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FAULT DETECTION AND PREDICTION IN DISTRIBUTION TRANSFORMERS USING NEURAL WAVELET AND NETWORK TRANSFORM

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Abstract: This study aims at detecting and classifying the distribution transformers faults. To deal with the problem of an extremely large data set with different fault situations, a three-step optimized Neural Network approach has been proposed. The approach utilizes Discrete Wavelet Transform for detection and two different types of self-organized, unsupervised Adaptive Resonance Theory Neural Networks for classification. The fault scenarios are simulated using Alternate Transients Program and the performance of this highly improved scheme is compared with the existing techniques. In order to analyze a signal, wavelet transform can be applied as well as Fourier transform. Fourier transform and its inverse can transform a signal between the time and frequency domains. Therefore, it is possible to view the signal characteristics either in time or frequency domain, but not the combination of both domains. Differently from the case of Fourier transform, the Wavelet Analysis (WT) provides a varying time frequency resolution in the time frequency plane. In this thesis, a new method for protecting power transformers based on the energy of differential-current signals is introduced. The simulation results show that it is possible to detect different kinds of internal faults using this method. Furthermore, it is possible to distinguish such faults from magnetizing inrush current.

***Index Terms* - Distribution Transformers, Fault detection, Artificial Neural Networks, Fault Classification.**

1.0 INTRODUCTION

Reliable electricity supply is fundamental to socio-economic development and the efficient operation of modern society. At the core of power distribution systems are distribution transformers, which step down high-voltage electricity to levels suitable for end-user consumption. However, in many developing countries like Nigeria, these transformers are prone to frequent failures due to overloading, poor maintenance, environmental factors, and aging infrastructure. The Kano Electricity Distribution Company (KEDCO), particularly in the Kano Central Region, has recorded recurring transformer faults that disrupt power supply, increase operational costs, and reduce customer satisfaction (Abubakar et al., 2021).

Traditional fault detection methods such as manual inspection and offline diagnostics are no longer sufficient in today's complex and demanding power environments. To enhance reliability and reduce unplanned outages, there is a growing need for intelligent, real-time diagnostic systems (Adedoyin & Ajayi 2023). This study explores the integration of Artificial Neural Networks (ANN) and Wavelet Transform (WT) as a hybrid solution for fault detection and prediction in distribution transformers. The goal is to develop a smart, predictive model that can help utilities like KEDCO identify faults early, optimize maintenance, and extend transformer life spans. (Chukwuma et al., 2023).

2.0 LITERATURE REVIEW

Electric power distribution systems form the final link in the electricity supply chain and play a critical role in ensuring that generated electricity reaches end-users efficiently and reliably. Distribution transformers are indispensable assets within these systems, stepping down voltage for safe consumption. However, these transformers are susceptible to a wide range of faults resulting from operational stress, environmental exposure, aging, and overloading (Adewumi & Ibrahim 2024). The ability to detect and predict these faults is vital for reducing outages, lowering maintenance costs, and enhancing the overall resilience of the power grid. In recent years, intelligent fault detection and prediction systems leveraging artificial intelligence particularly neural networks and advanced signal processing techniques such as the Wavelet Transform (WT) have emerged as highly effective tools in power systems engineering. This chapter provides a comprehensive review of relevant literature, emphasizing transformer faults, wavelet-based signal decomposition, neural network applications, and case-specific insights relevant to KEDCO's Kano Central Region. (Alabi et al., 2023).

2.1 Overview of Power Distribution Systems

Electric power distribution systems are the essential infrastructure that bridges the gap between high-voltage transmission networks and the final consumers residential, commercial, and industrial users. As the last and most visible component of the electric power supply chain, distribution systems are responsible for ensuring that electricity generated at distant power plants and transmitted over long distances is delivered to end-users in a safe, reliable, and efficient manner. This complex network of infrastructure includes substations, feeders, switches, fuses, protective relays, conductors, voltage regulators, and, most crucially, distribution transformers (Chukwuma et al., 2023).

