

Hybrid CNN-BiLSTM Deep Learning Framework for Simultaneous Fault Detection, Classification, and Location in IEEE 14-Bus Power Transmission System

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Abstract - Power transmission systems are highly vulnerable to electrical faults such as single-line-to-ground (SLG), line-to-line-to-ground (LLG), and three-phase-to-ground (LLL) faults, which may lead to equipment damage and power outages if they are not identified and located in time. This paper presents a hybrid CNN-BiLSTM deep learning framework that simultaneously detects faults, classifies fault types, and identifies the faulted bus in the IEEE 14-bus power transmission system. A balanced dataset containing 8,520 training samples was created from 11,400 MATPOWER 8.1 Newton-Raphson power flow simulations. The simulations included $\pm 15\%$ random load variations and Gaussian measurement noise ($\sigma = 0.002$ pu) to represent realistic operating conditions. The dataset consists of 43 output classes, including one normal operating condition and 42 fault classes corresponding to three fault types across the 14 buses. The proposed model was trained using the Adam optimizer and a standard classification loss function, with the dataset divided into 80% for training and 20% for testing. On the test dataset, the model achieved an overall accuracy of 93.4%. The accuracies for SLG, LLG, and LLL fault classification were 93.5%, 92.1%, and 91.6%, respectively. The model also distinguished normal operating conditions from faulted conditions with 100% accuracy. The results confirm that the proposed CNN-BiLSTM framework constitutes a scalable, data-driven intelligent protection tool well-suited for modern power grids.

Keywords - BiLSTM; CNN; bus-level fault localization; deep learning; fault classification; fault detection; IEEE 14-bus system; MATPOWER; power system protection; transmission network.

I. INTRODUCTION

Reliable operation of electrical power transmission systems is fundamental to economic stability and social continuity. Electrical faults are one of the main threats to power system reliability. They may occur due to insulation failure, lightning strikes, equipment aging, or accidental contact. If not detected and cleared promptly, these faults can cause high fault currents, voltage drops, equipment damage, and interruptions in the power supply [1].

Conventional distance relay-based protection has been used in power systems for many years. However, it is designed for fixed operating conditions and does not adapt well to modern power systems with renewable energy sources, changing power generation, and bidirectional power flow. As a result, its performance may decrease under varying operating conditions. It also requires coordination between relay zones, has difficulty detecting high-impedance or multiple faults, and cannot learn from past fault data to improve its performance [2]-[4].

Machine learning and deep learning techniques have become effective alternatives for power system fault diagnosis. Convolutional Neural Networks (CNNs) are used to extract

useful features from measurements collected across different buses, while Bidirectional Long Short-Term Memory (BiLSTM) networks learn the relationships between these features by processing the data in both forward and backward directions. This helps the model better understand the overall condition of the power system and improves fault detection and classification accuracy [2], [18]. The combined CNN-

BiLSTM model is effective for bus-level fault localization. CNN identifies important features from the input data, while BiLSTM captures the relationships between them. Together, they help the model differentiate faults at nearby buses, even when the measured signals are very similar.

II. RELATED WORK

A. Deep Learning for Transmission Line Fault Diagnosis

Khalif et al. [2] proposed a DWT-CNN-BiLSTM model for multiclass transmission line fault classification, demonstrating that wavelet-domain preprocessing combined with a hybrid CNN-BiLSTM architecture significantly outperforms classical ML baselines in real-time fault identification. Pan et al. [5] developed a parameter-optimized

variational mode decomposition (VMD) approach coupled with dilated CNN-BiLSTM for early anomaly detection in electrical lines, highlighting the benefit of adaptive signal decomposition prior to deep feature extraction. Chen et al. [18] applied CNN-BiLSTM with a self-attention mechanism for fault area discrimination in ultra-high voltage (UHV) three-terminal hybrid DC transmission lines, achieving reliable localization under challenging transient conditions.

