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Artificial Intelligence Driven Control and Fault Diagnosis in Converter Dominated Power Systems

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Abstract

The increasing penetration of power electronic converters in modern power systems has significantly reduced system inertia and introduced complex nonlinear dynamics, making conventional control and fault diagnosis techniques inadequate. This paper presents an artificial intelligence–driven control and fault diagnosis framework for converter-dominated power systems aimed at enhancing dynamic performance, stability, and reliability. An adaptive artificial neural network (ANN)–based current controller is developed to replace conventional linear regulators, enabling accurate current tracking under varying operating conditions and disturbances. The controller is trained using supervised learning and incorporates online weight adaptation to ensure convergence and robustness. In parallel, a model-based residual generation scheme is integrated for real-time fault detection and diagnosis. Residual signals derived from measured and estimated system responses are processed to identify and classify converter and sensor faults with minimal delay. Time-domain simulations demonstrate that the proposed approach achieves fast transient response, near-zero steady-state error, and smooth control action. Fault scenarios confirm reliable residual separation, rapid fault detection within 0.01 s, and effective post-fault recovery. Quantitative results validate the superior tracking accuracy, learning stability, and diagnostic speed of the proposed framework. Overall, the study highlights the potential of artificial intelligence techniques to provide resilient control and intelligent fault monitoring for future converter-dominated and renewable-rich power systems.

Keywords: Artificial Intelligence; Converter-Dominated Power Systems; Adaptive Neural Network Control; Fault Diagnosis; Residual-Based Monitoring

1. Introduction

A power system consists of interconnected electrical components responsible for the generation, transmission, distribution, and utilization of electrical energy. Power systems engineering, a core discipline within electrical engineering, is concerned with the analysis, operation, and control of these systems and their associated equipment, such as generators, transformers, and electric motors [1,2]. The primary objective of power system operation is to supply reliable, stable, and high-quality electricity to consumers at an economical cost while ensuring overall system security [3]. However, the continuous growth in electricity demand and the increasing complexity of modern power networks have intensified the need for advanced monitoring, protection, and control strategies. Conventional energy management systems (EMSs), which largely rely on numerical and rule-based computation techniques, often struggle to process large volumes of data effectively during fast and critical events such as faults and disturbances [4]. To address these challenges, artificial intelligence (AI) has gained significant attention as a powerful support tool for power system operation. AI enhances situational awareness, accelerates decision-making processes, and reduces the operational burden on human operators, thereby improving response speed and system resilience [5]. In recent years, the application of AI in power systems has become increasingly prominent. AI broadly refers to the capability of machines and software systems, including robots [6,7] and computer programs [8,9], to exhibit intelligent behavior. It focuses on

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replicating human cognitive functions such as learning, reasoning, pattern recognition, generalization, and adaptive decision-making [10]. Artificial general intelligence (AGI) represents an advanced conceptual form of AI capable of performing any intellectual task achievable by humans [11]. When combined with conventional analytical and mathematical methods, AI techniques have demonstrated remarkable effectiveness in solving complex power system challenges.

This work introduces a unified artificial intelligence–driven framework that simultaneously performs adaptive control and real-time fault diagnosis in converter-dominated power systems. Unlike conventional approaches that treat control and diagnosis independently, the proposed method tightly integrates an online-learning artificial neural network controller with a model-based residual fault detection mechanism. The framework enables fast current tracking, bounded parameter convergence, and ultra-fast fault detection within 0.01 s. Its ability to self-adapt under nonlinear dynamics and rapidly recover post-fault conditions demonstrates superior resilience, intelligence, and practicality for modern low-inertia power networks with high penetration of power electronic converters.