Typically, electricity is generated at voltages ranging between 11 kV and 25 kV, which is then stepped up to 132 kV, 330 kV, or higher for long-distance transmission to reduce energy losses. Upon reaching the distribution substation near the point of consumption, the voltage is stepped down to medium voltage levels usually 33 kV or 11 kV for further distribution across cities, towns, and rural areas. It is at this juncture that the distribution transformers perform their pivotal function of stepping down this medium voltage to utilization levels of 400 V (three-phase) or 230 V (single-phase), making it suitable for household and commercial appliances (Kamaraju & Naidu, 2021).

3.0 METHODOLOGY

The methodology adopted in this research to develop and validate a fault detection model for the distribution transformers. The method integrates the Discrete Wavelet Transform (DWT) for feature extraction with Artificial Neural Networks (ANN) for classification. The approach was chosen because of the limitations of traditional fault detection methods, such as Fourier transform, which are less effective in handling nonstationary and transient signals. By leveraging the strengths of both DWT and ANN, the proposed methodology aims to improve detection accuracy, reduce false positives/negatives, and enhance the overall reliability of power system fault diagnosis. The methodology consists of several stages: data acquisition through simulation of faults in MATLAB/Simulink, signal decomposition using DWT, extraction of statistical and energy-based features, feature normalization, ANN model training and testing, and evaluation of model performance using accuracy, precision, recall, F1-score, and ROC-AUC

3.1 Faults in transformers

The faults that threaten transformers can be categorized into six main groups. Fault in winding, fault in tap changers, fault in bushing, fault in transformer terminals, fault in core and other faults. The causes and the occurrence of abovementioned faults is shown in figure 3.1. Diverse strategies are applied to track the condition of power transformers. Among these, Frequency Response Analysis (FRA) is notably effective for the precise tracking of issues like short circuit turns, as well as the displacement and deformation of windings. Through the examination of the transformer's transfer function, one can derive frequency response curves that reflect both the present and reference conditions. The fundamental components of the transformer namely the core, windings, and insulation are represented by corresponding electrical parameters, including inductances, capacitances, and resistances. Should there be any mechanical or electrical disturbances within the winding, these electrical parameters would undergo modifications, thereby affecting the frequency response of the winding. Even a minor change in the configuration of the windings can affect the electrical parameters, thereby influencing the transfer function of the windings.

