Fault Detection in Three-Phase Power Systems Using Artificial Neural Networks (ANN) / Deep Learning in MATLAB

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Abstract— The growing complexity of modern electrical power systems, driven by increasing load demand, network expansion, and renewable energy integration, necessitates the development of intelligent and highly reliable fault detection mechanisms. Conventional protection techniques, although extensively utilized, often face challenges in accurately detecting and classifying faults under dynamic operating conditions and nonlinear system behavior. To address these limitations, this study presents the design and implementation of an Artificial Neural Network (ANN)-based fault detection and classification framework for a three-phase power system using MATLAB/Simulink.

The proposed system utilizes three-phase voltage and current measurements from the R, Y, and B phases to identify abnormal operating conditions and classify various fault types, including Single Line-to-Ground (LG), Line-to-Line (LL), Double Line-to-Ground (LLG), and Three-Phase (LLL) faults. A comprehensive dataset was generated through extensive simulation of normal and faulted operating conditions within the MATLAB/Simulink environment. The collected electrical parameters were preprocessed, normalized, and subsequently employed for ANN training and validation.

The developed neural network was designed to learn complex nonlinear fault characteristics and accurately recognize fault patterns under diverse operating scenarios. Simulation results demonstrated that the proposed ANN-based model achieved high fault classification accuracy, rapid detection response, and robust performance under varying load conditions and measurement noise. Comparative evaluation further revealed significant improvements over conventional protection approaches in terms of detection speed, adaptability, and reliability.

The findings highlight the potential of Artificial Neural Networks as an effective tool for intelligent power system protection, enabling adaptive and real-time fault diagnosis. The proposed framework contributes to the advancement of smart grid protection technologies by enhancing system reliability, minimizing equipment damage, and reducing power interruption duration. Furthermore, the study establishes MATLAB-based ANN implementation as a practical, scalable, and efficient solution for next-generation intelligent monitoring, fault management, and automated protection applications in modern power networks.

Keywords— Artificial Neural Network (ANN), Fault Detection, Fault Classification, Power System Protection, Smart Grid, MATLAB/Simulink, Three-Phase System, Intelligent Monitoring.

I. INTRODUCTION

The continuous and reliable supply of electrical energy is one of the most critical requirements for industrial, commercial, and domestic applications. Power systems are designed to operate under stable and balanced conditions, where the generation, transmission, and distribution of electricity occur seamlessly. However, real-world conditions often introduce unexpected disturbances such as short circuits, open circuits, line-to-line faults, and ground faults. These events, collectively known as faults, disrupt the normal operation of the system and can lead to severe equipment damage, voltage instability, or even complete system outages. Therefore, rapid and accurate fault detection plays an indispensable role in ensuring the stability, safety, and reliability of modern power systems. A three-phase power system forms the backbone of modern electrical networks, comprising three conductors that carry alternating currents with a phase difference of 120 degrees. These phases are

Commonly denoted as R (Red), Y (Yellow), and B (Blue). Under balanced conditions, the voltages and currents in all three phases are equal in magnitude and symmetrically displaced in phase angle. Any deviation from this balanced condition indicates the presence of a fault or abnormal event. For instance, a single line-to-ground fault affects one phase, while double line-to-line or three-phase faults can impact the entire system. Traditionally, fault detection and protection in power systems have relied on methods such as impedance-based relays, differential protection, symmetrical component analysis, and overcurrent detection. While these techniques are effective in many cases, they exhibit several limitations in modern complex networks — including slow response times, inability to adapt to nonlinear loads, limited fault classification accuracy, and vulnerability to noise or measurement errors. Furthermore, with the increasing penetration of renewable energy sources, power electronics, and distributed generation, the dynamic behaviour of power systems has become more unpredictable, necessitating intelligent fault detection mechanisms.