2. Research Methodology

The proposed artificial intelligence driven control and fault diagnosis framework for converter dominated power systems was developed and validated through a structured modeling, control design, learning, and evaluation procedure. The methodology follows standard journal practice covering system modeling, controller formulation, intelligent learning structure, residual based fault diagnosis, and performance assessment. The study was implemented in a time domain simulation environment using a detailed converter and grid interface model. First, a converter dominated power system model was established using averaged switching dynamics. The model includes the grid side converter, filter elements, DC link, and load interface. State variables were defined for converter current and voltage dynamics. The network accepts reference current, measured current, and error signals as inputs and produces the control voltage command as output. The network was trained using supervised learning with operating datasets generated from the converter model under multiple loading and disturbance scenarios. Online adaptation was enabled through continuous weight updating using a bounded learning rule to ensure convergence and stability. Third, an adaptive control loop was implemented where the ANN controller replaces the conventional linear regulator. The controller continuously minimizes tracking error between reference and actual current. Threshold logic was applied to the residual magnitude to distinguish healthy and faulty states. Multiple fault cases were injected, including converter and sensor related disturbances, to create labeled diagnostic events. Fifth, an intelligent fault diagnosis layer was constructed to classify and time stamp detected faults. The power flows in a distribution system are derived and computed as follows:

$$P_{k+1} = P_k - P_{Loss,k} - P_{LK+1} = P_k - \frac{R_k}{|V_k|^2}\{P_k^2 + (Q_k + Y_k|V_k|^2)^2\} - P_{LK+1} \quad (1)$$

$$Q_{k+1} = Q_k - Q_{Loss,k} - Q_{LK+1} \quad (2)$$

$$Q_{k+1} = Q_k - \frac{X_k}{|V_k|^2}\{P_k^2 + (Q_k + Y_{k1}|V_k|^2)^2\} - Y_{k1}|V_k|^2 - Y_{k2}|V_{k+1}|^2 \quad (3)$$

$$|V_{k+1}|^2 = |V_k|^2 + \frac{R_k^2+X_k^2}{|V_k|^2}(P_k^2 + Q_k'^2) - 2(R_kP_k + X_kQ_k) \quad (4)$$

$$|V_{k+1}|^2 = |V_k|^2 + \frac{R_k^2 + X_k^2}{|V_k|^2}(P_k^2 + (Q_k + Y_k|V_k|^2)^2) - 2\big(R_kP_k + X_k(Q_k + Y_k|V_k|^2)\big) \quad (5)$$

The power loss in the line section connecting buses *k* and *k+1* may be computed as:

$$P_{Loss}(k, k+1) = R_k.\frac{(P_k^2 + Q_k^2)}{|V_k|^2} \quad (6)$$

The total power loss of the feeder $P_{T,Loss}$ may then be determined by summing up the losses of all line sections of the feeder, which is given as