B. Equipment and System-Level Fault Diagnosis

For power transformers, Afsharisefat et al. [36] demonstrated that VMD-CNN-BiLSTM applied to differential current signals outperforms frequency domain methods for internal fault detection. Shouran et al. [24] validated a hybrid feature extraction and deep learning framework for dissolved gas analysis-based transformer fault classification using real industrial data. In rotating machinery, Bharatheedasan et al. [8] confirmed CNN-BiLSTM capability for simultaneous fault diagnosis and remaining useful life (RUL) estimation in rolling bearings—evidence of the architecture's multi-task learning capacity. For renewable energy systems, Omran et al. [4] proposed a BiLSTM-based detector for DC series arc faults in photovoltaic installations.

C. Research Gaps and Motivation

A review of the existing literature highlights three key research gaps. First, most studies focus only on fault classification and do not combine fault detection, fault classification, and bus-level fault localization in a single model. Second, only a few studies have evaluated their methods on the IEEE 14-bus system while considering multiple fault classes, load variations, and measurement noise. Third, the benefits of using BiLSTM instead of a standard LSTM for fault diagnosis based on steady-state bus measurements have not been thoroughly investigated. The proposed work addresses these limitations by developing and evaluating a unified CNN-BiLSTM-based fault diagnosis framework.

III. SYSTEM DESCRIPTION AND DATASET GENERATION

A. IEEE 14-Bus Test System

The IEEE 14-bus test system is a widely used benchmark model for testing and validating power system analysis and protection techniques. It consists of 14 buses, 5 synchronous generators, 11 load buses, 17 transmission lines, and 3 transformers (20 branches in total). Under nominal conditions, the system delivers approximately 259 MW of active power and 73 MVAR of reactive power. Bus 1 serves as the slack reference; Buses 2, 3, 6, and 8 are voltage-controlled (PV) generator buses; the remaining buses are load (PQ) buses. The network's meshed topology—combining both radial feeders and interconnected loops—produces spatially overlapping fault signatures across buses, making it an appropriate and demanding testbed for intelligent localization algorithms. The single-line diagram of the IEEE 14-bus system is shown in Fig. 1.

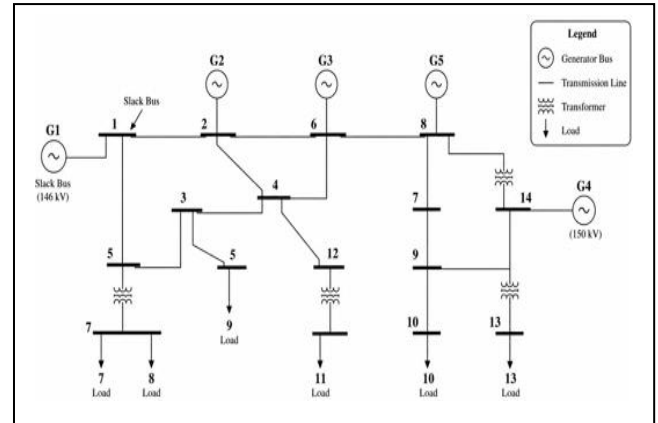


Fig. 1. Single-line diagram of the IEEE 14-bus benchmark system

B. Fault Modeling in MATPOWER 8.1

All fault scenarios were simulated in MATLAB using the MATPOWER 8.1 toolbox. The Newton–Raphson power flow method was used to calculate the steady-state operating condition of the IEEE 14-bus system under different fault conditions. To simulate a fault, an additional shunt fault admittance (Y_f) was added to the diagonal element of the bus admittance matrix (Y_{bus}) at the faulted bus, as shown in (1)

$$Y_{bus_faulted}(f,f) = Y_{bus_normal}(f,f) + Y_f \dots \dots \dots (1)$$

A fault impedance of $Z_f = 0.05$ pu was used, which corresponds to a fault admittance of $Y_f = 20$ pu. Different fault types were represented by applying different fault admittance values.

A value of 20 pu was used for Single-Line-to-Ground (SLG) faults, 12 pu for Line-to-Line-to-Ground (LLG) faults, and 30 pu for Three-Phase-to-Ground (LLL) faults. These values were selected to represent different fault severities and to generate realistic fault conditions for the transmission system.

