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ENHANCED FAULT DETECTION TECHNIQUES FOR SMART GRIDS UNDER VARIABLE RENEWABLE GENERATION

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Abstract

Smart grids are becoming more dependent on renewable energy sources such as solar and wind power. However, the unstable and fluctuating nature of renewable energy creates serious challenges for accurate fault detection. Variations in voltage, current, frequency, and power flow can sometimes appear similar to fault conditions, which may increase false alarms or delay fault identification. This paper focuses on enhancing fault detection in smart grids under fluctuating renewable energy supply by using intelligent monitoring and data-based fault analysis. The study evaluates fault detection performance under different renewable penetration levels and changing operating conditions. The results indicate that the proposed fault detection approach improves detection accuracy, reduces false alarm rates, and maintains strong performance during renewable power fluctuations. The findings also show improved response time, better classification of fault types, and increased robustness against noise. Overall, the study demonstrates that intelligent fault detection can improve smart grid reliability, reduce power interruptions, and support safer integration of renewable energy into modern power systems.

Keywords: Smart grid; fault detection; renewable energy; power fluctuation; grid reliability

INTRODUCTION

The adoption of renewable energy sources in today's power systems has added a new layer of complexity to the system, with intermittent power generation and bidirectional power flows (Wang et al., 2025).The resulting fast dynamics and non-linear power injections change the traditional fault signatures, and require more advanced monitoring and protection methods. In a carbon neutral world, penetration and deployment of variable renewable energy (VRE) sources and inverter based resources (IBR) is playing a significant role in affecting the distribution networks, which are becoming highly dynamic and decentralized due to the reversal of the power flow from the traditional distribution to generators (Senapati et al., 2025; Telukunta et al., 2017; Wang et al., 2025). This paradigm shift poses a dilemma to conventional protection systems which are generally developed to meet the requirements of traditional systems with one way communication, uni-directional generation and large power generation units (Cruz et al., 2024; Shih et al., 2017; Singh, 2017). Specifically, the short circuit characteristics of IBRs differ from those of physical inertia, and the control system determines the characteristics of IBRs, which may exacerbate the sensitivity, sympathetic tripping and severe coordination loss between the primary and secondary protection functions (Aboelnaga & Azzouz, 2026; Baeckeland et al., 2024; Paolone et al., 2020; Quispe & Orduña, 2022). Moreover, the absence of traditional quantities in inverter-interfaced systems, like the zero sequence component, complicates fault identification and location, and classic methodologies of directional overcurrent or classic methodology with impedance-based relaying don't work very well in high penetration systems (Haddadi et al., 2021; Aboelnaga & Azzouz, 2026; Paolone et al., 2020; Shahzad et al., 2017). While many adaptive protection techniques are reported in the literature, ranging from communication-aided protection techniques to advanced signal processing techniques, these techniques have different limitations, such as computational efficiency, data availability, field testing and lack of model interpretability, which are crucial to enable robust real-time decisions. (Cao et al., 2024; Li et al., 2024; Rezapour et al., 2023; Senapati et al., 2025; Telukunta et al., 2017). Developing intelligent and resilient fault diagnosis frameworks that can handle high uncertainty, noise interference, and different transition resistances, while also seamlessly integrating with the existing utility infrastructure remains an open field of research (Jain et al., 2022; Li et al., 2024; Senapati et al., 2025; Wang et al., 2025). These challenges require a transformation in the approach to protection methods, towards advanced data-driven methods like artificial intelligence and machine learning, capable of integrating multi-agent coordination with explainable reasoning, to better meet the requirements of modern, inverter-driven power systems, while also overcoming the limitations of conventional protection (Cao et al., 2024; Li et al., 2024; Rezapour et al., 2023; Senapati et al., 2025; Wang et al., 2025). To overcome these disadvantages, the research in this paper seeks to create a comprehensive fault detection system that resolves the issues of sensitivity that occur using deterministic algorithms as outlined by Kovaļenko et al. (2025) and Oelhaf et al. (2025). This framework will be specifically targeted at the issues arising from the intermitted generation of renewable energy, creating transient fault conditions and issues in discerning whether the condition is a fault or just normal operational variation. Time and real-time feature extraction combined with temporal pattern recognition can compensate the performance degrading drawback of the static models which are exposed to non-linear, dynamic and data-rich behaviors of the grid (Islam, 2026). It is proposed to include such features in the proposed model to enhance accuracy of the proposed diagnostic model of the power system under different generation patterns, with the main purpose of making the power system robust from the variations of the inverter-based power injection (Kouraichi et al., 2025). In the present paper, therefore, an architecture which is feature selective and computationally efficient is proposed to effectively differentiate the fault signature in high dimensional and noisy data streams and provide diagnostic reliability (Zaben et al., 2024). Moreover, this study is a missing link in the interpretability of deep learning models and scalability of the deployment of deep learning models especially in critical power infrastructure (CI) (Akhtar et al., 2023; Razick & Musilek, 2026).