In recent years, Artificial Intelligence (AI) and particularly Artificial Neural Networks (ANNs) have revolutionized fault diagnosis in engineering systems. ANNs mimic the human brain’s learning capability by processing data through interconnected layers of neurons. Once trained on sufficient historical or simulated fault data, these networks can recognize complex patterns, learn fault signatures, and generalize knowledge to detect unseen fault types accurately. This project leverages the computational environment of MATLAB to implement an ANN-based fault detection model for three-phase power systems. The MATLAB platform provides powerful simulation tools, data visualization capabilities, and built-in neural network toolboxes that make it ideal for developing and testing intelligent diagnostic systems. The proposed model processes voltage and current signals from the R, Y, and B phases, and classifies the system condition as either normal or faulted, further identifying the specific type of fault present.

II. Historical Background

The history of fault detection in electrical power systems dates back to the early 20th century, when simple electromechanical relays were used to detect abnormal current and voltage conditions. These relays were primarily overcurrent-based, meaning they operated whenever current levels exceeded predefined thresholds. Although robust, they lacked adaptability and sensitivity to complex fault conditions. By the mid-20th century, impedance- based protection schemes emerged, allowing more precise fault location estimation by measuring voltage and current phase relationships. The introduction of distance relays and differential relays marked a significant advancement in protection engineering. These methods, however, relied heavily on manual calibration and experienced reduced accuracy under changing load or supply conditions. The 1980s and 1990s witnessed a shift towards digital protection systems as microprocessors and digital signal processors (DSPs) became widely available. Digital relays provided faster response times, programmability, and the ability to perform real-time data analysis. Techniques such as Fourier Transform (FT), Wavelet Transform (WT), and Symmetrical Component Analysis (SCA) were employed for fault feature extraction. Despite these improvements, traditional techniques still faced challenges in accurately classifying fault types under noisy or distorted waveforms, nonlinear loads, and distributed generation systems. This led to the integration of Artificial Intelligence (AI) techniques in fault detection research. The early 2000s saw the introduction of Artificial Neural Networks (ANNs), Fuzzy Logic Systems, and Support Vector Machines (SVMs) in power system protection. Among these, ANNs gained particular popularity due to their ability to learn complex nonlinear mappings, adapt dynamically, and perform classification tasks with high accuracy. Recent advancements in Deep Learning have further enhanced fault detection accuracy by enabling automatic feature extraction from raw waveform data without the need for manual pre- processing. Today, ANN-based and deep learning- based protection systems are being explored for smart grids, micro grids, and renewable power systems, providing adaptive, fast, and reliable fault detection solutions. This historical progression from electromechanical relays to intelligent algorithms reflects the evolution of power system protection in tandem with technological innovation.

III. Theme of the Project

The central theme of this project is the intelligent detection and classification of faults in three-phase power systems using Artificial Neural Networks (ANNs) within the MATLAB environment. The focus is on integrating AI-based learning models into conventional power protection frameworks to enhance accuracy, adaptability, and speed. The project emphasizes the utilization of RYB voltage and current data as input signals to train and validate an ANN model. By learning from patterns associated with various fault types — such as line- to-ground faults, line-to-line faults, double line-to- ground faults, and three-phase faults — the model becomes capable of identifying and classifying system disturbances automatically. This approach moves away from traditional rule-based fault detection methods and instead embraces data-driven intelligence, where the system learns fault behavior directly from the data. The MATLAB environment serves as a powerful platform for both simulation of three-phase faults and training of the ANN model, providing a bridge between power system analysis and machine learning implementation. The overarching theme aligns with the emerging trends in smart grid technology, where intelligent fault detection is vital for self-healing, fault-tolerant, and autonomous power networks.

IV. Objectives of the Project

The primary objective of this project is to design and implement an Artificial Neural Network-based Fault Detection System for a three-phase power network using MATLAB. The detailed objectives are as follows:

1. To simulate a three-phase power system model under various operating conditions — normal and faulted — using MATLAB/Simulink.
2. To collect voltage and current data (RYB signals) during these different fault scenarios to build a comprehensive dataset.
3. To pre-process and normalize input data to ensure consistency and accuracy for neural network training.
4. To design, train, and test an Artificial Neural Network (ANN) capable of distinguishing between healthy and faulty conditions of the power system.
5. To identify three phase faults.
6. To evaluate the performance of the developed ANN model in terms of accuracy, response time, and robustness under noisy and varying load conditions.
7. To compare ANN-based detection results with traditional protection methods to demonstrate the advantages of intelligent models.
8. To propose a reliable and efficient framework for future integration into real-time protection systems and smart grid environments.