C. Feature Extraction

Each converged power flow solution provides four electrical measurements at every bus voltage magnitude (V_{mag}), voltage angle (V_{ang}), active power load (P_{load}), and reactive power load (Q_{load}). For the IEEE 14-bus system, these measurements form a 4×14 feature matrix, resulting in 56 input features for each sample.

Together, these features represent the steady-state operating condition of the power system.

D. Dataset Construction

A total of 11,400 simulation scenarios were generated; 3,000 under normal operating conditions and taking 200 per fault class gives 8,400 fault scenarios as calculated in (2)

$$14 \text{ buses} \times 3 \text{ fault types} = 42 \text{ fault classes} \times 200 = 8,400 \dots (2)$$

To represent realistic operating conditions, the load at each bus was randomly varied within $\pm 15\%$ of its nominal value. In addition, Gaussian noise with a standard deviation of 0.002 pu was added to all input features to simulate measurement errors and communication noise in practical PMU-based monitoring systems.

The dataset was organized into 43 output classes. Class 1 represents the normal operating condition, while Classes 2–15, 16–29, and 30–43 represent SLG, LLG, and LLLG faults at buses 1 to 14, respectively. After applying z-score normalization and balancing the dataset, the final dataset contained 8,520 samples, including approximately 420 normal samples and about 2,700 samples for each fault type. The dataset was intentionally designed to include more fault samples than normal samples so that the model could learn fault characteristics more effectively and improve its fault detection capability. The detailed dataset statistics are presented in Table I.

TABLE I DATASET COMPOSITION AND CLASS DISTRIBUTION AFTER BALANCING

Category	Labels	Raw Scenarios	Balanced Samples	Share (%)
Normal Operation	1	3,000	~420	5%
SLG Faults (14 buses)	2–15	~2,800	~2,700	32%
LLG Faults (14 buses)	16–29	~2,750	~2,700	32%
LLLG Faults (14 buses)	30–43	~2,700	~2,700	32%
Total	43	~11,250	~8,520	100%

Fig.2. shows the Pie chart illustrating the intentionally fault-dominated class balance, with normal samples comprising only 5% to ensure the model prioritises fault sensitivity. The fault-dominated distribution ensures the model prioritizes fault sensitivity over majority-class prediction.

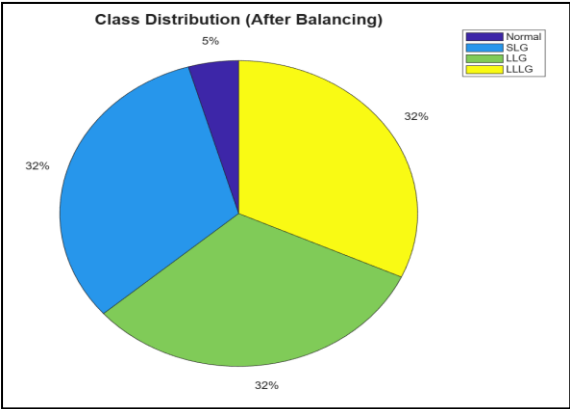


Fig. 2. Class distribution after balancing strategy: Normal (5%), SLG (32%), LLG (32%), LLLG (32%)

Fig.3. is the Bar chart showing per-class sample counts across all 43 classes, confirming approximately equal representation (~200 samples) for every fault class after balancing Red dashed lines demarcate fault type boundaries. Each fault class contains approximately 200 samples after balancing.

