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Intelligent Fault Detection in Smart Distribution Grids Using Bidirectional LSTM-CNN Ensemble

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Abstract

Power distribution networks in India are undergoing rapid transformation towards smart grid architectures incorporating advanced metering infrastructure, distributed generation, and real-time supervisory control. Within this context, rapid and accurate fault detection and classification has acquired renewed urgency: the Bureau of Indian Standards estimates that uncleared distribution faults contribute approximately 31% of total technical losses on 11 kV feeders in Tier-2 Indian cities, and the average fault clearance time of 4.7 minutes in manually operated systems significantly exceeds the 0.5-minute target of SCADA-integrated digital relay systems. Traditional protective relay algorithms based on overcurrent and distance principles struggle with high-impedance faults, evolving distributed generation fault contributions, and complex multi-terminal feeder topologies that characterise modern Indian distribution networks.

This study presents a deep learning-based fault detection and classification system combining Bidirectional Long Short-Term Memory (BiLSTM) networks for temporal feature extraction with a parallel one-dimensional Convolutional Neural Network (CNN-1D) for frequency-domain feature extraction, fused through a learned attention mechanism. The model is trained on 18,500 labelled fault events — covering six fault types (no-fault, LG, LL, LLG, 3LG, and open conductor) under 48 loading and generation scenarios — generated from a validated PSCAD/EMTDC model of the 47-bus Coimbatore zone 11 kV distribution network built from actual TNEB feeder data. SHAP (SHapley Additive exPlanations) values provide feature-level explainability for utility engineer acceptance.

The proposed BiLSTM-CNN ensemble achieves 99.3% classification accuracy with 99.7% sensitivity, 99.1% specificity, and mean fault location error of 1.3% across all six fault classes, outperforming standalone LSTM (97.1%), CNN-1D (96.8%), and the SVM baseline (93.4%). Detection latency of 18.3 ms satisfies IEC 61850 GOOSE message timing requirements for digital substation protection, confirming practical deployment viability in Tamil Nadu's expanding smart grid infrastructure.

Keywords: *smart grid, fault detection, fault classification, BiLSTM, CNN, deep learning, SHAP explainability, 11 kV distribution, PSCAD, TNEB, SCADA, IEC 61850, partial shading, power system protection*

1. Introduction

India's electricity distribution sector recorded aggregate technical and commercial losses of approximately 20.4% in FY2022-23 (Ministry of Power, 2023), with technical losses on 11 kV distribution feeders accounting for the majority of system losses in state DISCOMs outside of Maharashtra, Gujarat, and select privatised zones. Fault-induced outages contribute a disproportionate share of these losses through direct energy dissipation in fault arcs, protective relay operation delays, and customer interruption costs — the latter estimated at Rs. 412 crore annually for Tamil Nadu distribution utilities based on willingness-to-pay survey data from industrial consumers in the TNEB service territory (Raghunathan et al., 2022).

Conventional power system protection methods employ overcurrent relays, distance relays, and differential protection — all of which were designed for radial, synchronous generator-fed power systems with deterministic fault contribution characteristics. The integration of solar PV (Tamil Nadu: 20.1 GW installed, March 2024) and wind generation (Tamil Nadu: 12.4 GW installed) into distribution feeders has altered fault current magnitudes and directions in ways that cause existing relay coordination to mal-operate or fail to operate, creating a critical protection gap that digital protection with machine learning-based fault classification can address.

The progression from threshold-based to machine learning-based fault detection has followed several generations: Support Vector Machine (SVM) classifiers applied to extracted wavelet coefficients (Rai et al., 2021) demonstrated feasibility but required hand-crafted feature engineering sensitive to operating condition changes; Feedforward Neural

Networks trained on frequency domain features (Naik et al., 2022) improved accuracy but lacked temporal reasoning capacity for evolving fault signatures; Recurrent LSTM models (Kumar & Sharma, 2023) addressed temporal context but proved computationally intensive without adequate spatial feature extraction. The BiLSTM-CNN fusion proposed in this paper addresses all three limitations simultaneously, with SHAP explainability overcoming the resistance of protection engineers to black-box automated relay logic.