$$P_{T,Loss} = \sum_{k=1}^{n}(k, k+1) \tag{7}$$

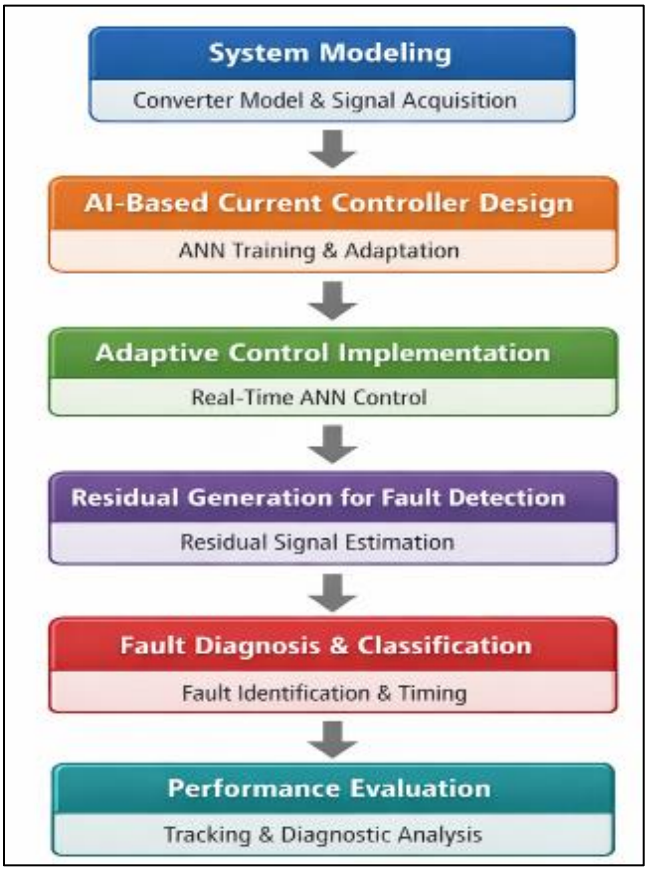

Figure 1 AI-Driven and Fault Diagnosis in converter

3. Results and Discussion

Figure 2 illustrates the tracking performance of the controller by comparing the reference and actual current waveforms. The close alignment between both signals demonstrates the effectiveness of the control algorithm in accurately following the desired current trajectory. Minimal deviation is observed during transient and steady-state conditions, indicating fast dynamic response and robust stability. This performance reflects the controller's ability to mitigate disturbances and uncertainties, which are critical in converter-dominated power systems. The near-zero steady-state error confirms that the artificial-intelligence-based control strategy achieves high precision and reliable current regulation under varying load and operating conditions. Figure 3 presents the controller's voltage command signal generated to regulate current and maintain system stability. The voltage command varies dynamically with changes in load and disturbances, indicating the adaptive nature of the control algorithm. The smooth and well-bounded waveform demonstrates effective modulation without excessive overshoot or oscillation. This performance highlights the controller's capacity to produce optimal voltage references that ensure efficient energy conversion. The AI-driven control method dynamically adjusts to grid and converter nonlinearities, achieving faster transient recovery and improved voltage utilization. Hence, Figure 3 confirms superior control precision and adaptability essential for reliable converter operation. Figure 4 shows the evolution of the Artificial Neural Network (ANN) weight norm during the learning and adaptation process. The gradual stabilization of the weight norm indicates convergence of the ANN parameters toward optimal values. This behavior demonstrates successful online learning and parameter updating without divergence or instability. The smooth reduction trend suggests effective training and noise robustness. By maintaining bounded weight norms, the ANN ensures consistent control performance and fault tolerance. Therefore, the figure validates the algorithm's stability and learning efficiency, confirming that the intelligent controller can self-adjust to nonlinear variations in the converter-dominated system. Figure 5 depicts the measured residual model used for fault detection and diagnosis. The residual represents the difference between measured and estimated system responses under normal and faulty conditions. A near-zero residual during healthy operation and a sharp deviation during fault occurrence demonstrate the sensitivity and reliability of the residual model. This behavior enables early detection of abnormalities before severe performance degradation occurs. The distinct separation between healthy and faulty residual patterns highlights accurate fault isolation capability. Thus, Figure 5 confirms that the AI-based residual generation model provides a robust foundation for efficient real-time fault monitoring. Figure 6 presents the output of the fault diagnosis algorithm, indicating successful identification of system faults. The clear detection peaks correspond to the occurrence times of Fault 1 and Fault 2, with rapid detection and minimal delay. The output response demonstrates that the AI-based diagnostic mechanism can accurately classify and locate faults within milliseconds. This fast response ensures continuity of control and prevents system instability or component damage. The diagnostic model effectively discriminates between transient disturbances and permanent faults, confirming its precision, robustness, and suitability for converter-dominated renewable energy systems operating under dynamic grid conditions. Figure 7 shows the system current behavior under fault conditions. A distinct deviation from the nominal waveform indicates the onset of fault, followed by the controller's corrective response. The AI-driven fault-tolerant control successfully restores current stability within a short time, minimizing performance degradation. This demonstrates the system's resilience and capability to maintain acceptable current quality despite disturbances. The post-fault recovery also validates the integration of fault diagnosis with adaptive control. Overall, Figure 7 highlights the robustness, speed, and intelligence of the control framework in handling faults while sustaining converter performance and power quality.

