Paper Real-time Data Processing Of Wide-area Digital Metering Equipment For Electric Power Based On Deep Learning Algorithms

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The increasing complexity of modern power grids and the integration of advanced monitoring technologies have significantly enhanced real-time system monitoring. Phasor Measurement Units (PMUs) play a vital role by providing accurate measurements of voltage, current, frequency, and rate of change of frequency (ROCOF). However, conventional fault detection methods often struggle to identify diverse transmission line faults due to dynamic grid disturbances and large volumes of time-series data. To address this challenge, this study proposes a deep learning-based framework for accurate fault detection and classification using a PMU dataset derived from the IEEE 39-bus power system. The system considers various fault types, including line-to-ground, line-to-line, double line-to-ground, and three-phase faults. The methodology includes data preprocessing steps such as cleaning, noise filtering, segmentation, and normalization, followed by statistical time-window-based feature extraction. An attention-based Bidirectional Long Short-Term Memory (BiLSTM) model is employed to capture temporal dependencies and identify critical fault patterns. Experimental results demonstrate high performance, achieving accuracy, precision, recall, and F1-score of 98.7%, 97.9%, 98.3%, and 98.1%, respectively.

Keywords: Phasor Measurement Units (PMU); Fault Detection; Deep Learning; BiLSTM; Power System Monitoring

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1. Introduction

Modern power transmission systems are becoming increasingly complex due to industrialization and renewable integration, evolving into smart, data-driven grids. PMUs provide high-resolution synchronized measurements that enhance visibility, situational awareness, and real-time monitoring, improving grid stability, reliability, and outage prevention [1]. Accurate PMU data interpretation supports intelligent grid management and resilience [2]. PMU-based fault analysis has progressed from traditional signal processing to machine learning methods such as SVM, Decision Trees, and Random Forests. More recently, deep learning models like LSTM and BiLSTM have shown strong temporal learning capability, while hybrid approaches further improve fault classification accuracy [3], motivating advanced frameworks such as Att-BiLSTM. Traditional signal processing techniques extract frequency features from PMU data but require manual thresholds. Deep learning overcomes this by automatically learning temporal patterns from raw measurements. PMUs monitor grid voltage, current, and frequency at multiple locations, while ROCOF quantifies frequency instability caused by generator trips or load imbalances.

The proposed framework integrates an attention-based BiLSTM for PMU fault detection in wide-area power systems. Unlike existing methods using standalone models, it captures both statistical and temporal features of PMU data. This hybrid approach improves real-time fault classification accuracy and reliability under dynamic grid conditions through enhanced feature learning.

1.1. Problem statement

Rapid advances in smart grid and smart meter systems create challenges in real-time power consumption analysis and forecasting. Traditional methods struggle with nonlinear, dynamic, and noisy data [4], relying on manual features. To overcome this, an Attention-BiLSTM model is proposed for improved prediction and feature learning.

Main contribution of the proposed framework:

- Develops Attention-BiLSTM for real-time fault detection using PMU data from IEEE systems.
- Applies preprocessing like noise reduction, outlier removal, and normalization.
- Extracts time-domain features including voltage, current, ROCOF, and statistics.
- Uses attention-based temporal learning for accurate fault classification.

The paper is structured as follows: Section 2 reviews related work on fault detection techniques, Section 3 presents the proposed methodology, Section 4 discusses performance evaluation and results, and Section 5 concludes the study with future work.