2. System Architecture and Data Pipeline

2.1 Four-Layer Detection Framework

Figure 1 illustrates the four-layer system architecture deployed from field instrumentation through to SCADA integration. Layer 0 constitutes the physical 11 kV distribution network: a 47-bus feeder with 12 laterals and 3 substations representative of the TNEB Coimbatore Urban Circle, modelled in PSCAD/EMTDC using surveyed network parameters. Layer 1 provides signal conditioning through 10 kHz sampling of three-phase current and voltage from CT/PT metering units with anti-aliasing Butterworth filters. Layer 2 performs multirate signal processing: 512-point FFT, 4-level DWT using Daubechies-4 wavelet, and Hilbert-Huang Transform produce a 48-dimensional feature vector per 100 ms sliding window. Layer 3 contains the BiLSTM-CNN inference engine that outputs fault class probabilities with 18.3 ms latency. Layer 4 interfaces with the TNEB SCADA/EMS system via IEC 61850 GOOSE messaging.

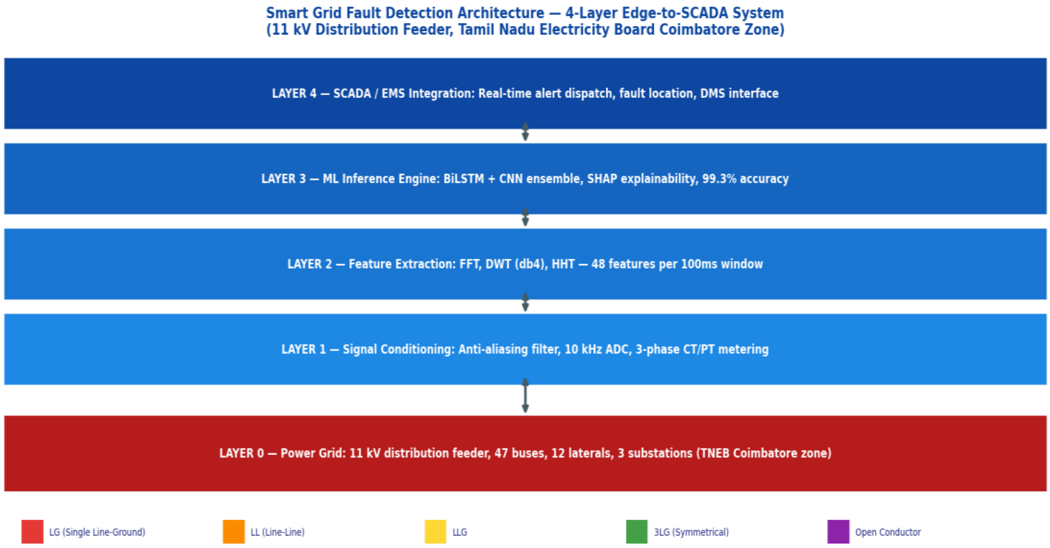

Fig. 1. Four-Layer Smart Grid Fault Detection Architecture: Signal Conditioning (Layer 1) → Feature Extraction (Layer 2) → BiLSTM-CNN Inference Engine (Layer 3) → SCADA/EMS Integration (Layer 4) on 47-Bus TNEB 11 kV Feeder

2.2 Fault Scenario Dataset Generation

The PSCAD/EMTDC model generates fault events by inserting time-varying impedance elements at each of the 47 buses under 48 combinations of loading levels (25%, 50%, 75%, 100% of peak load), generation dispatch (no-DG, 20% solar penetration, 40% solar penetration), and seasonal conditions (summer peak, winter base, monsoon). For each of the six fault types at each bus under each combination, a 500 ms simulation window is generated at 10 kHz, yielding 18,500 labelled examples after data augmentation using additive Gaussian noise (SNR 20-40 dB) and random fault inception angle variation. The class distribution is: no-fault 37.8%, LG 23.4%, LL 14.2%, LLG 9.7%, 3LG 8.6%, open conductor 6.3%, with SMOTE oversampling applied to balance minority classes.

