

# A Cyber Physical Framework for Intelligent Fault Detection and Predictive Maintenance in Digital Power Grids

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## Abstract

**INTRODUCTION:** The increasing complexity of modern digital power grids demands intelligent and reliable fault detection and predictive maintenance solutions to ensure operational stability, resilience, and efficient asset management. Integrating cyber–physical systems with advanced deep learning techniques enables accurate monitoring and proactive maintenance of power transmission networks.

**OBJECTIVES:** This study proposes a unified GRU-based cyber–physical framework for intelligent fault detection, fault classification, fault localization, and risk-based predictive maintenance in power transmission systems, while improving diagnostic accuracy, interpretability, and maintenance decision-making.

**METHODS:** The proposed framework integrates multi-parametric voltage and current measurements from the physical layer with a gated recurrent unit (GRU) model in the cyber layer to capture the temporal dynamics of fault evolution. Domain-informed electrical features, including voltage deviation, phase imbalance index, and current severity index, are incorporated to improve physical interpretability. A multi-task learning strategy is employed to simultaneously detect faults, classify fault types, identify faulted transmission lines, estimate fault locations, and generate a risk-based maintenance index for proactive maintenance prioritization.

**RESULTS:** The proposed framework achieved a fault classification accuracy of 98.61%, with precision of 0.9864, recall of 0.9861, and F1-score of 0.9861. Fault localization was performed with a low mean absolute error (MAE) of 0.0303, demonstrating high localization accuracy. The risk-based maintenance index effectively supported proactive maintenance prioritization for transmission assets.

**CONCLUSION:** The proposed GRU-based cyber–physical framework provides an effective and scalable solution for intelligent power grid monitoring by integrating accurate fault detection, precise fault localization, and predictive maintenance within a unified architecture. The framework enhances operational reliability and supports data-driven maintenance strategies for next-generation digital power grids.

**Keywords:** Cyber–Physical Power Systems, Fault Detection, GRU, Fault Localization, Predictive Maintenance

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## 1. Introduction

Modern power transmission networks are undergoing rapid transformation due to increasing system complexity, higher

power demand, and the integration of distributed and renewable energy resources [1]. These changes introduce dynamic operating conditions that elevate the risk of faults and equipment failures in high-voltage transmission lines [2]. Reliable and timely fault detection, accurate fault

localization, and proactive maintenance strategies are therefore essential to ensure grid stability, minimize downtime, and reduce economic losses [3,4].

Conventional fault detection and protection techniques in power systems primarily rely on threshold-based relays and rule-driven logic [5,6]. While these methods are effective for well-defined fault scenarios, they often struggle to capture complex interactions among multiple electrical parameters and lack adaptability to evolving grid conditions [7]. Furthermore, traditional approaches provide limited support for intelligent fault classification and predictive maintenance, which are increasingly required in modern digital power grids [8,9].

Recent advances in machine learning (ML) and deep learning (DL) have enabled data-driven fault analysis using multi-parametric electrical measurements [10,11]. Models such as support vector machines, decision trees, and artificial neural networks have been explored for fault detection and classification tasks [12]. However, many of these models fail to effectively capture dependencies among correlated measurements or exhibit reduced performance when applied to complex, high-dimensional power system data [13,14].

Recurrent neural networks (RNNs), particularly Gated Recurrent Units (GRUs), have demonstrated strong capability in modeling sequential patterns and learning progression characteristics in electrical signals. [15,16]. GRUs offer a computationally efficient alternative to long short-term memory (LSTM) networks while maintaining strong performance in capturing temporal and contextual relationships [17]. When integrated within a cyber-physical system framework, GRU-based models can enable intelligent monitoring, fault localization, and risk-based maintenance planning for digital power [18,19].

In this study, a GRU-based cyber-physical framework is proposed for intelligent fault detection, classification, localization, and predictive maintenance in 110 kV power transmission systems. The framework is evaluated using a publicly available dataset generated through DIGSILENT PowerFactory simulations, which provides comprehensive voltage and current measurements under both faulted and normal operating conditions. By leveraging multi-parametric electrical features and the supervised learning, the proposed approach enables accurate identification of fault types, precise localization of faulted transmission lines and positions, and assessment of fault risk for preventive maintenance decision-making.

## 1.1 Primary Contributions

- **Unified Simulation-Validated Cyber-Physical Framework Design:** A single integrated framework is proposed that jointly performs fault detection, classification, localization, and risk-based predictive maintenance, enabling coordinated fault management rather than isolated task execution.
- **Physically Interpretable Temporal Learning:** The framework combines engineered electrical features with a GRU-based temporal model to capture fault

progression dynamics while maintaining physical interpretability.

- **Risk-Informed and Scalable Design:** Fault detection outcomes are linked with maintenance risk assessment, and the framework is validated in a reproducible cyber-physical simulation environment, designed to support scalable real-time deployment and supports extensibility toward continuous learning, forming a conceptual closed-loop CPS formulation.

The paper is structured as follows: Section 1 presents the motivation and need for a unified cyber-physical fault detection and predictive maintenance framework. Section 2 reviews existing research and identifies gaps. Section 3 defines the problem and research objectives. Section 4 describes the proposed GRU-based methodology for fault detection, localization, and maintenance. Section 5 reports experimental results, Section 6 provides analysis, and Section 7 concludes with future research directions.

## 2. Literature Survey

Nishtar et al. [20] developed a hybrid neuro-fuzzy FDI framework for digital power grids achieving 97.2% accuracy with low false positive and negative rates on the IEEE 33-bus system, while Wu et al. [21] proposed a DC grid monitoring method using hybrid feature selection and ensemble learning (LightGBM, CatBoost, TabNet) achieving 94.0% accuracy and strong F1-score on SmartDC data. Al-Anbuky et al. [22] introduced a cyber-physical fault detection approach for electrical motors using FFT features and ANN classification, demonstrating high accuracy and reduced false alarms in dynamic conditions. Shukla et al. [23] presented an IoT-based induction motor fault detection system using sensor fusion and Random Forest on an embedded platform.

Vignes et al. [24] proposed an AI-driven cyber-physical cybersecurity framework using LSTM and Random Forest with SHAP and adversarial training achieving 99.798%/98.19% accuracy on edge devices, while Pillai et al. [25] achieved 98.7% PV fault classification using Random Forest on real plant data; Hosseini et al. [26] developed a BWO-BiLSTM model with 98.5% accuracy and 5 ms detection for EV-integrated grids, and Teta et al. [27] proposed a lightweight CNN-based PV fault model with high robustness under noisy conditions; Chen et al. [28] achieved 94.5% accuracy with Bayes-LSTM-Attention outperforming SVMs, and Tunio et al. [29] reported that TCN reached the best performance with 99.9% accuracy over BiLSTM and GRU.

Despite advances in fault detection and predictive maintenance, existing studies still face limitations such as reliance on offline simulations (Nishtar et al. [20] ; Chen et al. [28]), centralized and domain-specific models for DC grids or cybersecurity (Wu et al. [21] ; Vignes et al. [24] ), lack of scalability from motor or PV-level systems to full grid networks (Al-Anbuky et al. [22] ; Shukla et al. [23] ; Pillai et al. [25]; Teta et al. [27]), and high computational complexity

in deep learning approaches limiting real-time deployment (Hosseini et al. [26] ; Tunio et al. [29] ), highlighting the need for a unified, scalable cyber–physical framework for real-time multi-asset fault detection. Boumkheld et al. [30] developed a real-time cyber-physical co-simulation framework to analyze the impact of cyber-attacks on distance relay backup protection, demonstrating vulnerabilities in smart-grid protection systems; however, the study focused mainly on attack impact analysis rather than intelligent fault detection, localization, and predictive maintenance.

Recent studies demonstrate advances in temporal deep learning and intelligent power-system maintenance, Khandelwal et al. [31] developing an attention-GRU-based fault classifier, and Tunio et al. [32] evaluating deep-learning models using simulated and real-time sequential transmission-line data. Liang et al. [33] further demonstrated the application of deep learning for power-system fault maintenance. However, existing approaches remain limited by model-specific fault diagnosis, insufficient integration of fault detection, classification, localization, and maintenance functions, and limited validation across comprehensive cyber–physical grid scenarios, highlighting the need for a unified and scalable GRU-based cyber–physical framework for real-time multi-task fault management.

### 3. Problem Statement

Despite advances in intelligent fault detection and predictive maintenance, existing studies still face key limitations such as reliance on offline simulation datasets without real-time validation (Nishtar et al. [20] ; Chen et al. [28]), focus on isolated subsystems like DC grids, PV systems, or EV feeders rather than full grid-level modeling (Wu et al. [21] ; Pillai et al. [25] ; Shukla et al. [23]), high computational complexity and centralized training that limit scalability in cyber–physical environments (Hosseini et al. [26] ; Tunio et al. [29]), and the lack of integrated frameworks that jointly address fault detection, cybersecurity, and predictive maintenance (Vignes et al. [24] ; Al-Anbuky et al. [22]). These gaps highlight the need for a unified cyber–physical framework for scalable and intelligent fault detection in digital power grids.

