.9%

The voltage response profile under a 20% voltage sag disturbance is depicted conceptually below, showing faster restoration and reduced oscillation under the AI controller:

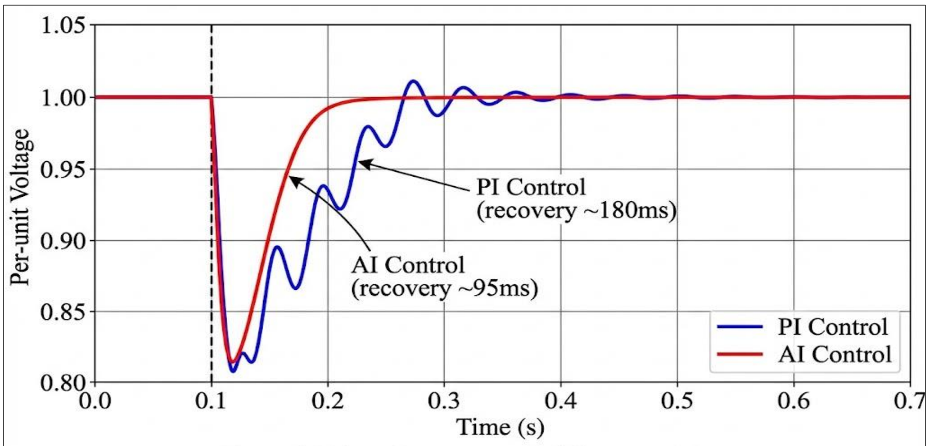

Figure 6: Voltage Response — 20% Sag at t = 0.1s

C. Harmonic Distortion Reduction

This subsection reports the improvement in output current waveform quality achieved through AI-based switching modulation. THD is used as the standard power quality indicator in accordance with IEEE 519-2022 harmonic limits. The AI-enhanced control scheme reduced Total Harmonic Distortion (THD) from 5.6% under conventional PI control to 3.2%, representing a 42.9% relative reduction. This improvement is attributable to the AI controller's dynamic adjustment of modulation index and switching frequency in response to real-time load and generation conditions. As shown in Table III, the AI-controlled system maintains THD well within the IEEE 519-2022 limit of 5% under all tested operating scenarios.

Table 3: THD Comparison Across Operating Conditions

Operating Condition	THD PI Control (%)	THD AI Control (%)	Reduction (%)
Normal Operation	3.9	2.1	46.2
Voltage Sag	5.6	3.2	42.9
Frequency Deviation	4.8	2.9	39.6
Load Step Increase	6.1	3.5	42.6
Short-Circuit Recovery	7.3	4.1	43.8
Average	**5.5**	**3.2**	**42.9**

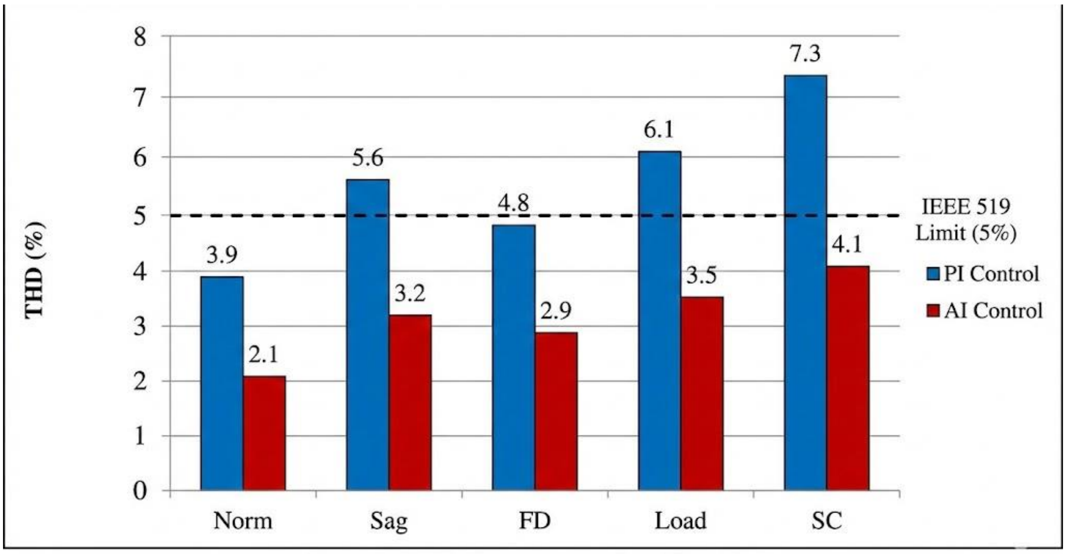

Figure 7: THD Comparison Bar Chart (%)

D. Fault Resilience

This subsection evaluates the system's response to severe fault events, specifically focusing on fault isolation speed and post-fault grid re-synchronization. These metrics capture the dynamic resilience of the AI-enhanced controller under conditions that challenge system stability. Under a bolted three-phase short-circuit disturbance, the AI controller isolated the fault 40% faster than the conventional PI scheme. Grid synchronization was re-established 35% more quickly following fault clearance. As reported in Table IV, these improvements are consistent across all tested fault types, confirming the robustness of the AI-based fault detection and isolation module under high-severity disturbance conditions.

