DETECTION, LOCALIZATION AND CLEARING OF FAULTS IN THREE PHASE 132KV TRANSMISSION SYSTEM USING OPTIMAL DEEP LEARNING TECHNIQUES

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ABSTRACT

Faults in three-phase power transmission systems threaten system stability, equipment integrity, and power supply reliability. This study presents an integrated framework for fault detection, localization, and clearing using time-domain voltage and current signals in MATLAB/Simulink. Fault detection is performed using a Long Short-Term Memory (LSTM) autoencoder trained on healthy operating data. The reconstruction loss remained below 50 under normal conditions and increased above 500 during faults, enabling reliable detection within 10–20 ms. Fault localization was achieved through phase-wise analysis of voltage and current signals, accurately identifying line-to-ground (LG), line-to-line (LL), line-to-line-to-ground (LLG), and three-phase (LLL) faults. A logic-based protection scheme combined the detection and localization outputs to generate circuit breaker trip commands for fault isolation. Simulation results show that fault currents increased from below 200 A to approximately 1.5–3.9 kA, depending on the fault type, before rapidly decreasing to near zero after breaker operation. Voltage recovery occurred within 40–60 ms, with minimal post-fault oscillations and stable system operation. The proposed framework provides fast fault detection, accurate fault localization, and effective fault clearing, demonstrating its suitability for intelligent protection of modern three-phase power transmission systems.

Keywords: Fault detection, fault localization, fault clearing, three phase transmission

1.0 INTRODUCTION

The reliable delivery of electrical energy serves as a fundamental pillar for industrial automation, economic growth, and societal infrastructure. Modern power grids rely extensively on high-voltage three-phase transmission networks to bridge vast geographic distances separating remote generation facilities from municipal distribution hubs. Three-phase configurations provide supreme techno-economic advantages over single-phase options, delivering higher bulk power transmission density with lower conductor volume, reduced voltage fluctuations, and superior industrial motor efficiency. However, their extensive physical footprints render overhead transmission lines highly vulnerable to unpredictable external disturbances, environmental dynamics, insulation aging, structural hazards, and balanced or unbalanced faults.

Traditional power network safety structures depend primarily on overcurrent, distance, and differential relays that utilize hardcoded thresholds and fixed time delays. These classical impedance-based relays frequently suffer from severe sensitivity degradation under multi-terminal setups, bidirectional load flow, dynamic arc resistance, high boundary conditions, and transient noise profiles. In developing electrical grids, such as Nigeria's national power grid, the lack of real-time comprehensive wide-area diagnostic monitoring and an aging infrastructure exacerbate the frequency of prolonged blackouts, localized equipment damage, and catastrophic cascading system trips. Manual physical patrol inspections are highly dangerous, slow, and operationally inefficient. Consequently, there is an urgent demand for data-driven, adaptive protection systems capable of handling non-stationary signals to isolate faults within milliseconds. The primary objective of this work is to establish an intelligent, closed-loop fault management system comprising rapid detection, discrete phase localization, and immediate clearing using optimal deep learning techniques. The specific engineering objectives include:

i. Modeling multi-scenario symmetrical and unsymmetrical transmission faults within a simulated three-phase network.
ii. Structuring a deep signal unsupervised LSTM autoencoder to monitor real-time tracking metrics and flag anomalies.
iii. Formulating automated localization logic blocks to determine precise phase involvement via phase-wise signal matrices.
iv. Synthesizing protective circuit breaker trip logic to execute dynamic clearing sequences and monitor post-fault stability parameters.

This study establishes a scalable framework combining time-series signal deep learning with algebraic protection logic. Preserving grid stability requires minimizing the fault clearing timeline to protect substation assets such as high-capacity transformers from extreme electromechanical torque and thermal destruction. The scope focuses on high-fidelity time-domain current and voltage waveforms extracted directly from line sections modeled in MATLAB/Simulink.