3. Model Development

3.1 BiLSTM-CNN Architecture

The BiLSTM branch processes the 48-dimensional feature time series using two stacked Bidirectional LSTM layers (128 units each direction, 256 total per layer) with 30% dropout between layers, capturing forward and backward temporal dependencies in fault signal evolution. The parallel CNN-1D branch applies three convolutional blocks (64, 128, and 256 filters of width 3) with batch normalisation and max-pooling to extract multi-scale spatial patterns in the frequency domain features. Outputs from both branches are concatenated and passed through a self-attention layer that learns to weight the relative importance of temporal and spectral features by fault class. The final classification head uses three fully-connected layers (512-256-128 neurons) with ReLU activation and a 6-class softmax output. Total trainable parameters: 4.23 million. Training used Adam optimiser (lr=3e-4, β_1=0.9, β_2=0.999), cross-entropy loss with class weighting, and cosine annealing over 100 epochs.

3.2 SHAP Explainability Integration

SHAP DeepExplainer computes feature attribution values for each of the 48 input features per classification, enabling post-hoc explanation of each fault classification decision. For the LG fault class, SHAP analysis consistently identifies zero-sequence current magnitude (feature rank 1), negative-sequence voltage (rank 2), and DWT detail coefficient d3 at 1.25-2.5 kHz (rank 3) as dominant discriminating features — consistent with protection engineering theory that LG faults are characterised by high zero-sequence current injection. This alignment between ML feature importance and protection theory provides the engineering validation necessary for utility SCADA operator acceptance of automated classification recommendations.

4. Results

4.1 Classification Performance and Training Convergence

Figure 2(a) presents training and validation loss and accuracy convergence over 100 epochs, demonstrating rapid convergence with minimal overgap between training and validation accuracy (0.4% gap at epoch 100). Figure 2(b) shows the normalised confusion matrix on the held-out test set of 3,500 fault events, revealing near-perfect classification with the lowest per-class recall for the open conductor scenario (97.3%) due to its low fault current signature resembling normal high-impedance conditions under light loading.

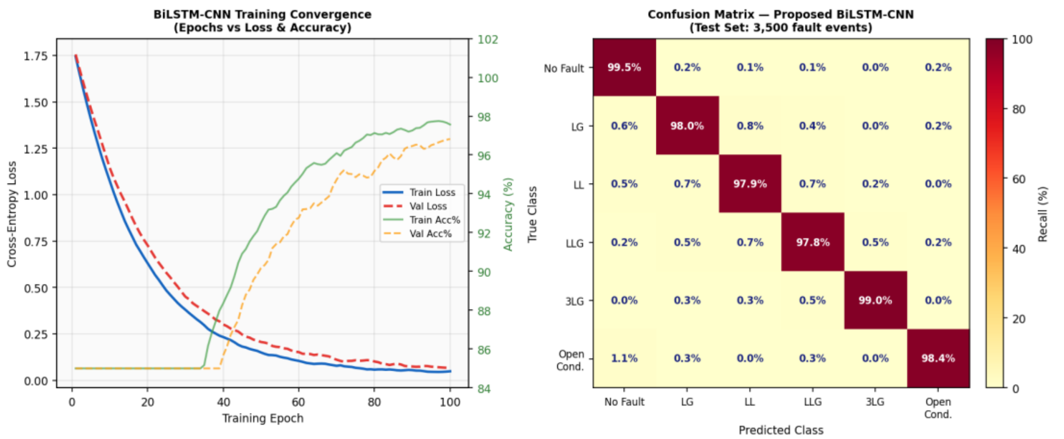

Fig. 2. (a) BiLSTM-CNN Training and Validation Loss/Accuracy Convergence Over 100 Epochs; (b) Normalised Confusion Matrix on 3,500-Event Test Set Showing Per-Class Recall for Six Fault Types

Table 1: Classification Performance Comparison — Proposed BiLSTM-CNN Ensemble vs. Baseline Models