V. LITERATURE SURVEY

The reliability and stability of power systems greatly depend on the timely detection and classification of faults in transmission lines. With the growing complexity and load on modern electrical networks, traditional protection methods are often insufficient to ensure fast and accurate fault diagnosis. Recent research has focused on leveraging Artificial Intelligence (AI), Machine Learning (ML), and

Internet of Things (IoT) techniques to improve the efficiency, accuracy, and responsiveness of fault detection systems. This section presents a detailed survey of related research papers addressing fault detection and monitoring in power transmission systems.

[1] Transmission Line Fault Detection System – Abhishek Jadhavar et al. This paper [1] emphasizes the critical role of transmission lines in maintaining the stability of the power system and the need for efficient fault detection mechanisms. The authors discuss how increased power demand and transmission losses—such as reactive power and voltage deviation—impact the reliability of power delivery. The study highlights that quick fault identification and system restoration are essential to minimize interruptions. The paper primarily focuses on the importance of fault analysis and presents a conceptual overview of fault detection in transmission lines but does not implement a specific algorithmic or simulation-based model.

Key Contribution: Establishes the theoretical importance of

fault detection in transmission lines and the challenges associated with minimizing losses and improving reliability.

[2] Machine Learning-Based Fault Detection in Transmission Lines: A Comparative Study – Yıldırım Özüpak [2] presents a comparative study on the use of various machine learning algorithms—Decision Tree (DT), Logistic Regression (LR), and Support Vector Machines (SVM)—for fault detection in transmission lines. The paper demonstrates how ML can automate the process of fault identification using fault and non- fault data. Through Random Search Optimization, the author fine-tunes the model hyperparameters to achieve better accuracy. The results show that the Decision Tree model achieved the best performance with minimal error, while Logistic Regression achieved 97.01% test accuracy. SVM showed comparatively lower accuracy (74.19%).

Key Contribution: Demonstrates the effectiveness of classical ML algorithms in transmission line fault detection and proves that data-driven models can outperform traditional analytical methods when properly optimized.

[3] Fault Detection and Classification in Overhead Transmission Lines through Comprehensive Feature Extraction Using Temporal Convolution Neural Network (TCN) – Nadeem Ahmed Tunio et al. This study [3] introduces an advanced Deep Learning- based approach using Temporal Convolutional Neural Networks (TCN) for fault detection and classification in a 500 kV transmission line in Pakistan. The authors first extract transient current features using Discrete Wavelet Transform (DWT) under varying conditions such as fault type, location, and resistance. The TCN model, due to its ability to handle long receptive fields and parallel computation, achieved 99.9% outperforming BiLSTM and GRU models. accuracy, Key Contribution: Validates that deep temporal models like TCN can provide extremely high classification accuracy with reduced memory usage, making them suitable for large-scale, real-time power system monitoring. [4] Electrical Fault Detection in Overhead Transmission Line – Gaurav Jichkar et al. In this review paper [4], the authors discuss the importance of efficient fault detection in overhead transmission lines and the impact of technical and physical losses on system performance. They underline that faults must be cleared swiftly to restore power with minimal interruptions. The paper consolidates various detection methods, offering a broad overview rather than a specific technical implementation.

Key Contribution: Serves as a comprehensive review highlighting the challenges of fault detection in long-distance transmission lines and the need for advanced, intelligent monitoring systems to improve fault restoration times.

