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Identification and Classification of Electrical Faults in Power Transmission using Extreme Learning Machine

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Abstract: *Ensuring the reliability and safety of electrical power transmission lines is a major challenge, especially when unexpected faults occur. Quick and accurate identification of these faults is essential to minimize damage, reduce downtime, and maintain system stability. In this work, an intelligent approach using the Extreme Learning Machine (ELM) is proposed for detecting and classifying different types of faults in transmission lines.*

The ELM algorithm, known for its simple structure and fast training speed, is applied to classify fault types based on voltage and current signal data collected under various fault conditions. To improve classification performance, key features are extracted from the waveform data using statistical and signal processing methods. These features help the ELM model effectively distinguish between different fault types such as single line-to-ground, line-to-line, double line-to-ground, and three-phase faults.

Simulation results show that the proposed ELM-based method offers high accuracy and fast response time, making it a promising solution for real-time fault monitoring in modern power systems. The outcomes also highlight the model's robustness in handling noisy and distorted signals, proving its practical value in smart grid applications.

Keywords: Fault Detection (FD), Fault Classification (FC), Transmission Line (TL), MATLAB, Extreme Learning Machine (ELM), Receiver Operating Characteristics Curve (ROC), Area Under the Curve (AUC), Single-Layer Feedforward Neural Networks (SLFNs), Artificial Neural Network (ANN), Support Vector Machine (SVM)

I. INTRODUCTION

Electric power transmission systems play a vital role in delivering electricity from generating stations to consumers. As our dependence on electrical energy continues to grow, the reliability and stability of these systems have become more important than ever. However, transmission lines are constantly exposed to environmental stresses, equipment aging, and other external factors, which makes them vulnerable to faults. These faultswhether caused by lightning, insulation failure, or mechanical damagecan disrupt power flow, damage infrastructure, and even lead to widespread outages if not addressed promptly.

Detecting and classifying faults accurately and quickly is essential to prevent damage and restore normal operation. Conventional protection methods, such as impedance-based relays and model-driven fault analysis, have long been used to monitor and respond to faults. While these systems are well-established, they sometimes fall short in terms of speed, adaptability, or performance under noisy or uncertain conditionsespecially as power systems become more complex and dynamic.

To address these limitations, researchers and engineers have increasingly turned to intelligent data-driven methods, particularly machine learning techniques, for power system monitoring and protection. One such method is the Extreme Learning Machine (ELM), a fast and efficient learning algorithm for single-hidden-layer feedforward neural networks.

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ELM stands out for its rapid training process, minimal parameter tuning, and strong generalization ability, making it an excellent candidate for real-time fault detection and classification tasks.

In this study, we explore the use of ELM to identify and classify different types of faults in high-voltage power transmission lines. By analyzing voltage and current signals collected during fault conditions, the model is trained to recognize patterns that indicate specific fault types, such as single line-to-ground, line-to-line, and three-phase faults. The goal is to create a system that not only delivers high accuracy but also responds quickly enough to support real-time protective relaying.

This research aims to demonstrate that integrating ELM into fault detection frameworks can enhance the reliability, speed, and precision of power system protection, offering a practical solution for modern smart grids and future energy systems.

II. LITERATURE SURVEY

Md. Omaer Faruq Goni [1] introduced a machine learning-based method for detecting and classifying transmission line faults, considering two lines with differing configurations in terms of sources and loads. This approach was evaluated against traditional Artificial Neural Networks (ANN), with the proposed model demonstrating improved accuracy and faster computation.

Ozan Turanlı and Yurdagül Benteşen Yakut [2] explored fault classification using a deep learning model based on Convolutional Neural Networks (CNN). Their study employed both real-world fault data—sourced from a power distribution company—and simulated data generated using Simulink to ensure model robustness across varied scenarios.

Shameem Hasan and Md. Toufikuzzaman [3] employed multiple machine learning techniques, including Neural Networks (NN), Extreme Gradient Boosting (XGBoost), and Light Gradient Boosting Machine (LightGBM). Among these, LightGBM exhibited the best performance in terms of prediction accuracy and efficiency in fault detection and classification.

R. P. Hasabe and A. P. Vaidya[4] presented a hybrid method combining Discrete Wavelet Transform (DWT) and neural networks. Features were extracted from current waveforms using DWT and then fed into a neural network for effective fault classification.

Yordanos Dametw Mamuyaet al.[5] proposed a machine learning-based fault location and classification technique tailored for radial distribution networks. Their model accounted for both balanced and unbalanced load conditions and incorporated discrete wavelet transforms to extract meaningful features from the signal, achieving high accuracy and reliability.

Sruti V. S., Vidhun M., John J. Thanikkal, and JosilyJose[6] developed a fault location model utilizing wavelet transform and ANN. Faults were simulated at intervals along a 100 km transmission line, and Clark's transformation was used to decouple voltage and current signals. Daubechies4 wavelet was applied for feature extraction, which were then input to an ANN for classification.

Ömer Özdemir, RaşitKöker, and Nihat Pamuk [7] evaluated several machine learning algorithms—such as Naive Bayes, K-Nearest Neighbors (KNN), Decision Trees, SVM, Ensemble methods, and Neural Networks—for fault detection, location, and classification. With 67% of the data used for validation and 33% for testing, the neural network model achieved a high classification accuracy of 99.97%.