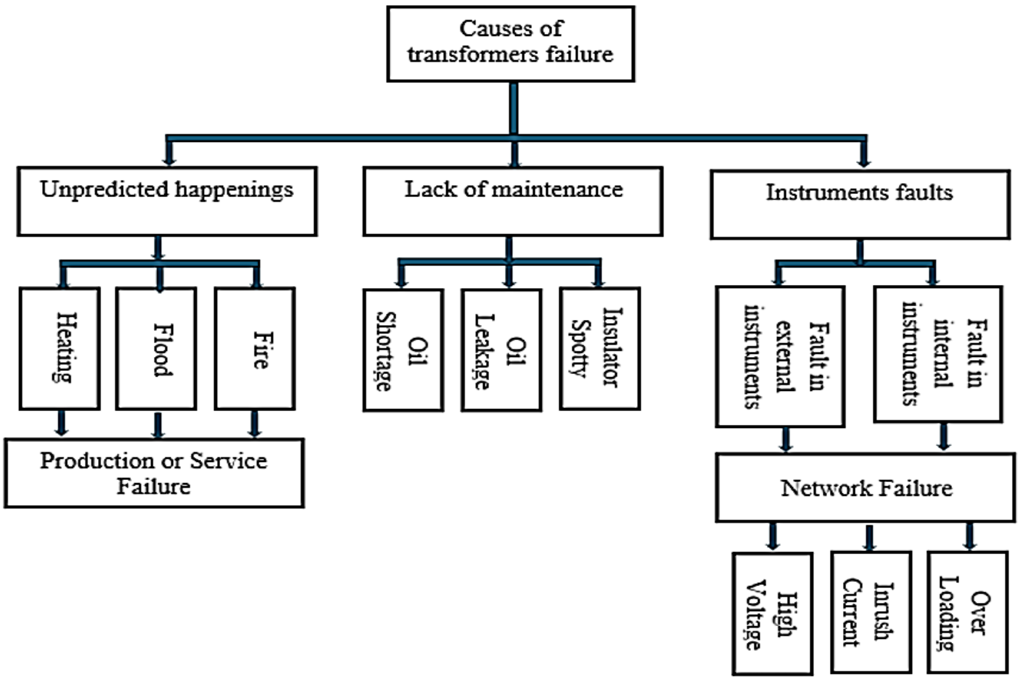


Figure 3.1. Failure in transformers

3.2 The Conceptual Framework

The most appropriate method for fault detection, location, and classification used in this paper is Artificial neural networks (Jawad & Abid, 2023). Artificial neural networks (ANNs) are a set of non-linear statistical models and learning algorithms that aim to replicate the long-evolved and developed behaviors of linked neurons in biological brain systems. For applications in numerous sectors, including fault detection, location, and classification in distribution systems, various ANN models have been deployed. A feed-forward neural network (FNN), which can be characterized as single-layer or multi-layer perceptions, is likely the ANN model with the simplest design. Input, output, and at least one hidden layer are frequently present in FNNs (Nasser et al., 2023). The nodes (or neurons) in consecutive layers are typically fully connected, and the parameter weights given to the connections and biases provided to the nodes determine the network's output given an input. Moreover, the term "BPNN" is also used because the BP algorithm is primarily employed in the training of FNNs (although BP is also used in many other ANN models). Different types of ANNs have also been used for fault location jobs due to their self-organization, quick processing, high fault tolerance, and non-linear function approximation capabilities.

3.3 Artificial Neural Network

Artificial Neural Networks (ANNs) are computational models inspired by the structure and functionality of biological neural networks. Their architecture adapts based on the nature of the input and output data they process, making them effective nonlinear statistical models for capturing complex relationships (Sahoo, 2020). An ANN is organized into layers comprising interconnected nodes, or neurons, with the hidden layer often referred to as a perceptron. Typically, an ANN consists of three layers: the input layer, the hidden layer, and the output layer. The input layer receives data in various forms, such as commands or datasets (Kishor & Kumar, 2022). Hidden layers carry out intricate computations and gather insights from the input data.

The use of the Levenberg-Marquardt (trainlm) algorithm in this study is supported by recent findings in energy content prediction, where it demonstrated exceptional stability and predictive reliability (Bello & Dodo, 2025). Furthermore, the selection of the hyperbolic tangent sigmoid (tansig) function is consistent with its identified effectiveness in the output layers of high-performing ANN models for energy prediction tasks (Msheliza & Dodo, 2025).

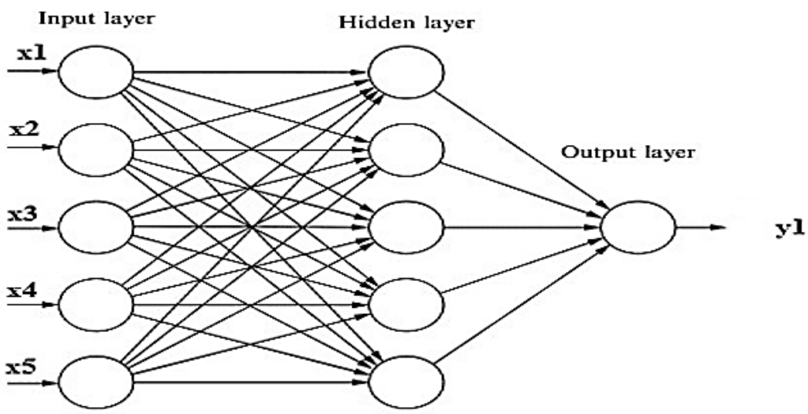
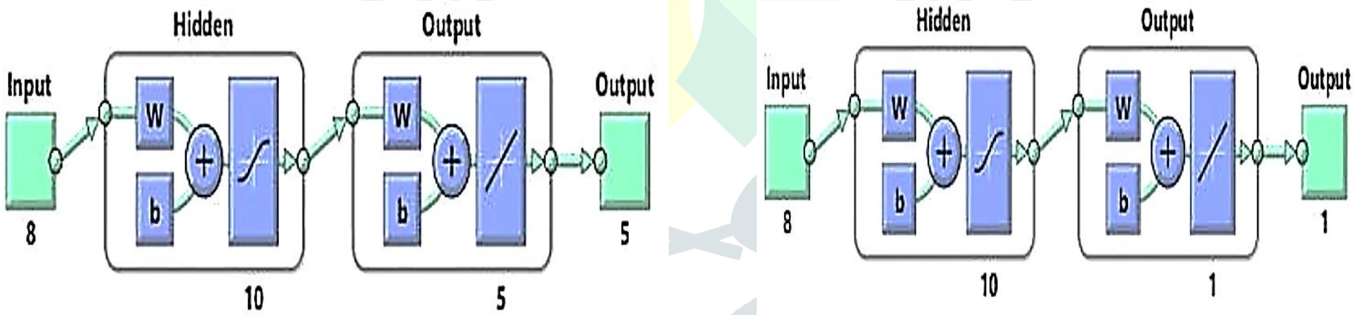