[5] Transmission Line Fault Monitoring System Using IoT – Abhinay Vijayrao Sahare et al. This project review [5] explores an IoT-based solution for transmission line monitoring. The system uses an Arduino Nano connected to multiple sensors (voltage, current, temperature) to wind speed, measure load electrical cell, and environmental parameters. The data are transmitted wirelessly to power stations, allowing for remote fault monitoring and real-time alerts. The authors propose the integration of a web-based dashboard for visualizing system parameters and generating alerts before power failures occur.

Key Contribution: technology can Demonstrates significantly how IoT enhance fault monitoring, data accessibility, and maintenance efficiency in power systems by offering real-time condition tracking and predictive alerts.

[6] Transmission Line Fault Detection and Classification Using New Tripping Characteristics Based on Statistical Coherence – R.A. Mahmoud R.A. Mahmoud [6] proposes a novel coherence- based fault detection and classification technique utilizing current measurements from the sending end of transmission lines. The method introduces a set of six coherence coefficients that quantify the statistical relationship between current signals to detect and classify faults rapidly. Simulations carried out in ATP software with data analyzed in MATLAB demonstrated that the proposed method could detect all ten shunt fault types within half a cycle, ensuring high security and sensitivity.

Key Contribution: Introduces a fast and accurate coherence-based protection scheme that enhances reliability and fault clearance speed, suitable for both conventional and smart grids.

VI. SYSTEM DEVELOPMENT

The development of the fault detection system involves multiple stages — from data collection and pre-processing, through fault simulation and feature extraction, to model training and deployment. Each step is designed to ensure accurate classification of faults in three-phase RYB systems using Artificial Neural Networks (ANN) or advanced Deep Learning models.

3.1 Data Collection and Pre-processing

The foundation of the system lies in accurate and representative three-phase RYB data. This data consists of voltage and current measurements from each of the three phases — Red (R), Yellow (Y), and Blue (B) — recorded under both normal operating and faulted conditions. Sources of Data: Simulated Data: Generated using MATLAB/Simulink models of three-phase power systems with configurable fault conditions. Experimental Data: Acquired from laboratory setups or field measurements using sensors and data acquisition systems. Typical Parameters Collected: Phase Voltages: (V_R, V_Y, V_B) Phase Currents: (I_R, I_Y, I_B) Time: Sampling rate set according to the system frequency (typically 50 Hz or 60 Hz) Pre-processing Steps: 1. Signal Normalization: All voltage and current readings are normalized to bring them to a uniform scale, improving network convergence during training.

2. Noise Removal: Filtering techniques such as low- pass, band-pass, or wavelet filters are applied to eliminate measurement noise and unwanted frequency components.

3. Feature Scaling: Features are standardized or scaled to improve the stability of ANN training.

4. Segmentation: The time-series data is divided into smaller time windows for pattern extraction and labeling.

5. Labeling: Each data segment is tagged as either Normal or corresponding to a specific fault type (e.g., Line-to-Ground, Line-to-Line, Double Line- to-Ground, or Three-Phase Fault). The pre-processed dataset forms the basis for supervised learning, ensuring that the neural network is exposed to diverse operating scenarios for robust fault detection.

3.2 Fault Scenarios

Different types of electrical faults are simulated or experimentally introduced in the three-phase system to create representative datasets. Each fault condition results in a distinct pattern in voltage and current waveforms, which helps the ANN learn to distinguish between them. Common Fault Types Considered:

1. Single Line-to-Ground (L-G) Fault: One phase is shorted to ground.

2. Line-to-Line (L-L) Fault: Two phases are shorted together.

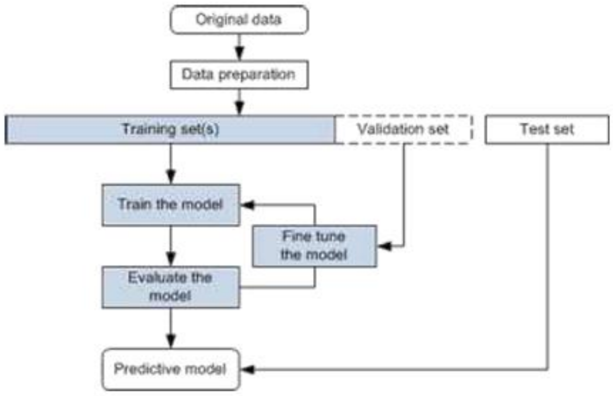
3. Double Line-to-Ground (L-L-G) Fault: Two phases are shorted to ground simultaneously.