### 3.1 Research Objectives

To overcome the identified limitations, the objectives of this research are as follows:

- To develop a unified cyber–physical framework integrating physical sensor data and cyber intelligence for fault detection and predictive maintenance in digital power grids.
- To develop an integrated and computationally efficient cyber–physical framework for intelligent fault detection and predictive maintenance in digital power grids, validated through high-fidelity simulation data.
- To design a computationally efficient and adaptive learning mechanism suitable for edge–cloud deployment, achieving high accuracy, precision, recall, and F1-score.
- To jointly address fault detection, system health assessment, and predictive maintenance within a single intelligent cyber–physical framework.

### 4. Methodology

The proposed GRU-based cyber–physical framework processes voltage and current data to learn temporal patterns for fault detection, classification, and localization in the digital power grids. It also includes a risk assessment module for predictive maintenance, enabling accurate and proactive grid reliability management.

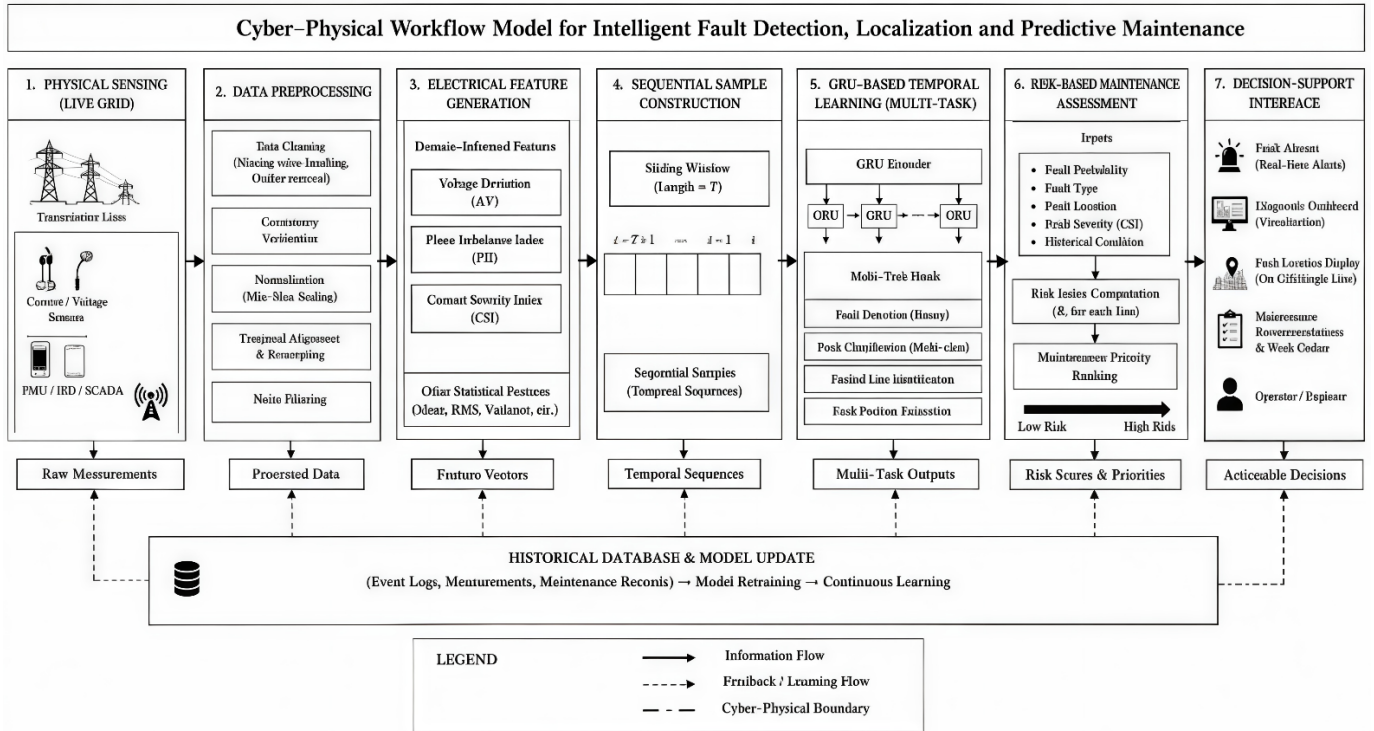


**Figure 1.** Cyber-Physical Framework for GRU-Based Fault Detection, Localization, and Predictive Maintenance in Digital Power Grids

Figure 1 shows a GRU-based framework for fault detection, classification, localization, and predictive maintenance using processed voltage/current data with sliding-window and multi-task learning for improved grid reliability.

#### 4.1 Data Collection

Multi-parametric voltage and current data from a simulated 110 kV system (DIGSILENT PowerFactory) available on Mendeley Data [34] includes labeled normal and fault conditions with fault type, line, and location (0–100%) for supervised learning and evaluation.

The data acquisition process represents synchronized measurements from the voltage and current sensing points of the simulated 110 kV transmission system. Voltage, current, and associated electrical measurements are generated at the same simulation time instants and assigned a common timestamp to maintain temporal consistency among measurement channels. The acquired measurements are organized chronologically according to the simulation time step, thereby preserving the temporal evolution of normal and fault conditions. The synchronized measurements are subsequently transferred to the cyber layer for preprocessing, normalization, and sequential sample construction. A sliding-window strategy with a sequence length of five consecutive time steps is then applied to form the temporal input

sequences required by the GRU model. This synchronized acquisition and temporal sampling procedure ensures that measurements corresponding to the same grid state are processed jointly and enables the cyber layer to capture the progression of fault-related electrical variations before generating detection, classification, localization, and maintenance outputs.

#### 4.2 Data Preprocessing

Raw measurements are pre-processed to improve data quality and ensure compatibility with GRU-based learning.

##### 4.2.1 Data Cleaning and Consistency Verification

Raw electrical data is cleaned by removing duplicates and verifying consistency and completeness to ensure reliable inputs for GRU model training.

##### 4.2.2 Min-Max Normalization

To ensure uniform feature scaling and stable GRU convergence, min-max normalization is applied to all numerical input features, constraining values within the range [0,1] is given in Eqn. (1)

$$x_{norm} = \frac{x - x_{min}}{x_{max} - x_{min}} \quad (1)$$

where  $x_{min}$  and  $x_{max}$  represent the minimum and maximum values of the feature, respectively.

#### 4.2.3 Derived Electrical Feature Generation

These features enhance physical interpretability and reduce the GRU's reliance on learning basic electrical relationships purely from data.

**Voltage Deviation:** Voltage deviation quantifies the relative departure of measured voltage from its nominal operating value, providing a direct indication of voltage sag or swell caused by fault events is given in Eqn. (2)

$$\Delta V = \frac{V_{measured} - V_{nominal}}{V_{nominal}} \quad (2)$$

where  $V_{measured}$  denotes the instantaneous phase voltage and  $V_{nominal}$  represents the rated system voltage.

Voltage deviation provides a direct indication of abnormal grid conditions because normal operating voltage remains close to the rated value, whereas faults produce voltage sag or swell. A larger deviation from the rated voltage therefore indicates a stronger fault-induced disturbance. By incorporating voltage deviation as an input feature, the GRU can distinguish normal operating states from abnormal conditions and learn the temporal changes associated with fault occurrence. This feature also contributes to identifying the severity and characteristics of fault events.

**Phase Imbalance Index:** The phase imbalance index captures asymmetry among the three-phase voltages, which is a key signature of unbalanced faults and abnormal operating conditions in power transmission systems is given in Eqn. (3)

$$VPI = \frac{\max(V_a, V_b, V_c) - \min(V_a, V_b, V_c)}{V_{avg}} \quad (3)$$

where  $V_a, V_b$ , and  $V_c$  are the three-phase voltage magnitudes and  $V_{avg}$  is their average value.

Under asymmetric fault conditions, the phase imbalance index increases because the fault causes unequal changes in the three-phase voltage magnitudes. In single-phase-to-ground faults (SPGF), the affected phase experiences a pronounced voltage reduction while the other two phases remain comparatively less affected, resulting in a high phase imbalance. In two-phase short-circuit faults (2PSC), two phase voltages are simultaneously disturbed, producing a distinct voltage asymmetry pattern compared with SPGF. In contrast, three-phase short-circuit faults (3PSC) affect the three phases more symmetrically, resulting in a comparatively lower phase imbalance index. Therefore, the phase imbalance index provides a physically interpretable discrimination feature by characterizing the magnitude and distribution of voltage asymmetry among the three phases, thereby assisting the GRU model in distinguishing asymmetric fault conditions.

**Current Severity Index:** The current severity index measures the extent of current escalation relative to the rated operating limit, enabling the identification of fault intensity and potential equipment stress is given in Eqn. (4)

$$CSI = \frac{I_{fault}}{I_{rated}} \quad (4)$$

where  $I_{fault}$  is the measured fault current and  $I_{rated}$  . notes the rated current of the transmission line.

