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A PROBABILISTIC APPROACH TO POWER SYSTEM FAULT DIAGNOSIS: INTEGRATING MONTE CARLO SIMULATION AND NEURAL NETWORKS FOR ROBUST FAULT DETECTION IN UNIVERSITY DISTRIBUTION GRIDS

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ABSTRACT

This study presents a probabilistic methodology for automated fault detection, classification, and location in the Abubakar Tafawa Balewa University (ATBU) Faculty of Engineering power distribution network. The proposed framework integrates Monte Carlo simulation, Discrete Wavelet Transform (DWT), and Artificial Neural Networks (ANNs) to improve the robustness and generalization of intelligent fault diagnosis under varying network and fault conditions. A total of 1,000 independent Monte Carlo simulations were performed in MATLAB/Simulink, with systematic randomization of key fault and network parameters to represent a broad range of operating conditions. Each simulation cycle considered twelve distinct system states, comprising single-phase-to-ground, double-phase-to-ground, phase-to-phase, three-phase, and balanced fault conditions, resulting in a labelled dataset of 12,000

observations. The DWT, using the Daubechies-4 (db4) mother wavelet, was applied to 28 measured current signals to extract their maximum absolute detail coefficients, producing a 28-dimensional feature vector for ANN-based fault classification. The classification model employed a single hidden layer containing 100 neurons and achieved macro-averaged F1-scores exceeding 0.99 across the evaluated network sections. In addition, a Bayesian Regularization-based ANN regression model was developed for fault-location estimation and demonstrated low prediction error and strong generalization performance. The results demonstrate that the integration of Monte Carlo simulation, DWT, and ANN provides an effective and robust framework for intelligent fault diagnosis in institutional distribution networks. The proposed methodology offers a potential basis for developing adaptive and cost-effective fault-monitoring systems for university and other medium-scale distribution networks.

KEYWORDS: Monte Carlo Simulation; Artificial Neural Network; Discrete Wavelet Transform; Fault Detection; Fault Classification; Fault Location; Power Distribution Network; University Distribution Grid.

INTRODUCTION

Electrical power distribution networks constitute a vital component of modern power systems, serving as the critical link between transmission infrastructures and end users. These networks ensure the reliable and continuous delivery of electrical energy to residential, commercial, and industrial consumers through interconnected feeders, transformers, substations, and protective devices operating under varying environmental and loading conditions (Azmi *et al.*, 2022). Despite technological advancements in power systems, distribution networks remain highly susceptible to operational disturbances and fault conditions that negatively affect system reliability, stability, and power quality (Saad *et al.*, 2024).

Faults in electrical distribution systems may arise from insulation deterioration, lightning strikes, switching transients, equipment aging, short circuits, conductor failure, environmental contamination, overloading, and mechanical damage (Moldovan and Buzdugan, 2023). These faults commonly manifest as single-line-to-ground, line-to-line, double-line-to-ground, or three-phase symmetrical faults. If faults are not rapidly detected and isolated, they can result in voltage instability, equipment damage, prolonged power outages, increased maintenance costs, and significant economic losses to utilities and consumers (Fu *et al.*, 2024).

Furthermore, the growing integration of renewable energy resources, distributed generation systems, and smart-grid technologies has increased the operational complexity of modern distribution systems, thereby reducing the effectiveness of conventional fault diagnosis approaches.

Traditionally, fault detection and location in power systems have relied on protective relay coordination, impedance-based calculations, travelling wave techniques, and manual inspection methods. Although these techniques are widely used in practical operations, they exhibit several limitations under modern network conditions. Manual inspection procedures are labour-intensive, time-consuming, and unsuitable for large, interconnected distribution systems. Similarly, impedance-based and relay-based methods often experience reduced fault-location accuracy due to varying fault resistance, load uncertainty, changes in network topology, and distributed generation integration (Alhanaf *et al.*, 2024). In addition, conventional methods may struggle to differentiate transient disturbances from actual fault conditions, leading to delayed fault isolation and restoration. These challenges have created the need for intelligent and adaptive fault diagnosis systems capable of providing accurate, automated, and real-time fault detection, classification, and location (Shao *et al.*, 2025).