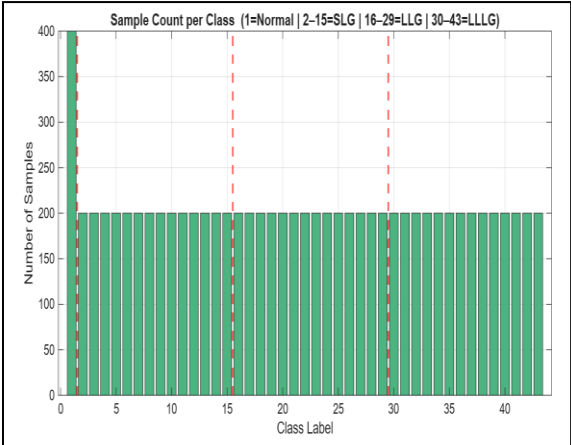


Fig. 3. Per-class sample count across all 43 classes

IV. PROPOSED CNN-BILSTM ARCHITECTURE

A. Design Rationale

In a meshed power system, a fault causes changes in voltage and current at the faulted bus as well as at nearby buses. These changes create distinct spatial patterns in the measurement data. CNNs can effectively learn these patterns, making them suitable for fault localization. Second, faults occurring at nearby buses, such as Buses 4 and 5, often produce very similar measurement patterns, making them difficult to distinguish. BiLSTM addresses this by analyzing information from all 14 buses in both forward and backward directions, allowing the model to better identify the correct fault location. The BiLSTM layer processes the extracted features in both forward and backward directions. The outputs from the two directions are then combined to form a single feature vector, as given in (3)

$$h_t = [h \rightarrow_t; h \leftarrow_t], \quad h_t \in \mathbb{R}^{256} \dots \dots \dots (3)$$

The BiLSTM consists of 128 hidden units in the forward hidden layer and 128 hidden units in the backward hidden layer, which are combined to produce a 256-dimensional feature vector.

B. Layer-by-Layer Description

The proposed network takes a 4×14 input feature matrix and processes it through three 1D convolutional blocks to extract important spatial features.

The first convolutional block uses 64 filters, followed by Batch Normalization (BN) and ReLU activation. The second block uses 128 filters, followed by BN, ReLU, and a Max Pooling layer that reduces the feature length from 14 to 7. The third block applies 256 filters, followed by BN and ReLU, to generate a rich set of spatial features. These features are then passed to a BiLSTM layer with 128 hidden units in both the forward and backward hidden layers, whose outputs are combined to form a 256-dimensional feature vector. Finally, the extracted features are processed through fully connected layers with Dropout (p=0.30) and a Softmax output layer to classify the input into one of the 43 classes. The overall network architecture is shown in Fig. 4, while the detailed layer specifications are provided in Table II.

TABLE II CNN-BiLSTM LAYER-BY-LAYER CONFIGURATION AND TRAINABLE PARAMETER COUNT

Layer	Configuration	Output Shape	Parameters	Activation
Input	4 features × 14 bus steps	4×14	—	—
Conv1D-1	64 filters, k=3, same-pad, BN	64×14	~832	ReLU
Conv1D-2	128 filters, k=3, MaxPool(2), BN	128×7	~24,960	ReLU
Conv1D-3	256 filters, k=3, same-pad, BN	256×7	~98,560	ReLU
BiLSTM	128 units × 2 directions	256	~395,264	tanh/sigmoid
Layer	Configuration	Output Shape	Parameters	Activation
Dropout-1 + FC-1	p=0.30; 256 neurons	256	~65,792	ReLU
Dropout-2 + FC-2	p=0.30; 43 neurons	43	~11,051	Softmax
Total	—	—	~596,459	—