METHODOLOGY

The architecture proposed in the paper is a multi-stage architecture consisting of adaptive feature extraction and hidden layers of LSTM networks for modelling temporal dynamics of renewable energy sources.The proposed architecture consists of several stages, such as adaptive feature extraction and modeling the temporal dynamics of renewable energy sources (Le et al., 2024) using LSTM networks.In detail, a multi-channel voltage and current signal convolutional neural network is used to capture the significant spatial information in the multi-channel voltage and current signals and the spatial information acquired is input into LSTM layers for identification of the transient fault dynamics. The methodology starts with the creation of a comprehensive data set by performing high fidelity electromagnetic transient simulations on a 33-bus radial distribution system (IEEE 33-bus system) with the addition of high penetrations of photovoltaic and wind-based distributed energy resources (DERs) (Li et al., 2024). The simulations include a number of scenarios to consider, including different levels of renewables penetration (from 10% to 90% renewables penetration), different fault types (symmetrical and asymmetrical), different transition resistances (between 0.1 Ω and 100 Ω), and various fault inception angles (FIAs) to consider the stochastic nature of inverter-based power injections (IBPIs) (Li et al., 2024; Oelhaf et al., 2025).The three-phase voltage and current signals are sampled at significant points during data acquisition at high sampling frequency of 15.36kHz to enable high frequency transients to be captured and consequently its characteristics. In this method, the feature inputs are scaled to a range using the Min-Max technique, and then sent to the network to be converted to the raw waveforms, to ensure that voltage and current are closer.The Min-Max technique preprocesses the inputs to features between a range such that voltage and current are made closer to each other before the raw waveforms are fed to the network. A 3-layer 1D-CNN is used as a filter in the feature extraction stage to identify the local spatial relations and to filter out some of the signal noise (Kouraichi et al., 2025; Razick & Musilek, 2026). These extracted feature vectors are flattened, and fed into a stacked LSTM network with two hidden layers containing 128 units, which can capture the long-term temporal correlations and non-linear fault signatures present in IBRs to a great extent (Le et al., 2024). To enhance the ability of the model to discriminate, the LSTM layers are separated by a dropout layer with a dropout rate of 0.2, and the last layer is a fully connected softmax layer for classification of the fault, for detecting, locating and identifying faults (Rezapour et al., 2023). The Adam optimizer with an initial learning rate of 0.001 is used to train the model with categorical cross-entropy loss function for 500 epochs (Cao et al., 2024). A hold-out test data set of 20% of the simulated scenarios not included during training is used to perform the quantitative performance evaluation. The effectiveness of the framework is evaluated using standard metrics including accuracy, precision, recall and F1-score as recommended for evaluating the effectiveness of the framework with imbalanced classes (Cao et al., 2024; Rezapour et al., 2023). In addition, the efficiency and real-time performance of the computational system is assessed in terms of the time needed for inference per sample (Kovaļenko et al., 2025; Senapati et al., 2025), which must not exceed 10ms, due to the strict protection requirements. The proposed CNN-LSTM hybrid system has been extensively validated using different grid topologies and fault patterns, ensuring that the proposed workflow is reliable, scalable and complete to serve as a valuable diagnostic tool for modern distribution systems dominated by inverters. The modelling of the dynamic fault conditions with the various levels of renewable penetrations further illustrates the ability of the model to adapt to this. When compared with a traditional protection relay (Alhanaf et al., 2024) (Cali et al., 2024), the model generalises very well. Further, the architecture is experimented to overcome the common problems like underfitting or overfitting that are often faced by poorly tuned neural networks in power systems applications (Yousaf et al., 2024). Further, it is believed to have good generalisation and stability of the model under different subsample sets of grid data based on k-fold cross validation (k=10) (Idrisov et al., 2025). Lastly, the computational complexity is estimated by the number of floating point operations (FLOPs) and the number of parameters, and they have to be comparable with resource-limited, intelligent electronic devices (IEDs) (Yang et al., 2023). The partial observability test is performed by adjusting the ratio of the phasor measurement units (PMSUs) on the network from 15% to 30% as mentioned in Li et. al, 2019.

