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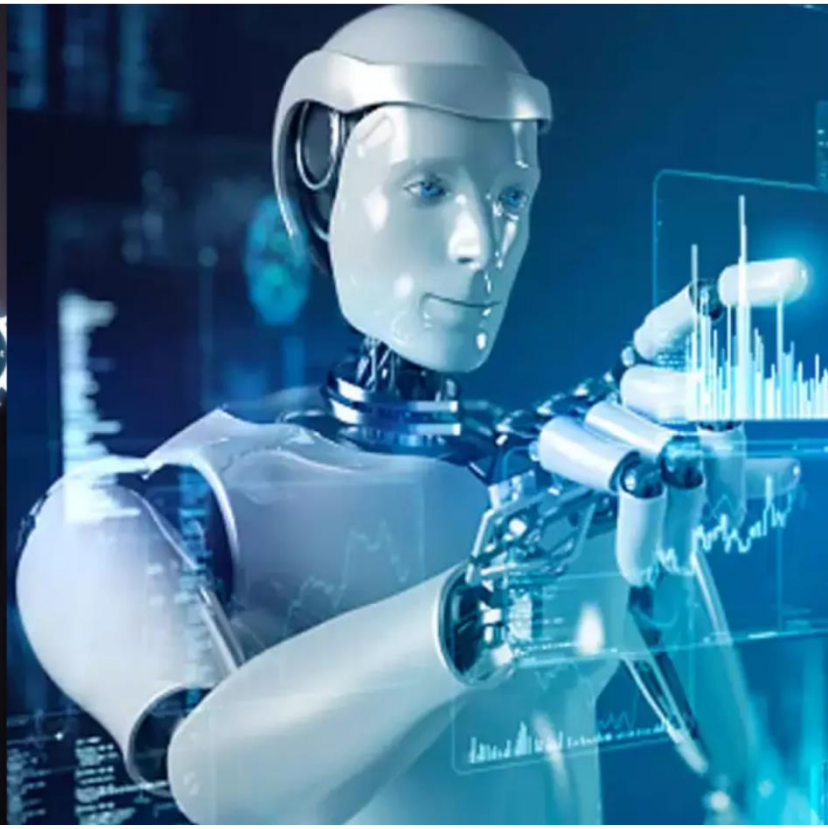

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Comparative Study on Detection and Classification of Transmission Line Faults using Soft Computing Technique

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ABSTRACT: Reliable operation of the electric grid depends heavily on fast and accurate fault detection in transmission lines. When a fault occurs, isolating the faulty section without affecting healthy areas is essential for safety and uninterrupted power delivery. Ideally, protection devices closest to the fault should act first to avoid unnecessary disruptions upstream. This study uses Extreme Learning Machine (ELM), a machine learning approach, to classify faults in transmission lines. A simulation was built in MATLAB Simulink, where various symmetrical and unsymmetrical faults were introduced using a three-phase fault block. The generated data was normalized, then split for training and testing the ELM model. The model's accuracy in identifying fault types was evaluated using a confusion matrix, demonstrating its potential for improving grid reliability.

KEYWORDS: Fault Detection (FD), Fault Classification (FC), Transmission Line (TL), MATLAB, Extreme Learning Machine (ELM), Artificial Neural Network (ANN), Receiver Operating Characteristics Curve (ROC), Area Under the Curve (AUC).

I. INTRODUCTION

Power systems are a cornerstone of national infrastructure, directly influencing economic development. A well-structured power network ensures operational efficiency, system stability, and high reliability. The power system consists of three primary components: generation, transmission, and distribution. Electricity is generated from sources like hydro, thermal, nuclear, and increasingly from renewable energy, which is gaining momentum in the modern energy sector. Since power plants are generally situated in remote areas to mitigate environmental and safety risks, the generated power is transmitted over long distances using Extra High Voltage (EHV) lines to load centers, where it is then stepped down to regional feeder-level voltages.

With the nation's energy demand rising steadily, designing a dependable and stable power infrastructure is more important than ever. Faults in the system—such as symmetrical and unsymmetrical faults, equipment failure, line disconnections, transient disturbances, overloads, aging infrastructure, and human error—can cause outages and reduce system reliability. While achieving a completely fault-free system is impractical, minimizing their impact through strategic design and accurate fault identification is essential.

Timely fault detection and classification are critical for system protection, helping maintain service continuity and preventing widespread failures. Many modern approaches rely on intelligent techniques, such as machine learning (ML) and deep learning, to enhance accuracy and response times. Researchers have applied a variety of algorithms, including Extreme Learning Machine (ELM), Decision Tree (DT), and K-Nearest Neighbors (KNN), to improve fault classification.

Several notable studies have explored this area. Md. Omaer Faruq Goni [1] compared machine learning with traditional artificial neural networks (ANN) for classifying faults on different transmission lines, with ML showing faster and more accurate results. Ozan Turanlı and Yurdagül Benteşen Yakut [2] used convolutional neural networks

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(CNN) with both real and simulated datasets to evaluate fault classification performance. Another study by Shameem Hasan and Md. Toufikuzzaman [3] employed techniques like Neural Networks, Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machines (LightGBM), with LightGBM achieving superior accuracy and speed.

Among these techniques, the Extreme Learning Machine (ELM) has proven especially effective due to its fast training capabilities and high classification precision. This study proposes a fault classification method using the ELM algorithm, applied to fault data generated from a simulated transmission line model in MATLAB Simulink. The objective is to enhance system protection by improving the speed and reliability of fault identification.