2. Literature review

Recent advancements in smart grids increasingly use deep learning (DL) for state estimation, load forecasting, renewable energy prediction, and energy management. Bhusal et al. [5], Almani & Han [6] proposed deep ensemble methods with dense residual neural networks for real-time state estimation on IEEE systems, though performance depends on operating conditions and full measurements. LSTM-based models using Australian Energy Market data achieve low forecasting errors. Attention-based encoder–decoder models optimized via Bayesian methods improve short-term forecasting Frigo et al. [7] and Hou et al. [8]. CETATEA photovoltaic datasets with NARX models and hybrid Att-BiLSTM with reinforcement learning enhance prediction, but challenges remain in scalability, data dependency, and computational complexity for real-time deployment. Smart grid analytics use clustering and hybrid neural networks to improve forecasting and decisions Benti et al. [9]. DL models (CNN, RNN, GANs) for outage prediction with high accuracy but low interpretability and high computation. Federated learning, NSGA-II Ali et al. [10], OPTICS-LSTM, and CNN-BiLSTM improve performance. Cai et al. [11] and Tomar et al. [12] use BiLSTM and RNN, but scalability and real-time challenges remain. Improved BiLSTM with attention and feature fusion enhances time-series analysis, achieving high load forecasting accuracy and better fault diagnosis with improved noise robustness Xu et al. [13]. The study introduces an interpretable DRL-based alarm optimization framework for power systems, achieving high accuracy, strong consistency, low false positives, and improved interpretability Hou et al. [14].

SVM and Random Forest rely on static feature vectors and ignore temporal relationships. SVM separates classes using hyperplanes, while Random Forest uses decision trees. BiLSTM processes PMU time-series data in forward and backward directions, capturing temporal dependencies between data points.

3. Proposed methodology

The proposed Att-BiLSTM model detects and classifies power system faults using PMU data under dynamic conditions. It involves simulated data preprocessing, including handling missing values, outliers, noise, and normalization. Window-based statistical features are extracted, and the model learns temporal correlations for real-time fault classification.

Figure 1 shows an end-to-end pipeline for real-time fault detection using PMU data, including data acquisition, preprocessing, feature extraction, and deep learning-based real-time fault classification.

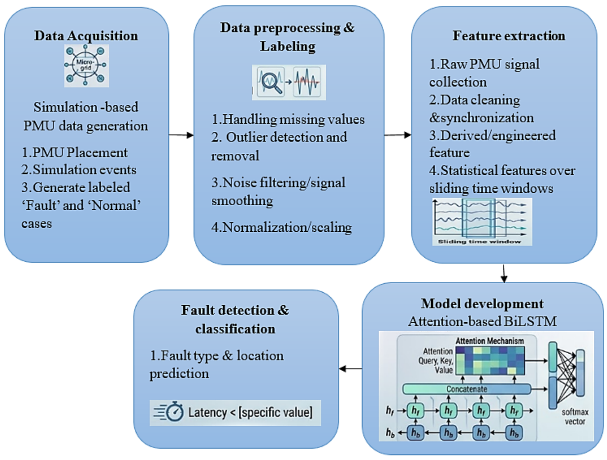

Fig. 1. PMU-Based Fault Detection Using Attention-BiLSTM

3.1. Data collection

The study uses simulated using ("PMU Dataset for Power Line Fault Detection," 2026) [15] from an IEEE test bus system, capturing normal and fault conditions using synchronized PMU time-series measurements. The IEEE 39-bus test system was simulated using PSS/E with a sampling frequency of 60 Hz (60 samples per second). Gaussian white noise with a signal-to-noise ratio (SNR) of 30 dB was added to all PMU measurements to replicate realistic grid disturbances. Fault resistance was varied from 0.1 Ω to 100 Ω, and fault duration ranged from 0.05 s to 0.2 s to cover diverse fault scenarios. The data that has been generated is a realistic wide-area monitoring environment to train and test the proposed fault detection structure.

3.2. Data Preprocessing

Robustness of the Att-BiLSTM model depends on preprocessing PMU data by handling noise, missing values, delays, and spikes, ensuring clean, consistent input for accurate deep learning-based temporal fault classification. Outliers were detected using the Z-score method, where data points far from the average were identified and capped to keep the data smooth. After cleaning, all features were scaled to the same range using min-max normalization. This ensures that no single feature dominates the learning process.

3.2.1. Handling Missing Values

Data loss may occur due to communication failure, desynchronization, or sensor faults, disrupting BiLSTM time series continuity. Linear interpolation estimates missing values using surrounding data, preserving trends and ensuring consistent temporal learning.