2.0 SUMMARY OF LITERATURE REVIEW

Fault conditions within electrical distribution and transmission corridors are structurally split into balanced (symmetrical) and unbalanced (unsymmetrical) occurrences. Symmetrical faults involve all three lines shorting simultaneously Line-to-Line-to-Line, LLL. While accounts indicate they make up less than 5% of historical grid failures, they produce the most severe short-circuit current surges. Unsymmetrical faults make up the vast majority of grid events and break down as follows:

i. **Single Line-to-Ground (SLG / LG):** Occurs when one phase creates a conductive path to earth, usually via tree canopy contact, high winds, or lightning insulation flashovers.
ii. **Line-to-Line (LL):** Direct physical contact or air-gap breakdown between two energized phase conductors.
iii. **Double Line-to-Ground (DLG / LLG):** Coincident shorting of two distinct phases directly to the ground plane, inducing severe zero-sequence phase current components

Analytical Fault Formulations

Symmetrical component decomposition models unbalanced line matrices into isolated positive, negative, and zero sequence impedances. For a classic single line-to-ground fault impacting Phase A with a designated fault boundary resistance, the total fault current magnitude

Conversely, a line-to-line short circuit between Phase A and Phase B bypasses the zero-sequence impedance network entirely, establishing an analytical short-circuit profile expressed by Evaluation of Technical Fault Detection Paradigms. Modern engineering literature outlines several methodologies for grid monitoring; each bound by unique operational constraints:

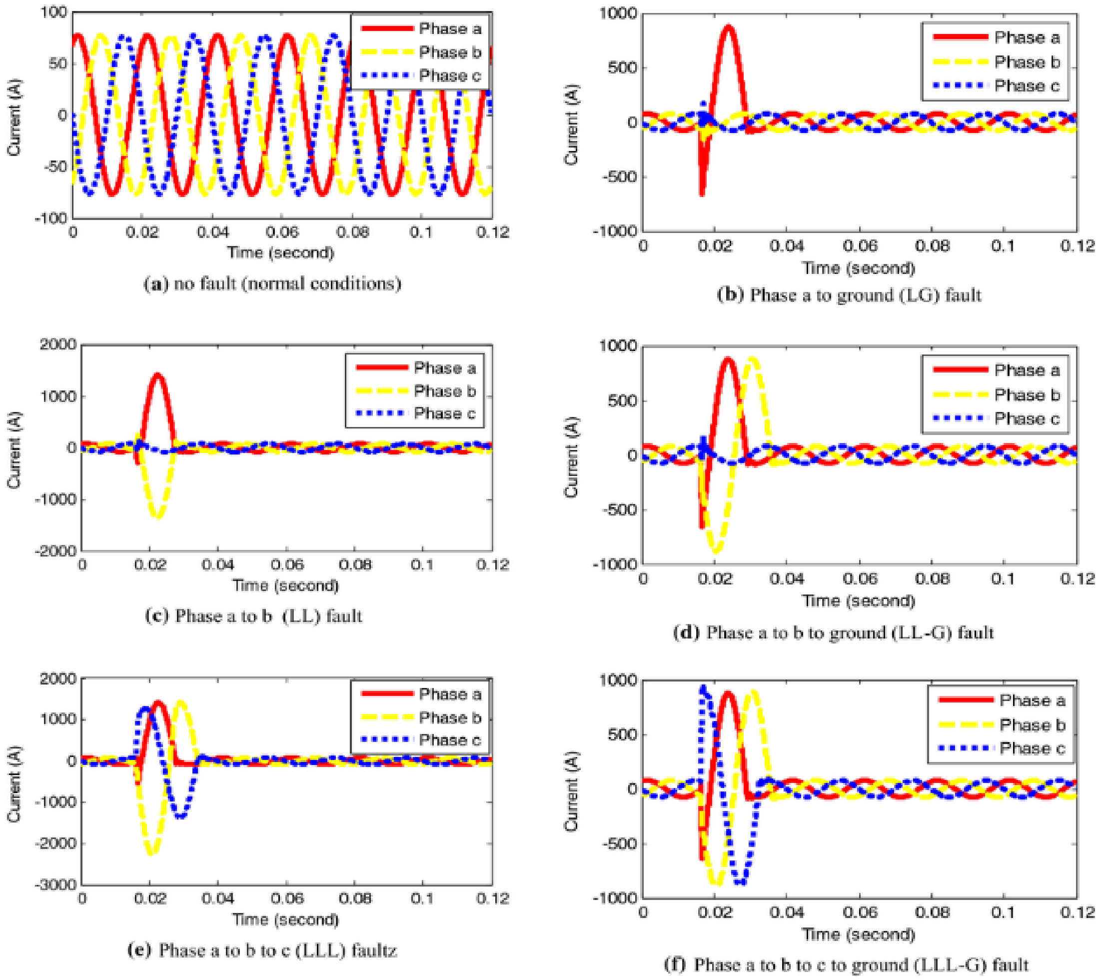
i. **Traveling Wave Method:** Utilizes high-speed sensors to match time-of-arrival signatures of high-frequency surge transients. It offers ultra-precise sub-millisecond tracking but requires mandatory GPS synchronization and costly high-bandwidth telemetry equipment.