II. PROPOSED FRAMEWORK FOR FAULT DETECTION AND CLASSIFICATION

In this study, a robust and efficient methodology is proposed for the detection and classification of faults in transmission lines using the Extreme Learning Machine (ELM) algorithm. Electrical fault diagnosis plays a vital role in maintaining the safety, reliability, and efficiency of power systems. Prompt and accurate identification of faults is essential to prevent system failures and minimize power outages. The power grid, comprising components such as transformers, generators, and transmission lines, requires well-coordinated protection mechanisms to ensure that only the protective devices nearest to the fault are activated—thus avoiding widespread disruption.

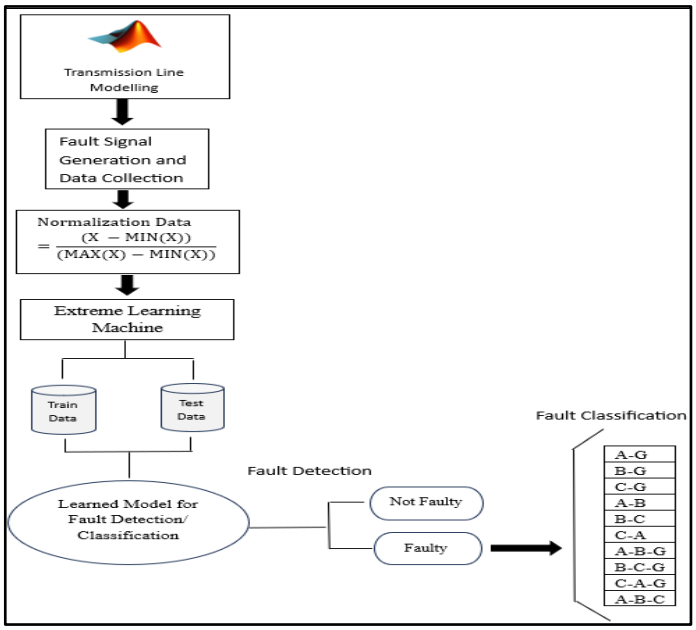

Fig. 1: Proposed Method for Fault Detection and Classification

The proposed approach combines simulation-based modeling with machine learning. A detailed transmission line model is developed in a simulation environment to generate voltage and current signals under various fault conditions, including single line-to-ground, line-to-line, double line-to-ground, and three-phase faults. Key features are then extracted from these signals to capture unique fault characteristics. These features are normalized using Min-Max scaling to ensure uniformity in data processing. The refined data is used to train the ELM, which is capable of distinguishing between faulty and non-faulty conditions, as well as accurately classifying the type of fault. By leveraging the speed and learning capabilities of ELM, the proposed system ensures fast, reliable, and real-time fault detection, thereby enhancing the protection, stability, and overall operational integrity of the power grid.

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III. TEST SYSTEM

In this study, fault detection and classification are performed using a simulated transmission line model, as illustrated in Fig. 2. The simulation is carried out using MATLAB Simulink, with a 150 km transmission line modeled for analysis. A Voltage-Current Measurement block is used to capture electrical signals under different fault conditions, forming the basis of the dataset. A dedicated fault block is configured to simulate both unsymmetrical faults (such as L-G, L-L, and L-L-G) and symmetrical faults (L-L-L and L-L-L-G). In total, eleven distinct fault types are simulated: A-G, B-G, C-G, A-B, B-C, C-A, A-B-G, B-C-G, C-A-G, A-B-C, and A-B-C-G. The resulting voltage and current waveforms from these scenarios are recorded to build a comprehensive dataset.

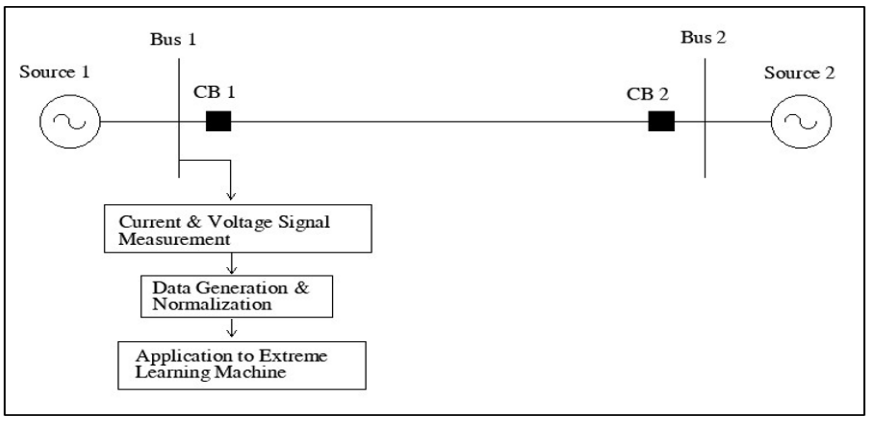

Fig. 2: Transmission Line Model

The simulation runs at a sampling frequency of 3.84 kHz, which provides sufficient resolution to accurately capture the dynamics of voltage and current waveforms under various fault conditions. The system operates at a fundamental frequency of 50 Hz. Voltage and current signals are measured through respective measurement blocks in Simulink. These signals are then normalized and used to train and test the fault classification model. A confusion matrix is generated to evaluate the performance of the model in detecting and categorizing different types of faults along the transmission line.

Parameters Details:

Parameter	Value
Transmission Line Length	150 km
Voltage Level	500 kV
Frequency	50 Hz
Source Impedance (G1)	17.177 + j45.529 Ω
Source Impedance (G2)	15.31 + j45.925 Ω
Positive Seq. Impedance	4.983 + j117.83 Ω
Zero Seq. Impedance	12.682 + j364.196 Ω
Positive Seq. Admittance	j1.468 mS
Zero Seq. Admittance	j1.099 mS
Fault Types Simulated	11 (A-G, B-G, C-G, A-B, ..., A-B-C-G)
Measurement Blocks	Voltage & Current Measurement
Tools Used	MATLAB Simulink

Table. Test Model Parameters

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NORMALIZATION

After simulating the transmission line model, a dataset comprising voltage and current signals is obtained. To enhance the performance and consistency of the classification model, normalization of the dataset is a crucial step. Normalization ensures that all feature values are brought within a common scale, which helps maintain the relative relationships between them while preventing any one feature from dominating due to differences in magnitude.