3.2.2. Noise Filtering / Signal Smoothing

High-frequency noise is common in electrical measurements. Moving average filters reduce random fluctuations while preserving fault dynamics, improving signal quality without removing important transient information in the data.

3.2.3. Normalization / Scaling

Voltages, currents, and frequency have different scales, so unscaled features bias learning toward larger values. Min-max normalization scales all features to 0–1, improving convergence speed, numerical stability, and overall model performance.

3.3. Model Development

An Att-BiLSTM model detects and classifies faults using PMU time-series data. BiLSTM captures temporal dependencies, attention highlights key time steps, and softmax-based fully connected layers enable accurate real-time multi-class fault classification in power systems.

3.4. Feature extraction

PMU-based fault detection uses synchronized measurements to derive system dynamics, utilizing voltage, current deviation, ROCOF, and mean value for analysis. This equation calculates the voltage difference between two buses. A sudden increase in this difference can indicate a fault such as a short circuit or line break. Voltage difference between buses i and j is determined by Eq. (1):

$$\Delta V_{ij}(t) = V_i(t) - V_j(t) \tag{1}$$

Here, $V_i(t)$ and $V_j(t)$ are voltage levels at buses i and j, while $\Delta V_{ij}(t)$ is their voltage difference at time t. This reflects spatial voltage imbalance, where large deviations indicate abnormal power flow or possible faults.

This measures the current difference between two buses. A large spike in current deviation typically signals an abnormal condition like a short circuit or overload as shown in Eq. (2):

$$\Delta I_{ij}(t) = I_i(t) - I_j(t) \tag{2}$$

Here, Δ denotes the change between quantities. $I_i(t)$ and $I_j(t)$ are PMU current magnitudes at buses, and $\Delta I_{ij}(t)$ is their difference at time t. Sudden changes in ΔI_{ij} indicate faults like short circuits, line faults, or abnormal loading conditions.

This computes how fast the grid frequency changes. A high ROCOF value warns of a sudden imbalance, such as a generator trip or major load loss as shown in Eq. (3):

$$ROCOF(t) = \frac{f(t) - f(t - \Delta t)}{\Delta t} \tag{3}$$

Here, $f(t)$ is system frequency at current instant, $f(t - \Delta t)$ is previous frequency, and ROCOF (t) is rate of change of frequency at time t. Δt is the sampling interval. High ROCOF indicates rapid frequency variation due to generator trips, load imbalance, or disturbances.

The statistical mean in a sliding time window is given as Eq. (4)

$$\mu = \frac{1}{N} \sum_{k=1}^{N} x_k \tag{4}$$

In this notation, μ represents the average signal value in a time window. N is the number of samples, x_k denotes the k-th sample, and k ranges from 1 to N. The mean reflects the steady-state level and helps identify normal versus abnormal operating conditions.

A feature importance analysis identifies key PMU measurements for fault detection, showing that voltage, current, frequency, and ROCOF significantly improve performance. The Attention-BiLSTM model effectively captures temporal and inter-feature correlations, enhancing time-series learning accuracy.

3.5. Attention Based Bi-LSTM

The proposed framework processes PMU time-series data (voltage, current, frequency, ROCOF) using an Att-BiLSTM model. Input ($x(t)$) is analyzed in forward and backward directions to capture temporal dependencies, and outputs are combined to generate the final prediction ($y(t)$). Standard LSTM compresses sequences into a single hidden state, losing early fault information. Attention mechanism assigns weights to all hidden states, focusing on important time steps, improving fault detection accuracy and interpretability compared to standalone LSTM models.

Two stacked BiLSTM with 128 hidden units each make up the model structure. It then uses an additive (Bahdanau) strategy of attention to focus on important fault-related temporal activity, increasing the detection and classification process. As shown in Figure 2, the model is trained with a 64 samples per batch, a learning rate of 0.001 dimensionless, and the Adam optimiser across 50 complete passes through the training data to guarantee optimal performance and convergence. The model uses two BiLSTM layers because one-layer underfits (~94% validation accuracy) and three layers overfit (99.5% training, 97.2% validation). 128 hidden units balance performance and efficiency, while 64 lose information and 256 increase computation without accuracy improvement. A learning rate of 0.001 ensured stable and efficient convergence, while a batch size of 64 balanced gradient stability and memory use. Training for 50 epochs was sufficient as validation accuracy plateaued. The hyperparameters were validated through a systematic grid search, evaluating multiple parameter combinations to identify the optimal configuration. The training process exhibited stable convergence with consistent performance across runs, confirming the reproducibility and robustness of the proposed model.