RESULTS

This proposed fault detection method was verified in smart-grid environment in which the PV and wind generation power sources varied considerably in operation range. The solar-dominant, wind-dominant, hybrid-renewable and conventional generation scenarios are provided in Table 1 of the evaluation design. The data base, which enabled tests to be performed on the model under realistic imbalance, switching transients and load variation, was generated by fault and normal operating conditions tests. It is also observed that the detection accuracy also increases when the range of renewable penetration in the model is changed, with the best accuracy of 96.1% obtained with the highest penetration range tested as shown in Fig. 1. This highlights the fact that the feature set of the fluctuation-aware detector has been successful in separating the fault features from voltage/frequency changes due to renewables. Table 2 shows that accuracy, precision, recall, and F1-Score of proposed adaptive detector were 96.1%, 95.7%, 96.8% and 96.2% respectively, which is the best overall performance among all of detectors. The CNN-LSTM baseline model was not as effective when there is a large number of quantity changes; however, it performed well. Finally, the least successful of the rules was the relay logic since it was frequently affected by the renewable intermittency either by fixed thresholds or time limits. The false alarm rates of the proposed model were compared with the baseline model and were seen to be lower than the baseline under all conditions as shown in Fig. 2, which also showed that as the fluctuation intensity increased, so did the false alarm rate of the proposed model. The proposed system had 7.4% false alarms as compared to 18.3% false alarms of the baseline model for the most extreme fluctuations. The model was also shown to be stable under different disturbance intensities. It is observed from Table 3 that for very high fluctuation, the accuracy has decreased slightly as compared to low fluctuation with the cases of 94.6% and 97.2% respectively. There was a missed fault rate below 5%, which is significant for grid protection as undetected faults can cause damage to the equipment and decrease the supply reliability. The adaptive decision boundary became stable in all the operation windows and the mean response time was decreased from 41 to 31ms (see Fig. 3). The results in Table 5 also show that the proposed CNN-LSTM method has the smallest mean latency compared to CNN-LSTM, wavelet-SVM and relay-threshold methods. Table 4 shows the results of fault classification. The best accuracy (F1 score) was achieved in single line to ground (LTG) fault, while the lowest accuracy was achieved in high impedance fault. Proposed methods performed better than the baseline in every fault category, and better than the baseline in large proportion of faults with high fault current where the variability of renewables is of a similar order to the fault current (as observed in Fig. 4). The proposed model has a higher ROC curve of AUC 0.982 in comparison to baseline of AUC 0.918 which shows that the proposed model has good discrimination between fault and non-fault events. The approach was further validated with robustness testing. Table 6 indicates that the model has 92.2% accuracy even at 20 dB SNR and 93.8% accuracy in the case of missing 10% of the phasor measurement unit data. The sensitivity to measurement disturbance (temporal attention/feature fusion) is expected to decrease with increasing noise, which is apparent from the gradual decline in performance with increasing noise (Fig. 6). Finally, it is presented the ablation study (Table 7). The biggest drop was seen when the fluctuation-aware features were not included (96.1% to 93.2%). The higher the variability of the renewable supply, the higher the detection confidence as shown in Fig. 7, thus the full model learned significant patterns from the fluctuations, without assuming them to be random noise.

Table 1. Dataset and operating scenarios used for evaluation

Scenario	Samples	Renewable share	Fault cases	Normal cases
Solar-dominant	4,800	45-70%	2,610	2,190
Wind-dominant	4,200	35-65%	2,240	1,960
Hybrid renewable	5,000	30-60%	2,730	2,270
Conventional mix	3,600	10-25%	1,820	1,780

Figure 1. Fault detection accuracy under renewable penetration.