Lastly, Ligang Tang, Om Prakash Mahela, Baseem Khan, and Yini Miro [8] proposed a method integrating Stockwell Transform (ST) and Hilbert Transform (HT) for analyzing fault signals. Their findings indicated superior performance of this method over traditional DWT-based and other time–frequency analysis approaches.

III. PROPOSED METHODOLOGY

This study utilizes the Extreme Learning Machine (ELM) to develop an effective framework for detecting and classifying faults in electrical power systems. The proposed approach is outlined in Figure 1. ELM has shown promising results in a variety of applications, including fault diagnosis in electrical networks, due to its fast learning speed and strong generalization capability.

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Accurate fault detection and classification are essential for maintaining the safety, reliability, and efficiency of power systems. In high-voltage grids, which include critical components such as transformers, generators, and transmission lines, identifying faults promptly helps prevent damage and minimize system disruptions. Proper coordination between protective devices is also crucial—only the devices nearest to the fault should operate, preventing unnecessary power outages across larger sections of the grid.

Given the complexity of modern power networks, a reliable and fast-responding system is necessary to distinguish between different types of faults and trigger appropriate protective actions. This research aims to contribute a robust, intelligent solution using ELM that enhances fault identification and supports the stable operation of the power grid.

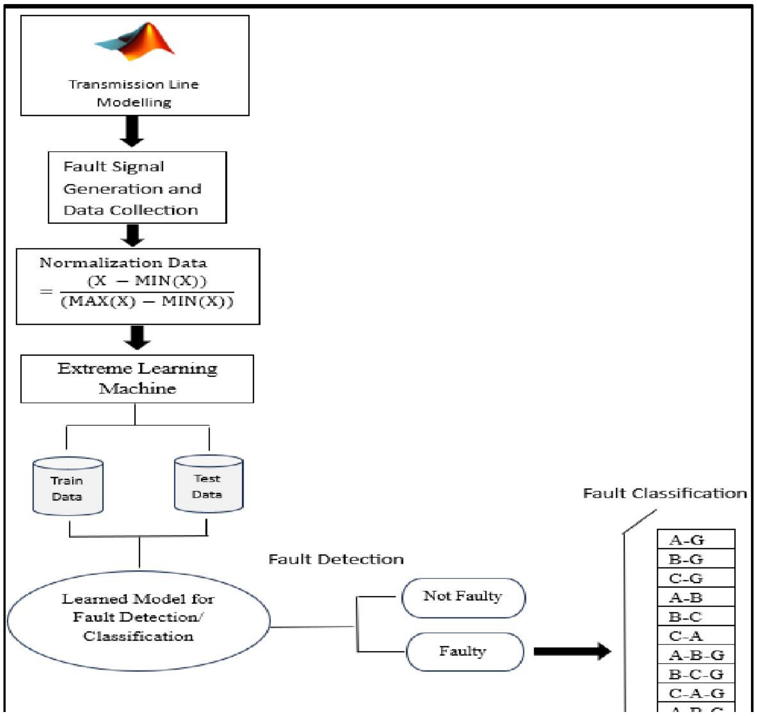

Fig. 1: Proposed Method for Fault identification and Classification

The methodology proposed for fault identification and classification in transmission lines follows a structured approach that integrates simulation techniques with the capabilities of an Extreme Learning Machine (ELM). The process begins by modeling a transmission line in a simulation environment, where various fault scenarios are createdsuch as single line-to-ground, line-to-line, double line-to-ground, and three-phase faults. From these simulated events, voltage and current signals are collected to represent the system's behavior under different fault conditions.

Next, relevant features are extracted from the signal data to capture unique patterns associated with each fault type. To ensure consistency and improve the learning performance, these features are normalized using Min-Max scaling. The refined data is then used to train the ELM model, which is designed to differentiate between normal and faulty conditions, as well as accurately classify the specific fault type.

This approach enables rapid and accurate fault detection, making it highly suitable for real-time protection in power systems. By improving the speed and reliability of fault identification, the method contributes to enhanced grid stability and more efficient system operation.

IV. SIMULATION MODEL

In this study, fault identification and classification were carried out using a simulated transmission line model, as illustrated in Figure 2. The simulation was conducted using MATLAB Simulink, which provided a flexible environment for modeling and analyzing power system behavior. A 150 km long transmission line was modeled, and

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voltage-current measurement blocks were incorporated to capture the electrical signals during different operating conditions.

To simulate fault scenarios, a dedicated fault block was used to introduce various types of faults into the system. Both unsymmetrical faults such as line-to-ground (L-G), line-to-line (L-L), and double line-to-ground (L-L-G) and symmetrical faults including three-phase (L-L-L) and three-phase-to-ground (L-L-L-G) were generated. In total, eleven distinct fault types were 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.

For each fault condition, the corresponding voltage and current waveforms were recorded, forming a comprehensive dataset. This dataset was later used to train the Extreme Learning Machine (ELM) model for accurate fault identification and classification.