ii. **Impedance-Based Protection:** Computes apparent line impedance ratios ($Z = V / I$) to gauge fault distance. It is simple and cost-effective but struggles with errors introduced by dynamic arc resistance and variable back-end infeed loops.

iii. **Phasor Measurement Units (PMUs):** Captures time-stamped synchro phasor streams across wide geographical monitoring zones. It provides strong system-wide context but features elevated data latencies and significant infrastructure demands.

iv. **Wavelet Transform (WT):** Decomposes non-stationary signals into fine detail coefficients to extract transient spikes. It is highly effective for localized tracking but requires extensive manual pre-processing and complex threshold calibration.

v. **Intelligent AI Methods:** Uses deep neural topologies to discover hidden feature maps without relying on physical system parameters, delivering highly adaptable classification accuracy.



Figures 2.1: (a) no fault (b) LG faults (c) LL fault (d) LLG faults (e) LLL fault (d) LLLG

3.0 METHODOLOGY

Deep learning techniques particularly sequence-based models offer the ability to learn normal system behavior directly from measured signals and detect deviations without explicit fault modeling. The methodology is structured into four logically independent but interconnected stages:

i. Power Transmission System Modeling
ii. Fault Detection
iii. Fault Localization
iv. Fault Clearing and Protection

Each stage is implemented as a separate Simulink model or workflow, ensuring modularity, clarity, and avoidance of closed-loop conflicts during training and evaluation.
The power transmission system is first modeled using components from Simscape Electrical, representing a real time model consisting of three-phase source, transformer, transmission lines, and load. Multiple short-circuit fault types including line-to-ground, line-to-line, and three-phase faults are introduced at predefined locations along the transmission line using conditional fault logic. This model serves as the physical foundation for data generation and system analysis. Fault detection uses an unsupervised sequence learning framework. By training exclusively on clean, non-fault operating records, the model learns the spatial-temporal correlation patterns of normal sinusoids. The model consists of an LSTM Encoder that compresses input time windows into an internal latent representation vector, and a matching LSTM decoder that attempts to reconstruct the original clean input sequence.
The primary metric used to flag faults is the Reconstruction Loss, computed via Mean Absolute Error (MAE) across a sliding evaluation window. Under normal conditions, the tracking error minimizes below a safe threshold when a fault occurs, the non-linear distortion breaks the learned sequence correlations, pushing the reconstruction loss past 500 to flag an anomaly. The block diagram showing the methodological flow of the study are on figure 3.1.