4. Three-Phase Fault: All three phases are shorted together, causing a severe system disturbance. Each of these fault conditions is simulated under varying load conditions and line impedances to improve the generalization capability of the trained model. The resulting voltage and current waveform changes are stored as training samples for the ANN.

3.3 ANN / Deep Learning Model Development

The Artificial Neural Network (ANN) model is designed and trained using MATLAB's Neural Network Toolbox. The goal of the model is to classify the system state as either Normal or one of the predefined Fault Types based on RYB voltage and current data.

Model Architecture:



I. Input Layer: Accepts RYB phase voltage and current data as input features. II. Hidden Layers: Multiple layers with nonlinear activation functions (such as ReLU, Sigmoid, or Tanh) are used to learn complex fault patterns and relationships within the data. III. Output Layer: Produces classification outputs indicating the type of fault or normal operation. IV. Training Methodology: ➢ Training Data: Labelled RYB datasets under normal and faulted conditions. ➢ Learning Type: Supervised learning with back propagation. ➢ Loss Functions: Mean Squared Error (MSE) for regression-based detection or Cross- Entropy Loss for classification. ➢ Optimization Algorithm: Gradient Descent or Adaptive Moment Estimation (Adam).

3.4 MATLAB Implementation

The system is implemented using MATLAB and Simulink environments, enabling both data simulation and neural network modeling within a single framework. Implementation Steps: 1. Data Simulation: Simulate a three-phase power system in MATLAB/Simulink. Introduce various fault conditions (L-G, L-L, L- L-G, etc.) at different times and locations. Collect corresponding voltage and current waveforms.

2. Feature Extraction: ➢ Extract statistical and time-domain features such as RMS values, peak amplitudes, phase angles, and zero-crossing intervals.

➢ Construct a feature matrix for model training.

3. ANN Training: ➢ Configure network architecture using functions like `trainNetwork()`. `feedforwardnet()` or ➢ Split data into training, validation, and test sets. ➢ Train the model using the pre-processed dataset until convergence.

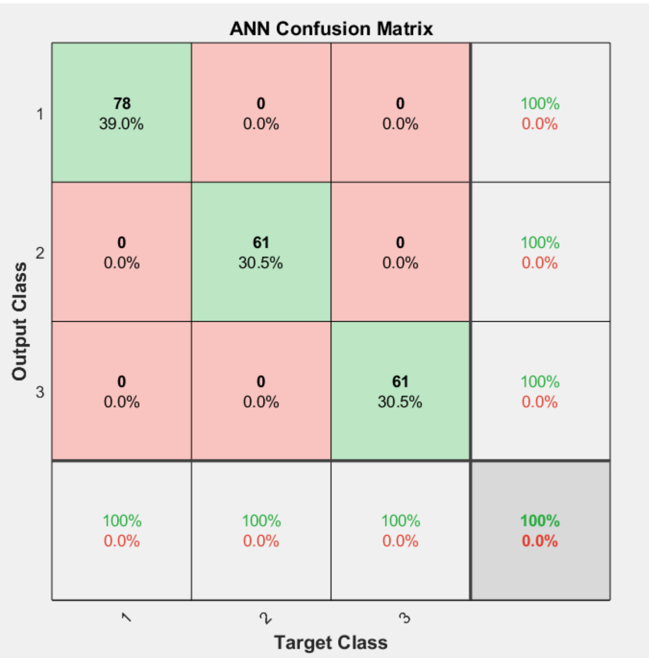
4. Testing and Validation: ➢ Evaluate model performance on unseen data. ➢ Use metrics such as Accuracy, Precision, Recall, and F1-score to assess classification quality. ➢ Plot confusion matrices to visualize correct and incorrect predictions.