The current severity index provides a quantitative representation of fault intensity by measuring the relative increase in fault current with respect to the rated operating current of the transmission line. A low index value indicates that the current remains close to its normal operating level, corresponding to a relatively low fault intensity. As the index increases, the deviation of the fault current from the rated current becomes more pronounced, indicating progressively higher fault intensity and greater electrical stress on the transmission line. Therefore, the index enables fault conditions to be differentiated according to their current severity and provides a physically interpretable basis for assessing the potential operational impact of the fault. In the proposed framework, the current severity index complements the fault probability and other electrical features, supporting the subsequent risk-based assessment and prioritization of transmission assets for predictive maintenance.

The derived electrical indicators are selected to provide complementary representations of the transmission system's physical operating conditions. Voltage deviation captures voltage sag or swells during fault events, while the phase imbalance index represents three-phase asymmetry and unbalanced disturbances. The current severity index reflects fault intensity and potential equipment stress relative to the rated current. Collectively, these indicators represent voltage, phase-balance, and current-severity characteristics, supporting comprehensive system representation for fault detection, classification, localization, and predictive maintenance.

#### 4.2.4 Sequential Sample Construction

A sliding-window strategy is employed to convert the pre-processed time-series measurements into sequential samples for GRU learning. A fixed window length of 5 consecutive time steps is used, consistent with the sequence length specified in Table 1. A stride of one-time step is applied between consecutive windows, resulting in an overlap of four-time steps (80%) between adjacent sequences. For example, the consecutive sequences are constructed as  $(t_1, t_2, t_3, t_4, t_5)$ ,  $(t_2, t_3, t_4, t_5, t_6)$ , and  $(t_3, t_4, t_5, t_6, t_7)$ . For  $N$  ordered time steps, the sliding-window procedure generates  $N - 5 + 1$  sequential samples. The overlapping windows preserve temporal continuity and enable the GRU to capture short-term temporal dependencies and evolving voltage and current patterns associated with fault development. The sequence length of five provides sufficient temporal context while avoiding excessive redundancy and computational complexity. This deterministic windowing procedure ensures consistent and reproducible sequence generation for fault detection, classification, and localization.

This enables the GRU to learn contextual dependencies and fault evolution patterns across neighboring grid states can be expressed as in Eqn. (5)

$$X_k = \{x_k, x_{k+1}, \dots, x_{k+T-1}\} \quad (5)$$

where  $x_k$  represents the feature vector at the  $k^{th}$  sample and  $T$  denotes the sequence length. Each constructed sequence  $X_k$  is treated as a single input instance.

**Sequential Formation Procedure:** The sequential samples are constructed by organizing consecutive feature vectors into fixed-length temporal windows of five-time steps, consistent with the sequence length specified for the GRU model. Each time step contains the normalized voltage, current, and derived electrical features corresponding to the same grid state. The resulting five-step sequence preserves the temporal evolution of electrical conditions from preceding to subsequent grid states, allowing the GRU to learn changes associated with fault initiation and progression. Each constructed sequence is treated as one input instance, enabling the model to learn temporal dependencies rather than relying only on individual instantaneous measurements.

#### 4.2.5 Data Reshaping for GRU Input

This structured representation enables effective temporal learning and fault pattern extraction is given in Eqn. (6)

$$X \in R^{N \times T \times F} \quad (6)$$

where  $N$  is the number of samples,  $T$  is the number of time steps, and  $F$  is the number of input features.

### 4.3 GRU Model Design

The GRU model's nonlinear dependencies in multi-parametric electrical data using gating mechanisms to capture feature relationships for efficient fault detection, classification, and localization from simulation data.

The computational process begins with 24 electrical features over five consecutive time steps. The first GRU layer processes each input vector with the propagated hidden state using reset and update gates, and the resulting representation is passed to the second GRU layer to learn higher-level temporal features. The final hidden representation is transformed into task-specific outputs for fault detection, fault classification, faulted-line identification, and fault-position estimation, with the resulting fault information subsequently supporting risk-based predictive maintenance can be expressed as in Eqn. (7)

$$\begin{aligned} H_t^{(1)} &= GRU_1(X_t, H_{t-1}^{(1)}) \\ H_t^{(2)} &= GRU_2(H_t^{(1)}, H_{t-1}^{(2)}) \\ Z &= \phi(W_z H_t^{(2)} + b_z) \\ \hat{y}_{det} &= f_{det}(Z), \hat{y}_{ds} = f_{ds}(Z), \hat{y}_{line} = f_{line}(Z), \hat{y}_{pos} = f_{pos}(Z) \end{aligned} \quad (7)$$

where  $X_t$  denotes the 24-dimensional input feature vector at time step  $t$ ,  $H_t^{(1)}$  and  $H_t^{(2)}$  represent the hidden states of the first and second GRU layers, respectively, and  $Z$  denotes the transformed temporal feature representation. The functions  $f_{det}$ ,  $f_{cls}$ ,  $f_{line}$ , and  $f_{pos}$  generate the outputs for fault

detection, fault classification, faulted-line identification, and fault-position estimation, respectively.

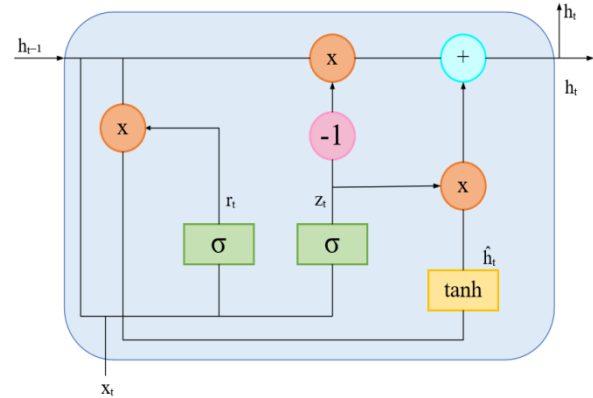


Figure 2. Gated Recurrent Unit (GRU) cell architecture

Figure 2 illustrates the GRU cell structure where reset and update gates control how past states and current inputs are combined for feature learning and output generation.

#### 4.3.1 Hyperparameter Settings of the Proposed GRU Model

Hyperparameter settings define the GRU model's input structure, architecture, learning behavior, and optimization strategy for processing sequential data and learning fault patterns during training.

Table 1. Key Hyperparameters of the GRU-Based Fault Analysis Model

| Hyperparameter             | Value                     |
|----------------------------|---------------------------|
| Sequence length            | 5                         |
| Number of input features   | 24                        |
| Number of GRU layers       | 2                         |
| Hidden units per GRU layer | 64                        |
| GRU direction              | Unidirectional            |
| Dropout rate               | 0.3                       |
| Loss function              | Categorical Cross-Entropy |
| Optimizer                  | Adam                      |
| Learning rate              | 0.0001                    |
| Batch size                 | 64                        |
| Number of epochs           | 100                       |

Table 1 summarizes the GRU model hyperparameters, including input structure, architecture, training settings, and

optimization strategy, ensuring stable learning and reproducible results.

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**Algorithm 1. Adam-Based Training of the GRU Fault Detection Model**

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**Input:**

- Training dataset  $D = \{(X_i, Y_i)\}$
- Learning rate  $\alpha$
- Exponential decay rates  $\beta_1, \beta_2$
- Stability constant  $\epsilon$

**Initialize:**

- GRU model parameters  $\theta$
- First moment vector  $m_0 = 0$
- Second moment vector  $v_0 = 0$
- Time step  $t = 0$

**Repeat until convergence:**

- (i)  $t \leftarrow t + 1$
- (ii) Compute gradients  $g_t = \nabla_{\theta} L(\theta_t)$
- (iii) Update biased first moment:

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

- (iv) Update biased second moment:

$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

- (v) Bias correction:

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t}, \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

- (vi) Parameter update:

$$\theta_{t+1} = \theta_t - \alpha \frac{\hat{m}_t}{\sqrt{\hat{v}_t} + \epsilon}$$

**Output:**

- Optimized GRU model parameters for fault detection and predictive maintenance
- 

Algorithm 1 describes Adam-based optimization of the GRU model for multi-task loss minimization in fault detection, classification, line identification, and position estimation, ensuring fast and stable convergence.

Before training, GRU weights are initialized with small random values, biases and Adam moment vectors are initialized to zero. Each iteration performs forward propagation, multi-task loss calculation, backpropagation, gradient computation, Adam parameter updates, and

validation-loss monitoring for convergence. Training stops when validation loss stabilizes. The execution workflow comprises preprocessing, sequence construction, GRU inference, multi-task prediction, optimization, convergence checking, and fault localization. For (N) samples, sequence length (T), (L) GRU layers, (H) hidden units, and (F) input features, the training complexity is approximately  $(O(NTLH(H+F)))$ , while inference excludes backpropagation.