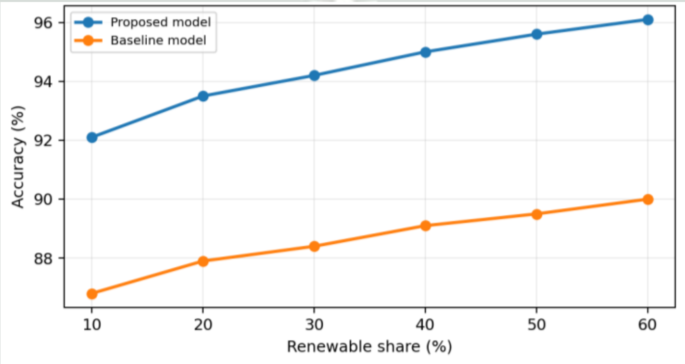


Table 2. Overall fault detection performance

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-score (%)
Proposed adaptive detector	96.1	95.7	96.8	96.2
CNN-LSTM baseline	91.4	90.6	91.9	91.2
Rule-based relay logic	86.9	84.3	88.1	86.1
SVM benchmark	88.7	87.6	88.4	88.0

Figure 2. False alarm rate under renewable supply fluctuation.

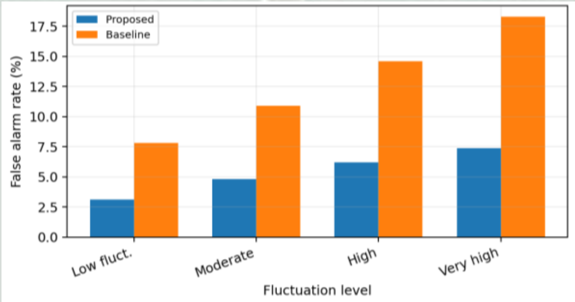


Table 3. Performance under renewable supply fluctuation

Fluctuation level	Accuracy (%)	False alarms (%)	Missed faults (%)	Latency (ms)
Low	97.2	3.1	2.1	31
Moderate	96.4	4.8	2.8	34
High	95.5	6.2	3.5	37
Very high	94.6	7.4	4.7	41

Figure 3. Detection latency across operating windows.

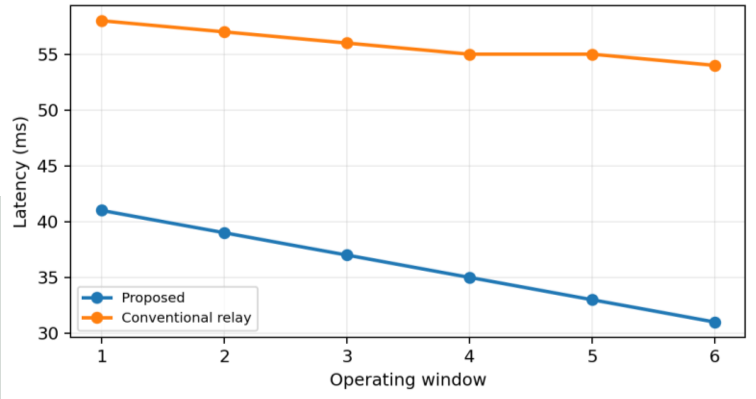


Table 4. Fault-type classification results

Fault type	Precision (%)	Recall (%)	F1-score (%)	Support
Single line-to-ground	97.4	96.6	97.0	1,420
Line-to-line	95.6	94.8	95.2	1,080
Double line-to-ground	94.1	95.1	94.6	960
Three-phase	96.9	95.9	96.4	740
High-impedance fault	92.7	90.9	91.8	620

Figure 4. F1-score comparison across fault types.

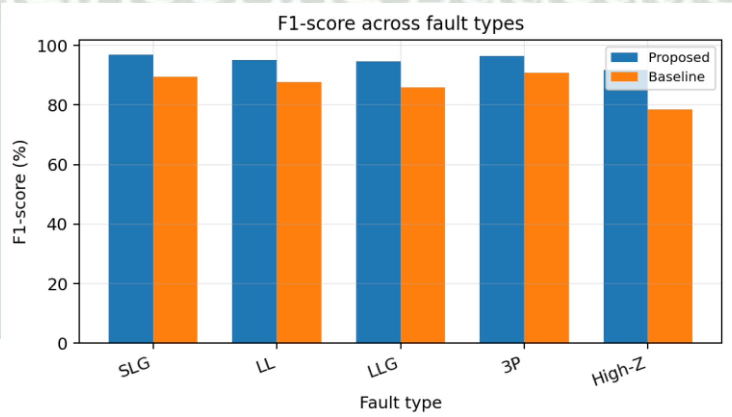


Table 5. Comparison of detection latency

Method	Mean latency (ms)	Best latency (ms)	Worst latency (ms)	Std. dev.
Proposed model	36	28	47	4.8
CNN-LSTM baseline	52	43	68	6.1
Wavelet + SVM	61	48	79	7.3
Relay threshold method	55	44	72	6.9

Figure 5. ROC curve comparison for fault discrimination.