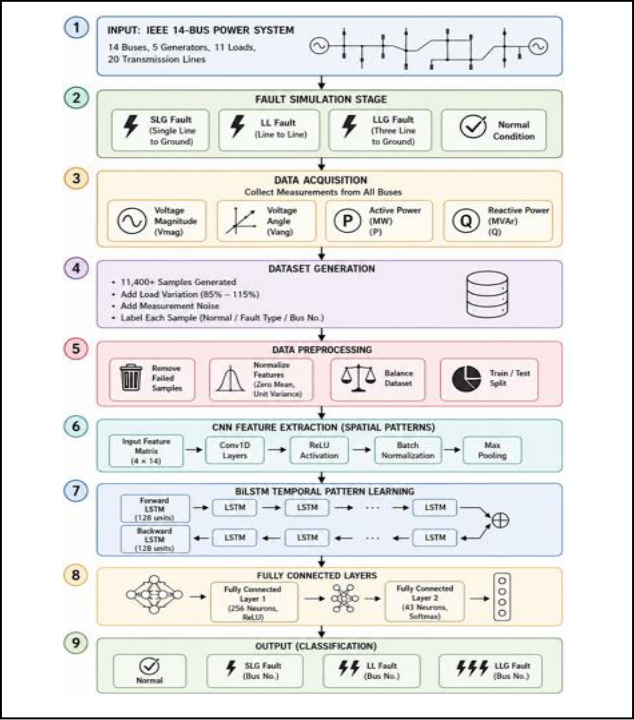


Fig. 4. Network Architecture

C. Training Configuration

The proposed model was trained using the Adam optimizer with an initial learning rate of 0.001. The learning rate was reduced by half after every 20 training epochs to improve model convergence. An 80:20 train–test split was used, resulting in approximately 6,816 training samples and 1,704 testing samples. Stratified sampling was applied to maintain the same class distribution in both datasets. The model was trained with a batch size of 32. L2 regularization was used to reduce overfitting, and early stopping was applied to stop training when the validation performance did not improve for 10 consecutive checks. All experiments were carried out in MATLAB R2026a with MATPOWER 8.1. A random seed

of 42 was used to ensure that the results could be reproduced. The complete training parameters are listed in Table III.

TABLE III TRAINING HYPERPARAMETERS AND CONFIGURATION

Hyperparameter	Value	Rationale
Optimizer	Adam	Adaptive learning rate with momentum
Initial Learning Rate	0.001	Standard starting point for Adam
Hyperparameter	Value	Rationale
LR Reduction Factor / Period	0.5 / every 20 epochs	Gradual annealing for convergence
Maximum Epochs	80	Upper bound with early stopping
Mini-Batch Size	32	Balance between speed and gradient quality
L2 Regularization	1×10^{-4}	Penalize large weights to reduce overfitting
Early Stopping Patience	10 validation checks	Halt when validation loss stagnates
Train / Test Split	80% / 20% (stratified)	Standard ML partition preserving class ratios
Random Seed	42	Full experiment reproducibility
Total Trainable Parameters	~596,459	Compact model suitable for real-time deployment

V. RESULTS AND DISCUSSION

A. Overall Classification Performance

The performance of the proposed CNN–BiLSTM model was evaluated using the test dataset, which contained 1,704 samples that were not used during training. The model achieved an overall classification accuracy of 93.4%, correctly classifying 1,591 out of 1,704 test samples. The classification accuracies for SLG, LLG, and LLLG faults were 93.5%, 92.1%, and 91.6%, respectively, as shown in Table IV. In addition, the model correctly identified all normal operating conditions, achieving 100% accuracy in distinguishing normal and faulted states without any missed faults or false alarms.

These results show that the proposed model can accurately classify all 43 output classes, even under different fault conditions, load variations, and measurement noise.

TABLE IV PER-CATEGORY TEST ACCURACY ON HELD-OUT TEST SET

Fault Category	Test Samples	Correctly Classified	Accuracy (%)
Normal Operation	~84	~84	100.0
SLG Faults (14 classes)	~540	~505	93.5
LLG Faults (14 classes)	~540	~497	92.1

LLLG Faults (14 classes)	~540	~495	91.6
Overall (43-class)	1,704	~1,591	93.4

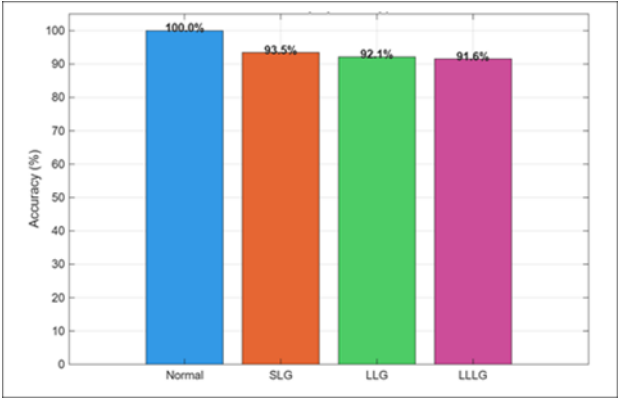


Fig. 5. Classification accuracy by fault category

Fig. 5 shows a grouped bar chart comparing the classification accuracy of different fault types. The results indicate that the proposed model performs consistently well, with the accuracy for all fault types remaining above 91.6%.