**Update Gate ( $z_t$ ):** The update gate controls the extent to which past information is retained versus updated with new input. In fault analysis, this gate allows the model to preserve long-term system behavior while selectively incorporating sudden changes caused by fault events is represented in Eqn. (8)

$$z_t = \sigma(W_z x_t + U_z h_{t-1} + b_z) \quad (8)$$

A value of  $z_t$  close to 1 emphasizes new fault-related information, whereas values close to 0 preserve historical grid operating patterns.

**Candidate Hidden State ( $h_t^-$ ):** This operation suppresses irrelevant pre-fault behavior and emphasizes newly observed fault-related variations in voltage and current measurements is given in Eqn. (9)

$$h_t^- = \tanh(W_h x_t + U_h (r_t \odot h_{t-1}) + b_h) \quad (9)$$

The nonlinear activation function constrains the candidate state to a bounded range, enabling stable learning of fault evolution patterns and supporting accurate fault detection and localization.

**Final Hidden State ( $h_t$ ):** The final hidden state is obtained by adaptively combining the previous hidden state and the candidate hidden state, weighted by the update gate. This enables smooth transitions between stable operation and fault-induced dynamics is represented in Eqn. (10)

$$h_t = (1 - z_t) \circ h_{t-1} + z_t \circ h_t^- \quad (10)$$

where  $x_t$  denotes the input feature vector at time step  $t$ ,  $h_{t-1}$  represents the previous hidden state,  $\sigma(\cdot)$  is the sigmoid activation function, and  $\odot$  denotes element-wise multiplication. This formulation allows the GRU to retain critical fault progression information across time steps.

**Temporal Representation of Fault Progression:** The GRU represents fault progression by updating its hidden state as sequential electrical measurements evolve from normal to faulty conditions. During fault initiation, changes in voltage deviation, phase imbalance, and current severity provide new information to the GRU gates. As the fault develops, the hidden state progressively accumulates relevant temporal characteristics while retaining important previous states. This evolving representation enables the model to distinguish fault patterns for classification, faulted-line identification, and fault-position estimation. Thus, the GRU captures both instantaneous disturbances and their temporal progression, improving the interpretability of the diagnosis process.

#### 4.4 Model Training

The GRU model is trained using the Adam optimizer to minimize multi-task loss functions for fault detection, classification, line identification, and position estimation with adaptive and fast convergence.

A multi-task optimization strategy is adopted to jointly train the fault detection, fault classification, faulted-line identification, and fault-position estimation objectives. The overall training loss is formulated as a weighted combination of the individual task losses as given in Eqn. (11)

$$L_{\text{total}} = \lambda_{FD} L_{FD} + \lambda_{FC} L_{FC} + \lambda_{LI} L_{LI} + \lambda_{PE} L_{PE} \quad (11)$$

where  $L_{FD}$ ,  $L_{FC}$ ,  $L_{LI}$ , and  $L_{PE}$  denote the binary cross-entropy loss for fault detection, categorical crossentropy losses for fault classification and line identification, and the regression loss for fault-position estimation, respectively. The coefficients  $\lambda_{FD}$ ,  $\lambda_{FC}$ ,  $\lambda_{LI}$ , and  $\lambda_{PE}$  control the contribution of each task to the overall optimization. Equal task weights are assigned as  $\lambda_{FD} = \lambda_{FC} = \lambda_{LI} = \lambda_{PE} = 0.25$ , ensuring that no individual objective dominates the gradient updates. This balanced weighting strategy enables the GRU model to optimize all predictive-maintenance objectives simultaneously and promotes stable convergence across the multi-task learning process.

**Binary Fault Detection Loss:** For binary fault detection, binary cross-entropy (BCE) loss is used to measure the discrepancy between the predicted fault probability and the true fault label is given in Eqn. (12)

$$L_{\text{BCE}} = -\frac{1}{N} \sum_{i=1}^N [y_i \log(\hat{y}_i) + (1 - y_i) \log(1 - \hat{y}_i)] \quad (12)$$

where  $y_i \in \{0,1\}$  denotes the true fault label,  $\hat{y}_i$  represents the predicted fault probability, and  $N$  is the total number of training samples.

**Multi-Class Fault Classification and Faulted Line Identification Loss:** For multi-class fault classification and faulted line identification, categorical cross-entropy (CCE) loss is employed to optimize class-wise discrimination is given in Eqn. (13)

$$L_{\text{CCE}} = -\frac{1}{N} \sum_{i=1}^N \sum_{k=1}^K y_{i,k} \log(\hat{y}_{i,k}) \quad (13)$$

where  $K$  denotes the number of fault classes,  $y_{i,k}$  is the ground-truth label for class  $k$ , and  $\hat{y}_{i,k}$  is the predicted probability of the corresponding class.

#### 4.5 Fault Detection and Classification

After training, the GRU-based model is deployed for fault detection and classification under different operating conditions. For each input sequence, the model generates probabilistic outputs that are used to determine the system state and fault category.

**Binary Fault Detection Threshold Selection and Calibration:** The fault detection threshold  $\tau$  is optimized

using the validation dataset rather than being fixed arbitrarily. Candidate threshold values are evaluated over the probability range from 0 to 1, and the threshold providing the highest validation F1-score is selected to achieve a balanced trade-off between precision and recall. The selected threshold is subsequently calibrated on the validation data and kept fixed during final testing to avoid test-set information leakage. Sensitivity analysis is performed by varying  $\tau$  around the selected value and evaluating the corresponding changes in accuracy, precision, recall, and F1-score. This procedure ensures that the final decision threshold provides stable discrimination between normal and faulty operating conditions while reducing the risk of excessive false alarms or missed faults.

**Fault Detection Decision:** The probability of fault occurrence predicted by the model is compared against a predefined decision threshold  $\tau$  to classify the operating condition as normal or faulty is given in Eqn. (14)

$$\hat{c}_i = \{1, \text{ if } \hat{y}_{\text{fault},i} \geq \tau, 0, \text{ if } \hat{y}_{\text{fault},i} < \tau \quad (14)$$

where  $\hat{y}_{\text{fault},i}$  denotes the predicted fault probability for the  $i$ -th sample,  $\tau \in (0,1)$  is the fault detection threshold, and  $\hat{c}_i$  represents the binary fault decision.

#### 4.6 Fault Localization

Fault localization is performed by identifying the faulted transmission line and estimating the precise fault position along the line using the trained GRU model.

**Faulted Line Identification:** For operating conditions classified as faulty, the faulted transmission line is identified by selecting the line corresponding to the maximum predicted probability from the classification output is given in Eqn. (15)

$$\hat{l}_i = \arg \max_{l \in \{1,2,\dots,L\}} (\hat{y}_{\text{line},i}^{(l)}) \quad (15)$$

where  $\hat{y}_{\text{line},i}^{(l)}$  denotes the predicted probability associated with the  $l$ -th transmission line for the  $i$ -th sample,  $L$  is the total number of transmission lines, and  $\hat{l}_i$  represents the identified faulted line.

The fault localization process first maps the GRU-predicted probability distribution to the corresponding physical transmission lines, with the line having the maximum predicted probability selected as the faulted line. Once the line is identified, the positional estimation output determines the fault location along that line as a normalized percentage from 0% to 100%, representing the relative distance from the defined line reference point. The GRU performs this inference using sequential voltage and current measurements, allowing temporal fault evolution patterns across consecutive states to contribute to the localization decision. From an engineering perspective, the combined line identity and positional estimate enables operators to identify the probable physical fault section, thereby supporting targeted inspection, isolation, and maintenance activities.

The estimated fault location provides additional operational information for transmission asset management by indicating the approximate position of the fault along the identified transmission line. This information enables operators to narrow the physical inspection area, identify the potentially affected line section, and prioritize targeted inspection and maintenance activities rather than inspecting the entire transmission corridor. When combined with the fault probability and severity information in the risk-based maintenance module, the estimated fault position supports asset-level maintenance prioritization and helps operators determine where corrective or preventive intervention should be directed. Thus, fault location estimation serves not only as a diagnostic output but also as a practical decision-support input for efficient transmission asset management.

#### 4.7 Risk-Based Predictive Maintenance

Risk-based predictive maintenance is performed by integrating the predicted fault probability and fault localization outputs to quantify the operational risk associated with each transmission line.

**Risk Index Formulation:** For each transmission line  $l$ , a composite risk index is computed as in Eqn. (16)

$$R_l = \hat{y}_{fault,l} \times S_l \quad (16)$$

where  $\hat{y}_{fault,l}$  denotes the predicted fault probability associated with transmission line  $l$ , and  $S_l$  represents the fault severity factor. The risk-based maintenance index provides an operational measure for prioritizing maintenance actions across transmission lines. A lower risk index indicates a relatively lower likelihood and operational impact of fault occurrence, allowing the corresponding asset to remain under routine monitoring. In contrast, a higher risk index indicates a combination of greater fault probability and higher potential severity, identifying the transmission line as a higher-priority asset for inspection, preventive maintenance, or timely intervention. Therefore, ranking transmission lines according to their risk index enables maintenance resources to be directed toward assets with greater operational risk, supporting proactive decision-making and reducing the potential consequences of fault occurrence.