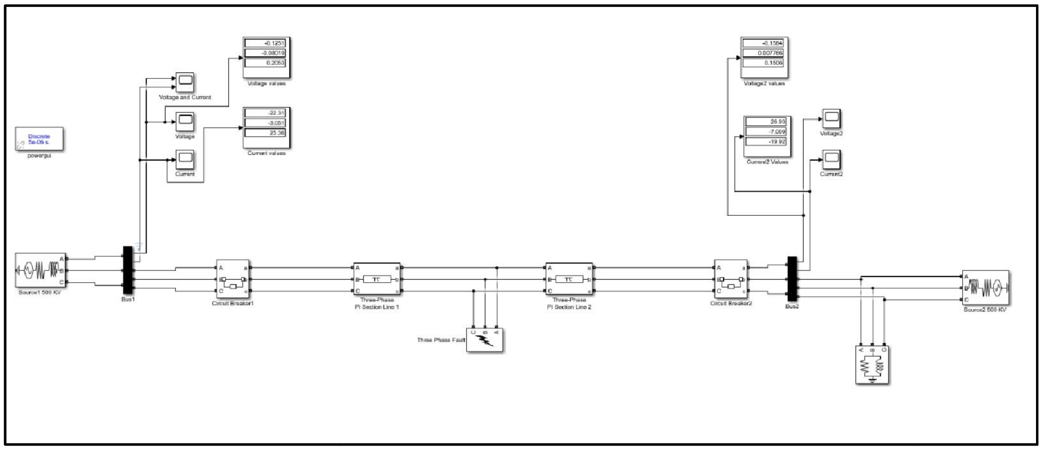

Fig. 2: Transmission line simulation model.

Parameters Detail

This study models a two-bus power system with two generators, G1 and G2, rated at 500∠20 kV and 500∠0 kV, and connected by a 150 km transmission line. G1 and G2 have equivalent impedances of 17.177 + j45.529 Ω and 15.31 + j45.925 Ω, respectively. The transmission line has positive and zero-sequence impedances of 4.983 + j117.83 Ω and 12.682 + j364.196 Ω, and sequence admittances of j1.468 m℧ and j1.099 m℧.

Circuit breakers are placed at both ends of the line (Bus 1 and Bus 2), and the system operates at 60 Hz with a sampling frequency of 3.84 kHz. Voltage and current signals are captured using measurement blocks in MATLAB Simulink. These signals are normalized and used to train and test the ELM model, with results evaluated using a confusion matrix for accurate fault detection and classification.

V. EXTREME LEARNING MACHINE

The Extreme Learning Machine (ELM) is an efficient learning algorithm designed for single-layer feedforward neural networks (SLFNs). Initially introduced by Huang et al., ELM was developed to address the limitations of traditional neural networks, particularly the slow training and convergence issues associated with backpropagation. ELM offers fast training speeds, strong generalization capability, and straightforward implementation, making it especially effective for real-time applications like fault detection and classification in power systems.

One of the key strengths of ELM lies in its ability to quickly learn complex patterns from input data while maintaining high accuracy and low computational cost. These features make ELM a suitable solution for modern power networks and smart grids, where timely and accurate fault identification is crucial.

Structurally, ELM consists of a single hidden layer. Input features are randomly projected into this hidden layer using randomly assigned weights and biases. Instead of using time-consuming iterative training methods, ELM calculates the output weights in one step using the Moore–Penrose pseudo-inverse. This significantly reduces training time while preserving accuracy.

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For a dataset with N samples, each having n features, the inputs are passed through L hidden neurons using an activation function such as sigmoid, sine, or radial basis. The resulting outputs from the hidden layer form a matrix H. The final output weights (β) are computed using:

$\beta = H^{\dagger}T$ (Equation 1)

Here, H† represents the pseudo-inverse of the hidden layer output matrix, and T is the matrix of target outputs. This direct, analytical approach eliminates the need for iterative learning, making ELM a fast and effective tool for real-time fault classification.