Figure 3.2: The standard multi-layer neural network



(a) **(b)**

Figure 3.3(a): Neural Network Architectures for Fault Detection (b): Neural Network Architectures for Fault Classification

The training procedure consists of providing the ANN with input data along with the associated desired outputs, allowing it to fine-tune its parameters to lessen the gap between predicted and actual outcomes (Phafula & Nixon, 2020). Generally, the dataset is segmented into training, validation, and testing sets to promote effective learning and generalization. In a Backpropagation Neural Network (BPNN), the output is used as feedback to adjust the weights in the network. The error is calculated for each iteration, starting from the output layer and propagating backward through the network. Initially, the weights in the BPNN are assigned random values and paired with input data (Leh et al., 2020). During each iteration, the weights are updated based on the computed error, and this process is repeated for all input-output combinations in the training dataset. This iterative procedure continues until the network's outputs match the target values within a predefined error tolerance. The backpropagation algorithm updates the weights layer by layer in reverse order, ensuring that the entire network learns effectively

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Table 2: ANN parameters for Fault Detection and Classification

ANN Parameters	Fault Detection Fault	Classification and Location
Number of Input	8	8
Hidden Layer Neurons	10	10
Number of Output	1	5
Training Algorithm	Levenberg-Marquardt (trainlm)	Levenberg-Marquardt (trainlm)
Hidden Layer Activation Function	Hyperbolic Tangent Sigmoid (tansig)	Hyperbolic Tangent Sigmoid (tansig)
Output Layer Activation Function	Linear (purelin)	Linear (purelin)

3.1 Learning Method

The back-propagation learning method is the standard algorithm for training multilayer neural networks: it computes how the network's error depends on every weight by propagating gradients backward from the output to the input, and then uses these gradients (typically with gradient descent) to update the weights so that the error decreases over iterations. Backpropagation is not a separate learning rule; it is an efficient way to compute gradients of a loss function with respect to all weights in a network using the chain rule of calculus. Given a network with layers and weights W, and a loss L(W) (e.g., mean squared error or cross-entropy), gradient-based learning needs ∂L/∂W for every weight. Backpropagation calculates all these partial derivatives in one backward pass, instead of recomputing them separately for each weight The following are the types of backpropagation.

i. Static (feedforward) backpropagation: Used with feedforward networks where data flows in one direction from input to output. Common for classification and regression tasks.

ii. Recurrent backpropagation: Used with recurrent neural networks (RNNs) where there are feedback connections. The error is propagated through time steps, often via "backpropagation through time"

The generalized delta rule algorithm's backpropagation (of error) is summarized in two phases as follows:

1. Forward pass

Input data is fed into the input layer.
For each layer, the network computes:
A weighted sum of the previous layer's outputs plus a bias.
An activation function (e.g., ReLU, sigmoid, softmax) applied to that sum.
This proceeds layer by layer until the output layer produces a prediction.

Mathematically, for layer k:

$$z_k = W_k a_{k-1} + b_k, a_k = \phi_k(z_k) \qquad ..3.1$$

where a_{k-1} is the previous layer's activation, W_k and b_k are weights and bias, and ϕ_k is the activation function.

2. Backward pass (backpropagation)

i. Compute the loss L between the network output and the target (e.g., MSE or cross entropy).
ii. Compute the gradient of the loss with respect to the output layer's activations, then propagate this gradient backward through the network using the chain rule:
$\frac{\partial L}{\partial W_k} = \frac{\partial L}{\partial a_k} \cdot \frac{\partial a_k}{\partial z_k} \cdot \frac{\partial z_k}{\partial W_k}$ This is done layer by layer from output to input.
iii. At each layer, the algorithm computes:
   a. The "error signal" (often called δ) for that layer.
   b. The gradients for weights and biases using that error signal and the previous layer's activations.