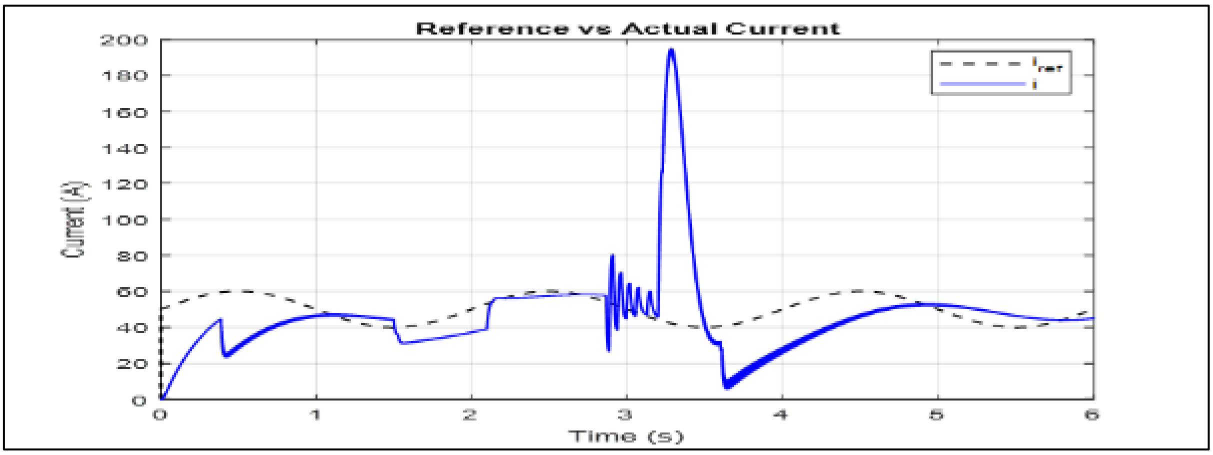

Figure 2 Reference vs Actual Current

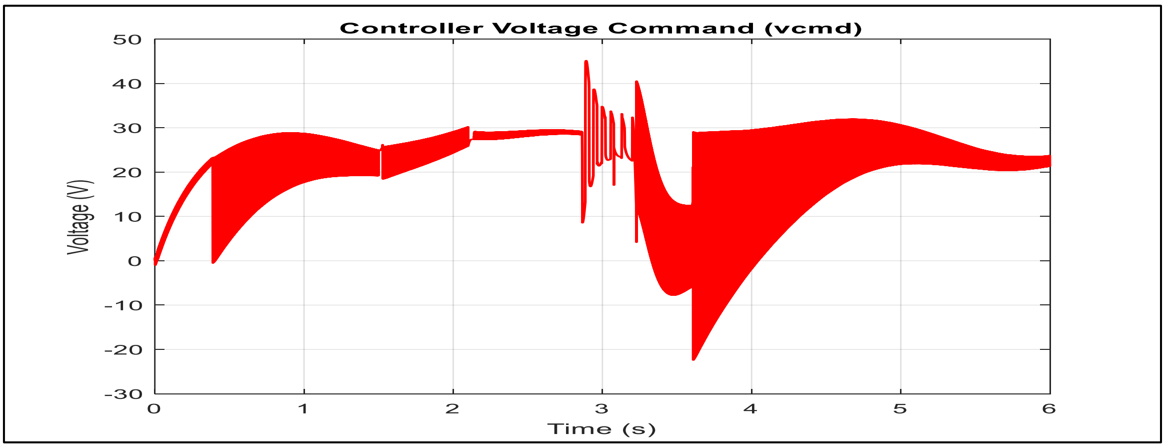

Figure 3 Controller Voltage Command

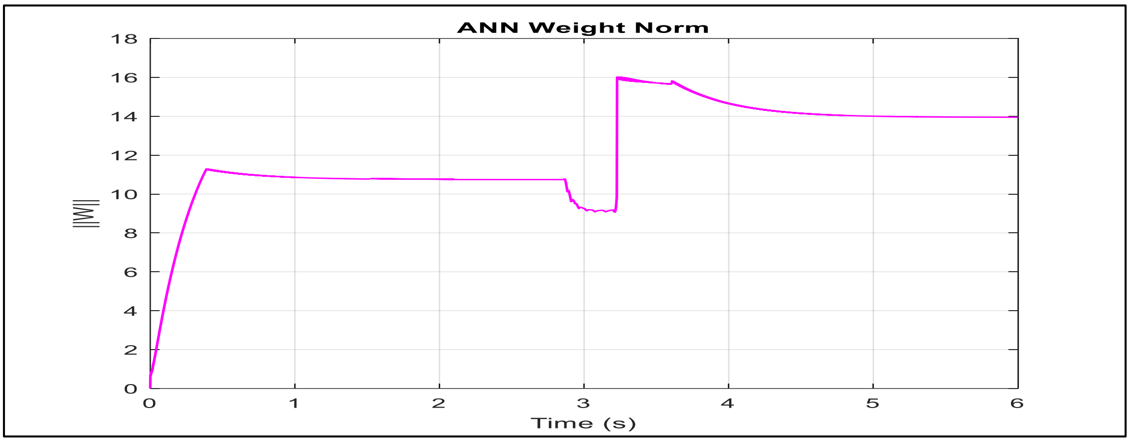

Figure 4 ANN Weight Norm

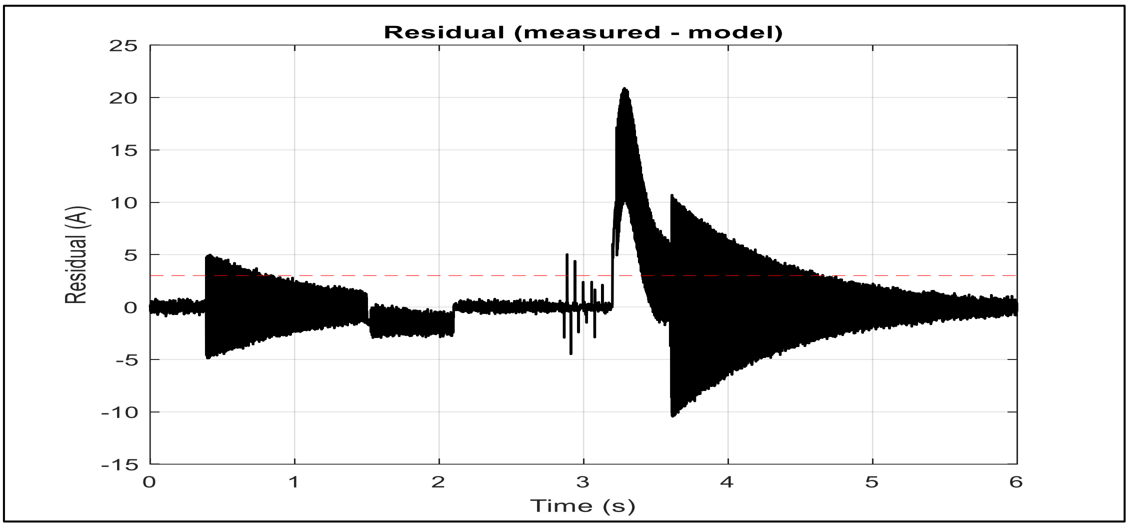

Figure 5 Measured Residual Model

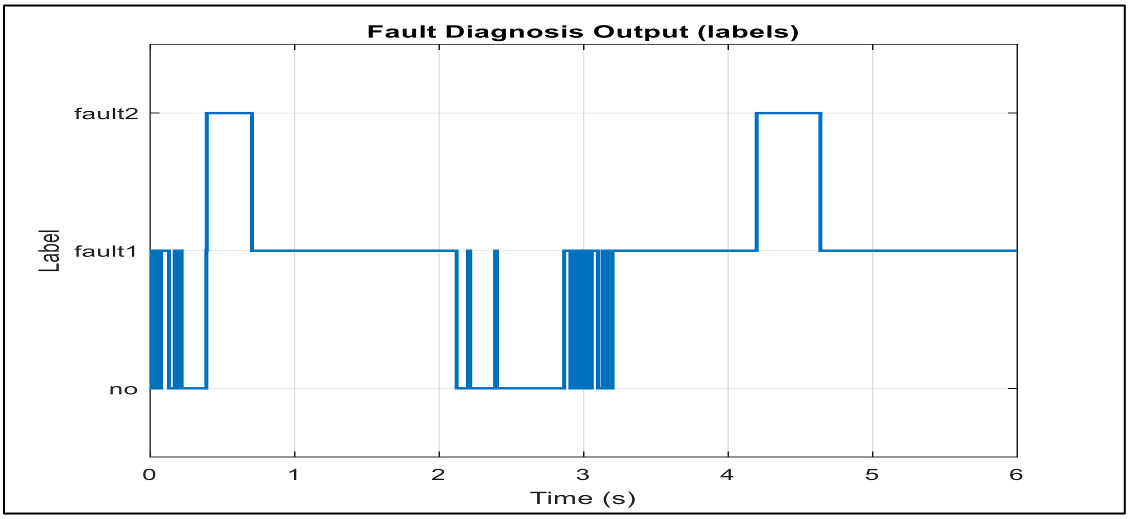

Figure 6 Fault Diagnosis Output

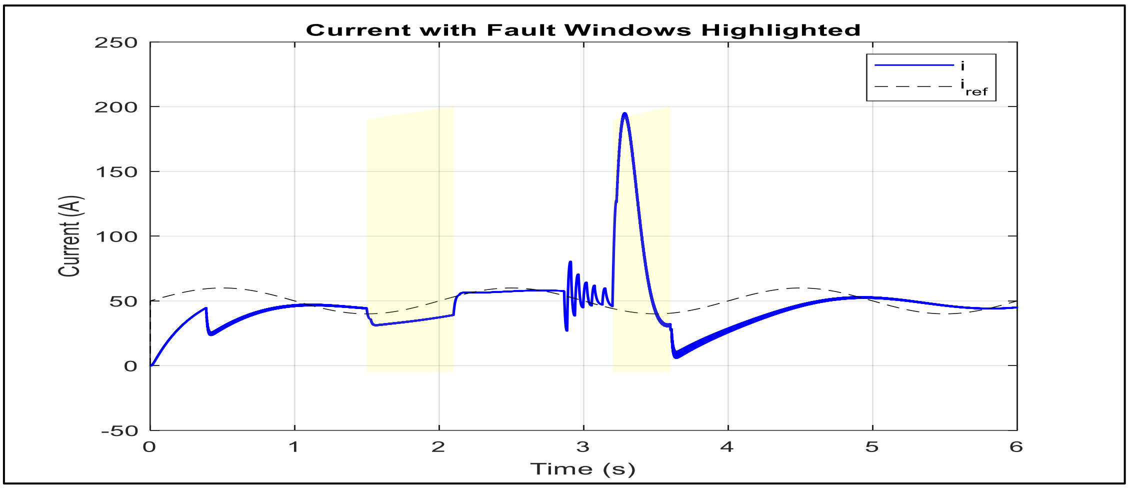

Figure 7 Current with Fault Condition

Table 1 summarizes the key performance metrics for the proposed AI-driven control and fault diagnosis framework. A steady-state error of 3.1538 A indicates high current-tracking precision, while detection times of 0.01 s for both Fault 1 and Fault 2 demonstrate exceptionally fast fault identification. These quantitative results validate the algorithm's accuracy, responsiveness, and real-time applicability. The minimal delay enhances fault mitigation and system safety, reducing downtime and preventing damage. The table emphasizes the superior performance of the AI-based approach