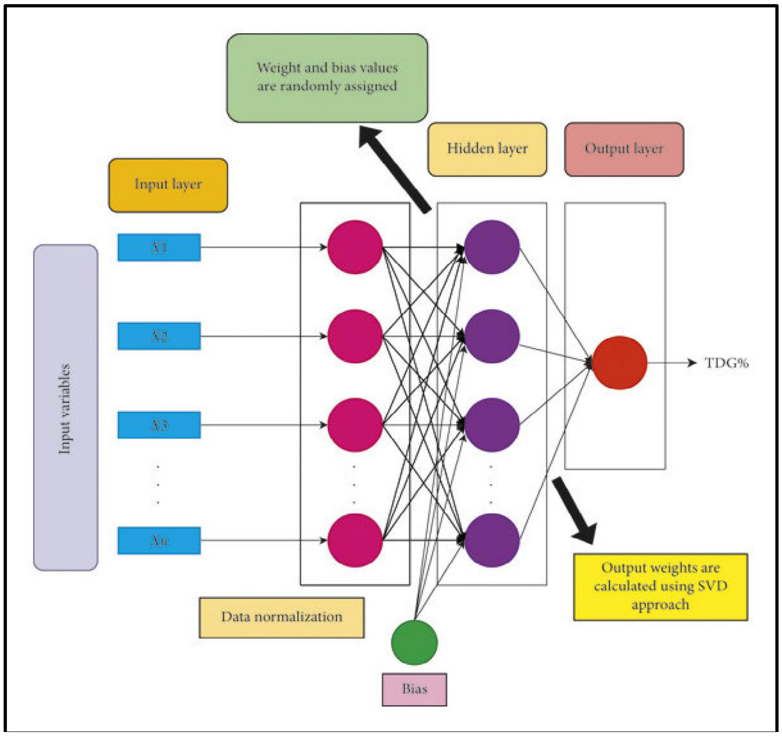

Fig. 3: ELM classifier structure

In this research, the Extreme Learning Machine (ELM) is applied to detect and classify eleven types of transmission line faults using MATLAB. Voltage and current waveforms are simulated under realistic fault conditions, incorporating transient disturbances and noise to create a comprehensive and diverse dataset. The simulated faults include 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-Grepresenting various categories such as L-G, L-L, L-L-G, and L-L-L faults. These scenarios are modeled using the setup shown in Figure 2, with fault conditions generated at every 10 km along the transmission line. Variations in fault resistance (ranging from 0Ω to 50Ω) and fault inception angles (from 0° to 180° in 30° steps) are also considered to enhance the robustness of the dataset.

Before training, the voltage and current signals are normalized using Min-Max scaling to ensure consistency and improve the learning performance of the model. The ELM is then trained using 30% of the normalized dataset, while the remaining 70% is used to test and validate the model's classification accuracy. Input weights are randomly assigned, and output weights are calculated analytically, allowing for rapid and efficient training. The performance of the model is evaluated using confusion matrices and classification metrics, confirming its effectiveness in accurately identifying and classifying faults in transmission lines.

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VI. COMPARATIVE TABLE: ELM, ANN AND SVM

Sr. No.	Aspect	ELM (Extreme Learning Machine)	ANN (Artificial Neural Network)	SVM (Support Vector Machine)
1	**Model Type**	Single hidden-layer feedforward network	Multi-layer neural network (can be shallow or deep)	Geometric classifier based on separating hyperplanes
2	**Training Approach**	Randomly initializes input weights; solves output weights analytically (no loops)	Uses backpropagation to adjust weights iteratively over many epochs	Solves an optimization problem to maximize the margin between classes
3	**Speed of Training**	Extremely fast—usually needs only one pass	Slow—can take hours or days for deep networks	Moderate—faster than deep ANN, slower than ELM
4	**Accuracy**	Good on many tasks but depends on hidden nodes and data quality	High accuracy if properly trained and regularized	Excellent on small to medium-sized datasets, especially with proper kernel
5	**Scalability**	Limited by memory (matrix inversion); best for small/medium datasets	Scales well with large datasets (especially using GPUs)	Struggles with very large datasets due to kernel matrix
6	**Complexity**	Simple architecture and logic	Flexible and complex—supports deep and wide configurations	Mathematically sophisticated but conceptually clean
7	**Flexibility**	Limited (one hidden layer only)	Very flexible—can model highly nonlinear and complex relationships	Somewhat limited to classification and regression unless modified
8	**Use of Kernels**	Not by default (kernel ELM variants exist)	Not kernel-based (but nonlinearities handled via activation functions)	Strong kernel support (linear, RBF, polynomial, sigmoid)
9	**Hyperparameter Tuning**	Minimal (only number of hidden neurons, activation function)	Extensive—layers, units, learning rate, batch size, optimizer, etc.	Requires tuning of kernel, penalty parameter (C), gamma (for RBF)
10	**Memory Usage**	Moderate—needs to store hidden layer matrix and pseudo-inverse	High—especially for deep networks and large batch sizes	Can be high (especially with nonlinear kernels and large feature sets)
11	**Interpretability**	Low to moderate—hard to explain specific neuron behavior	Low—often treated as a "black box"	Moderate to high—especially for linear SVMs, where the hyperplane can be visualized
12	**Overfitting Risk**	Can overfit with too many hidden neurons	High if not properly regularized (dropout, L2, etc.)	Low—good generalization due to margin maximization
13	**Online/Real-time Use**	Very suitable due to fast training and update	Not ideal—training is too slow for real-time	Possible with linear SVM; not ideal for online

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		capability	updates	learning
14	**Best Application Areas**	Real-time systems, embedded AI, rapid prototyping	Deep learning tasks: vision, audio, language	Text classification, bioinformatics, fraud detection
15	**Multiclass Handling**	Supports multiclass naturally	Native support through softmax or multiple outputs	Not native—requires one-vs-one or one-vs-all strategy

VII. RESULTS

Output Waveforms

The transmission line model was simulated under several operating conditions to analyze its behavior during faults. These conditions include a healthy system (no fault), as well as various types of faults: single line-to-ground (L-G), line-to-line (L-L), double line-to-ground (L-L-G), three-phase fault (L-L-L), and a three-phase-to-ground fault (L-L-L-G).

Figure 4 illustrates the voltage and current waveforms for the system operating under normal (healthy) conditions. As expected, the signals are smooth and undisturbed, indicating stable system performance.

Figures 5 through 9 depict the system's response under different fault scenarios. Both asymmetrical faults (L-G, L-L, L-L-G) and symmetrical faults (L-L-L and L-L-L-G) were simulated. The faults were introduced during the time interval from 0.1 seconds to 0.2 seconds. During this window, noticeable disturbances appear in the voltage and current waveforms.

Although some faults may initially occur on a single phase, their impact often propagates across all phases, leading to widespread waveform distortion. If not addressed promptly, such disturbances can severely affect system stability. This highlights the critical need for fast and well-coordinated protective mechanisms. Efficient protection systems must isolate only the affected parts of the network to ensure that the remaining healthy sections continue operating reliably.

