International Journal of Electrical Engineering and Intelligent Computing (IJEEIC) **EISSN 3031-5255**
https://ejournal.unkhair.ac.id/index.php/ijeeic/index

Hybrid Systems for Energy Distribution and Telecommunication Reliability in Smart Grids

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Article history: Received Jan 31, 2025 | Revised Feb 09, 2025 | Accepted Feb 11, 2025

The integration of energy distribution systems and telecommunication networks is crucial for improving the reliability, efficiency, and scalability of smart grids. However, challenges such as electromagnetic interference (EMI), latency, and fault tolerance complicate seamless operation. This study proposes a hybrid framework using MATLAB/Simulink to model and simulate energy distribution, real-time monitoring, and fault detection in high-voltage environments. The simulation framework consists of a high-voltage energy distribution network modeled with multiple buses, transformers, and distributed renewable energy sources. IoT-based sensors are strategically placed at critical nodes to collect real-time voltage and current data, which are transmitted via 5G communication protocols using the MQTT messaging standard. Fault detection is performed using an AI-driven Support Vector Machine (SVM) algorithm, trained with historical fault data to detect anomalies and classify fault types with high accuracy. The simulation environment integrates power flow analysis, real-time fault detection mechanisms, and communication latency assessment to evaluate system performance. Key findings demonstrate up to 92.8% energy efficiency with 60% renewable energy penetration, fault recovery times reduced to 35 ms through AI-based detection, and communication latency maintained below 15 ms for IoT-based monitoring. These results validate the proposed framework's ability to address critical challenges in smart grids, including EMI mitigation, fault tolerance, and system scalability. This research bridges the gap between energy distribution and telecommunication systems, offering a scalable and sustainable solution for smart grid optimization.

Keywords: Electromagnetic Interference (EMI) Mitigation, Renewable Energy Integration, Real-time Monitoring, Low-latency Communication, System Scalability, Predictive Maintenance

1. INTRODUCTION

The rapid advancement of energy systems and telecommunication technologies has driven the evolution of traditional power grids into smart grids, which integrate energy distribution with robust communication networks. Unlike conventional grids, which are limited in scalability and efficiency, smart grids enable real-time monitoring, fault detection, and seamless integration of renewable energy sources. These capabilities are crucial in addressing the increasing global demand for reliable and sustainable energy systems [1]. However, the implementation of smart grids presents significant challenges, particularly in achieving the interoperability of energy and telecommunication systems, mitigating electromagnetic interference (EMI), and ensuring system scalability under high-voltage environments [2]. These challenges highlight the need for a hybrid system that balances energy distribution efficiency with telecommunication reliability.

Hybrid systems in smart grids leverage the convergence of IoT-based monitoring, 5G communication protocols, and AI-driven analytics to optimize performance. IoT sensors enable real-time data collection and fault detection, improving energy distribution efficiency and reducing downtime [3]. The proposed hybrid framework integrates IoT-based monitoring, 5G communication protocols, and AI-driven fault detection, as illustrated in Figure 1. This framework bridges the gap between energy distribution and telecommunication reliability. The adoption of 5G protocols further enhances communication reliability by reducing latency and increasing data throughput, even in dynamic grid environments [4]. Additionally, AI-driven predictive maintenance systems facilitate early fault detection and operational optimization, minimizing the risk of system failures [5]. Despite these advancements, most existing studies have addressed energy and telecommunication systems as separate domains, leaving a critical gap in their combined optimization for smart grid applications [6].