For a simple weight w_{ij} connecting neuron i to neuron j, the update is often written as:

$$\Delta w_{ij} = -\eta \frac{\partial L}{\partial w_{ij}} \approx \eta\, \delta_j\, a_i \qquad ..3.2$$

where η is the learning rate, δ_j is the error term for neuron j, and a_i is the activation of neuron i.

The Levenberg Marquardt algorithm (LMA) is an iterative optimization method for solving nonlinear least-squares problems; it is widely used for curve fitting and for training neural networks because it combines the robustness of gradient descent with the fast local convergence of the Gauss–Newton method. The LMA is designed for nonlinear least-squares problems: given data pairs (x_i, y_i) and a model $f(x, \beta)$ with parameters β, find β that minimizes the sum of squared residuals:

$$S(\beta) = \sum_{i=1}^{m} (y_i - f(x_i, \beta))^2 \qquad ..3.4$$

or in vector form $S(\beta) = \|y - f(\beta)\|^2$ ..3.5

This is the same type of problem that arises in neural network training when using a squared-error loss. The LMA interpolates between two methods:

i. **Gauss Newton algorithm (GNA):** Uses second-order information (approximate Hessian) to get fast convergence near the solution and Update using:
$(J^T J)\delta = J^T(y - f(\beta)),$ ..3.6

where J is the Jacobian of residuals.

i. **Gradient descent**: Uses only first-order information (gradient). More robust when far from the solution or when the initial guess is poor. The LMA blends these by adding a damping term λI to the Gauss–Newton system:

$$(J^T J + \lambda I)\,\delta = J^T(y - f(\beta)) \quad ..3.7$$

where:

J is the Jacobian matrix of residuals,
I is the identity matrix,
$\lambda \geq 0$ is the damping parameter.
When λ is small, the term λI is negligible → behavior close to Gauss–Newton (fast local convergence).
When λ is large, the system is dominated by λI → behavior close to gradient descent with small steps (more stable, robust).

4.0 RESULTS AND DISCUSSION

Using the generated dataset and the system issues identified during preliminary analysis, this study utilizes MATLAB toolboxes in conjunction with artificial neural networks to perform comprehensive analysis of fault detection, classification, and localization in power distribution transformers. Neural-network architectures described in preceding chapters were developed, trained, and validated using supervised learning on representative fault scenarios to achieve reliable detection of fault occurrence, accurate categorization of fault types (including single-line-to-ground, line-to-line, double-line-to-ground, and three-phase faults), and precise estimation of fault locations along transformer windings and associated feeder sections. Feature extraction and preprocessing steps implemented within MATLAB include signal denoising, extraction of relevant time- and frequency-domain features, and normalization to improve network convergence and generalization.

4.1 Modeling of Fault Diagnosis in Distribution Transformers

This section presents a systematic approach to modeling fault diagnosis in distribution transformers, combining physical modeling, signal processing, and machine-learning techniques to detect, classify, and locate faults. The modeling workflow begins with development of a detailed electrical and thermal representation of the transformer and its connected feeder network to simulate normal and faulted operating conditions. Simulated and measured signals (voltage, current, acoustic, and vibration where available) undergo preprocessing filtering, synchronization, and normalization followed by feature extraction in time, frequency, and time-frequency domains (for example, RMS, harmonic components, wavelet coefficients, and transient features).