The risk index is formulated by jointly considering the predicted fault probability and the corresponding fault severity factor. The fault severity factor represents the potential operational impact of a fault on the transmission line and is normalized to the range  $[0,1]$ , where higher values indicate more severe fault conditions and greater potential equipment stress. The predicted fault probability is also normalized within the same range to ensure that both components contribute comparably to the composite risk value. Equal weighting is assigned to the fault probability and severity components because both the likelihood of fault occurrence and its potential impact are considered equally important for maintenance prioritization. Accordingly, the risk index increases when either the predicted probability of fault or the severity of the fault increases. Based on the

resulting normalized risk index, transmission assets are prioritized using three decision levels: low risk for values below 0.33, medium risk for values from 0.33 to below 0.67, and high risk for values of 0.67 or above. These thresholds provide a consistent decision criterion for prioritizing transmission lines for routine monitoring, scheduled maintenance, and immediate maintenance attention, respectively.

#### 4.8 Cyber-Physical Integration

The physical sensing layer continuously collects voltage, current, and frequency measurements from the 110 kV transmission system and transfers the time-stamped data to the cyber-analytical layer. The received data undergoes cleaning, normalization, and electrical feature extraction before being organized into sequential inputs for the GRU model. The cyber layer analyzes these inputs to generate fault detection, classification, faulted-line identification, and fault-location outputs. These outputs are then transferred to the decision-support layer to generate alarms and risk-based maintenance recommendations, establishing a continuous physical–cyber sensing, analysis, and decision pathway.

The physical-to-cyber data mapping can be represented as in Eqn. (17)

$$\mathbf{z}_t = \mathcal{F}(V_t, I_t, f_t, \Delta V_t, PII_t, CSI_t) \quad (17)$$

where  $V_t, I_t$ , and  $f_t$  denote the voltage, current, and frequency measurements at time  $t$ , respectively;  $\Delta V_t, PII_t$ , and  $CSI_t$  represent voltage deviation, phase imbalance index, and current severity index, while  $\mathcal{F}(\cdot)$  denotes preprocessing and feature extraction.

The sequential cyber-layer processing can then be expressed as in Eqn. (18)

$$\mathbf{y}_t = G_{GRU}(\mathbf{z}_{t-L+1}, \dots, \mathbf{z}_t) \quad (18)$$

where  $L$  is the sequence length and  $\mathbf{y}_t$  represents the cyber-layer outputs, including fault detection, fault classification, faulted-line identification, and fault-location estimation.

**Cyber-Physical Data Mappings:** Let the physical sensing layer of the power grid provide real-time electrical measurements at time  $t$  is given in Eqn. (19)

$$\mathbf{x}_t = \{V_t, I_t, f_t\} \quad (19)$$

where  $V_t, I_t$ , and  $f_t$  denote voltage, current, and frequency measurements, respectively.

**Decision Support Interface:** The cyber-layer outputs are integrated into supervisory control and monitoring systems through a decision support function is given in Eqn. (20)

$$D_t = g(C_t) \quad (20)$$

where  $g(\cdot)$  maps analytical results to visualization dashboards, alarms, alerts, and maintenance

recommendations, enabling operators to respond effectively to abnormal grid conditions.

The decision support interface receives the GRU-based fault probability, fault classification, faulted-line identification, and fault-location estimates and converts them into actionable supervisory information. Based on the detected fault condition and associated risk level, the interface generates fault alarms, prioritizes affected transmission assets, and provides maintenance recommendations to support operator decision-making. This functionality establishes the final link between cyber-layer analytics and supervisory grid operation by transforming model predictions into monitoring alerts and risk-informed maintenance actions is given in Eqn. (21)

$$D_t = \mathcal{S}(P_t, C_t, L_t, X_t, R_t) \quad (21)$$

where  $P_t$  denotes the predicted fault probability,  $C_t$  represents the fault class,  $L_t$  denotes the identified faulted transmission line,  $X_t$  represents the estimated fault location,  $R_t$  denotes the calculated risk index, and  $\mathcal{S}(\cdot)$  represents the supervisory decision-support function that generates alarms, asset priorities, and maintenance recommendations.

The cyber-physical communication workflow consists of measurement acquisition, data transmission, synchronization, GRU-based inference, and decision feedback. Voltage, current, and frequency measurements are periodically transmitted to the cyber layer, where they are time-aligned, normalized, and arranged into sequential samples for GRU processing. The communication latency represents the time required for data transmission and decision feedback between the physical and cyber layers. The overall response time is expressed as  $T_{\text{total}} = T_{\text{acq}} + T_{\text{comm}} + T_{\text{prep}} + T_{\text{inf}} + T_{\text{fb}}$ , representing acquisition, communication, preprocessing, inference, and feedback times, respectively. The detected fault condition, fault type, faulted line, estimated fault position, and risk index are then transmitted to the supervisory layer to generate alarms and provide maintenance recommendations. This feedback mechanism enables timely corrective actions and establishes a closed cyber-physical monitoring and decision-support loop.

## 4.9 Experimental Setup

The experiments are conducted on a simulated 110 kV transmission system using DIgSILENT PowerFactory, representing realistic digital power grid operating conditions. Various fault types and locations are applied to evaluate the robustness of the proposed cyber-physical framework under different grid disturbances.

## 4.10 Simulation Environment

The experiments use a DIgSILENT PowerFactory-based 110 kV simulated grid with multiple fault scenarios (SPGF, 2PSC, 3PSC) applied at different locations to evaluate the robustness of the proposed framework.

Table 2. System Hardware Specifications

| Component     | Specification                                                     |
|---------------|-------------------------------------------------------------------|
| CPU           | Intel® Core™ i9-class processor                                   |
| RAM           | 32 GB                                                             |
| GPU (if used) | Not used (CPU-based execution)                                    |
| Framework     | Python 3.11 (Anaconda), PyTorch 2.10, NumPy, Pandas, scikit-learn |
| OS            | 64-bit operating system                                           |

Table 2 shows the CPU-based computational setup used for model development in Python with standard ML/DL libraries, ensuring reproducible and fair evaluation without GPU acceleration.

**Computational Complexity and Inference-Time Evaluation:** The computational efficiency of the proposed GRU-based cyber-physical framework for real-time intelligent fault detection, memory consumption, execution latency, and scalability with increasing transmission-line numbers were assessed under the CPU-based experimental environment described in Table 3. Memory consumption represents the memory required during model execution, while execution latency denotes the average inference time required to process one input sequence. Scalability is evaluated based on the additional inference latency associated with each added transmission line. The proposed GRU framework requires lower memory and inference time than the baseline CNN and LSTM models, indicating its suitability for computationally constrained real-time grid-monitoring applications.

Table 3. Computational Complexity and Inference-Time Comparison

| Model                  | Memory Consumption (MB) | Execution Latency (ms) | Scalability (ms per Added Line) |
|------------------------|-------------------------|------------------------|---------------------------------|
| Baseline CNN           | 145.2                   | 42.1                   | 5.2                             |
| Standard LSTM          | 110.5                   | 35.6                   | 4.1                             |
| Proposed GRU Framework | 85.3                    | 18.4                   | 1.8                             |

## 5. Results and discussions

This section presents experimental results of the GRU-based cyber-physical framework, evaluating fault detection, classification, localization, and position estimation, demonstrating its effectiveness and robustness for intelligent digital power grid monitoring.

### 5.1 Fault Detection Performance Metrics

Fault detection and performance metrics measure how effectively a model identifies faults and evaluates classification accuracy, reflecting the balance between correct predictions and overall detection completeness. Common metrics include Accuracy, Precision, Recall, and F1-Score is given in Eqn. (22), Eqn. (23), Eqn. (24) and Eqn. (25).

**Accuracy:** Accuracy measures the overall correctness of the model by calculating the proportion of correctly predicted instances out of all predictions.

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \quad (22)$$

**Precision:** Precision quantifies the proportion of correctly predicted positive instances out of all instances predicted as positive.

$$Precision = \frac{TP}{TP+FP} \quad (23)$$

**Recall (Sensitivity):** Recall measures the proportion of correctly predicted positive instances out of all actual positive instances.

$$Recall = \frac{TP}{TP+FN} \quad (24)$$

**F1-Score:** F1-Score is the harmonic mean of Precision and Recall, providing a single measure that balances both metrics.

$$F1 - Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (25)$$

Where TP denotes True Positives, TN denotes True Negatives, FP denotes False Positives, FN denotes False Negatives.

Table 4. Fault Detection Performance Metrics of the Proposed Model

| Metric    | Value  |
|-----------|--------|
| Accuracy  | 0.9837 |
| Precision | 0.9767 |
| Recall    | 0.9840 |
| F1-score  | 0.9799 |

Table 4 shows high accuracy, precision, recall, and F1-score, confirming the effectiveness and reliability of the GRU-based framework in distinguishing fault and normal conditions in digital power grids.