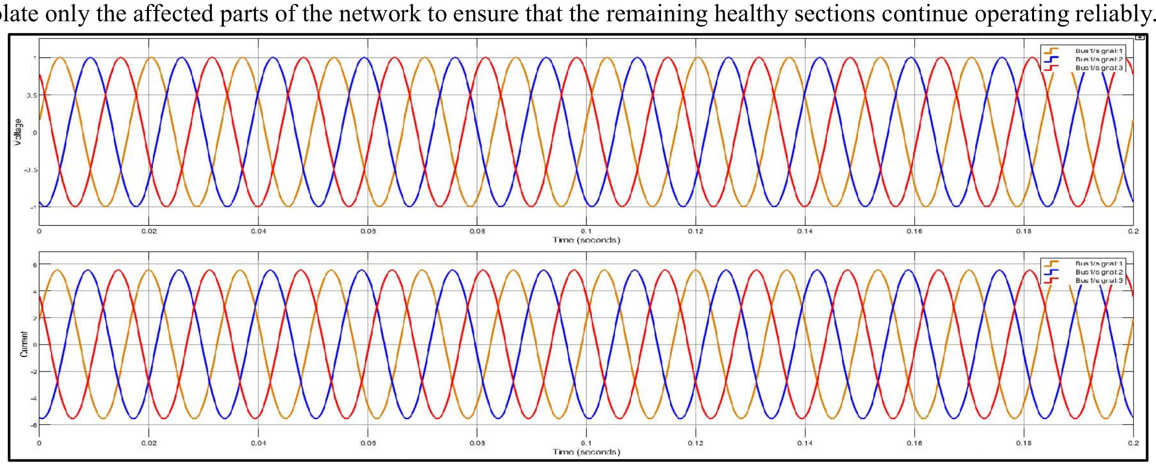

Fig. 4: Healthy system.

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A-G fault:

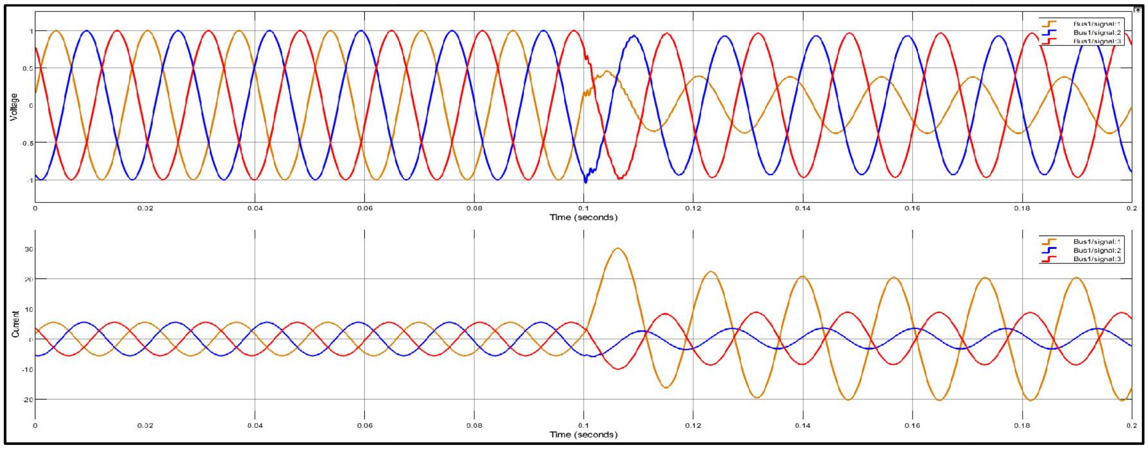

Fig. 5: Unsymmetrical fault: Line-Ground fault. (A phase- Ground).

A-B Fault:

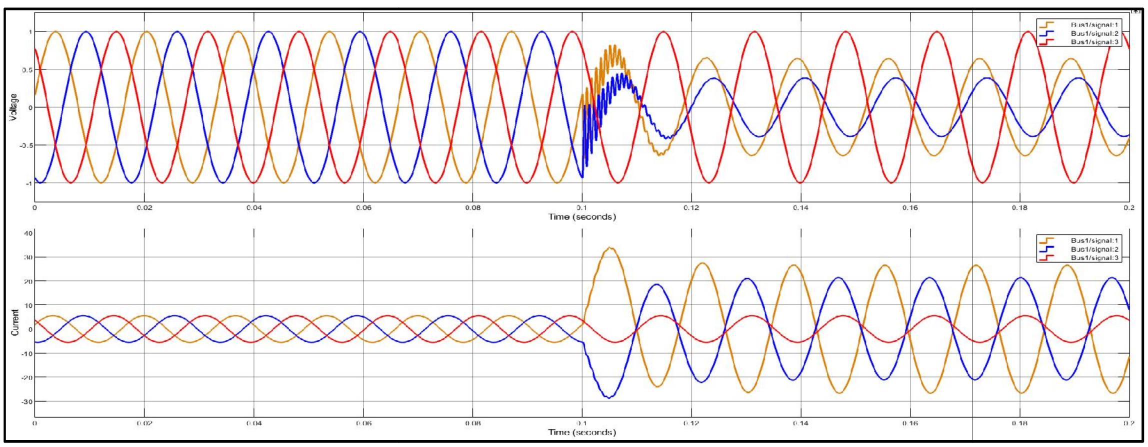

Fig. 6: Unsymmetrical fault: Line-Line fault. (A phase- B phase).