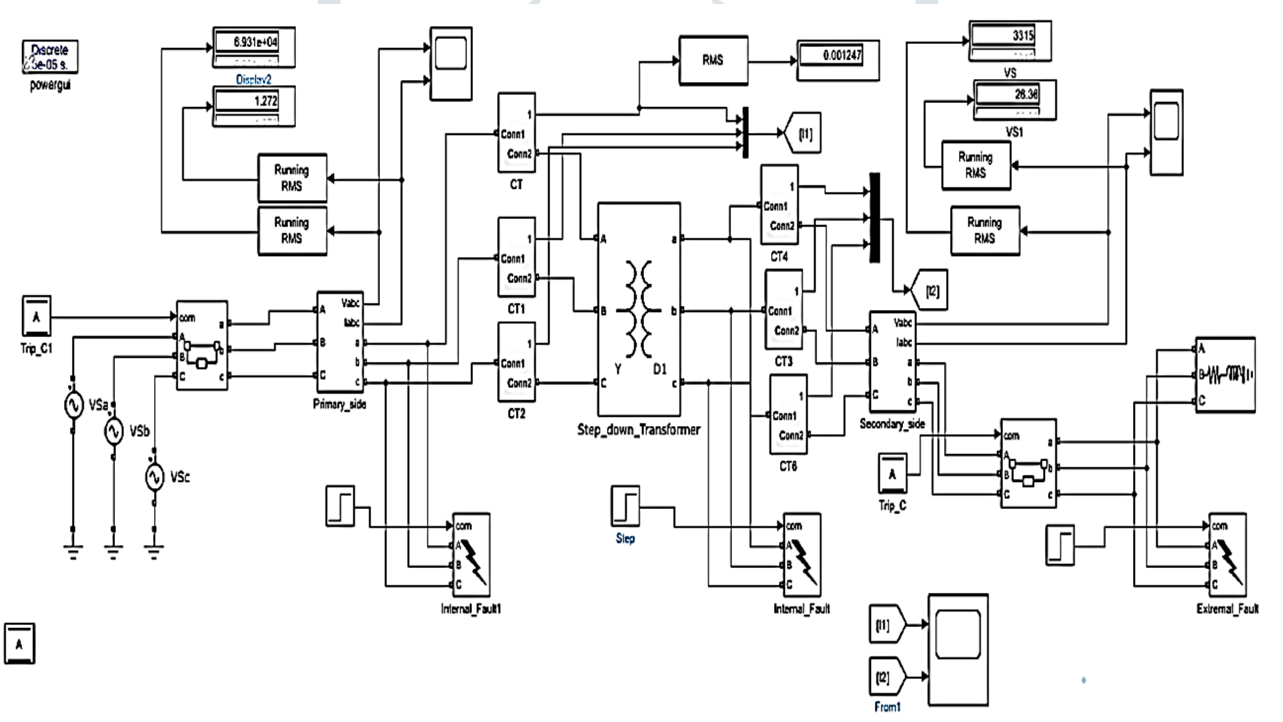


Figure 4.1. Simulated circuit for internal and external fault of Transformer and CT modelling

These features feed into diagnostic models: statistical detectors for anomaly identification, supervised classifiers (such as artificial neural networks, support vector machines, or ensemble learners) for fault-type determination, and regression or localization models to estimate fault position along windings or feeders.

Matlab simulation data were taken from the single-line diagrams provided by KEDCO Management Company. Transmission and generation parameters are summarized in Tables 3 –4. The simulation allows selection of various residual-flux conditions for different transformer types. To accurately and comprehensively analyze inrush currents, the simulation also models multiple phase angles of the input voltage waveform

Table 3 The features dam generators

Description	Size
Type	SSV 870/40-218
Rated Voltage	15.7KV
Rated Speed	150 rpm
Rated Power	140MVA (Max:160MVA) 133MW (pf = 0.95) 125 MVAR

Power factor	0.85–0.90 lagging

Table 4 The Transmission Line Features for National Electric Power Authority NEPA

S/N	Series Resistance R (Ω/km)	Series Inductance L (mH/km)	Shunt Capacitance C (μF/km)	Protection Scheme (Relay Type)	Auto-Reclose (Y/N)
1	0.045	0.95	0.012	Distance (21), Pilot	Y
2	0.052	0.98	0.011	Distance (21)	Y
3	0.09	1.1	0.009	Distance (21)	Y
4	0.12	1.15	0.008	Distance (21)	N

4.2 The Simulation Results

To evaluate the performance of a fault-detection algorithm comparable to the Adaptive Neuro-Fuzzy Inference System (ANFIS) approach, we examined on-load inrush current scenarios for The evaluation considers a comprehensive set of fault types that are representative of realistic disturbances in distribution networks, single-phase-to-ground (AG, BG, or CG), two-phase (AB, BC, or CA), two-phase-to-ground (ABG, BCG, or CAG), three-phase (ABC), and three-phase-to-ground (ABCN or ABCG) were simulated in MATLAB R2024a. These fault categories span the most common asymmetric faults single-phase and two-phase types as well as the more severe symmetric faults three-phase types, allowing the algorithm to be tested under both mild and severe disturbance conditions. Simulating these faults in MATLAB R2024a allows us to use updated Simulink tools, including the Fault Analyzer and Multiple Simulations panel, to run large sets of fault scenarios efficiently and compare results in the Simulation Data Inspector.