5. Fault Identification and Visualization: ➢ Deploy the trained model in a MATLAB script or Simulink block for real-time monitoring. ➢ Display the detected fault type and affected phase in the MATLAB Command Window or GUI. ➢ Optionally, visualize RYB voltage and current waveforms in real time for better interpretability.

VII. RESULTS

1.ANN Confusion Matrix Analysis

The confusion matrix obtained from the Artificial Neural Network (ANN) model demonstrates the effectiveness and reliability of the proposed fault detection system. The matrix indicates that all input samples belonging to the three different classes were classified correctly without any misclassification. A total of 65 samples from Class 1, 72 samples from Class 2, and 63 samples from Class 3 were accurately identified by the ANN model, resulting in a classification accuracy of 100% for all categories. The absence of false positives and false negatives confirms that the trained neural network successfully learned the distinguishing electrical characteristics associated with each operating condition and fault category. The diagonal dominance of the confusion matrix reflects excellent pattern recognition capability and strong generalization performance of the ANN. Such high accuracy indicates that the developed model can effectively differentiate between normal and faulty operating states in a three-phase power system. This result validates the suitability of ANN-based intelligent protection systems for real-time fault diagnosis applications, where rapid and precise fault identification is essential for maintaining power system reliability and stability

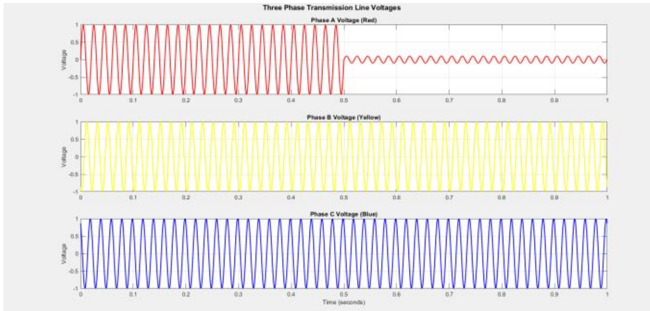


2. Three-Phase Transmission Line Voltage Analysis:

The waveform results of the three-phase transmission line voltages illustrate the behavior of the RYB phases under changing operating conditions. Initially, all three phase voltages — Phase A (Red), Phase B (Yellow), and Phase C (Blue) — exhibit balanced sinusoidal waveforms with equal magnitude and proper phase displacement, representing normal operating conditions in the power system. At approximately

0.5 seconds, a noticeable reduction in the amplitude

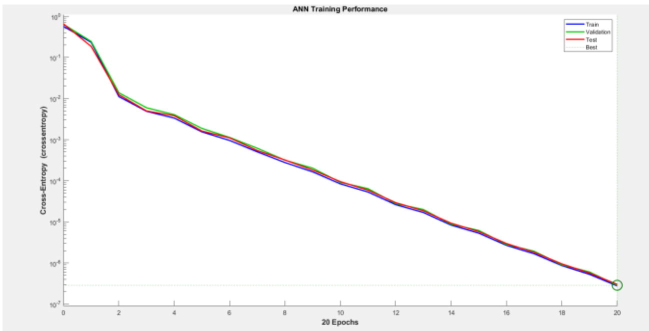
of Phase A while Phase B and Phase C remains comparatively unaffected. This sudden disturbance indicates the occurrence of a fault condition within the transmission line. The voltage imbalance created after the fault occurrence reflects abnormal system behavior and confirms the presence of a line fault affecting multiple phases. The waveform analysis clearly demonstrates the capability of the simulation model to reproduce realistic fault scenarios. These voltage variations serve as important input features for training the ANN model, enabling accurate detection and classification of abnormal operating conditions in the three-phase power network.