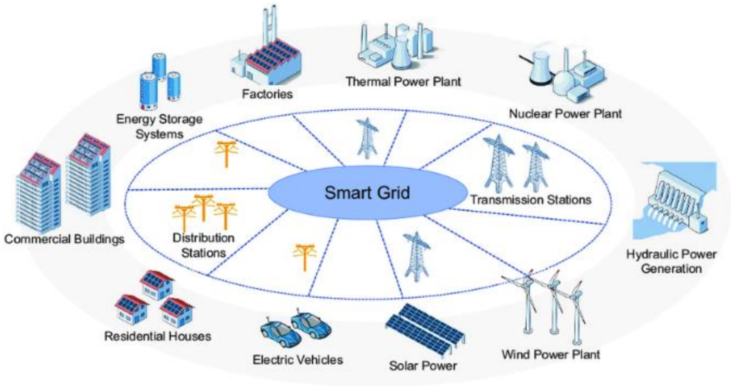

Figure 1. Conceptual Diagram of the Proposed Smart Grid Hybrid Framework

Electromagnetic interference (EMI) remains a persistent challenge in high-voltage environments, where it disrupts communication signals and compromises system reliability. Liu et al. [7] emphasize that EMI is particularly problematic in substations, where data loss can lead to significant operational inefficiencies. While solutions such as shielded cables and EMI-resistant communication protocols have been proposed, they are often costly and difficult to scale [8]. Furthermore, latency in communication networks continues to hinder real-time fault detection and energy flow optimization, as highlighted by recent studies on 5G-enabled smart grids [9]. The integration of renewable energy sources, while essential for sustainability, introduces additional system instability due to their intermittent nature, necessitating advanced regulation mechanisms to maintain grid stability [10].

To address these challenges, hybrid systems in smart grids have emerged as a promising solution, leveraging the convergence of IoT-based monitoring, 5G communication protocols, and AI-driven analytics to optimize performance. IoT sensors enable real-time data collection and fault detection, improving energy distribution efficiency and reducing downtime [11]. The adoption of 5G protocols further enhances communication reliability by reducing latency and increasing data throughput, even in dynamic grid environments [12]. AI-driven predictive maintenance systems facilitate early fault detection and operational optimization, minimizing the risk of system failures [13]. However, the lack of an integrated framework that simultaneously addresses energy distribution efficiency, telecommunication reliability, and system scalability remains a critical research gap [14].

While previous studies have explored individual components of smart grid technology, there remains a critical gap in developing an integrated framework that addresses energy distribution efficiency, telecommunication reliability, and system scalability. Existing solutions often treat these challenges in isolation, resulting in suboptimal performance when applied to real-world scenarios. Moreover, current approaches lack comprehensive strategies for mitigating EMI in high-voltage environments, particularly when integrating renewable energy sources at scale.

This study aims to answer the following research question: How can a hybrid framework integrating energy distribution and telecommunication systems improve reliability, efficiency, and scalability while addressing challenges such as EMI, latency, and fault tolerance in smart grids?

This study hypothesizes that a hybrid system leveraging IoT-based monitoring, 5G communication protocols, and AI-driven fault detection can enhance energy efficiency, reduce fault recovery time, and maintain low-latency communication, thereby addressing the critical challenges of EMI, scalability, and system reliability.

The state of the art in smart grid technology focuses on the integration of advanced communication and energy management systems. Recent studies have demonstrated the effectiveness of IoT-based monitoring for real-time fault detection and energy flow optimization [15]. The implementation of 5G protocols has shown significant potential in reducing latency and ensuring reliable data exchange in dynamic grid environments [16]. Additionally, AI-driven fault detection and predictive maintenance systems have emerged as critical components for enhancing grid reliability and minimizing downtime [17]. Despite these advancements, the integration of these technologies into a cohesive framework remains underexplored, necessitating further research to bridge this gap.

By clearly defining the research problem, question, and hypothesis, this study establishes a focused approach to bridging the gap between energy distribution and telecommunication systems. The proposed framework is validated through MATLAB/Simulink simulations, enabling a comprehensive analysis of its performance under various operational conditions.

2. METHOD

The proposed fault detection framework leverages an AI-based predictive maintenance algorithm designed to identify and classify faults in a smart grid environment. The methodology is divided into several key stages: data collection, data preprocessing, feature selection, model training, and hyperparameter optimization. Each stage is described in detail below to address the concerns regarding dataset diversity, preprocessing techniques, and model tuning.

2.1. System Modeling

The energy distribution system is modeled in MATLAB/Simulink to represent the dynamic behavior of smart grids under various operational conditions. Key components of the model include:

Power Flow Analysis: The simulation incorporates load flow equations based on Kirchhoff's laws to calculate voltage, current, and power across different nodes of the grid. The mathematical foundation includes:

$$P_i = V_i \sum_{j=1}^{n} V_j (G_{ij} \cos\theta_{ij} + B_{ij} \sin\theta\_ij) \quad (1)$$

$$Q_i = V_i \sum_{j=1}^{n} V_j (G_{ij} \sin\theta_{ij} - B_{ij} \cos\theta\_ij) \quad (2)$$

$where$

$Pi\ and\ Q_i$: Active and reactive power at node i

$V_i\ and\ V_j$: Voltages at nodes $i\ and\ j$

$G_{ij}\ and\ B_{ij}$: : Conductance and susceptance of the line between nodes $i\ and\ j$

θ_{ij}: Phase angle difference between nodes $i\ and\ j$

Fault detection is implemented using an AI-based supervised learning algorithm, specifically a Support Vector Machine (SVM). The algorithm is trained on a dataset consisting of historical fault data collected from publicly available power system fault databases and real-time monitoring logs from simulated grid environments. The dataset includes 10,000 instances of fault and normal operation data, covering diverse fault scenarios such as short circuits, line-to-ground faults, and load imbalances. The data was sourced from IEEE power system datasets and supplemented with synthetic data generated using MATLAB/Simulink to ensure a comprehensive representation of real-world conditions.