A-B-G fault:

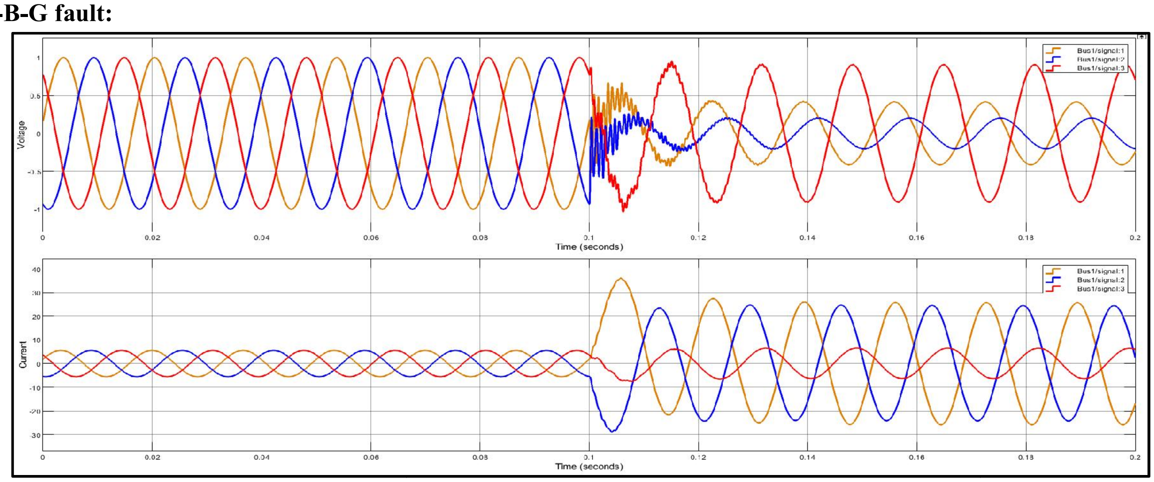

Fig. 7: Unsymmetrical fault: Line-Line-Ground fault. (A phase-B phase-Ground).

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A-B-C fault:

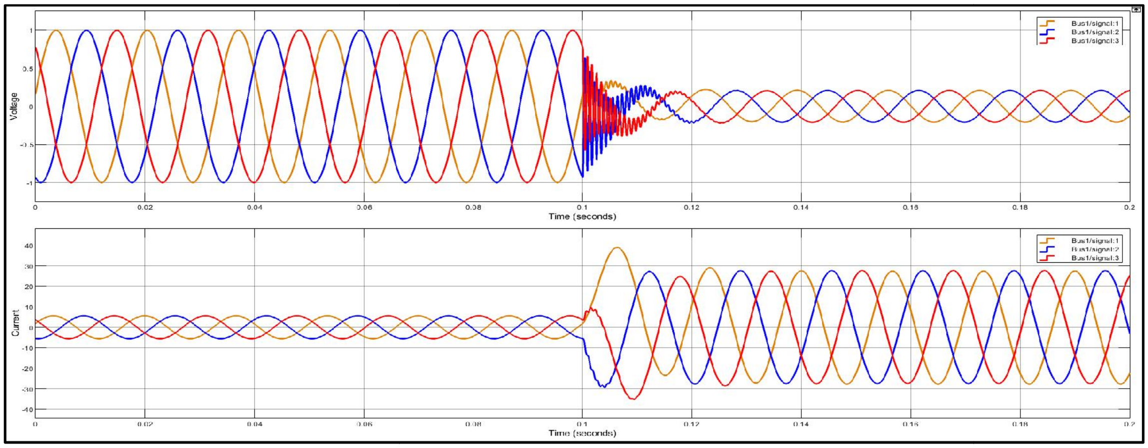

Fig. 8: Symmetrical fault: Line-Line-Line fault. (A phase- B phase-C phase).

A-B-C-G fault:

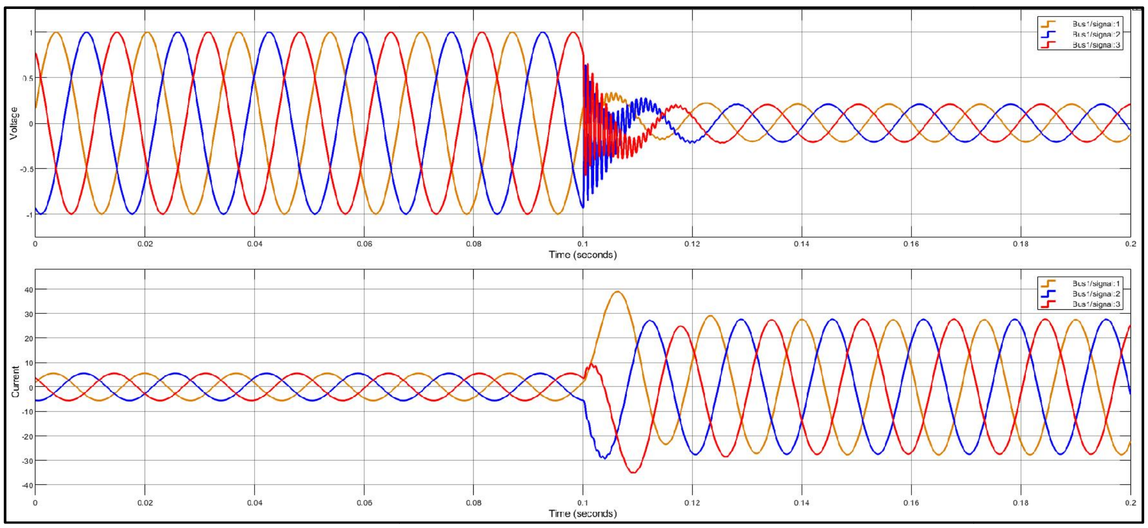

Fig. 9: Symmetrical fault: Line-Line-Line-Ground fault. (A phase-B phase-C phase-Ground).

Fault Identification& Classification

The proposed model was thoroughly tested using fault data obtained from simulations involving both symmetrical and unsymmetrical fault conditions within the transmission system. The objective was to evaluate the model's capability in accurately classifying and detecting various types of faults.

To assess classification performance, a confusion matrix was generated using all test samples, as shown in Figure 13. The model achieved a remarkable 100% accuracy, successfully identifying each type of fault without any errors. This highlights the robustness and reliability of the implemented Extreme Learning Machine (ELM) model in handling complex fault scenarios.

To further validate the classification performance, Receiver Operating Characteristic (ROC) curves were plotted for each fault class, as illustrated in Figure 10. These curves display the relationship between the true positive rate and the false positive rate across different threshold values. For all fault categories, the ROC curves yielded an Area Under the

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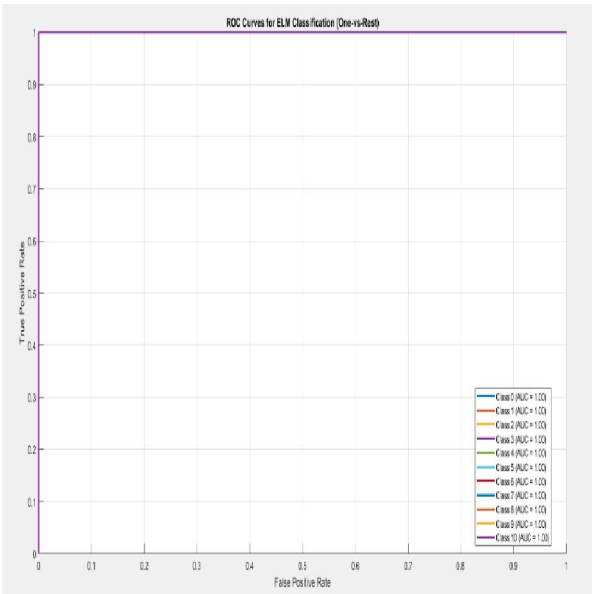
Curve (AUC) of 100%, indicating perfect discrimination between fault classes and confirming the high effectiveness of the classification model.

In addition to classifying faults, the model was also evaluated for fault detection—that is, identifying whether or not a fault has occurred in the system. The detection performance results are summarized in the fault detection table (see Figure). Once again, the ROC curve for fault detection, shown in Figure 11, achieved an AUC of 100%, demonstrating the model's exceptional accuracy in distinguishing between healthy and faulty system states.

These results confirm that the proposed ELM-based model not only classifies different fault types with high precision but also reliably detects the occurrence of faults, making it a valuable tool for real-time power system monitoring and protection.



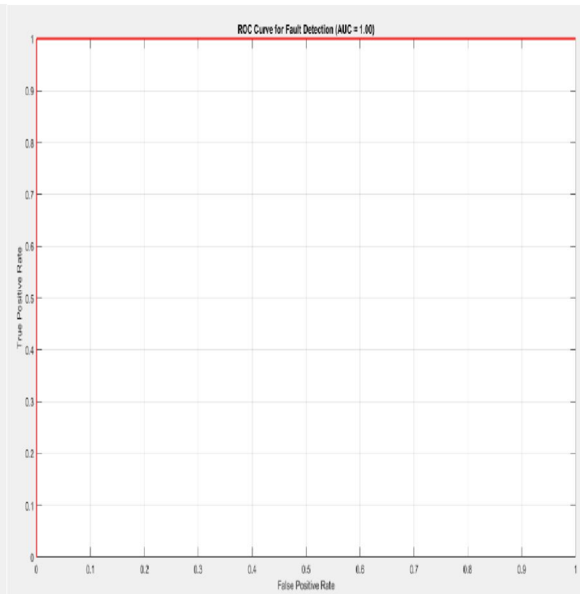


Fig. 10: Receiver operating characteristics for FC Fig. 11: Receiver operating characteristics for FI