Without normalization, the model's learning process can become unstable, and the loss function may exhibit erratic behaviour during training. To address this, Min-Max normalization is applied in this study. This technique transforms each feature to a specific range, typically between 0 and 1, without distorting the underlying distribution or relationships among the data.

The Min-Max normalization used in this work is mathematically defined as:

$$\text{Normalization data} = \frac{(X - \text{MIN}(X))}{(\text{MAX}(X) - \text{MIN}(X))} \qquad (1)$$

EXTREME LEARNING MACHINE:

Extreme Learning Machine (ELM) is a fast and efficient machine learning technique designed for Single-Layer Feedforward Neural Networks (SLFNs). First introduced by Huang et al., ELM was developed to overcome the drawbacks commonly faced in traditional neural networks—particularly the slow training speed and convergence issues associated with gradient-based methods like backpropagation.

What makes ELM particularly advantageous is its ability to train quickly, generalize well, and require minimal tuning, making it ideal for real-time applications such as fault detection and classification in power systems. In this context, ELM demonstrates the capacity to learn complex patterns from electrical signal data (such as voltage and current waveforms) and to accurately classify fault types with low computational cost.

ELM architecture consists of just a single hidden layer. Unlike conventional neural networks where both input and output weights are adjusted during training, in ELM, the input weights and biases of the hidden layer are randomly assigned and remain fixed. Only the weights connecting the hidden layer to the output layer are calculated during training.

Once the input features pass through the hidden neurons—using an activation function like sigmoid, sine, or radial basis—the resulting outputs form a matrix denoted as H (the hidden layer output matrix). The output weights (β) are then computed analytically using the Moore–Penrose pseudo-inverse of matrix H. This eliminates the need for iterative training and significantly reduces computational time.

The formula for calculating the output weights is:

$$\beta = H \dagger T \qquad (2)$$

- β – Output weight matrix
- H† – Moore–Penrose pseudo-inverse of the hidden layer output matrix
- T – Target output matrix

This direct learning approach allows ELM to rapidly and efficiently train on datasets, making it especially useful in environments where quick decision-making is crucial—such as detecting and classifying electrical faults in transmission lines. Its low training cost, high speed, and scalability make it a strong candidate for deployment in smart grids and modern power networks requiring real-time response capabilities.

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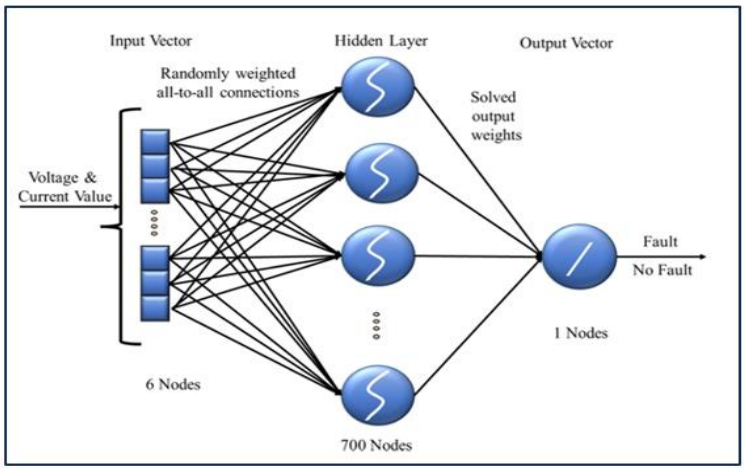

Fig. 3: ELM classifier structure

Implementation of ELM for Fault Detection and Classification in Transmission Lines

This study applies the Extreme Learning Machine (ELM) approach to detect and classify eleven distinct types of faults in transmission lines using MATLAB-based simulations. The voltage and current waveforms are generated under realistic operating conditions, incorporating transient disturbances and varying levels of noise to mimic practical scenarios.

1. Data Generation

Eleven fault types were modeled, derived from four primary fault categories: single line-to-ground (L-G), line-to-line (L-L), double line-to-ground (L-L-G), and three-phase faults (L-L-L). The specific fault cases considered include:

- **Single Line-to-Ground**: A-G, B-G, C-G
- **Line-to-Line**: A-B, B-C, C-A
- **Double Line-to-Ground**: A-B-G, B-C-G, C-A-G
- **Three-Phase**: A-B-C, A-B-C-G

These fault types were simulated using the transmission line model shown in Fig. 2. For each type, simulations were performed at every 10 km along the 150 km line. To capture a wide range of fault characteristics, variations in fault inception angles (0°, 30°, 60°, 90°, 120°, 150°, 180°) and fault resistances (0Ω, 2Ω, 4Ω, 6Ω, 8Ω, 10Ω, 50Ω) were included. Data for both fault and no-fault conditions were generated to support robust training and evaluation.

2. Model Training

The ELM model is trained using the voltage and current waveform data collected from the simulations. In this setup, **70% of the dataset** is used for training, allowing the model to learn distinct fault patterns. The remaining **30% is reserved for testing**, which assesses the model's ability to generalize and accurately classify unseen data.

During training, the ELM algorithm randomly assigns weights to the input layer and calculates the output weights analytically using the Moore–Penrose pseudo-inverse. This enables **rapid learning** and minimizes the computational load, making the method highly suitable for real-time implementation.