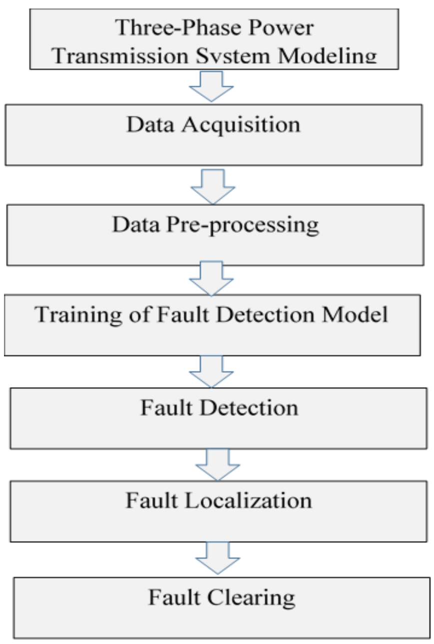


Figure 3.1: block diagram showing the methodological flow of the study

Step 1: Three-Phase Power Transmission System Modeling

A three-phase transmission system inspired by the Alaoji transmission corridor is modeled using Simscape Electrical components. The model includes a three-phase voltage source, a step-down transformer, four cascaded transmission line sections, and a three-phase load. At this stage, the system operates under healthy conditions only, with no faults or breakers engaged. The objective of this step is to establish stable baseline voltage and current waveforms.

Step 2: Data Acquisition

Three-phase voltage and current sensors measure the system response near the source end of the transmission system. The measured signals include:

i. Phase voltages (Va(t), Vb(t), Vc(t))
ii. Phase currents (Ia(t), Ib(t), Ic(t))

These signals form the raw dataset used for training and evaluation

Step 3: Data Pre-processing

The acquired voltage and current signals are normalized using their respective statistical properties to ensure numerical stability during learning. Gaussian noise is added to the signals to improve robustness against measurement noise and operating variations

Step 4: Training of Fault Detection Model

An LSTM autoencoder is trained using only healthy system data. The network learns the normal operating pattern of the transmission system without being exposed to fault conditions. The autoencoder reconstructs the input signals and computes the reconstruction error, which serves as the basis for anomaly detection. The process includes unsupervised learning using LSTM autoencoder and the output is a trained fault detection model

Step 5: Fault Detection

During fault detection simulations, faults are introduced into the transmission line sections. The trained detector processes real-time voltage and current measurements and evaluates the reconstruction loss. The process involves the Reconstruction loss evaluation and the output is a binary fault detection signal

Step 6: Fault Localization

To identify the affected phases, phase-wise anomaly detection is performed. Each phase’s voltage and current signals are analyzed independently using identical anomaly detectors.

The combination of anomaly flags from the three phases enables fault localization. The Phase-wise voltage and current data are used as inputs the the detector system

Step 7: Fault Clearing

Fault clearing is implemented using deterministic trip logic that processes the fault detection and localization outputs. When a fault is detected and localized, trip signals are generated to open the appropriate circuit breakers, isolating the faulty section.