B. Confusion Matrix Analysis

The 43 × 43 confusion matrix shown in Fig. 6 demonstrates that the proposed model accurately classifies most of the samples, as indicated by the strong diagonal pattern. A few misclassifications are observed, mainly between different fault types occurring at the same bus and between faults at nearby buses. These errors occur because similar fault conditions or neighbouring buses can produce similar electrical measurements. However, the number of such misclassifications is very small. Importantly, the model correctly distinguished all normal operating conditions from faulted conditions. No fault was classified as normal, and no normal operating condition was classified as a fault.

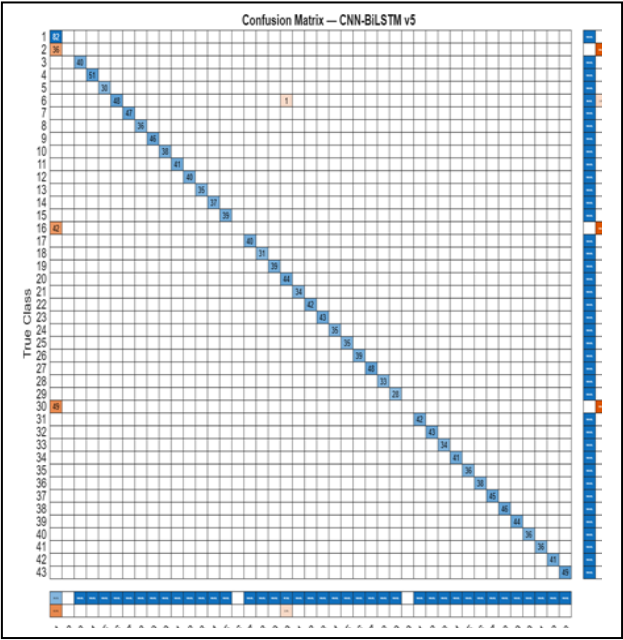


Fig. 6. Complete 43×43 confusion matrix for the CNN-BiLSTM model

C. Feature Importance Analysis

To identify the most important input feature for fault classification, the variation of each of the four input measurements was compared across all 43 output classes after applying z-score normalization. Features with larger variation between different classes provide more useful information for distinguishing fault conditions. The results of this analysis are presented in Table V and illustrated in Fig. 7.

TABLE V FEATURE INTER-CLASS VARIABILITY AS A PROXY FOR DISCRIMINATIVE POWER

Feature	Symbol	Inter-Class Std (normalized)	Discriminative Role
Voltage Angle	V_ang	0.302	Primary discriminator
Voltage Magnitude	V_mag	0.210	Secondary discriminator
Reactive Power Load	Q_load	0.077	Contextual (severity indicator)
Active Power Load	P_load	0.065	Contextual (severity indicator)