Recent developments in artificial intelligence and computational intelligence have significantly improved fault diagnosis capabilities in electrical power systems. Artificial Neural Networks (ANNs) have become one of the most effective machine learning techniques for pattern recognition, classification, and nonlinear modelling. ANNs can learn complex relationships between input and output variables through training with historical or simulated datasets. Their ability to generalize under uncertain operating conditions makes them suitable for analysing faults in dynamic power distribution networks (Li *et al.*, 2025). In addition to machine learning methods, signal processing techniques such as the Discrete Wavelet Transform (DWT) have demonstrated strong performance in transient fault analysis and feature extraction. Unlike conventional Fourier transform methods that provide only frequency-domain information, wavelet transforms enable simultaneous time-frequency analysis of non-stationary signals, allowing accurate identification of abrupt waveform changes and transient disturbances associated with power system faults (Kumar *et al.*, 2024). Furthermore, Monte Carlo simulation techniques have become increasingly important for evaluating the reliability and robustness of intelligent fault diagnosis systems. Monte Carlo simulation enables the generation of multiple fault scenarios by randomly varying network parameters such as fault resistance, fault location, loading conditions, fault type, and fault

inception angle. This stochastic simulation approach improves the diversity and representativeness of training datasets, thereby enhancing the predictive performance and generalization capability of machine learning models (Abud *et al.*, 2023). In addition, Monte Carlo simulation allows system performance evaluation under uncertain operating conditions that may be difficult, hazardous, or economically impractical to reproduce experimentally in real-life distribution systems (Kamel *et al.*, 2023).

Despite significant advances in fault detection, classification, and location in electrical power distribution networks through the application of ANNs, signal processing, and wavelet-based techniques, several critical challenges remain. Many existing approaches continue to rely on deterministic or impedance-based methods, which often experience reduced accuracy under varying load conditions, measurement noise, and network reconfigurations. Moreover, numerous ANN-based models are developed using limited or synthetic datasets, restricting their robustness and generalization under practical fault conditions. Although DWT has been widely adopted for transient feature extraction, it is commonly employed as a standalone technique rather than as part of an integrated intelligent framework capable of simultaneously performing fault detection, classification, and location.

Furthermore, most reported studies have been validated using standard IEEE benchmark systems, with limited investigation of real utility or institutional distribution networks. In particular, no documented study has examined intelligent fault diagnosis for the Faculty of Engineering power distribution network at Abubakar Tafawa Balewa University (ATBU), Yelwa Campus, leaving its fault characteristics and operational requirements largely unexplored. Additionally, the application of Monte Carlo simulation for generating diverse and realistic fault scenarios remains limited, especially in campus-based distribution systems. Few studies have integrated Monte Carlo simulation, DWT-based feature extraction, and ANN-based learning within a unified fault diagnosis framework.

This study addresses these gaps by developing an integrated Monte Carlo-DWT-ANN framework for intelligent fault diagnosis in the ATBU Faculty of Engineering power distribution network. The specific objectives of this research are to:

MATERIALS AND METHODS

System Under Study

The power network under investigation is the ATBU distribution network, which extends from the Centre of Industrial Studies (CIS) transformer to four Engineering blocks (Blocks A, B, C, and D) and three CIS sections: Machine, Welding and Fabrication, and Woodwork and

Fitting. The system comprises seven measurement zones, each monitored by three-phase current sensors that capture the phase currents (I_a , I_b , and I_c) and the corresponding ground current (I_g). This yields 21 phase-current signals and 7 ground-current signals, resulting in a total of 28 measured quantities per simulation run.

The network topology was modelled in MATLAB/Simulink based on the actual single-line diagram and measured line lengths obtained from the ATBU Works Department. Table 1 presents the line segment lengths for the distribution network.

Table 1: Line Segment and Measured Length of ATBU Faculty of Engineering Distribution Network.

Line ID	Block	Segment No.	From Node	To Node	Cable Type	Material	Length (m)
L1	Block A	1	CIS	J1	Amoured (uprised)	Copper	12.0
L2		2	J1	J2	Overhead (Al. alloy)	Aluminium	418.7
L3		3	J2	BLOCK A	Amoured	Copper	33.0
L4	Block B	1	CIS	J3	Amoured	Copper	12.0
L5		2	J3	J4	Overhead (Al. alloy)	Aluminium	109.0
L6		3	J4	BLOCK B	Amoured	Copper	17.0
L7	Block C	1	CIS	BLOCK C	Amoured	Copper	71.0
L8	Block D	1	CIS	BLOCK D	Amoured	Copper	35.0
L9	CIS 1	1	CIS	J5	Overhead (Al. alloy)	Aluminium	26.2
L10		2	J5	CIS 1	Amoured	Copper	16.2
L11	CIS 2	1	CIS	J6	Overhead (Al. alloy)	Aluminium	24.0
L12		2	J6	CIS 2	Amoured	Copper	12.0
L13	CIS 3	1	CIS	J7	Overhead (Al. alloy)	Aluminium	87.3
L14		2	J7	CIS 3	Amoured	Copper	37.0

Fault Parameter Randomization

To capture a wide operating envelope, nine independent stochastic parameters were randomized prior to each simulation trial using MATLAB's rand() function. The resulting

parameter values were obtained by scaling to the respective physical bounds summarized in Table 2.