3. Model Evaluation

The trained ELM model's performance is assessed using standard classification metrics and confusion matrices. These tools provide insights into the accuracy, precision, and reliability of the fault classification process, helping verify the effectiveness of the proposed approach in accurately identifying and distinguishing between different fault types.

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Performance Evaluation Metrics

To evaluate the effectiveness of the fault classification model, various standard performance metrics are employed. These metrics are widely used in the field of machine learning and are especially relevant for binary and multi-class classification problems.

One of the most commonly used metrics is the **Area Under the Receiver Operating Characteristic Curve (ROC AUC)**, which provides a comprehensive measure of a classifier's ability to distinguish between classes. ROC AUC has become a standard benchmark for binary classification tasks across various scientific and engineering domains.

In this study, seven key evaluation metrics are calculated based on the four fundamental components of a confusion matrix:

- **True Positive (TP):** Correctly predicted positive cases
- **True Negative (TN):** Correctly predicted negative cases
- **False Positive (FP):** Incorrectly predicted positive cases
- **False Negative (FN):** Incorrectly predicted negative cases

The performance indicators and their corresponding formulas are described below:

1. Accuracy (Acc)

Measures the overall correctness of the model by calculating the proportion of correctly predicted cases (both positives and negatives) out of the total samples:

$$\text{Acc} = \frac{\text{TP+TN}}{\text{TP+TN+FP+FN 2a}} * 100\% \qquad (3)$$

2. Precision (P)

Also known as Positive Predictive Value, precision reflects the proportion of correctly predicted positive cases out of all predicted positive cases:

$$\text{P} = \frac{\text{TP}}{\text{TP+FP}} \qquad (4)$$

3. Recall (R)

Also called **Sensitivity**, recall measures the proportion of actual positive cases that are correctly identified:

$$\text{R} = \frac{\text{TP}}{\text{TP+FN}} \qquad (5)$$

4. F1-Score

The F1 score represents the harmonic mean of precision and recall. It is particularly useful when dealing with imbalanced datasets where accuracy alone might be misleading: $\text{F1} - \text{score} = \frac{2\times(\text{Precision} \times \text{Recall})}{\text{Precision} + \text{Recall}}$ (6)

Confusion Matrix and ROC Curve

The **confusion matrix** is a compact way to visualize the classification performance of a model by displaying the counts of TP, TN, FP, and FN. From this matrix, various other metrics such as specificity and error rate can also be derived. Additionally, it serves as a foundation for plotting the **ROC curve**, which graphically illustrates the trade-off between sensitivity and specificity. The **ROC curve** helps evaluate how well the model distinguishes between classes, and the **AUC** value provides a single scalar value to summarize this performance.

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Comparative Analysis of ELM with ANN in Terms of Different Model Parameters For Fault Classification

Sr. No.	Parameter	ELM (Extreme Learning Machine)	ANN (Artificial Neural Network)
a.	Classification Accuracy (%)	100% (Perfect classification)	95–98% (Minor misclassifications observed)
b.	Training Time	≈ 0.5–1.2 seconds	≈ 25–60 seconds
c.	Prediction Time (per sample)	≈ 1–5 milliseconds	≈ 5–10 milliseconds
d.	Training Epochs	1 (non-iterative)	100–1000 (iterative)
e.	Learning Method	Analytical (Moore–Penrose pseudoinverse)	Backpropagation with gradient descent
f.	Hidden Layers	Single hidden layer	Typically 2–3 hidden layers
g.	Hidden Nodes	50–200 (optimized experimentally)	50–100 per layer
h.	Weight Initialization	Random (input weights fixed)	Random (updated during training)
i.	Weight Updates	Output layer only	All layers (forward and backward propagation)
j.	Number of Weight Multiplications	2 (Input → Hidden, Hidden → Output)	Multiple (per layer × epochs)
k.	Generalization Capability	High (fast convergence, robust to overfitting)	Moderate to High (requires regularization)
l.	Feature Sensitivity	High (requires well-selected features)	Moderate (can learn from raw data if deep)
m.	Hyperparameter Tuning	Low (hidden node number only)	High (learning rate, batch size, layers, etc.)
n.	Scalability to Larger Datasets	Excellent	Moderate
o.	Suitability for Real-Time Systems	Highly suitable	Less suitable due to longer training

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IV. RESULTS & ANALYSIS

Output Waveforms

The transmission line model was simulated under various conditions: healthy (no fault), L-G, L-L, L-L-L, and L-L-L-G faults. Figure 4 shows the system in a healthy state, with clean and stable voltage and current waveforms, indicating normal operation without any disturbances.

Figures 5 to 9 display the system's behavior under different fault scenarios, including both asymmetrical (L-G, L-L, L-L-G) and symmetrical (L-L-L, L-L-L-G) faults. These faults are introduced between 0.1 s and 0.2 s, during which clear disturbances in voltage and current waveforms are observed. Although a fault may occur in a single phase, its impact can spread across all phases. To prevent further system disruption, protective devices must act swiftly to isolate the fault. Proper coordination is crucial to disconnect only the affected section, ensuring the rest of the system remains operational.