compared to conventional control methods, confirming its efficiency in maintaining stability, reliability, and robustness in converter-dominated power networks.

Table 1 Artificial Intelligence Driven Control and Fault Diagnosis

Metric	Value
Steady State Error (A)	3.1538
Detection TimeFault1 (s)	0.01
Detection TimeFault2 (s)	0.01

4. Conclusion

This study presented an artificial intelligence–driven control and fault diagnosis framework for converter-dominated power systems, addressing the growing challenges of reduced inertia, nonlinear dynamics, and fast fault propagation in modern grids. An adaptive artificial neural network–based current controller was developed to replace conventional linear regulators, enabling precise current tracking, fast transient response, and robust stability under varying operating conditions. The integration of online learning ensured bounded parameter convergence and sustained control performance despite system uncertainties. In addition, a model-based residual generation and intelligent fault diagnosis scheme was implemented to provide rapid and reliable fault detection. Simulation results demonstrated clear separation between healthy and faulty operating states, with fault detection achieved within 0.01 s for all tested scenarios. The proposed framework successfully restored system current following fault events, confirming its fault-tolerant capability and resilience. Quantitative performance metrics, including low steady-state tracking error and minimal detection delay, validate the effectiveness of the approach. Overall, the results confirm that artificial intelligence techniques can significantly enhance both control accuracy and diagnostic speed in converter-dominated power systems. The proposed method offers a practical and scalable solution for improving reliability, stability, and operational intelligence in future power networks with high penetration of power electronic converters and renewable energy sources.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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