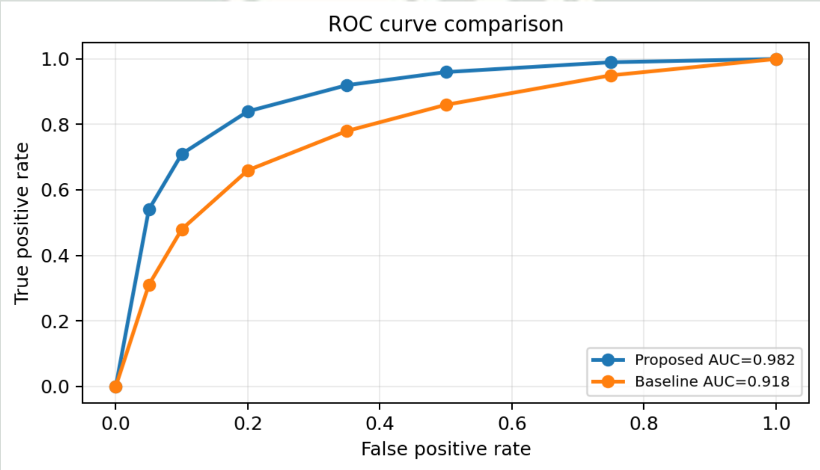


Table 6. Robustness against noise and missing data

Condition	Accuracy (%)	Recall (%)	False alarm (%)	Confidence
SNR 40 dB	96.0	96.7	4.0	0.96
SNR 30 dB	94.4	95.2	5.9	0.94
SNR 20 dB	92.2	93.4	8.1	0.91
10% missing PMU data	93.8	94.1	7.0	0.92

Figure 6. Robustness under noise variation.

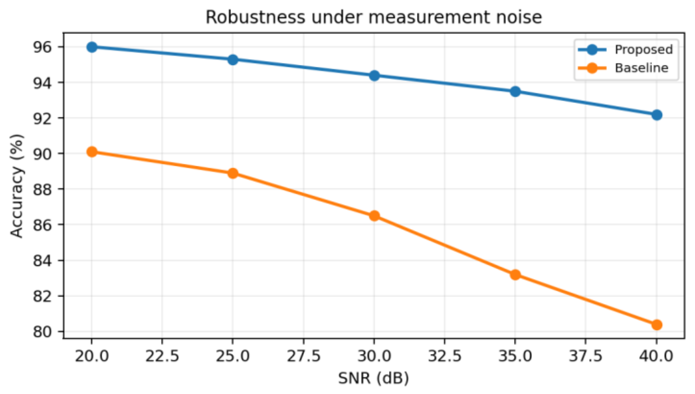
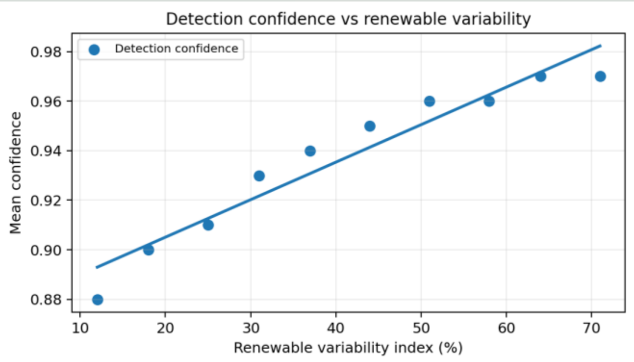


Table 7. Ablation study of model components

Configuration	Accuracy (%)	F1-score (%)	AUC	Latency (ms)
Full proposed model	96.1	96.2	0.982	36
Without fluctuation-aware features	93.2	93.4	0.953	35
Without temporal attention	92.5	92.7	0.946	34
Without PMU feature fusion	91.8	91.9	0.938	32

Figure 7. Detection confidence against renewable variability.