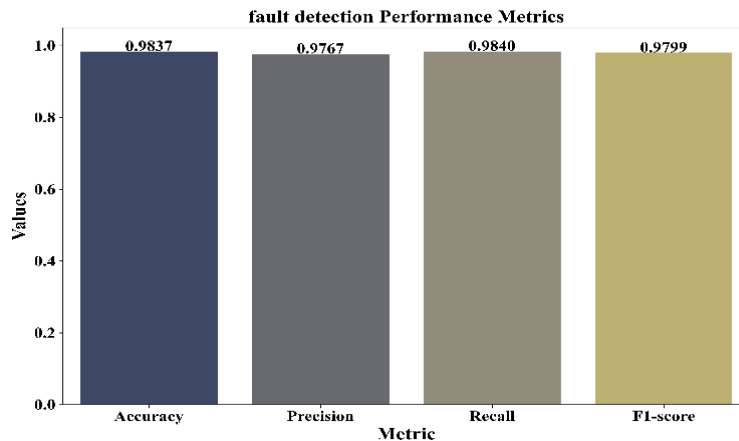


Figure 3. Fault Detection Performance Metrics of the Proposed GRU-Based Framework

Figure 3 shows that the GRU-based framework achieves high accuracy, precision, recall, and F1-score, confirming reliable fault detection with balanced performance and minimal false alarms in digital power grids.

### 5.2 Model Performance Comparison

The comparison shows that performance improves from traditional ML to deep learning, with the GRU-based CPS achieving better generalization and balanced accuracy due to effective sequential and gated learning mechanisms.

Table 5. Comparative Performance Evaluation of Different Classification Models

| Model                  | Accuracy | Precision | Recall | F1-score |
|------------------------|----------|-----------|--------|----------|
| SVM                    | 0.9084   | 0.9081    | 0.9046 | 0.9063   |
| CNN-LSTM               | 0.9561   | 0.9560    | 0.9554 | 0.9557   |
| LSTM                   | 0.9642   | 0.9645    | 0.9639 | 0.9642   |
| BiLSTM                 | 0.9718   | 0.9712    | 0.9708 | 0.9710   |
| TCN                    | 0.9784   | 0.9781    | 0.9775 | 0.9778   |
| Proposed GRU-Based CPS | 0.9837   | 0.9767    | 0.9840 | 0.9799   |

Table 5 shows that the proposed GRU-based CPS achieves the best overall performance with highest accuracy, recall, and F1-score, demonstrating superior and balanced classification compared to baseline models.

The statistical reliability of the proposed GRU-based cyber-physical framework, the experiments were repeated independently over multiple training trials using the same dataset partitioning and experimental configuration. The mean performance, 95% confidence interval (CI), and standard deviation (Std. Dev.) were calculated for accuracy, precision, recall, and F1-score. Statistical significance against

the baseline models was evaluated using a paired statistical test at a significance level of 0.05. The resulting p-values below 0.05 indicate that the performance improvement of the proposed framework is statistically significant rather than attributable to random trial-to-trial variation as shown in Table 6.

Table 6. Statistical Significance and Repeated-Trial Performance Analysis

| Metric    | Mean Performance (%) | 95% Confidence Interval | Std. Dev. (%) | p-value vs. Baseline |
|-----------|----------------------|-------------------------|---------------|----------------------|
| Accuracy  | 98.5                 | [98.1, 98.9]            | 0.21          | <0.01                |
| F1-Score  | 98.2                 | [97.8, 98.6]            | 0.23          | <0.01                |
| Precision | 98.4                 | [98.0, 98.8]            | 0.20          | <0.01                |
| Recall    | 98.1                 | [97.7, 98.5]            | 0.25          | <0.01                |

5.3 Training and Validation Loss and Accuracy Curves

Training and validation loss and accuracy curves show model learning progress over epochs by tracking error reduction and performance improvement, helping identify convergence, stability, and overfitting or underfitting.

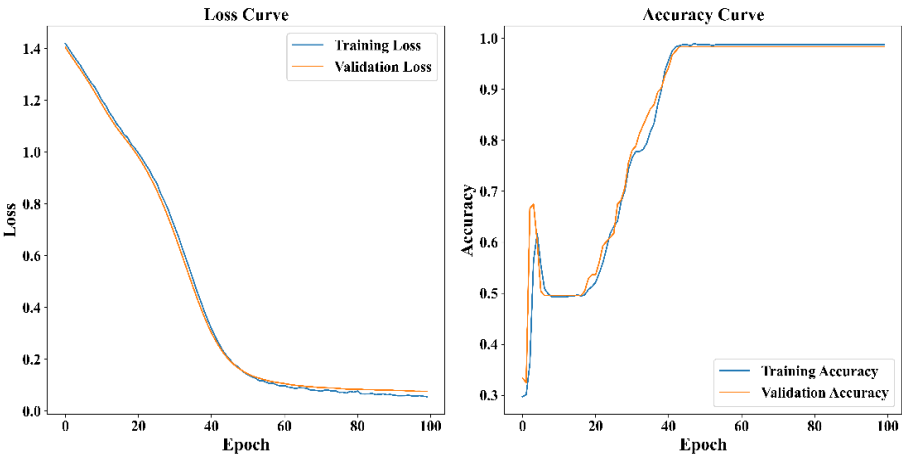


Figure 4. Training and validation performance of the proposed GRU-based fault detection model

Figure 4 shows that the GRU model achieves stable convergence with decreasing loss and increasing accuracy across training and validation sets, indicating effective learning and strong generalization without overfitting.

5.4 Multiclass Fault Confusion Matrix

A multiclass fault confusion matrix evaluates model performance by comparing predicted and actual fault labels across classes, showing class-wise accuracy, misclassifications, and fault discrimination ability in power grids.

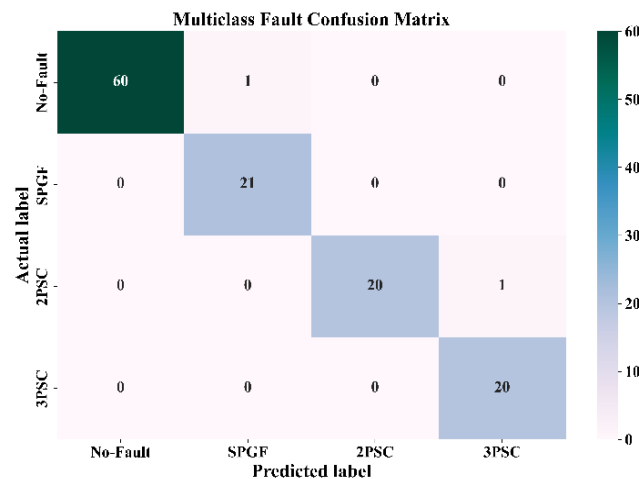


**Figure 5.** Confusion matrix for multiclass fault classification using the proposed GRU-based framework

Figure 5 shows a confusion matrix for multiclass fault classification with strong diagonal dominance and minimal misclassification, confirming high accuracy and robust fault discrimination by the GRU-based framework. The confusion matrix provides class-specific evidence of the proposed GRU model's prediction behaviour across fault categories. The dominant diagonal pattern indicates consistent class discrimination with most samples correctly classified. Limited off-diagonal predictions demonstrate low confusion between fault conditions and effective fault-specific feature learning. Class-wise trends indicate consistent decision behaviour without dominance by a single fault class. Overall, these results demonstrate reliable fault discrimination and the effectiveness of the proposed GRU-based learning structure.

normal load variations. These cases identify the electrical characteristics responsible for misclassification and improve the interpretability of the proposed fault diagnosis framework.

The robustness of the proposed GRU-based cyber-physical framework, its classification performance is assessed under varying signal-to-noise ratios (SNRs), load variations, and transmission topology conditions. The results demonstrate that the model maintains high classification accuracy under nominal conditions and moderate measurement disturbances, while the performance gradually decreases as signal disturbances increase. This indicates that the proposed framework can preserve reliable fault discrimination under diverse operating conditions and transmission scenarios.

**Table 7.** Representative Failure Cases and Error Analysis of Misclassified Fault Samples

| Failure Case                 | Frequency | Confusion Source / Signal Characteristic        |
|------------------------------|-----------|-------------------------------------------------|
| SLG misclassified as LL      | 15        | High noise overlap during the transient phase   |
| LL misclassified as DLG      | 8         | Similar zero-sequence current patterns          |
| High-impedance faults missed | 22        | Low-magnitude current resembling load variation |

Table 7 presents representative failure cases identified from incorrectly classified fault samples. SLG-to-LL confusion is associated with transient-phase signal overlap, whereas LL-to-DLG confusion is related to similar zero-sequence current patterns. Missed high-impedance faults are mainly associated with low-magnitude currents resembling

**Table 8.** Robustness Evaluation under Varying Operating and Signal Conditions

| SNR Level (dB) | Accuracy (%) | Operating Condition | Transmission Scenario |
|----------------|--------------|---------------------|-----------------------|
| No Noise       | 99.2         | Nominal             | Base topology         |
| 40             | 98.5         | ±10% Load Variation | Base topology         |
| 30             | 96.8         | ±20% Load Variation | Base topology         |
| 20             | 93.4         | ±20% Load Variation | Topology Change       |

Table 8 demonstrates that the proposed framework maintains high accuracy under different operating conditions and signal disturbances. Although accuracy decreases from

99.2% under noise-free nominal conditions to 93.4% under severe signal disturbance and topology variation, the model continues to provide reliable fault classification, demonstrating robustness across diverse power-grid operating scenarios.