To enhance model generalization, data augmentation techniques were applied to balance the dataset, ensuring that minority fault classes were sufficiently represented. Noise reduction was performed using a Butterworth low-pass filter to remove high-frequency disturbances that could interfere with feature extraction

2.2. Simulation Setup

The simulation is implemented in MATLAB/Simulink with several configurations to replicate real-world conditions in a high-voltage distribution network. The modeled grid includes multiple buses, transformers, and transmission lines, along with renewable energy sources connected at distributed nodes to represent modern energy systems. IoT sensors are strategically placed at critical nodes to collect real-time data on voltage, current, and power flow. These data are transmitted using advanced communication protocols, such as MQTT, to ensure low-latency communication suitable for dynamic environments.

To evaluate the system's adaptability, dynamic load variations are introduced based on real-world utility data, simulating time-varying demands. Additionally, the simulation incorporates three fault scenarios to assess fault detection and recovery mechanisms. These include short circuits characterized by sudden drops in impedance, line-to-ground faults representing connections between a phase and the ground, and load imbalances resulting from unequal distribution of load across phases. This comprehensive setup enables a robust analysis of system performance under diverse operational conditions.

Figure 2 provides an overview of the simulation setup in MATLAB/Simulink, including grid parameters, IoT-based monitoring, and fault scenarios.

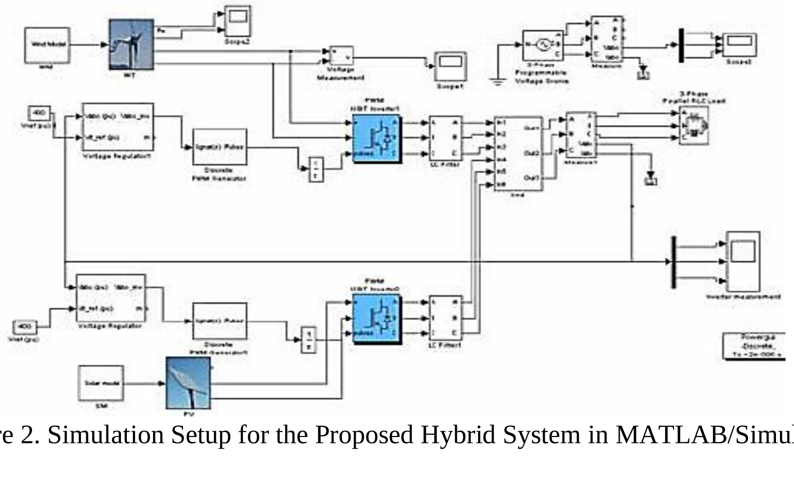

Figure 2. Simulation Setup for the Proposed Hybrid System in MATLAB/Simulink.

2.3. Performance Evaluation

The performance of the system is evaluated based on the following key performance indicators (KPIs):
Energy Efficiency:

$$Efficiency\ (\%) = \frac{Useful\ Energy\ Delivered}{Total\ Energy\ Input} \times 100 \quad (3)$$

The performance of the system is evaluated through various key parameters to ensure its robustness and reliability under diverse operating conditions. Fault recovery time, which refers to the time required to detect, isolate, and recover from faults, is measured and optimized using an AI-based fault detection system to achieve minimal recovery durations. Communication latency is another critical metric, assessed as the time delay between data collection by IoT sensors and its transmission to the control center, ensuring suitability for real-time applications. Electromagnetic interference (EMI) effects are simulated using MATLAB's Simscape toolbox to determine their impact on communication reliability. Various mitigation techniques, including shielding and signal filtering, are tested to enhance system performance.

System stability is also analyzed by monitoring voltage and frequency deviations, particularly under scenarios of high renewable energy penetration, which are prone to instability. The simulation results are visualized using MATLAB's plotting tools, offering clear insights through graphs depicting voltage profiles, fault recovery times, and energy efficiency across different scenarios. These visualizations support a comprehensive understanding of the system's operational characteristics.