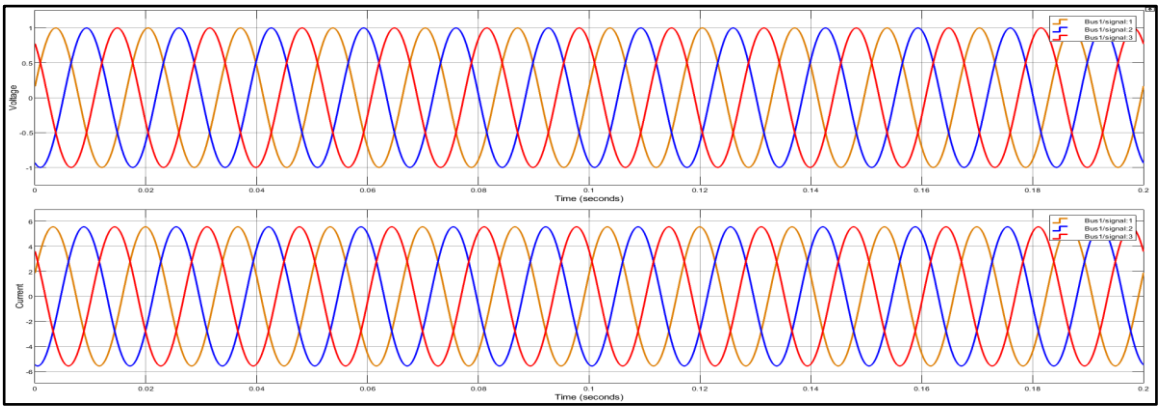

Fig. 4: Healthy system.

A-G fault:

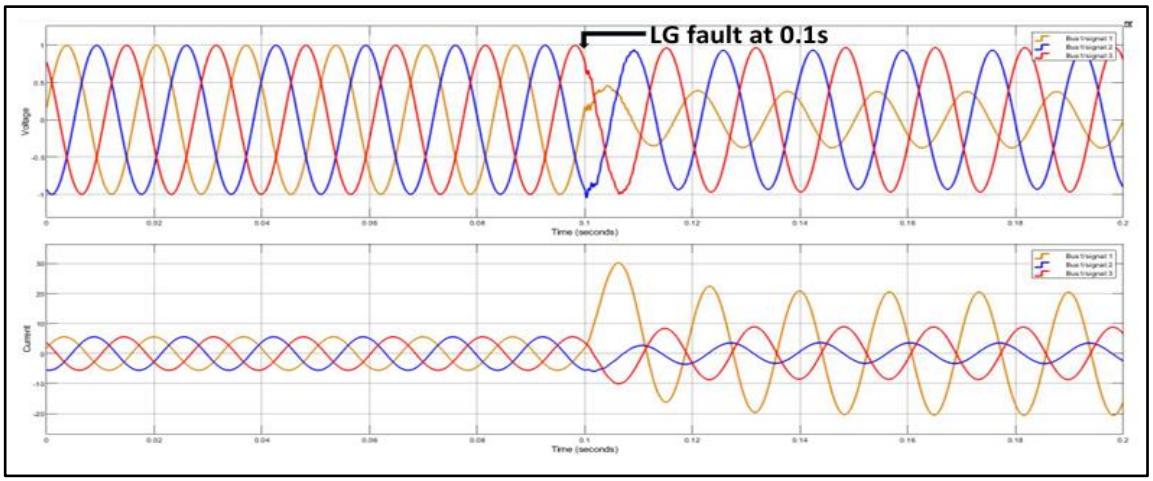

Fig. 5: Unsymmetrical fault: Line-Ground fault. (A phase- Ground)

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A-B Fault:

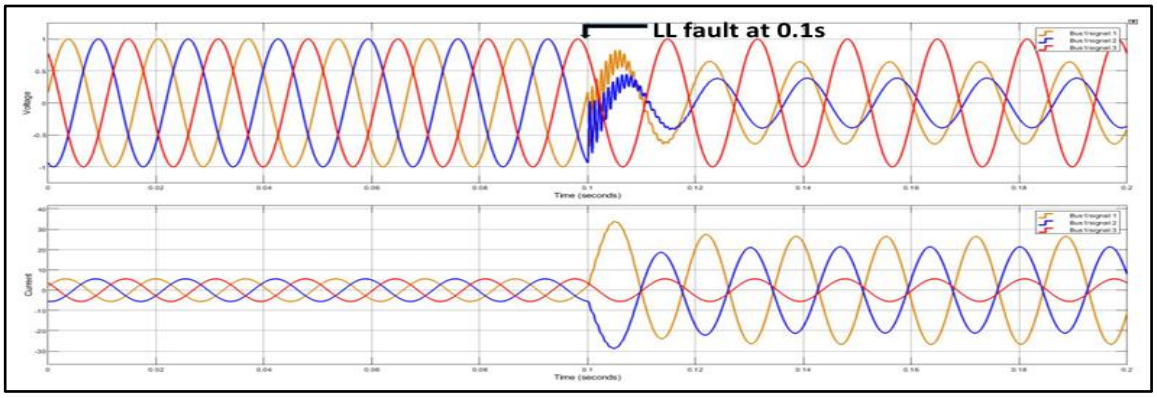

Fig. 6: Unsymmetrical fault: Line-Line fault. (A phase- B phase)

A-B-G fault:

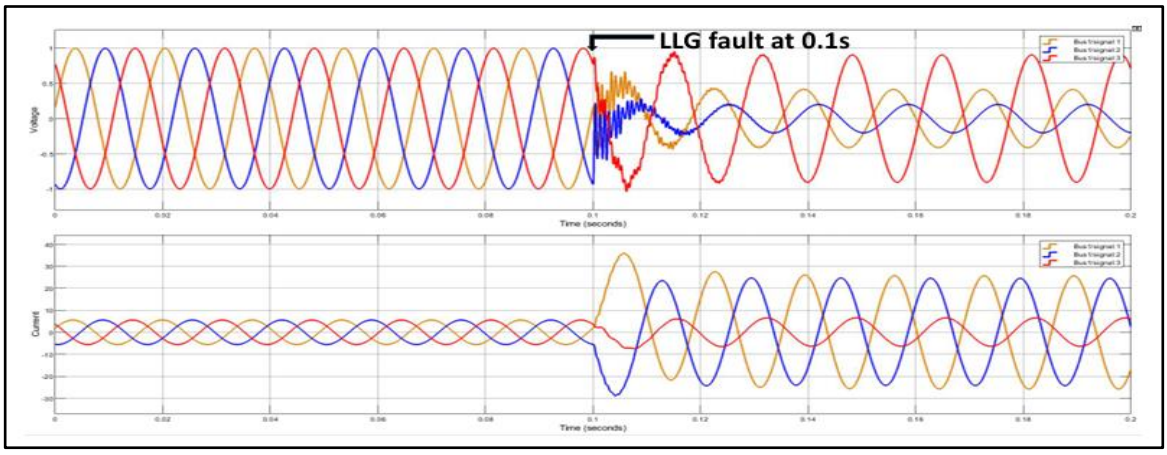

Fig. 7: Unsymmetrical fault: Line-Line-Ground fault. (A phase-B phase-Ground)

A-B-C fault:

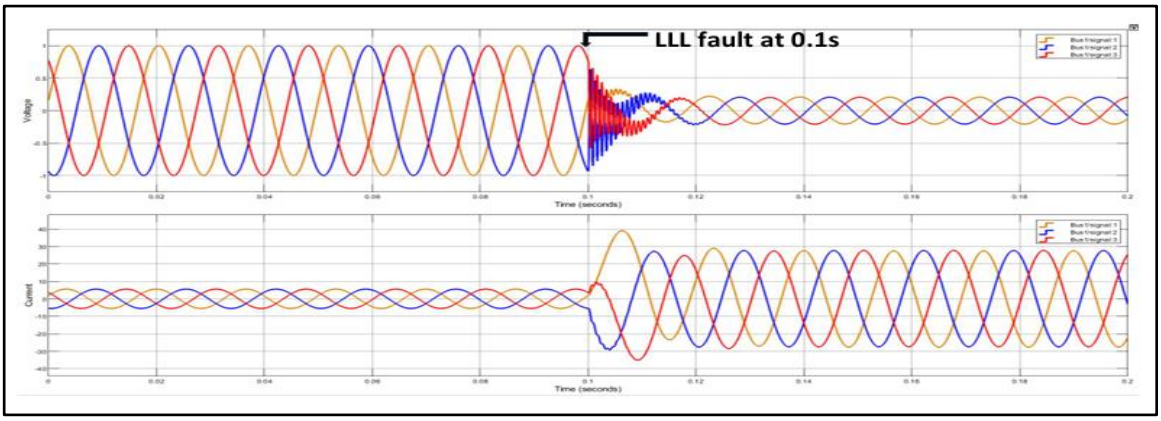

Fig. 8: Symmetrical fault: Line-Line-Line fault. (A phase- B phase-C phase)

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A-B-C-G fault:

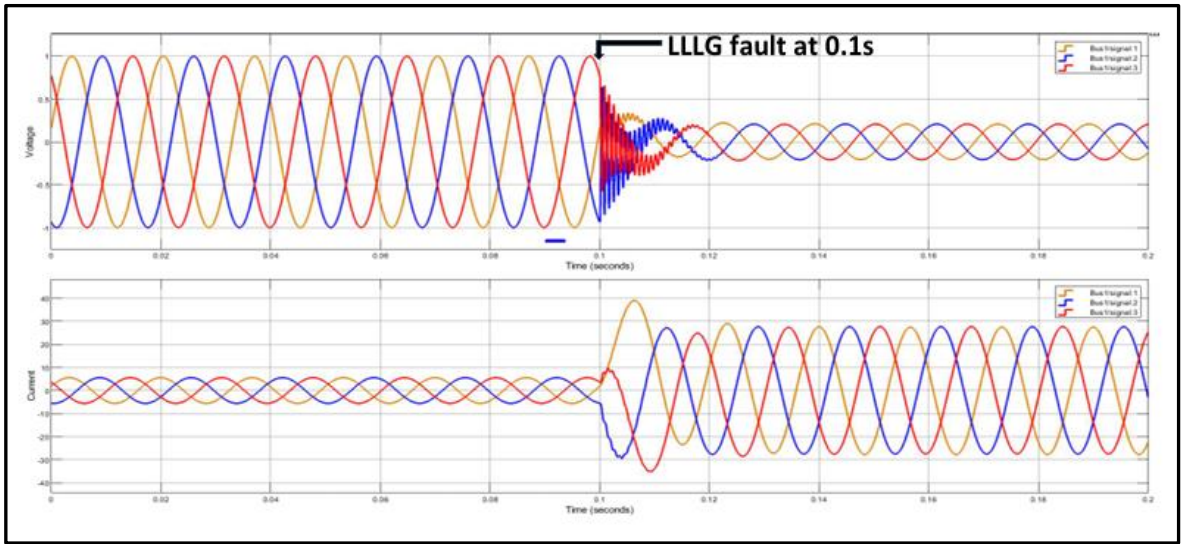

Fig. 9: Symmetrical fault: Line-Line-Line-Ground fault. (A phase-B phase-C phase-Ground)

Fault Detection and Classification Performance

The proposed Extreme Learning Machine (ELM) model was evaluated using data from simulations of both symmetrical and asymmetrical faults. The model demonstrated excellent classification capabilities, with a confusion matrix (Fig. 13) showing correct identification across all test samples, achieving a classification accuracy of 100%.

To further assess the model's performance, Receiver Operating Characteristic (ROC) curves were plotted for each fault class (Fig. 10). These curves illustrate the trade-off between the true positive rate and false positive rate across different threshold settings. The Area Under the Curve (AUC) was 100% for all classes, confirming the model's exceptional accuracy and reliability in classifying various fault types.