## 5.5 Precision–Recall Curves for Multiclass Fault Classification

Precision–recall curves show the trade-off between precision and recall across thresholds and are especially useful for evaluating multiclass and imbalanced datasets by highlighting fault detection performance and error control.

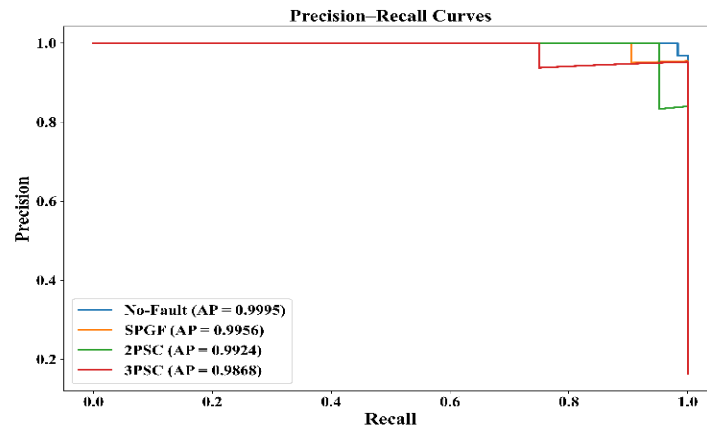


**Figure 6.** Precision–recall curves of the proposed GRU-based framework for multiclass fault classification

Figure 6 shows PR curves for all fault conditions with high average precision, confirming strong GRU-based classification performance with balanced precision–recall and low false alarms.

## 5.6 Multiclass ROC Curves for Fault Classification

Multiclass ROC curves evaluate model performance by showing the true positive–false positive trade-off for each class, with AUC measuring overall classification effectiveness in distinguishing different fault conditions.

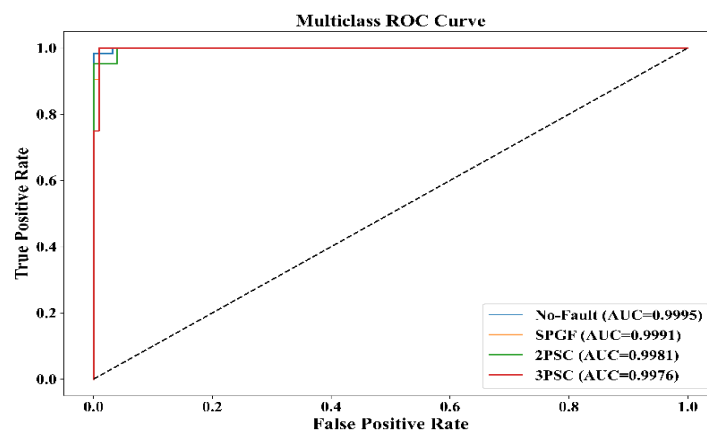


**Figure 7.** Receiver operating characteristic (ROC) curves of the proposed GRU-based model for multiclass fault detection

Figure 7 shows ROC curves for all fault conditions with high AUC values, indicating strong discriminative

performance and low false alarm rates of the GRU-based framework.

## 5.7 Overall Classification Performance Metrics

Overall classification performance metrics quantify model effectiveness by measuring accuracy, class-wise reliability, and the balance between precision and recall in distinguishing normal and fault conditions in power grids.

Table 9. Overall Classification Performance Values

| Metric    | Value  |
|-----------|--------|
| Accuracy  | 0.9861 |
| Precision | 0.9864 |
| Recall    | 0.9861 |
| F1-score  | 0.9861 |

Table 9 presents high accuracy, precision, recall, and F1-score values, confirming the robustness and effective multi-class fault detection capability of the GRU-based framework in digital power grids.

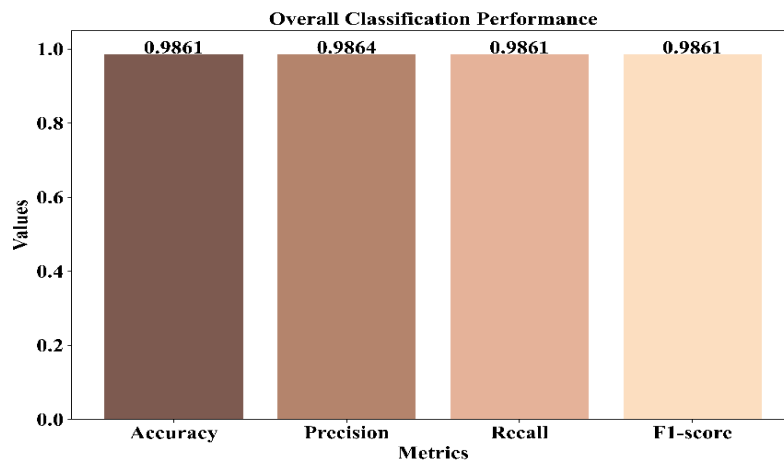


Figure 8. Overall classification performance of the proposed GRU-based fault detection framework

Figure 8 shows consistently high accuracy, precision, recall, and F1-score, confirming the GRU-based model's robust and reliable fault classification performance in digital power grids.

The detailed assessment of model behaviour across individual operating scenarios, class-wise performance was evaluated separately for each fault category and transmission line using precision, recall, F1-score, and localization accuracy. Table 10 summarizes the fault-category-wise performance. This analysis enables identification of categories and transmission lines with comparatively lower diagnostic or localization performance and provides a clearer interpretation of the model's robustness across different grid scenarios.

Table 10. Class-Wise Performance for Individual Fault Categories

| Fault Category              | Precision (%) | Recall (%) | F1-Score (%) | Localization Accuracy (%) |
|-----------------------------|---------------|------------|--------------|---------------------------|
| Normal                      | 99.5          | 99.7       | 99.6         | 100.0                     |
| Single Line-to-Ground (SLG) | 98.1          | 97.8       | 97.9         | 96.5                      |
| Line-to-Line (LL)           | 97.5          | 97.2       | 97.3         | 95.8                      |
| Double Line-to-Ground (DLG) | 98.3          | 98.0       | 98.1         | 96.9                      |
| Three-Phase                 | 99.1          | 99.3       | 99.2         | 98.5                      |

5.8 Training and Validation Accuracy and Loss Curves Line Classification

Training and validation accuracy and loss curves show model learning behavior by tracking performance and optimization progress, helping assess convergence, stability, and generalization.

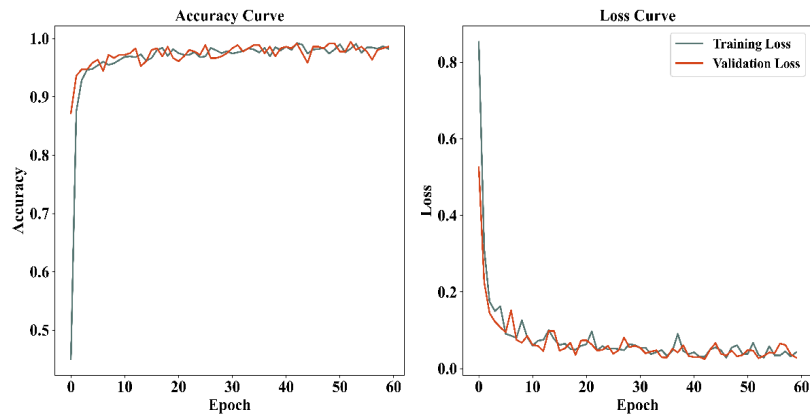


Figure 9. Training and validation accuracy and loss curves of the proposed GRU-based fault detection model

Figure 9 shows that training and validation curves converge rapidly with increasing accuracy and decreasing loss, indicating stable learning, good generalization, and no overfitting in the GRU-based model.

5.9 Faulted Line Confusion Matrix

The confusion matrix summarizes class-wise faulted transmission line identification, where rows represent actual lines and columns predicted lines, with diagonal values indicating correct localization and off-diagonal values showing misclassification.