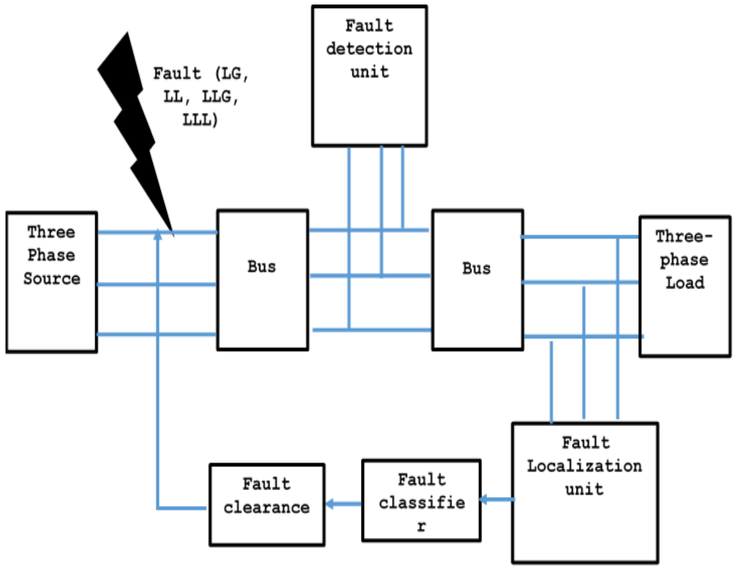


Figure 3.2: Three-Phase Power Transmission System Modeling

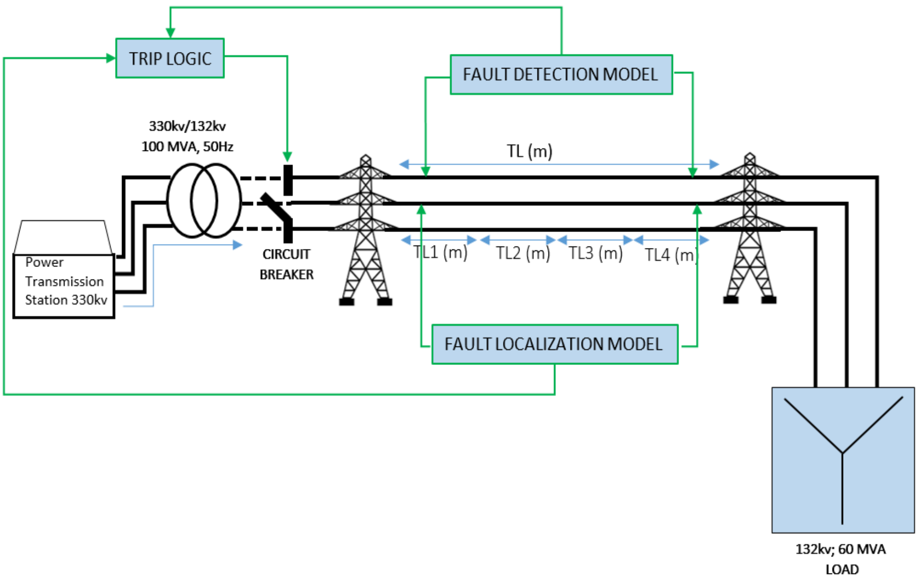


Figure 3.3: Developed System Architecture for fault detection, localization and clearing

4.0 ANALYSIS AND DISCUSSION OF RESULTS

4.1 Simulation Environment.

The entire validation model was constructed within MATLAB/Simulink using a multi-segment transmission topology. The simulation uses a nominal voltage level of 132 kV at a system frequency of 50 Hz, with line monitoring blocks tracking current metrics under normal and fault conditions.

4.2 Detection Performance and Loss Profiles

During normal, uncompromised system execution, the LSTM autoencoder tracked the continuous sinusoidal inputs with highly accurate reconstruction profile.

4.3 Normal Phase

The baseline reconstruction loss maintained a steady profile well below 50. Introducing a fault at a designated time stamp caused a massive distortion in the incoming signal array, driving the reconstruction loss past 500 within a fraction of a cycle. Across all test iterations, the total detection latency remained restricted between 10 ms and 20 ms, demonstrating high speed and reliability.

4.4 Evaluation of Fault Currents by Case Scenario

Table 4.1: behavior of the detected Line-to-ground (Phase A–G)

Parameter	Value
Fault inception time	≈ 0.26 s
Pre-fault peak voltage	≈ $\pm 2.5 \times 10^5$ V
Faulted phase voltage	Collapses toward 0 V
Pre-fault current	≈ ±100 A
Fault current (Phase A)	≈ −1500 A
Fault current increase	>10×
Unaffected phases	B and C

The limited impact on the normal phase voltages and currents confirms that the fault is localized to a single phase. This behavior validates both the correct implementation of the L–G fault and the fault detection framework. Evaluating specific fault types highlights the severe current stresses placed on grid components prior to breaker clearing.