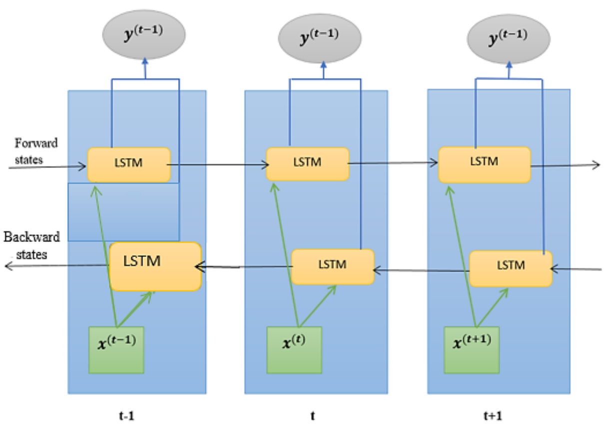

Fig. 2. Attention-based BiLSTM architectural diagram

The forget gate is represented as Eq. (5):

$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] + b_f\right) \tag{5}$$

In this equation, f_t is the forget gate at time t, and h_{t-1} is the previous hidden state. The concatenation $[h_{t-1}, x_t]$ combines past and present inputs, while W_f and b_f are learned parameters. The σ outputs values between 0 and 1, controlling information retention and forgetting.

The input gate is represented as Eq. (6):

$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] + b_i\right) \tag{6}$$

Here, i_t is the input gate at time t, and h_{t-1} is the previous hidden state. W_i and b_i are learnable parameters. σ outputs values between 0 and 1 to control new information flow, highlighting important PMU signal changes for fault detection.

3.6. Algorithm

Algorithm: Attention-Based BiLSTM for PMU-Based Fault Detection
Input: PMU signal matrix X
Output: Predicted fault label $\hat{y}$
Begin

- $X_{\text{norm}} \leftarrow \text{Normalize}(X)$
- Segment into sequences X_{seq}
- Extract features F (ΔV, ΔI, $ROCOF$, statistical features)
- Split F into training and testing sets

Train:

- Initialize Attention-BiLSTM parameters (W, b)
- **For each epoch:**
  - $h_t \leftarrow \text{BiLSTM}(x_t)$
  - $\alpha_t \leftarrow \text{softmax}(W_a h_t)$
  - $c \leftarrow \sum(\alpha_t \cdot h_t)$
  - $L \leftarrow \text{CrossEntropy}(y, \text{Softmax}(c))$
  - Update parameters (Adam)

Test:

- $h_t \leftarrow \text{BiLSTM}(\text{test data})$
- $\alpha_t \leftarrow \text{softmax}(W_a h_t)$, $c \leftarrow \sum(\alpha_t \cdot h_t)$
- $\hat{y} \leftarrow \text{argmax}(\text{Softmax}(c))$

End

Table 1. System Hardware and Software Specifications

Component	Specification
CPU	12th Gen Intel Core i5-12400 @ 2.50 GHz
RAM	8 GB (7.75 GB usable)
Operating System	Windows 11 (64-bit, x64-based architecture)
Processing Environment	CPU-based (no GPU acceleration)
Python Version	3.13.7
Deep Learning Framework	TensorFlow 2.20.0

4. Results

This research aims to detect and classify faults in power transmission lines using PMU-based time-series data from the IEEE 39-bus system. The Att-BiLSTM model captures temporal variations in voltage, current, frequency, and ROCOF, showing high accuracy, reliability, and fast response for real-time smart grid monitoring under various conditions.