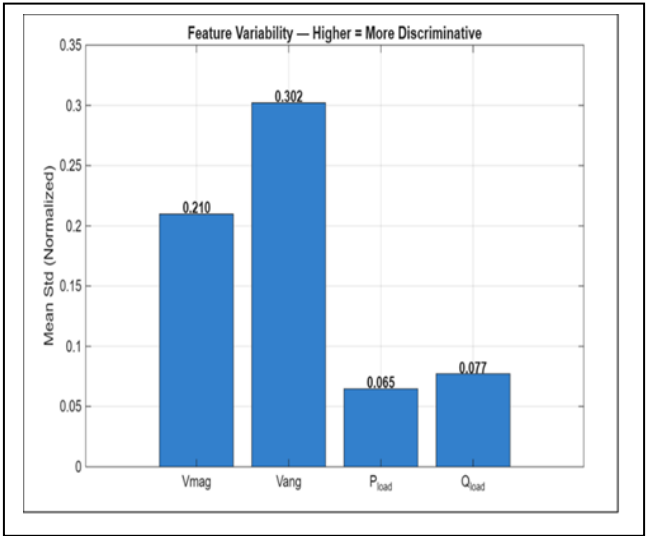


Fig. 7. Inter-class feature variability for each input measurement

The feature importance analysis showed that the voltage angle is the most important input feature for fault classification. Faults cause noticeable changes in the voltage angle across the power system, making it highly effective for identifying different fault conditions. Voltage magnitude was the second most important feature, as it reflects the voltage drop caused by a fault. Active and reactive power load measurements also contributed by helping the model distinguish fault conditions from normal changes in system loading. These results indicate that accurate voltage angle measurements from Phasor Measurement Units (PMUs) can significantly improve fault detection and localization performance.

D. Comparative Analysis

Table VI compares the conventional distance relay, the proposed CNN-BiLSTM model provides a more comprehensive and reliable solution for power system protection. Distance relays are designed mainly to detect faults based on preset impedance thresholds and may be affected by changing operating conditions, renewable energy integration, and load variations. In contrast, the proposed model accurately detects faults, classifies different fault types with more than 91% accuracy, and identifies the fault location at all 14 buses. It also learns directly from measurement data without relying on fixed settings or manual feature extraction, making it more suitable for modern power systems.

TABLE VI STRUCTURED COMPARISON: CNN-BiLSTM VS. ESTABLISHED FAULT DIAGNOSIS METHODS

Criterion	Distance Relay	CNN-BiLSTM (Proposed)
Feature Engineering Required	Manual (fixed thresholds)	Automatic (learned from data)
Fault Detection Accuracy	~95% (zone-dependent)	100% (perfect)
Fault Type Classification	Zone-based only	91.6–93.5%
Bus-Level Localization	Not supported	Full (43-class, all 14 buses)
Noise Robustness	Sensitive (threshold drift)	Robust (trained with $\sigma=0.002$ pu)
Load Change Adaptability	None (fixed settings)	Yes ($\pm 15\%$ variation in training)
Training Data Required	None (physics-based)	~8,520 balanced samples
Online Inference Speed	Very fast (relay logic)	Fast (single forward pass)

E. Limitations

The proposed work has some limitations that can be addressed in future research. First, the dataset is generated using steady-state power flow analysis and does not include transient effects, harmonics, or other dynamic fault characteristics observed in real power systems. Second, all data used for training and testing are obtained through simulation, and the model should be validated using real PMU fault data before practical implementation. Third, the model is developed and tested on the IEEE 14-bus system, so it may require retraining or transfer learning for larger or different network topologies. Finally, the dataset contains a balanced number of fault samples for each fault type, which does not represent actual power systems where Single-Line-to-Ground (SLG) faults occur much more frequently than other fault types.

VI. CONCLUSION

This paper presented a hybrid CNN-BiLSTM model for fault detection, fault type classification, and bus-level fault localization in the IEEE 14-bus power transmission system. The proposed model combines the feature extraction

capability of CNN with the sequence learning ability of BiLSTM to accurately identify different fault conditions using power system measurements.

The model was evaluated using a balanced dataset of 8,520 samples generated in MATPOWER 8.1. On the test dataset of 1,704 samples, it achieved an overall classification accuracy of 93.4%. The fault classification accuracies were 93.5% for SLG faults, 92.1% for LLG faults, and 91.6% for LLLG faults. In addition, the model correctly distinguished all normal operating conditions from fault conditions with 100% accuracy. Feature importance analysis showed that the voltage angle is the most informative input feature, highlighting the importance of PMU measurements for fault diagnosis. Compared with the conventional distance relay, the proposed model provides more accurate fault detection, fault classification, and bus-level fault localization while adapting better to different operating conditions.

Future work will focus on evaluating the proposed model on larger IEEE test systems, incorporating transient fault data for improved performance, applying transfer learning to adapt the model to different network topologies, and validating the proposed approach on real-time hardware platforms for practical implementation.

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