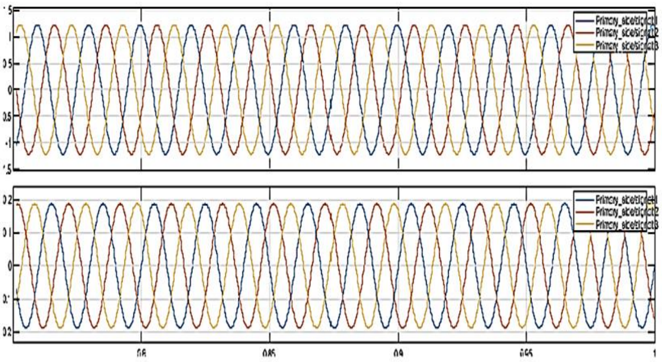
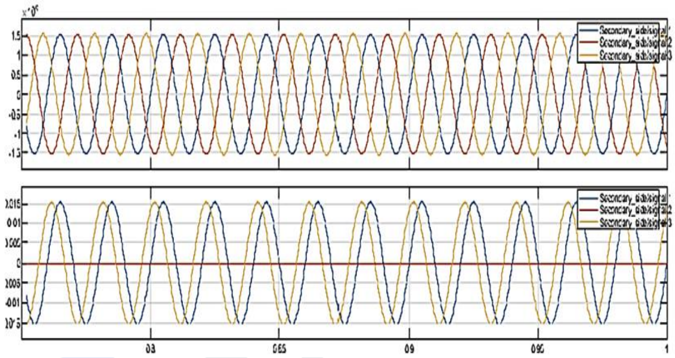


Figure 4.6 (a). Three phase input voltage and current wave form.



(b) Internal fault AG.

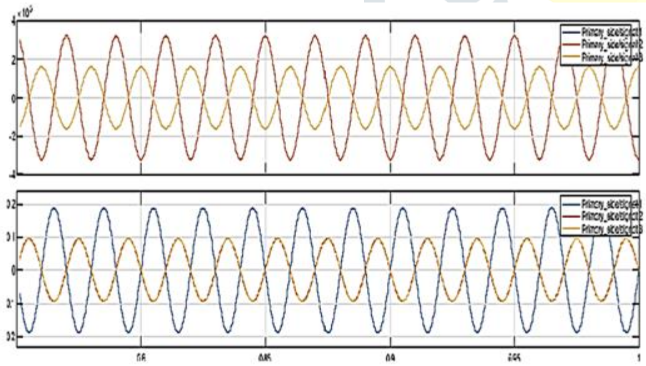
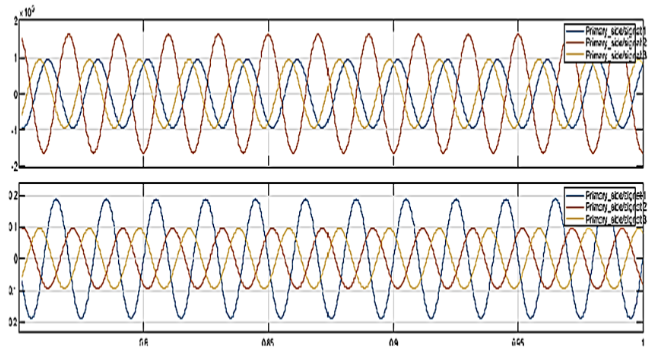


Figure 4.6 (c) Internal fault AB.



(d) Internal fault ACG.