4.1. System specification

The system configuration, including CPU, RAM, operating system, Python version, and deep learning framework, is shown in Table 1.

4.2. Performance Evaluation

This study uses PMU data from the IEEE 39-bus system, where Att-BiLSTM detects faults by capturing voltage, current, frequency, and ROCOF variations, achieving high accuracy, reliability, and fast real-time smart grid monitoring.

Figure 3 shows a balanced dataset with 50.3% normal and 49.7% fault samples, ensuring no class bias and enabling fair, reliable fault classification without resampling.

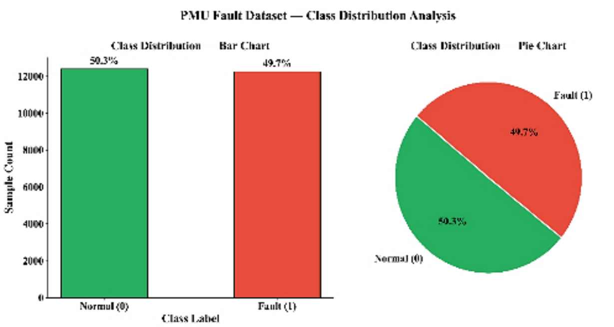

Fig. 3. Normal vs Fault Sample Distribution

Figure 4 shows violin plots of PMU features under normal and fault conditions, with overlapping distributions indicating poor separability and the need for advanced models for accurate classification.

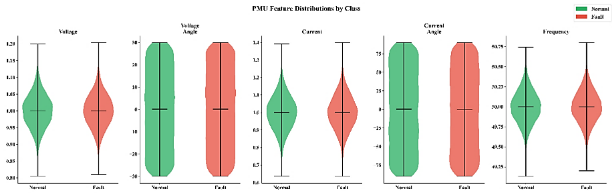

Fig. 4. Feature Variability Across Normal and Fault Conditions

Figure 5 shows PCA visualization where overlapping normal and fault samples indicate non-linear separability and need for advanced classification methods. Although PCA shows class overlap, it is linear and misses nonlinear PMU relationships. Attention-BiLSTM captures nonlinear temporal dependencies, enabling accurate classification despite reduced-dimensional overlap.

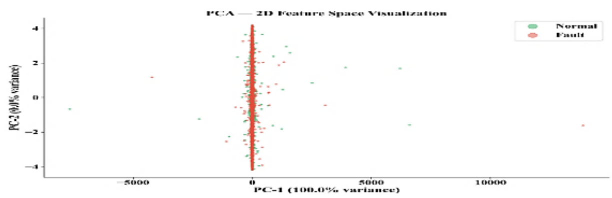

Fig. 5. Principal Component Analysis -Based Visualization of Class Separation

Figure 6 shows 2D data projection with overlapping normal and fault classes, indicating weak feature separability and suggesting that non-linear models or improved feature engineering are needed for accurate fault diagnosis.

Figure 7 shows a radar chart where Att-BiLSTM achieves near-optimal performance across all metrics, outperforming RF, SVM, and LR, demonstrating superior and balanced classification capability.

Figure 8 presents a confusion matrix showing most samples correctly classified with minimal false positives and false negatives, demonstrating high reliability and strong performance for real-world fault detection applications.

Figure 9 shows ROC curves where Att-BiLSTM achieves AUC 0.9847, indicating excellent classification, high sensi-