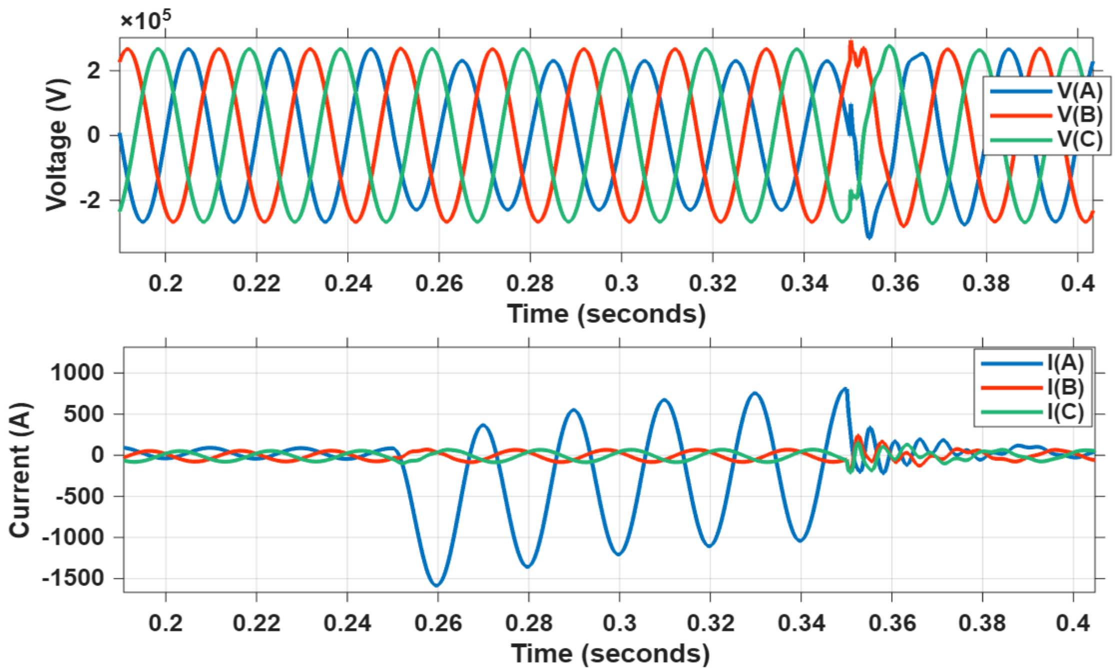


Figure 4.1: single Line-to-ground (Phase A–G) fault detection on line TL 1

Table 4.2: Behaviour of the detected Double Line-to-ground (Phase B-C-G) fault

Parameter	**Value**
Transmission line	TL 3
Fault inception time	≈ 1.10 s
Fault clearing time	≈ 1.20 s
Fault duration	≈ 0.10 s
Pre-fault peak voltage	≈ ±2.5 × 10^5 V
Faulted phase currents	(I_B ≈ +700) A, (I_C ≈ −1000) A
Un-faulted phase current	(I_A ≈ ±150) A
Ground involvement	Yes