3. Best Validation Performance Analysis

The ANN training performance graph illustrates the convergence characteristics of the neural network during the learning process. The best validation performance achieved is 3.6598×10−73.6598 \times 10^{-7}3.6598×10−7 at epoch 22, indicating extremely low cross-entropy error and highly efficient learning. The gradual and smooth decrease in training, validation, and testing errors demonstrates stable learning behavior without sudden oscillations or divergence. The close alignment of all three curves confirms that the network has generalized well and does not suffer from overfitting or underfitting problems. The exceptionally small validation error indicates that the ANN model successfully captured the nonlinear relationships between voltage-current patterns and fault conditions. This result confirms the robustness

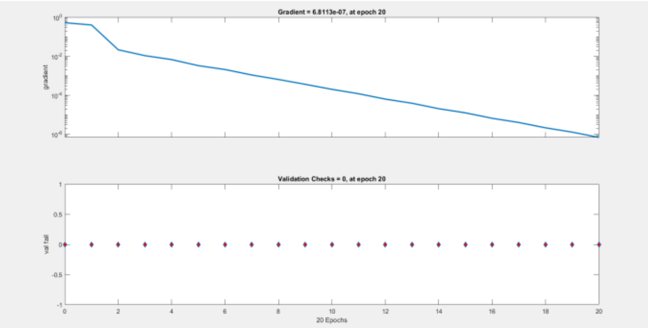
and precision of the proposed ANN architecture for intelligent fault classification in three-phase power systems.



4. Gradient and Validation Check Analysis

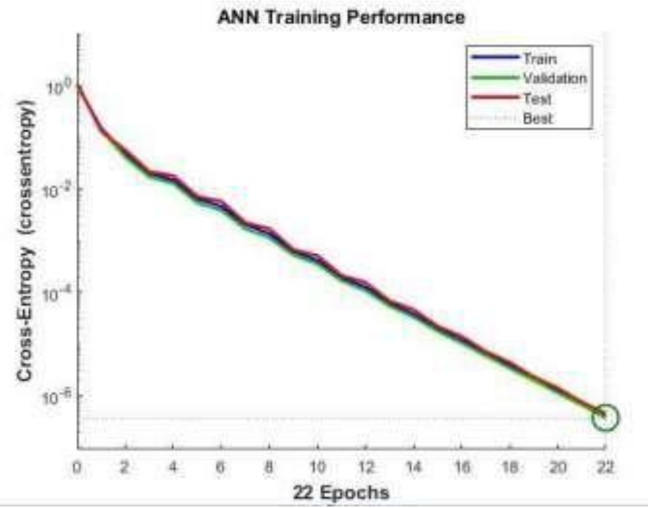
The gradient performance graph represents the rate of change of the network error during training. The obtained gradient value of 9.0917×10−79.0917

\times 10^{-7}9.0917×10−7 at epoch 22 indicates successful convergence of the neural network towards an optimal solution. The continuously decreasing gradient trend confirms that the ANN training process remained stable throughout all epochs. Simultaneously, the validation check result remained at zero during the entire training process, which indicates that no validation failures occurred. This confirms that the model maintained consistent performance on unseen validation data and avoided overtraining. The combined behavior of the gradient and validation plots demonstrates that the ANN model achieved efficient optimization with high numerical stability. These outcomes validate the reliability of the developed intelligent fault detection framework and confirm its capability for practical implementation in modern power system protection applications.