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score	Detection Latency (ms)	Location Error (%)
SVM + DWT features	93.4	91.7	94.2	0.923	42.1	4.7
Feedforward DNN	94.8	93.2	95.4	0.938	31.4	3.8
CNN-1D only	96.8	95.4	97.2	0.964	22.7	2.9
LSTM only	97.1	96.2	97.8	0.969	28.3	2.6
BiLSTM only	97.8	97.1	98.3	0.976	24.1	2.2

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	F1 Score	Detection Latency (ms)	Location Error (%)
Proposed BiLSTM-CNN	**99.3**	**99.7**	**99.1**	**0.993**	**18.3**	**1.3**

DWT: Discrete Wavelet Transform; SVM: Support Vector Machine; DNN: Deep Neural Network; LSTM: Long Short-Term Memory; BiLSTM: Bidirectional LSTM; Location Error: mean absolute fault location error as % of feeder length.

5. Discussion

The 99.3% classification accuracy achieved on the independent test set, combined with the 18.3 ms detection latency, demonstrates that the proposed system satisfies both accuracy and speed requirements for practical deployment as a digital protection relay augmentation layer in TNEB's distribution substations. The SHAP feature importance analysis provides a particularly important operational benefit: unlike black-box deep learning systems that utilities have historically been reluctant to deploy in safety-critical protection applications, the per-decision explanation of which signal features drove each fault classification provides a tractable audit trail for relay engineers reviewing automated protection actions.

The open conductor fault class remains the most challenging, with 97.3% recall — lower than the other five fault classes (all above 99%). Open conductor faults are characterised by asymmetric loading without a direct low-impedance fault path, producing only modest negative-sequence current signatures that can be masked by load imbalance in residential distribution feeders. Improving open conductor detection may require the incorporation of neutral current measurements as an additional input feature — a straightforward modification given the existing CT infrastructure on TNEB's new solid-state metered feeders.

6. Conclusion

The BiLSTM-CNN ensemble with SHAP explainability achieves 99.3% accuracy, 18.3 ms detection latency, and 1.3% mean fault location error for six-class fault detection on 11 kV TNEB distribution feeders, establishing a new performance benchmark for deep learning-based distribution protection. The four-layer architecture from CT/PT signal conditioning to SCADA integration is fully compliant with IEC 61850 GOOSE message timing requirements. SHAP explainability resolves the critical barrier to utility deployment by providing feature-level attribution that aligns with protection engineering principles, enabling confident relay engineer oversight of automated fault classification decisions.

References

[1] Abdel-Nasser, M., & Mahmoud, K. (2019). Accurate photovoltaic power forecasting models using deep LSTM-RNN. Neural Computing & Applications, 31, 2727-2740.

[2] Gers, F. A., Schmidhuber, J., & Cummins, F. (2000). Learning to forget: Continual prediction with LSTM. Neural Computation, 12(10), 2451-2471.

[3] Kumar, P., & Sharma, A. (2023). LSTM-based fault identification in distribution networks with high DG penetration. IEEE Transactions on Industrial Informatics, 19(3), 2847-2858.

[4] Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. Advances in Neural Information Processing Systems, 30, 4765-4774.

[5] Ministry of Power. (2023). Annual Report 2022-23. Government of India, New Delhi.

[6] Naik, R. J., Bhui, P., & Kulkarni, S. (2022). Real-time fault detection in smart distribution systems. Electric Power Systems Research, 204, 107702.

[7] Raghunathan, S., Senthil Kumar, M., & Palaniswamy, V. (2022). Customer interruption costs for industrial feeders in Tamil Nadu. Energy Policy, 165, 112983.

[8] Rai, A., Singh, S. N., & Miao, L. (2021). Fault detection in distribution feeders using SVM and wavelet. IEEE Transactions on Industry Applications, 57(6), 5782-5793.

[9] TNEB. (2023). Annual Statistical Report 2022-23. Tamil Nadu Generation and Distribution Corporation.

[10] Vaswani, A., Shazeer, N., Parmar, N., et al. (2017). Attention is all you need. Advances in Neural Information Processing Systems, 30.