In addition to classification, the model was also tested for its fault detection capability. As shown in the fault detection table and the ROC curve for detection (Fig. 11), the model consistently achieved 100% AUC, indicating perfect sensitivity and specificity in identifying the presence of faults.

Overall, the ELM-based approach proves to be highly effective in both detecting and classifying faults in the power system, ensuring reliable and accurate fault analysis.

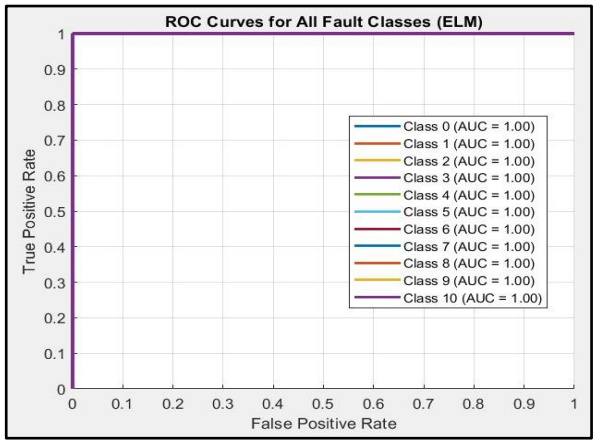

Fig. 10: ROC Curve for Fault Classification

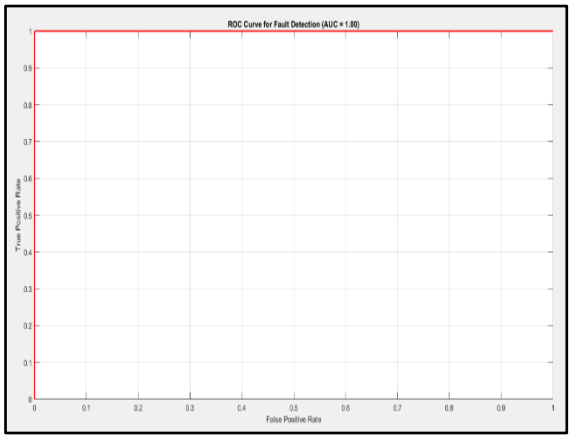

Fig. 11: ROC Curve for Fault Detection

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The Extreme Learning Machine (ELM) is designed to classify data using the structure of the classifier outlined in Figure 3. In this approach, the model continuously processes the dataset, analyzing each data point in real-time. The ELM then applies its learning algorithm to map the input features to the corresponding output classes. As the data flows through this process, the model evaluates and classifies the information effectively. The performance of the classification is captured and summarized in the confusion matrix, which provides a clear overview of how well the ELM model distinguishes between different classes based on the input data. This matrix helps assess the model's accuracy and its ability to correctly identify each class within the dataset.