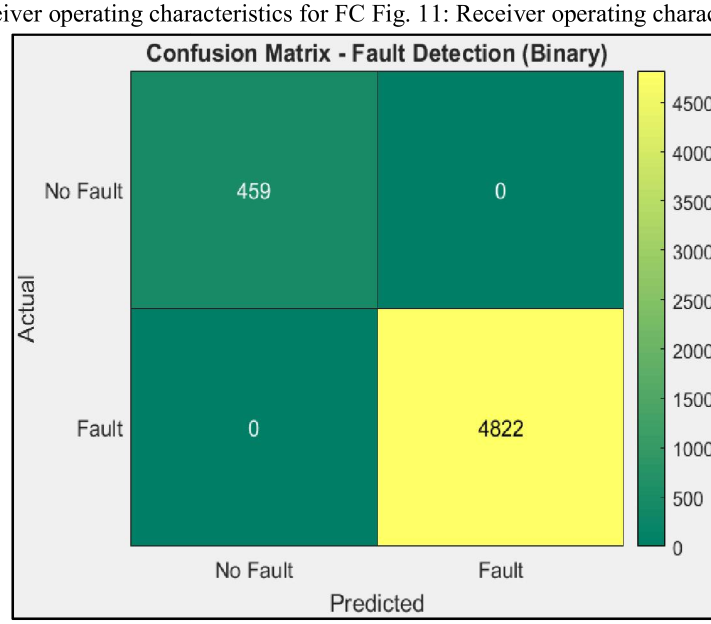


Fig. 12: Confusion matrix for fault identification

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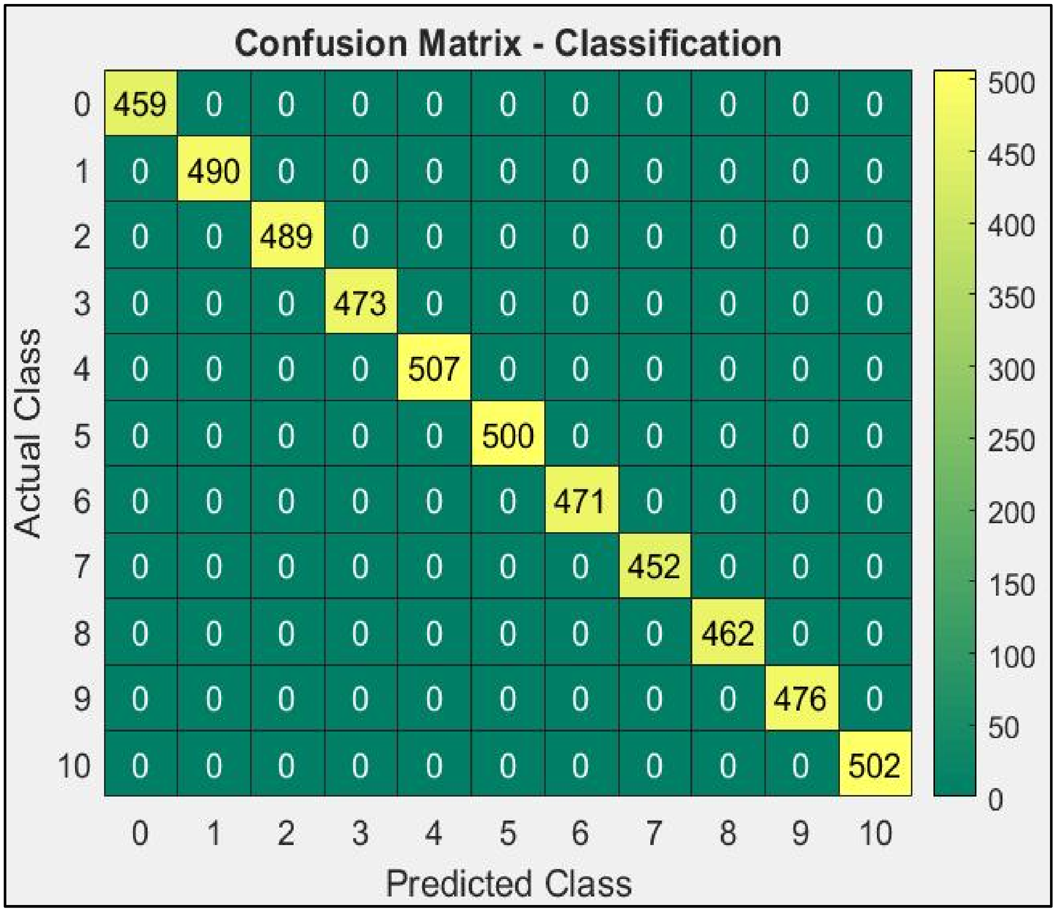

Fig. 13: Confusion matrix for fault classification

VIII. CONCLUSION

Protecting transmission lines from faults is a critical aspect of ensuring the stability and reliability of power systems. Effective coordination among protective devices is essential to isolate only the faulty sections of the grid, preventing unnecessary outages and minimizing disruption across the network.

In this study, a comprehensive analysis was conducted by simulating both unsymmetrical faultssuch as line-to-ground (L-G), line-to-line (L-L), and double line-to-ground (L-L-G)and symmetrical faults including line-to-line-to-line (L-L-L) and line-to-line-to-line-to-ground (L-L-L-G). A total of 11 distinct fault types were modelled: 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 Extreme Learning Machine (ELM) was employed for fault detection and classification. Results demonstrate that ELM provides rapid and accurate classification, making it a promising solution for real-time fault analysis in power systems. Its high computational efficiency and learning speed make it particularly suitable for large-scale grid monitoring.

In summary, the ELM-based approach offers a reliable and intelligent method for enhancing fault diagnosis and improving the resilience of transmission networks. With further development, this method has strong potential for broader application across power system protection schemes and fault management systems.

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