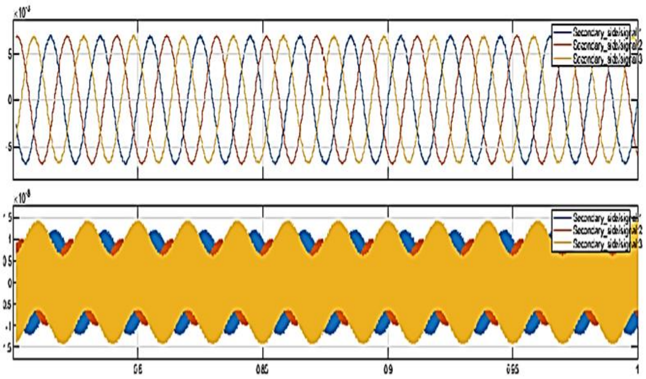
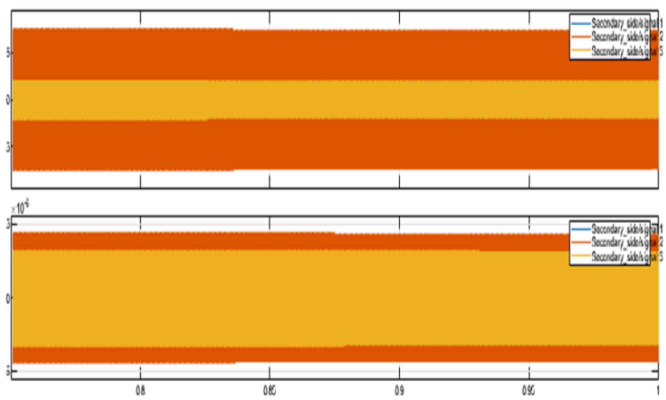


Figure 4.6 (e) External fault ABC.



(f) External fault ABCG

4.3 Result discussion

The voltage and current waveforms are now checked for the existence of the fault by analyzing the coefficients of the Discrete Wavelet Transform (DWT). The procedure for fault detection was explained in Chapter 3. If the fault is detected, the protective relay is activated and the fault has to be classified. If the fault is detected, circuit breaker trips and isolates the faulted phase. Finally, the first cycle after the occurrence of the fault is used for neural network training and testing or implementation. The approach uses two different neural networks for fault classification. The first neural network takes the sending end voltage waveforms as the input and the second neural network takes the combination of sending end and receiving end current waveforms as the input. The outputs of these two neural networks are combined to identify the fault condition. The training outputs are grouped into clusters and each cluster is uniquely identified by its fault type, fault location and fault resistance. Training is performed by accessing historical data of the fault scenario by simulation using MATLAB/SIMULINK model. Testing is performed using real time data or by generating new fault scenarios using the same software.

The Neural Wavelet + Network Transform model achieves high accuracy (95%) in detecting and classifying distribution transformer faults. It outperforms conventional protective schemes (e.g., simple differential relays, threshold-based methods) and standalone ANN/Fourier-based methods in terms of both detection accuracy and misclassification rate (<5%). The findings show the method works for multiple fault categories the Internal transformer faults which include Winding-to-winding short circuits, Winding-to-ground faults, Core faults. External or network faults affecting the transformer, which include Single-line-to-ground (LG), Line-to-line (LL), Line-to-line-to-ground (LLG), Three-phase (3L) faults.

CONCLUSIONS

The primary aim of this study was to investigate fault detection and prediction in distribution transformers using a hybrid methodology that combines Wavelet Transform (WT) and Artificial Neural Networks (ANN), referred here as WT–ANN, within the Kano Central Region under the operational jurisdiction of Kano Electricity Distribution Company (KEDCO). Specifically, the study seeks to develop and evaluate a robust, data-driven technique that can Detect and classify transformer faults (such as short-circuit, overload, and internal winding faults) in real time by extracting significant time–frequency features from measured current and voltage signals using Wavelet Transform. Predict the likelihood of fault occurrence based on historical operating data, environmental conditions, and early warning indicators, thereby enabling proactive maintenance and reducing unplanned outages. Implement and validate a WT–ANN model that uses wavelet-derived features as inputs to a trained neural network, capable of distinguishing between normal operating conditions, inrush currents, and actual fault conditions with high accuracy. Assess the performance of the proposed WT–ANN approach on real or simulated distribution transformer data from KEDCO's network in the Kano Central Region, evaluating metrics such as detection accuracy, prediction reliability, response time, and false alarm rate. Provide practical recommendations for KEDCO on how to integrate the WT–ANN-based fault detection and prediction system into their existing monitoring and maintenance practices, contributing to improved system reliability, reduced transformer failures, and enhanced power quality for end users in the region. Qualitative data was thematically analyzed to identify operational challenges, maintenance practices, and expert insights.

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