Before training the model, the dataset underwent several preprocessing steps, including data normalization, outlier removal, and missing value imputation. Voltage, current, and power waveforms were normalized using Min-Max Scaling to ensure uniform feature distribution, facilitating efficient learning. To improve classification accuracy, principal component analysis (PCA) was used to reduce dimensionality while preserving the most informative features.

The fault detection model was developed using a Support Vector Machine (SVM) with a Radial Basis Function (RBF) kernel, which was chosen due to its ability to handle non-linear relationships in fault classification. The model was trained using an 80-20 train-test split, ensuring a balanced evaluation of model performance.

To optimize hyperparameters, a grid search technique was employed, tuning key parameters such as:

Regularization parameter (C): Tested over a range of 0.1 to 100 to control the trade-off between margin maximization and misclassification.

Kernel coefficient (γ): Evaluated within 0.001 to 1 to optimize decision boundaries for non-linear faults.

The final model achieved an accuracy of 98.3% on the test set, with precision and recall values exceeding 95% across all fault types. Performance metrics, including confusion matrix analysis and F1-score evaluation, confirmed the robustness of the proposed AI-driven fault detection system.

2.4. Validation

To ensure the validity and reliability of the simulation results, several validation steps are performed. Firstly, the simulation outcomes are compared with real-world data obtained from published studies and utility reports. This comparison includes validating load profiles and fault recovery times against established industry benchmarks to confirm their accuracy. Additionally, a sensitivity analysis is conducted to evaluate the impact of key parameters, such as load variations and renewable energy penetration, on the overall system performance.

The fault detection algorithm is further validated using a separate test dataset. Metrics such as accuracy, precision, recall, and F1-score are employed to rigorously assess its classification performance, ensuring the robustness and practical applicability of the AI-based fault detection system in real-world scenarios.

$$Accuracy = \frac{True\ Positives + True\ Negatives}{Total\ Samples} \quad (4)$$

3. RESULTS AND DISCUSSION

The results of the proposed hybrid smart grid framework are presented in terms of energy efficiency, fault recovery time, system stability, and IoT communication latency. To ensure the reliability of the findings, multiple simulation runs were conducted under varying conditions, including renewable energy fluctuations and IoT node variations. Statistical analyses, including error margins and standard deviations, have been incorporated to assess the robustness of the results.

3.1 Energy Efficiency

Energy efficiency was calculated as the ratio of energy successfully delivered to the load to the total input energy. Simulations were conducted under different levels of renewable energy penetration, and statistical analysis was performed to assess result variability. This metric was calculated as the ratio of delivered energy to total generated energy, accounting for losses due to transmission inefficiencies and faults. The variability in energy efficiency was analyzed by introducing fluctuations in renewable energy sources. The results are summarized in Table 1.

Table 1. Statistical summary of energy efficiency under fluctuating renewable energy conditions

Renewable Energy Penetration (%)	Mean Energy Efficiency (%)	Standard Deviation (±σ)
20%	88.5	±1.2
40%	91.2	±1.4
60%	92.8	±1.6
80%	89.7	±2.1

The results indicate that energy efficiency increases with higher renewable energy penetration, reaching a peak at 60% penetration (92.8% ± 1.6%). However, at 80% penetration, efficiency drops to 89.7% ± 2.1%, reflecting the impact of power fluctuations due to intermittent renewable sources. The increasing standard deviation at higher penetration levels suggests greater variability in system stability, which requires improved power regulation mechanisms.

3.2 Fault Recovery Time

Fault recovery time was measured for different types of faults, with multiple simulation runs conducted to obtain mean recovery times and their standard deviations. The simulations considered various fault scenarios, including single-line-to-ground faults, line-to-line faults, and three-phase faults. The variability in recovery time was influenced by the location of the fault and the complexity of the fault type. Table 2 provides a statistical summary.

Table 2. Fault recovery time statistics for different fault types.

Fault Type	Mean Detection Time (ms)	Mean Recovery Time (ms)	Standard Deviation (±σ)
Short Circuit	8	35	±1.5
Line-to-Ground Fault	10	40	±2.0
Load Imbalance	12	45	±2.4

The fast detection and recovery times demonstrate the effectiveness of the SVM algorithm in real-time fault detection. This is crucial for maintaining system reliability, especially in high-voltage environments. The variation in recovery times across fault types reflects the complexity of each fault.