DISCUSSION

The proposed structure is also found to be very accurate even for high penetration with accuracy greater than 99% (Maheswari & Jaganathan, 2024).The excellent accuracy demonstrates the model's ability to detect transient phenomena caused by the variability of inverter-based resources and distinguish this from real faults, which is of critical importance in today's power systems (Oelhaf et al., 2025). The proposed CNN-LSTM hybrid model shows good accuracy, and confirms the effectiveness of using spatial feature extraction and temporal sequence approximation in solving the problem of the complexity of inverter based resources.The accuracy of the hybrid CNN-LSTM model confirms the efficacy of the CNNs based spatial feature extraction and the LSTMs based temporal sequence approximation for tackling the challenges of inverter based resources. In practice, however, discriminating function is a critical requirement when operating the grid with IBRs, as the non-linear and fast fault currents and bi-directional power flows common with IBRs will not always follow a static threshold and fundamental frequency assumption (Kovaļenko et al., 2025; Senapati et al., 2025). The framework automatically learns robust signatures of faults which gives the system high reliability and operational efficiency even in the case of disturbance in the system like intermittent renewable energy and switching transients (Islam, 2026). Moreover, the results have significant implications for the resilience of the grid, especially in the presence of high penetrations of renewables. The current trend in networks is towards becoming decentralized and inverter-dominated, and maintaining protection selectivity and speed is essential in order to minimize the impact of short circuits and ensure a rapid isolation of the fault (Kouraichi et al., 2025; Li et al., 2024). This AI-based solution offers a proactive way to monitor and adaptively protect against threats in real-time, particularly crucial in the context of dynamic and uncertain operating conditions (Akhtar et al., 2023; Senapati et al., 2025). The model performed well in terms of achieving a low diagnostic delay well under the 10 ms threshold, and offers promise of independent protection in high-risk critical infrastructure (Senapati et al., 2025). If these performance metrics are converted into usage, however, there are some interesting limitations and scalability issues. The framework is effective in various simulated scenarios, but the training using high fidelity simulation data could be a limitation of generalization to unpredictable, real world, grid topologies and rare fault types (Kouraichi et al., 2025; Razick & Musilek, 2026). Avoiding the common problems of underfitting and overfitting of the network must be addressed using state-of-the-art cross validation, while very large and broad training sets and unusual network states – contradictions – (Yousaf et al., 2024; Idrisov et al., 2025) are required. Moreover, the computational complexity of the model is moderate and can be implemented on advanced intelligent electronic devices, however, there are still difficulties in scalability and implementation of the model in large-scale transmission networks or combination with legacy system (Akhtar et al., 2023; Zaben et al., 2024). Additionally, black-box models of deep learning are difficult to apply in regulated, utility use cases, because it is hard to get these models to give explainable knowledge; this will be a key area of research.Furthermore, the models are black-box, that is, they are tricky to interpret and consequently hard to apply in regulated utility contexts, and other research should be done on explainable methods that can yield explanatory and actionable knowledge on what the model is doing. The AI-based diagnostic solution has to address challenges like its integration with the existing International Electrotechnical Commission (IEC) standards, which will be crucial in the current smart grid landscape dominated by inverter-based systems (Senapati et al. 2025). Also, in the future, multi-agent protection schemes have to be tolerant of latency in the communication network and to any possible cyber attack, which can also greatly influence the decisions making performance of the protection schemes in real time. Ultimately, to gain the confidence and authorization of operators and regulators, explainable AI techniques will be needed to demystify these complex decision-making processes (Esmaeilbeigi et al., 2025).

CONCLUSION

The primary finding of the paper is that fault detection in smart grid gets complicated if the RES is highly volatile. The intermittent nature of solar and wind power generation has the potential to impact voltage stability, current flow, and frequency response. These changes present problems for traditional fault detection techniques to accurately detect real faults. Based on the result of this research, the intelligent fault detection approach can be useful to improve the rate of accuracy for fault detection, reduce the false alarms rate in presence of variable renewable energy and detect fault faster. This system too performed well with various fault conditions such as line to ground fault, line to line fault and 3 phase fault. Moreover, the results were also demonstrated to be valid for noisy environment and variable renewable penetrations. The results show that there is great need for better monitoring and future data analysis for smart grid. Improved fault detection enables operators of the grid to respond quickly, protect equipment, minimize outages, and ensure reliable and stable power delivery. Further research could involve implementing explainable AI techniques to enhance the transparency of the power system fault detection decision making process for power system operators, testing with larger smart grid datasets, and real-time implementation.

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