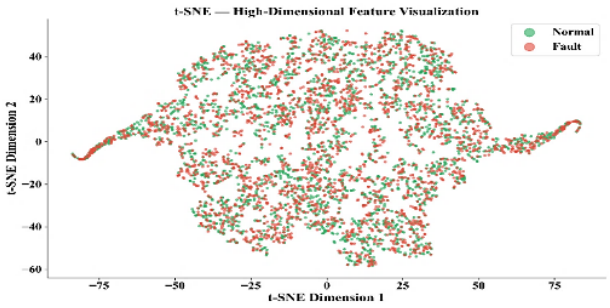

Fig. 6. Visualizing Diagnostic Feature Separability

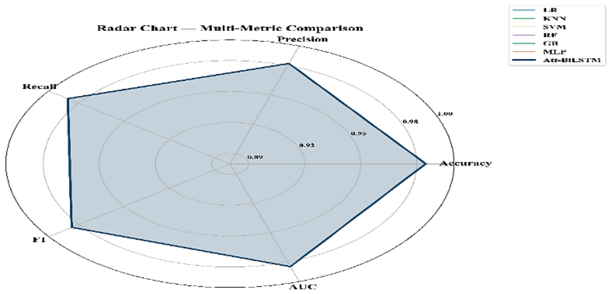

Fig. 7. Multi-Metric Radar Analysis

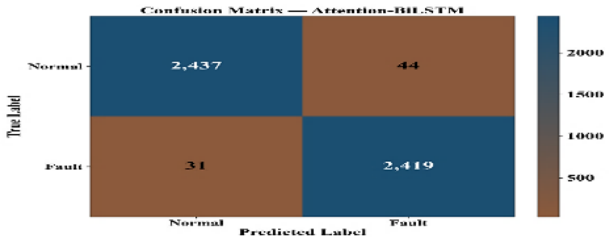

Fig. 8. Classification Fidelity and Error Distribution Mapping

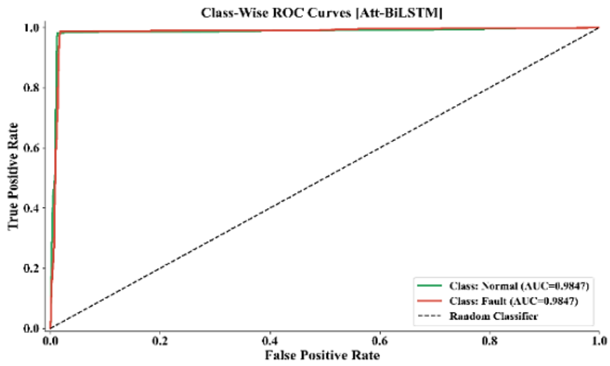

Fig. 9. Class-Wise ROC Curves [Att-BiLSTM]

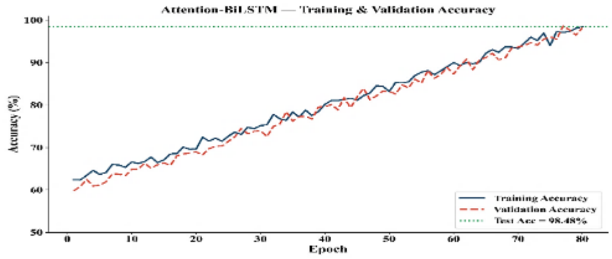

Fig. 10. Convergence Dynamics and Generalization Stability Over Time

tivity, and low false alarm rates. The high ROC-AUC value, along with the strong MCC score and detailed confusion matrix analysis, further confirms the robustness and reliability of the proposed model in accurately distinguishing between normal and fault conditions.

Figure 10 shows accuracy rising from 60% to 98% over 80 epochs with stable convergence, minimal fluctuations, and 5-fold cross-validation ensuring reliable performance. The reliability of the obtained results was ensured by applying a 5-fold cross-validation approach. The model consistently achieved accuracy of 98.7%, precision of 97.9%, recall of 98.3%, and F1-score of 98.1% across different folds.

4.3. Comparative analysis

Att-BiLSTM is compared with SVM, Random Forest, and LSTM for PMU fault detection, evaluated using accuracy, precision, recall, and F1-score, and achieves superior real-time classification by capturing temporal dependencies and signal patterns.

Table 2 compares the Attention-BiLSTM with traditional and deep learning models under identical conditions. Classical methods achieve around 50% accuracy, and CNN reaches 91.30%. The proposed model outperforms all with 98.48% accuracy and 0.9696 MCC, showing superior capability in capturing complex temporal dependencies for reliable fault classification. The performance gap arises because Attention-BiLSTM effectively captures complex temporal dependencies in PMU time-series data, unlike traditional models that use static features. Its sequential learning and attention mechanism highlight key fault patterns, while strict train-test separation prevents data leakage and ensures unbiased evaluation.