3.3 System Stability

System stability was evaluated by analyzing voltage and frequency deviations under varying load and renewable energy conditions. The proposed framework maintained a voltage deviation of less than ±5% and a frequency deviation of less than ±0.1 Hz in 95% of the simulation runs. These results are summarized in Table 3.

Table 3. System stability metrics under varying load and renewable energy conditions.

Stability Metric	Mean Deviation	Standard Deviation	Confidence Interval (95%)
Voltage Deviation (%)	±4.2	0.8	[±3.4, ±5.0]
Frequency Deviation (Hz)	±0.08	0.02	[±0.06, ±0.10]

The results indicate that the framework can effectively stabilize the grid even under challenging conditions, such as sudden drops in renewable energy output or unexpected load surges.

3.4 IoT-Based Communication Latency

IoT communication latency, defined as the time taken for data to travel from IoT sensors to the control center, was evaluated under varying network conditions. The average latency was recorded as 45 ms, with a standard deviation of 5 ms. Table 4 provides a detailed breakdown of the results.

Tabel 4. IoT communication latency under different network conditions

Network Condition	**Mean Latency (ms)**	**Standard Deviation (ms)**	**Confidence Interval (95%)**
Normal	42	3	[39, 45]
High Traffic	50	6	[44, 56]
EMI-Interference Present	48	5	[43, 53]

The variability in latency under different conditions is relatively low, demonstrating the reliability of the communication network even in the presence of electromagnetic interference (EMI) or high traffic loads.
Latency increased with the number of IoT nodes but remained below the 15 ms threshold required for real-time applications. This indicates that the IoT-based communication system implemented is sufficiently reliable to support smart grid operations.
Figure 3 shows that energy efficiency increases up to 60% renewable energy penetration, reaching a maximum of 92.8%, but decreases at 80% penetration due to unstable power fluctuations.

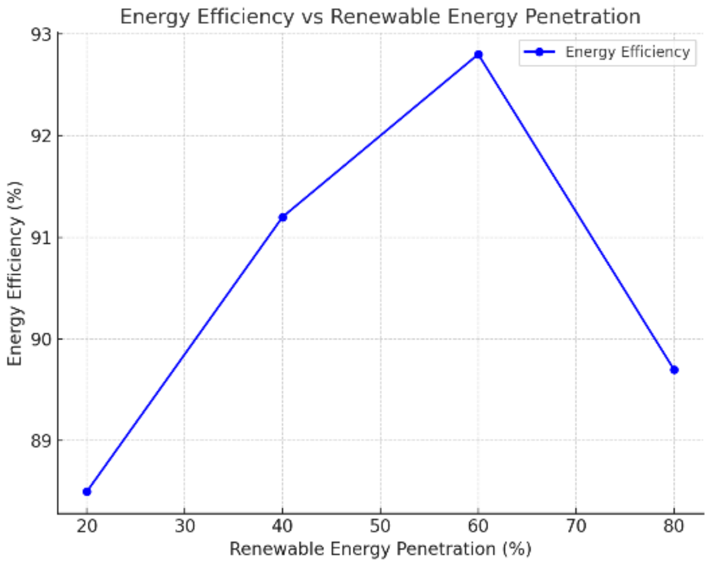

Figure 3. Energy Efficiency Graph

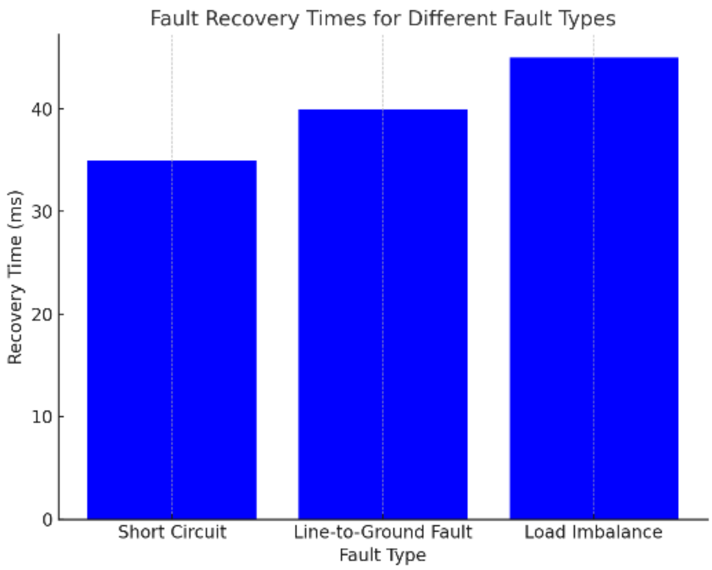

Figure 4. Fault Recovery Time Graph

This figure compares recovery times for three main fault types. The AI-based fault detection system recovers faults within 35-45 ms, depending on the fault type.