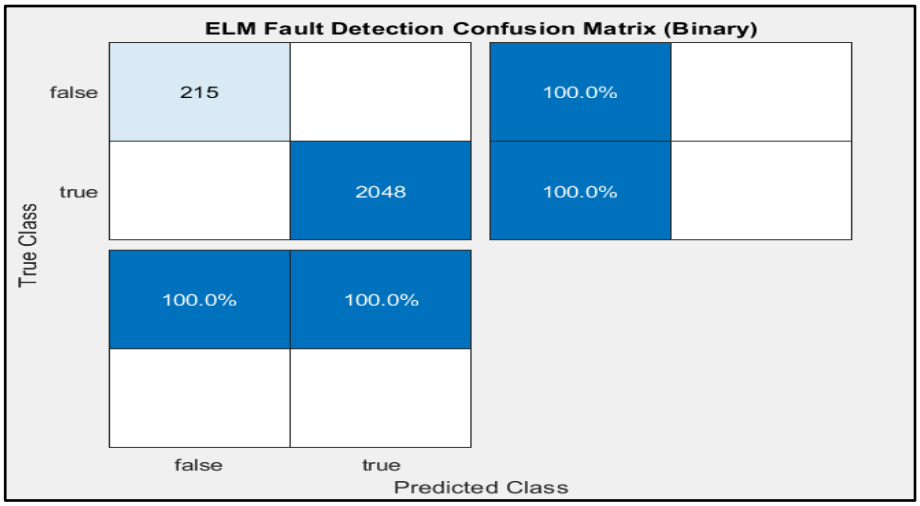

Fig. 12: Confusion Matrix for Fault Detection

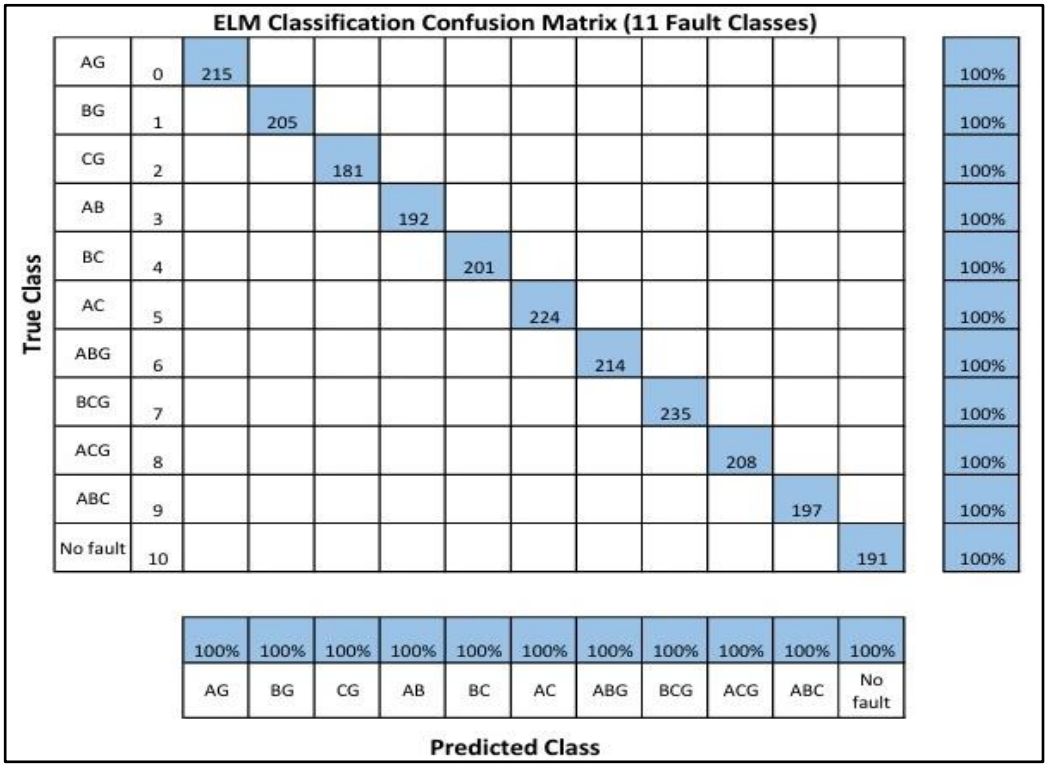

Fig. 13: Confusion Matrix for Fault Classification

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V. CONCLUSION

Ensuring the protection of transmission lines is a critical aspect of maintaining stability and reliability within power systems. Effective coordination between protective devices is essential to isolate only the faulted sections, thereby avoiding unnecessary outages across larger areas of the power grid.

In this study, a comprehensive set of faults—both symmetrical (L-L-L, L-L-L-G) and unsymmetrical (L-G, L-L, L-L-G)—were simulated. A total of 11 distinct fault types, including A-G, B-G, C-G, A-B, B-C, C-A, A-B-G, B-C-G, C-A-G, A-B-C, and A-B-C-G, were analyzed. For fault detection and classification, the Extreme Learning Machine (ELM) model was employed.

Compared to traditional Artificial Neural Networks (ANNs), the ELM demonstrated superior performance in terms of computational speed and accuracy. While ANNs typically require iterative training and longer convergence times, ELMs achieve high accuracy with significantly faster learning due to their single-pass learning mechanism. This makes ELMs particularly suitable for real-time fault monitoring and quick decision-making in power systems.

The results confirm that ELM-based models are not only effective in detecting and classifying faults but also offer a scalable and efficient solution for enhancing power system reliability. Given its accuracy, speed, and simplicity, the ELM approach holds great promise for widespread adoption in power system fault analysis and protective relaying applications.

REFERENCES

[1]. Md.Omaer Faruq Goni, Md. Nahiduzzaman , Md.Shamim Anower, Md.Mahabubur Rahman, Md.Robiul Islam, Mominul Ahsan, Julfikar Haider , Mohammad Shahjalal, (2023), Fast and Accurate Fault Detection and Classification in Transmission Lines using Extreme Learning Machine, e-Prime - Advances in Electrical Engineering, https://doi.org/10.1016/j.prime.2023.100107

[2]. Ozan Turanlı, andYurdagül Bente¸ sen Yakut, Classification of Faults in Power System Transmission Lines Using Deep Learning Methods with Real, Synthetic, and Public Datasets, International Journal for Research in Applied Science, https://doi.org/10.3390/app14209590.

[3]. Majid Jamil, Sanjeev Kumar Sharma and rajveer Singh, Fault Detection and Classification in Electrical Power Transmission System Using Artificial Neural Network, Springer Plus a springer open journal,https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-gtd.2019.1414

[4]. Shameem Hasan and Md. Toufikuzzaman, Fault Occurrence Detection and Classification of Fault Type in Electrical Power Transmission Line with Machine Learning Algorithms, International Journal on Electrical Engineering and Informatics (2022), DOI: 10.15676/ijeei.2022.14.3.9

[5]. R. P. Hasabe, A. P. Vaidya, Detection and classification of faults on 220 KV transmission line using wavelet transform and neural network, International Journal of Smart Grid and Clean Energy(2014), DOI: 10.12720/sgce.3.3.283-290

[6]. Yordanos Dametw Mamuya1, Yih-Der Lee, Jing-Wen Shen, Md Shafiullah and Cheng-Chien Kuo, Application of Machine Learning for Fault Classification and Location in a Radial Distribution Grid International Journal for Research in Applied Science(2020), https://doi.org/10.3390/app10144965

[7]. Sruti VS, Vidhun M,John J thanikkal, Josily Jose, Location of Transmission Line Faults Using Wavelet Transform and Artificial Neural Networks, International Journal of Science, Engineering and Management (IJSEM), Vol 3, Issue 6, June 2019

[8]. Ömer Özdemir, Ra¸ sit Köker and Nihat Pamuk,. Fault Classification and Precise Fault Location Detection in 400 kV High-Voltage Power Transmission Lines Using Machine Learning Algorithms. Processes 2025, 13, 527. https://doi.org/10.3390/pr13020527

[9]. Tang, L.; Mahela, O.P.; Khan, B.; Miro, Y, Current- and Voltage-Actuated Transmission Line Protection Scheme Using a Hybrid Combination of Signal Processing Techniques, Sustainability 2023, 15, 5715. https://doi.org/10.3390/su15075715

[10]. Sheesh Ram Ola, Amit Saraswat, Sunil Kumar Goyal, S.K. Jhajharia, Bhuvnesh Rathore, Om Prakash Mahela, Wigner distribution function and alienation coefficient-based transmission line protection scheme, https://ietresearch.onlinelibrary.wiley.com/doi/10.1049/iet-gtd.2019.1414

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