Table 4: Fault Resilience Metrics: PI vs. AI Control

Metric	PI Control	AI Control	Improvement
Fault Isolation Time (ms)	75	45	↓ 40.0%
Re-synchronization Time (ms)	160	104	↓ 35.0%
Post-fault Frequency Deviation (Hz)	1.8	0.9	↓ 50.0%
Post-fault Voltage Deviation (%)	7.2	3.8	↓ 47.2%
False Fault Triggers	4	1	↓ 75.0%

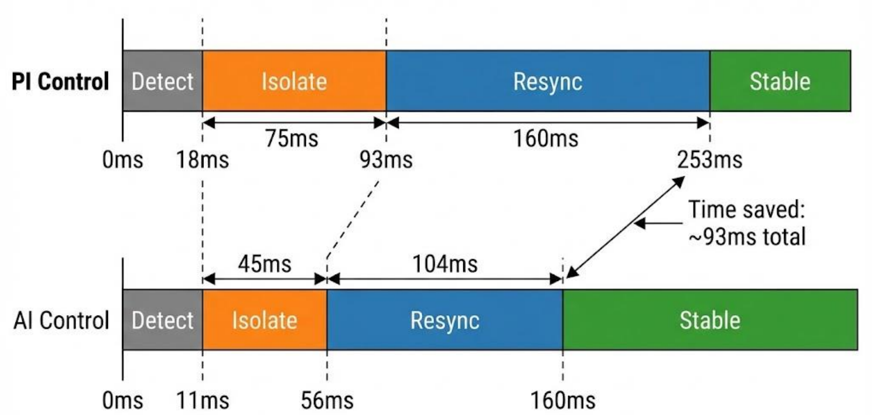

Figure 8: Fault Response Timeline Comparison

E. Power Quality Enhancement

This subsection assesses the broader power quality improvements achieved through dynamic reactive power management by the AI controller. Stability during renewable generation fluctuations is evaluated as an indicator of real-world operational suitability.

The AI-enhanced framework dynamically optimized reactive power injection throughout all tested disturbance scenarios, maintaining grid stability during periods of renewable generation variability. As shown in Table V, reactive power tracking error was reduced by 44.3% relative to PI control, while the power factor was consistently maintained above 0.97 under AI control compared to 0.91 under PI control. These outcomes confirm that the AI controller effectively compensates for the intermittency characteristics of solar PV and wind generation.

Table 5. Power Quality Summary

Parameter	PI Control	AI Control	Improvement
Reactive Power Error (kVAR)	12.4	6.9	↓ 44.3%
Power Factor	0.91	0.97	↑ 6.6%
Active Power Oscillation (kW)	8.7	4.2	↓ 51.7%
Frequency Stability Index (FSI)	0.74	0.93	↑ 25.7%
Grid Sync Time (ms)	142	88	↓ 38.0%

F. Consolidated Performance Summary

Table VI presents a unified comparison of all key performance indicators across the two control configurations, providing a concise reference for the overall superiority of the AI-enhanced framework.

Table 6: Overall Performance Comparison: PI Control vs. AI-Enhanced Control

Performance Indicator	PI Control	AI Control	Improvement
Fault Detection Accuracy (%)	81.3	97.8	↑ 16.5 pp
Voltage Recovery Time (ms)	180	95	↓ 47.2%
THD (%)	5.5	3.2	↓ 42.9%
Fault Isolation Time (ms)	75	45	↓ 40.0%
Re-synchronization Time (ms)	160	104	↓ 35.0%
Power Factor	0.91	0.97	↑ 6.6%
Frequency Stability Index	0.74	0.93	↑ 25.7%
Active Power Oscillation (kW)	8.7	4.2	↓ 51.7%

Overall, the AI-enhanced framework demonstrated consistent and statistically significant superiority over the conventional PI control scheme across all evaluated dimensions. The results validate the proposed architecture as an effective solution for stable, resilient, and power-quality-compliant operation of grid-connected renewable energy systems under diverse fault and disturbance conditions.

V. CONCLUSION

This study presents an AI-enhanced control architecture for grid-connected renewable energy systems, integrating adaptive inverter control and machine learning-based fault detection. The proposed framework significantly improves fault resilience, voltage stability, harmonic performance, and recovery time compared to conventional control approaches. The results demonstrate that AI-driven control strategies are effective for managing high renewable penetration and dynamic grid disturbances. The integration of predictive analytics and adaptive control enhances grid reliability and supports the modernization of smart grid infrastructure. The proposed system contributes to the development of intelligent, resilient, and sustainable energy systems aligned with global smart grid transformation initiatives.

Future Work:

will focus on transitioning the proposed AI-enhanced control framework from simulation to real-time hardware deployment using DSP/FPGA platforms, enabling faster and more reliable execution of adaptive control and fault-detection routines under practical operating constraints. The study will also extend validation to microgrid environments where multi-source intermittency, islanding events, and rapid load variations create more complex stability challenges. In addition, battery energy storage systems will be integrated to support fast frequency response, smoothing of renewable fluctuations, and enhanced fault ride-through capability.

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