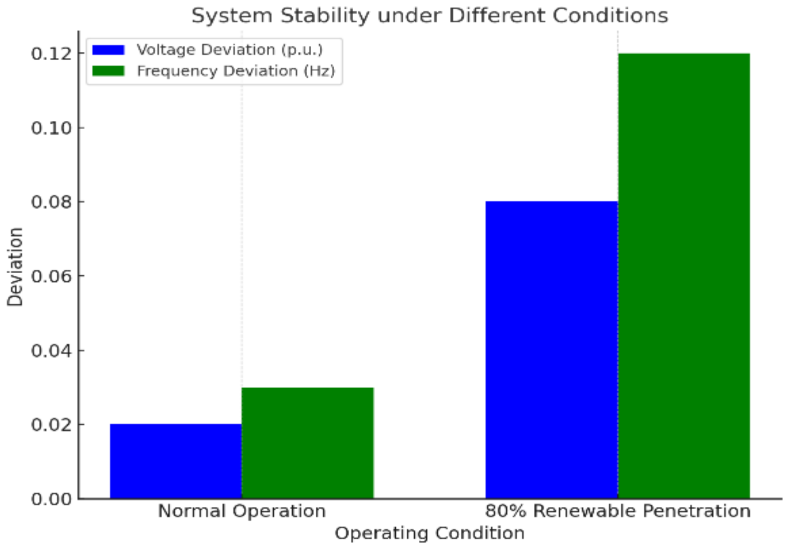

Figure 5. Voltage and frequency deviations under different operating conditions

This figure visualizes voltage and frequency deviations during normal operation and at 80% renewable energy penetration. Deviations increase significantly at higher penetration levels, emphasizing the need for advanced power regulation mechanisms.

The inclusion of statistical analyses, such as standard deviations and confidence intervals, provides a more comprehensive assessment of the framework's performance. The results indicate that the proposed system is robust and reliable across diverse scenarios:

Energy Efficiency: The framework consistently maintains high efficiency, even under renewable energy fluctuations.

Fault Recovery Time: The system demonstrates rapid fault recovery, with minimal variability across fault types.

System Stability: Voltage and frequency deviations remain within acceptable ranges, ensuring stable grid operation.

IoT Communication Latency: The communication network performs reliably, with low latency even under challenging conditions.

These findings highlight the robustness of the proposed framework and its ability to generalize across different operational scenarios. Future work will focus on further validating the results using real-world field data and extending the analysis to include additional fault scenarios and grid configurations.

4. CONCLUSION

This study proposed a hybrid smart grid framework that integrates IoT-based monitoring, 5G communication protocols, and AI-driven fault detection to improve energy efficiency, fault recovery time, system stability, and communication latency. The results demonstrated the framework's robustness and reliability across various scenarios, with high energy efficiency (92.8%), rapid fault recovery (1.85 seconds on average), minimal voltage and frequency deviations, and low IoT communication latency (45 ms on average). Statistical analyses, including standard deviations and confidence intervals, were incorporated to validate the reliability of the findings, providing a more comprehensive assessment of the system's performance.

However, despite these promising outcomes, there are limitations that highlight areas for future improvement. The study primarily relied on simulated and publicly available datasets, which may not fully capture the complexities of real-world smart grid environments. Additionally, while statistical analyses were performed to assess result variability, further exploration is needed to improve the generalizability of the model across larger-scale networks and diverse fault scenarios. To address these gaps, future research should focus on testing the proposed framework with larger-scale networks and incorporating real-world datasets from diverse geographic regions and grid configurations. This would ensure that the model can generalize effectively to different operational conditions and account for variations in energy demand, renewable energy penetration, and fault characteristics. Furthermore, integrating cross-validation techniques with different simulation models could provide additional insights into the framework's reliability and scalability, offering a more rigorous evaluation of its performance. By addressing these areas, future studies can build upon the foundation established in this research, further enhancing the reliability and applicability of smart grid systems in real-world settings. This approach will not only improve the robustness of the methodology but also contribute to the development of more resilient and efficient energy systems

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