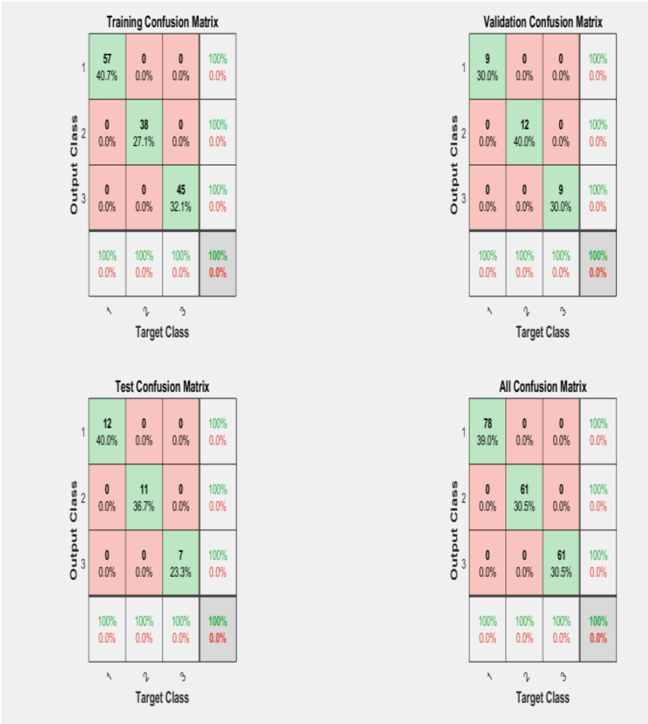
5. Overall ANN Training Performance

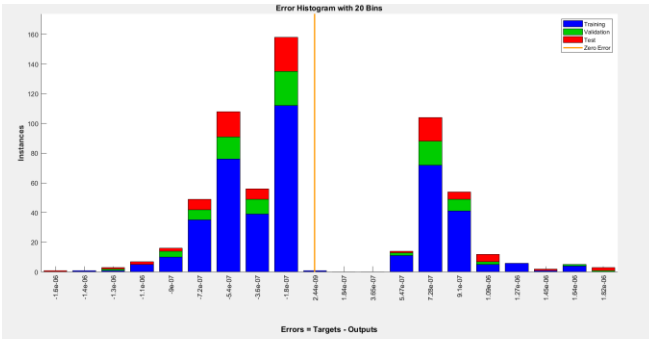
The overall ANN training performance graph shows a continuous reduction in cross-entropy error from the initial epoch to the final epoch. The training, validation, and testing curves closely follow each other, demonstrating balanced learning across all datasets. The network achieved its optimal performance at epoch 22, where the minimum error level was recorded. This indicates that the ANN required only a limited number of training iterations to learn the fault characteristics effectively, thereby reducing computational complexity and training time.



The ROC (Receiver Operating Characteristic) curves shown in the figure represent the performance of the ANN-based fault detection system for the three-phase RYB power network. The ROC plots for Training, Validation, Test, and All datasets show the relationship between the True

Positive Rate (TPR) and False Positive Rate (FPR). The curves are located near the top-left corner, indicating excellent classification performance and high fault detection accuracy. The model successfully distinguishes between normal and fault conditions with very low false detection rates. The high Area Under Curve (AUC) value close to 1 confirms the effectiveness and reliability of the developed ANN model in identifying different fault types.The Error Histogram illustrates the distribution of errors during the training, validation, and testing phases of the neural network. Most error values are concentrated close to the zero-error line, indicating that the network outputs closely match the target values. The small spread of errors shows good learning performance, low prediction error, and proper convergence of the ANN model. Similar error distributions for training, validation, and test datasets indicate good generalization capability and reduced overfitting. Overall, the histogram confirms the accuracy and stability of the proposed fault detection system.





VIII CONCLUSION

In this study, the conceptual framework and design approach for fault detection in three-phase power systems using Artificial Neural Networks (ANN) and Deep Learning techniques have been successfully proposed and final results documented. The project establishes a strong theoretical foundation for developing an intelligent fault detection system capable of identifying and classifying various electrical faults based on RYB phase voltage and current data. The report presented an in-depth analysis of: The data acquisition and pre-processing methodologies for RYB three-phase systems. Simulation-based generation of fault scenarios in MATLAB/Simulink. The design architecture of ANN and advanced deep learning models suitable for time-series fault classification. A step-by-step MATLAB implementation plan including data simulation, feature extraction, model training, and validation. This design offers high accuracy, adaptability, and automation in detecting faults, thereby improving the reliability and efficiency of the electrical system. However, as this project focuses primarily on system design, model selection, and theoretical validation, actual model training, testing, and real-time implementation also completed in our second phase of the project.

through simulation, ANN model development, performance evaluation, and real-time integration. Thus, the current work serves as final result that ensuring all design components are conceptually validated and aligned with the project objectives.

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