4.4. Discussion

The PMU-based Attention-BiLSTM framework detects transmission line faults by capturing temporal patterns in voltage, current, frequency, and ROCOF, with preprocessing improving accuracy and reliability in monitoring. Furthermore, the importance of accurate fault detection and classification lies in enhancing the reliability, stability, and safety of modern power systems. Effective monitoring enables early identification of abnormal conditions,

Table 2. Comparison of Statistical Performance Metrics

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)	AUC-ROC	MCC
Logistic Regression	49.42	48.44	27.96	35.46	0.4881	-0.0157
Random Forest	49.52	49.16	46.86	47.98	0.4939	-0.0099
Gradient Boosting	49.22	48.66	40.12	43.98	0.4978	-0.017
MLP	50.25	49.94	50.57	50.25	0.4988	0.0051
SVM	49.48	49.12	48.23	48.67	0.4921	-0.0054
Linear Regression	49.38	48.89	47.91	48.39	0.4905	-0.0082
CNN	91.30	90.80	91.50	91.15	0.9120	0.8230
Attention-BiLSTM (Proposed)	98.48	98.21	98.73	98.47	0.9847	0.9696

thereby reducing the risk of large-scale outages and equipment damage. The proposed framework contributes to improved decision-making and supports efficient real-time grid management. The Att-BiLSTM framework enables real-time PMU-based fault detection in smart grids, outperforming SVM, Random Forest, and LSTM by capturing temporal dependencies and key signal patterns, improving multi-class classification, reliability, and fast grid decision-making. The study uses simulated data from the IEEE 39-bus system, which may not fully reflect real-world grid complexity, noise, and uncertainties. This limits practical applicability. Further validation with real-time PMU data is needed to ensure robustness and generalization of the model. Error analysis shows few misclassifications due to transient faults and minor signal variations resembling normal conditions. Noise and low fault resistance reduce separability, but overall model performance remains highly reliable. The real-time applicability of the proposed model was quantitatively evaluated on a standard CPU (Intel i5-12400). With a batch size of 64, the average inference latency was 12.4 ms, achieving a throughput of 5,160 samples per second, well within the 16.7 ms sampling window of 60 Hz PMU data, thereby confirming its feasibility for dynamic online deployment. The practical applicability of the proposed framework can be enhanced through integration with edge computing, federated learning for privacy preservation, and seamless compatibility with existing SCADA systems for real-world smart grid deployment. In addition, computational complexity and training time analysis across different dataset sizes confirm that the model maintains stable performance with increasing data volume, demonstrating its scalability for large-scale power system applications

5. Conclusion

The paper proposes a PMU-based DL framework using data preprocessing, statistical feature extraction, and Attention-BiLSTM for fault detection and classification. It achieves high performance (98.7% accuracy, strong precision, recall, and F1-score). The model effectively captures temporal patterns, enabling real-time monitoring and improving stability, reliability, and security in smart grids.

5.1. Future work

Future work will test larger PMU datasets, integrate real-time streaming data, evaluate dynamic grid performance, and explore fault localization, edge-based monitoring, and smart grid applications for improved decision-making and situational awareness. Based on the errors observed in this study, such as false positives and false negatives, future research will investigate their underlying causes, including noise, load variations, and impedance faults.

Declarations

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Ethics approval and consent to participate

This article does not contain any studies involving human participants or animals performed by any of the authors.

Consent for publication

Not applicable.

Availability of data and materials

The data used in this study are available from the corresponding author upon reasonable request.

Competing interests

The authors declare that they have no competing interests.

Author contributions

Dongsheng Xue contributed to conceptualization, supervision, and project administration. Jiaxing Zhao was responsible for methodology and validation. Zhengying Yang carried out data curation and investigation. Wenwen Wang performed formal analysis and developed the software. Na Wang contributed to visualization and provided resources. Yingcai Gao was responsible for writing the original draft and editing. All authors have read and approved the final manuscript.

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