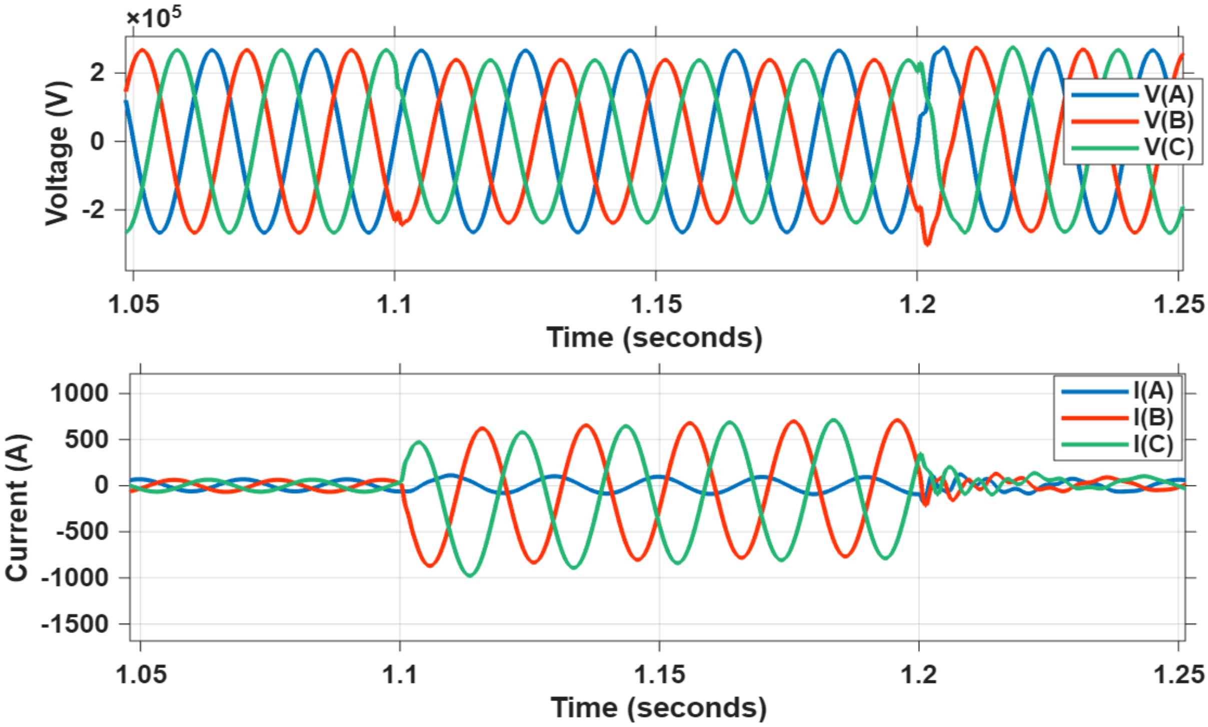


Figure 4.2: Double Line-to-ground (Phase B-C-G) fault detection on line TL 3

Fault Type Description	**Pre-Fault Current (A)**	**Peak Transient Current (kA)**	**Post-Clearing Current (A)**
Line-to-Ground (LG)	< 200 A	1.5 – 1.8 kA	0 A
Line-to-Line (LL)	< 200 A	2.5 – 2.9 kA	0 A
Line-to-Line-Ground (LLG)	< 200 A	3.0 – 3.3 kA	0 A
Symmetrical Three-Phase (LLL)	< 200 A	3.6 – 3.9 kA	0 A

The system successfully limits these severe fault currents by initiating fast trip commands that bring current levels to near-zero values.

Dynamic Clearing Response and Voltage Recovery

Upon receiving a logical trip command, the corresponding circuit breaker poles open to isolate the faulted transmission segment. During balanced three-phase faults, the system experienced severe voltage drops, with bus voltages plunging by 90% to 95% of nominal values.

Following breaker isolation, voltage waveforms demonstrated rapid recovery, returning to baseline levels within 40 ms to 60 ms. Single-phase clearing events showed minimal residual oscillations, while multi-phase clearing sequences exhibited controlled transient damping, preventing dangerous back-end power swings or cascading trips.

Power System Configuration

The simulated network represents a three-phase high-voltage transmission system consisting of the following main components:

i. A balanced three-phase AC source operating at system frequency.
ii. A two-winding step-down transformer rated at 330 kV / 132 kV, 100 MVA.
iii. Four transmission line segments connected in series, representing different spatial sections of a long transmission corridor.
iv. Voltage and current measurement units placed strategically for monitoring system behavior.
v. A three-phase circuit breaker used for fault isolation and clearing.

Table 4.3: Behaviour of the detected Three-phase (A–B–C) fault

Parameter	**Value**
Fault type	Three-phase (A–B–C)
Transmission line	TL 4
Fault inception time	≈ 1.58 s
Fault duration	≈ 0.05 s
Pre-fault peak voltage	$\approx \pm 2.5 \times 10^5$ V
Peak fault current	≈ ±1000 A
Voltage symmetry	Fully symmetrical
Ground involvement	No