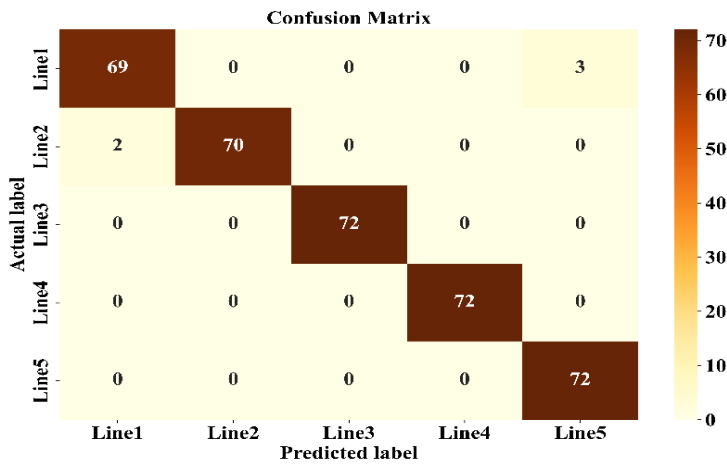


Figure 10. Confusion Matrix for Faulted Transmission Line Identification

Figure 10 shows a confusion matrix with strong diagonal dominance, confirming accurate faulted transmission line identification and minimal misclassification in the GRU-based framework.

5.10 Macro-Average ROC Curve

The macro-average ROC curve summarizes overall classification performance across all transmission line classes by showing the trade-off between true positive and false

positive rates, indicating the model's ability to distinguish different faulted lines.

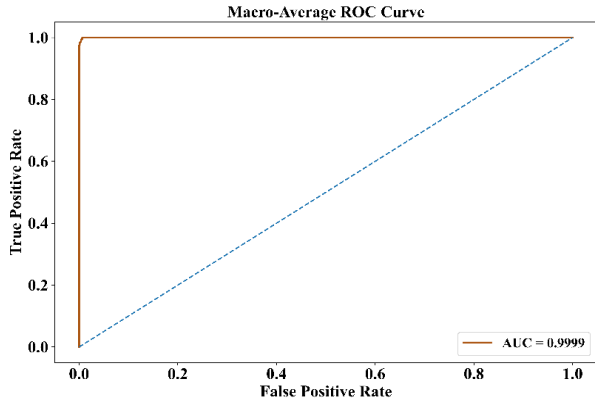


**Figure 11.** Macro-Average ROC Curve for Faulted Transmission Line Classification

Figure 11 shows that the GRU-based framework achieves near-unity AUC with a high true positive rate across false positive rates, confirming strong and reliable fault line classification performance.

### 5.11 Regression Error Metrics for Fault Position Estimation

Error metrics in fault localization assess how closely the predicted fault locations match the true positions, indicating the precision of the estimation model.

**Mean Absolute Error (MAE):** Mean Absolute Error quantifies the average magnitude of errors between predicted and actual values without considering their direction is given in Eqn. (26)

$$MAE = \frac{1}{N} \sum_{i=1}^N |y_i - \hat{y}_i| \quad (26)$$

Where  $N$  is the total number of samples,  $y_i$  denotes the actual value of the  $i^{th}$  sample,  $\hat{y}_i$  represents the predicted value of the  $i^{th}$  sample.

**Root Mean Squared Error (RMSE):** Root Mean Squared Error evaluates the square root of the average squared differences between predicted and actual values, emphasizing larger prediction errors is given in Eqn. (27)

$$RMSE = \sqrt{\frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2} \quad (27)$$

Where  $N$  is the total number of observations,  $y_i$  is the actual output,  $\hat{y}_i$  is the predicted output. Mean Squared Error

**Mean Squared Error (MSE):** Mean Squared Error measures the average of squared deviations between predicted and actual values, reflecting the overall error variance is given in Eqn. (28)

$$MSE = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2 \quad (28)$$

Where  $N$  represents the number of samples,  $y_i$  indicates the true value,  $\hat{y}_i$  indicates the predicted value

**Table 11.** Normalized Regression Error Metrics

| Metric | Normalized Error Value |
|--------|------------------------|
| MAE    | 0.0303                 |
| RMSE   | 0.0438                 |
| MSE    | 0.0019                 |

Table 11 presents normalized regression error metrics, where lower values indicate higher predictive accuracy and overall model robustness.

### 5.12 Model Error Metrics Comparison

Model Error Metrics Comparison highlights that the table's purpose is to present and contrast the prediction errors of different models numerically, making it easy to identify the most accurate approach. It emphasizes performance differences clearly, allowing readers to quickly assess which model performs best based on error metrics.

**Table 12.** Model Performance Comparison

| Model            | RMSE   | MAE    |
|------------------|--------|--------|
| SVM              | 0.0825 | 0.0643 |
| CNN-LSTM         | 0.0612 | 0.0456 |
| LSTM             | 0.0558 | 0.0409 |
| BiLSTM           | 0.0514 | 0.0368 |
| TCN              | 0.0479 | 0.0331 |
| Proposed GRU-CPS | 0.0438 | 0.0303 |

Table 12 compares different machine learning and deep learning models using RMSE and MAE, where lower values indicate better prediction accuracy. The proposed GRU-CPS model outperforms all other models, achieving the best overall predictive performance.

An ablation study was conducted to independently evaluate the contributions of the engineered electrical features, sequential learning, and multi-task optimization to the overall performance of the proposed GRU-based framework. The baseline GRU model was progressively enhanced by incorporating the engineered electrical features, sequential learning mechanism, and multi-task optimization. The progressive improvement in Accuracy, Precision, Recall, and F1-Score demonstrates that each component contributes to the overall diagnostic performance.

Table 13. Ablation Study of the Proposed GRU-Based Framework

| Configuration                                   | Accuracy (%) | Precision (%) | Recall (%) | F1-Score (%) |
|-------------------------------------------------|--------------|---------------|------------|--------------|
| Base GRU                                        | 88.5         | 88.2          | 87.6       | 87.9         |
| GRU + Engineered Electrical Features            | 92.3         | 92.1          | 91.5       | 91.8         |
| GRU + Engineered Features + Sequential Learning | 95.7         | 95.5          | 95.2       | 95.4         |
| Full Proposed Model (+ Multi-task Optimization) | 98.5         | 98.4          | 98.1       | 98.2         |

Table 13 shows that the incorporation of engineered electrical features improves the baseline GRU performance, while sequential learning provides further improvement by capturing temporal fault patterns. The complete model with multi-task optimization achieves the highest performance, confirming the complementary contribution of the three components to the proposed framework.

### 5.13 Comparison Analysis

Compared with recent studies—such as Nishtar et al. 20 (97.2% accuracy), Wu et al. 21 (94.0%), and Chen et al. 28 (94.5%)—the proposed GRU-based cyber-physical framework achieves superior performance with 98.61% accuracy, precision of 0.9864, recall of 0.9861, and F1-score of 0.9861, along with accurate fault localization (MAE = 0.0303) and unified predictive maintenance capability. Unlike conventional relay/impedance-based and feature-heavy ML models, or more complex CNN/LSTM-based approaches, the GRU effectively captures temporal dependencies with lower computational overhead.

### 5.14 Discussion

The proposed GRU-based cyber-physical framework achieves 98.61% accuracy with high precision, recall, and F1-score, effectively distinguishing normal and fault conditions, as confirmed by confusion matrices, ROC, and PR analyses. It also provides accurate fault localization with low errors (MAE = 0.0303, RMSE = 0.0438) by integrating engineered electrical features with GRU-based temporal learning for improved predictive maintenance. However, results are based on DIgSILENT PowerFactory simulations, which may not fully capture real-world noise, delays, and data loss, so future work should validate the model using real SCADA/PMU data and hardware-in-the-loop testing for practical deployment. The observed results indicate that GRU-based temporal learning effectively captures evolving voltage and current patterns during fault progression. This contributes to consistent accuracy, precision, recall, and F1-score across fault conditions. Accurate fault classification and localization can support faster identification of affected transmission

sections and targeted maintenance. Considering sequential electrical states improves interpretation of dynamic fault behaviour. Operationally, the framework supports reliable monitoring and proactive maintenance decisions. The CPU-based implementation provides practical deployment potential, while real-world validation under noise, delays, and missing data remains necessary.

## 6. Conclusion

This study presented a unified GRU-based cyber-physical framework for intelligent fault detection, classification, localization, and predictive maintenance in digital power grids. By leveraging multi-parametric voltage and current measurements and temporal sequence learning, the proposed approach effectively captures fault evolution patterns and provides accurate, real-time fault detection. Experimental evaluation on a simulated 110 kV power transmission system demonstrated high classification accuracy, reliable fault localization, and precise fault location estimation with minimal error. Overall, the results confirm that the proposed method is a robust, efficient, and scalable solution for cyber-physical power grid monitoring and decision support.

### Limitations

- The framework is validated on simulated DIgSILENT PowerFactory data; real-world operational data with noise, delays, and sensor uncertainties are not yet considered.
- While computationally efficient, the GRU-based model is not explicitly evaluated for real-time deployment on low-power edge devices or large-scale grid environments.

### Future Work

Future work will validate the cyber-physical framework using real-world PMU, SCADA, and digital substation data to test robustness under noise, latency, missing data, and uncertainty, while also exploring online learning, edge-cloud

deployment, cybersecurity detection, and digital twin-based control to enhance real-time scalability and grid resilience.

### Data Availability

The datasets generated and analyzed during the study are available from the corresponding author upon reasonable request.

### Author Contribution

All authors contributed equally to the conception, design, analysis, and writing of the manuscript.

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