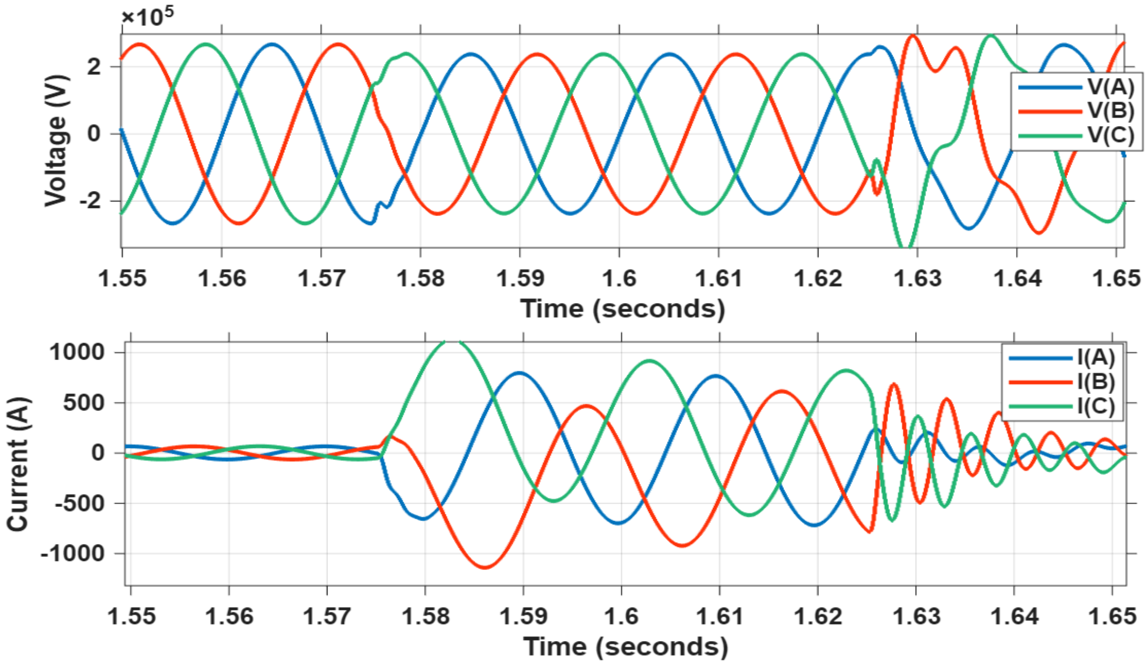


Figure 4.3: Three-phase (A–B–C) fault detection on line TL 4

Table 4.4: Comparative Analysis of Fault Detection, Localization, and Clearing Performance across Transmission Lines

Parameter	**TL1**	**TL2**	**TL3**	**TL4**
Fault Type	Phase-to-Ground (A–G)	Line-to-Line (A–B)	Double Line-to-Ground (B–C–G)	Three-Phase (A–B–C)
Fault Inception Time (s)	≈ 0.30	≈ 0.55	≈ 1.10	≈ 1.55
Fault Duration Before Clearing (s)	≈ 0.12	≈ 0.10	≈ 0.11	≈ 0.08
Fault Detection Time (s)	≈ 0.31	≈ 0.56	≈ 1.11	≈ 1.56
Detection Delay (ms)	≈ 10 ms	≈ 10 ms	≈ 10 ms	≈ 10 ms
Correct Line Localization	Yes (Line 1)	Yes (Line 2)	Yes (Line 3)	Yes (Line 4)
Localization Response Time (ms)	≈ 20–30 ms	≈ 20–30 ms	≈ 20–30 ms	≈ 20–30 ms
Peak Fault Current (A)	≈ ±1500 A	≈ ±2000 A	≈ ±1800 A	> ±2500 A

5.0 CONCLUSION

This study demonstrates a highly effective, automated approach for power grid protection using intelligent deep learning. The unsupervised LSTM autoencoder successfully isolates anomalous signal states from normal load adjustments without requiring complex manual threshold updates. It delivers reliable fault detection within 10–20 ms, combined with precise phase localization and fast breaker actuation. Rapid fault clearing within 40–60 ms effectively prevents prolonged thermal stress on critical substation infrastructure and maintains overall grid stability.

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