Table 2: Randomized Simulation Parameters.

Parameter	Description	Unit	Distribution	Min	Max
La	Block A Line length	M	Uniform	0	418.7
Lb	Block B Line length	M	Uniform	0	109.0
Lc	Block C Line length	M	Uniform	0	71.0
Ld	Block D Line length	M	Uniform	0	35.0
Lw	Welding Line length	M	Uniform	0	12.0
Lm	Machine Line length	M	Uniform	0	24.0
Lwd	Woodwork line length	M	Uniform	0	87.3
R _f	Fault resistance	Ohms	Uniform	0	0.01
R _g	Ground resistance	Ohms	Uniform	0	0.10

Fault Taxonomy and Class Definition

Twelve distinct system states were modelled, encompassing all practically significant shunt fault types together with a normal (no-fault) baseline. Table 3 presents the fault class definitions and corresponding one-hot label vectors.

Table 3: Fault Class Definitions and One-Hot Label Vectors.

No.	Model ID	Fault Description	Notation	One-Hot Label Vector y_i
1	A G	Single-phase-to-ground (Phase A)	A-G	[1,0,0,0,0,0,0,0,0,0,0]
2	B G	Single-phase-to-ground (Phase B)	B-G	[0,1,0,0,0,0,0,0,0,0,0]
3	C G	Single-phase-to-ground (Phase C)	C-G	[0,0,1,0,0,0,0,0,0,0,0]
4	AB G	Double-phase-to-ground (AB)	AB-G	[0,0,0,1,0,0,0,0,0,0,0]
5	AC G	Double-phase-to-ground (AC)	AC-G	[0,0,0,0,1,0,0,0,0,0,0]
6	BC G	Double-phase-to-ground (BC)	BC-G	[0,0,0,0,0,1,0,0,0,0,0]
7	AB	Phase-to-phase (AB)	AB	[0,0,0,0,0,0,1,0,0,0,0]
8	AC	Phase-to-phase (AC)	AC	[0,0,0,0,0,0,0,1,0,0,0]
9	BC	Phase-to-phase (BC)	BC	[0,0,0,0,0,0,0,0,1,0,0]
10	ABC G	Three-phase-to-ground	ABC-G	[0,0,0,0,0,0,0,0,0,1,0]
11	ABC	Three-phase (balanced)	ABC	[0,0,0,0,0,0,0,0,0,0,1]
12	normal1	Normal (no-fault) operation	—	[0,0,0,0,0,0,0,0,0,0,1]

Dataset Generation Procedure

Dataset generation followed a nested iterative scheme. The outer loop executed $m = 1,000$ independent Monte Carlo repetitions. Within each repetition, the inner loop cycled through all 12 fault models. At the onset of each inner-loop iteration, new values of R_f , R_g , and all seven line-length parameters were drawn from their respective uniform distributions. The corresponding Simulink model was then invoked via the MATLAB command, and the 28 current waveforms were recorded from the workspace.

Feature Extraction via Discrete Wavelet Transform

Each of the 28 current signals $x_k(n)$ was subjected to a one-level DWT decomposition using the Daubechies-4 (db4) mother wavelet, implemented via the MATLAB `wavedec()` function with decomposition level $L = 1$. For a discrete signal $x[n]$ of length N , the one-level DWT produced approximation and detail subbands through convolution with low-pass and high-pass filters, respectively.

From the level-1 detail coefficient vector $d_k[m]$, the scalar feature f_k was defined as the maximum of the absolute detail coefficients:

$$f_k = \max \left\{ \left| d_k[m] \right| : m = 1, 2, 3, \dots, \left\lfloor \frac{m}{2} \right\rfloor \right\} \quad \dots(3)$$

This statistic captures the peak high-frequency energy released during the fault transient. Applying this to all 28 signals yielded the 28-dimensional wavelet feature sub-vector.

ANN Classification Framework

The fault classification task was formulated as a supervised, multi-class, single-label classification problem. Given a labelled training set $\{(\phi_i, y_i)\}$ where $\phi_i \in \mathbb{R}^{28}$ is the feature vector and $y_i \in \{e_1, \dots, e_{12}\}$ is the one-hot label, the learning objective was to find a mapping that minimizes the categorical cross-entropy loss.

The classification model employed a single hidden layer containing 100 neurons with the hyperbolic tangent sigmoid (tansig) activation function. The output layer applied the SoftMax activation to convert raw scores into a proper probability distribution over the 12 classes. The network was trained using the Levenberg-Marquardt backpropagation algorithm.

The dataset of 12,000 observations was partitioned into training (70%), validation (15%), and test (15%) subsets using stratified random sampling to preserve class proportions across splits.

ANN Regression Framework

For fault location estimation, a second neural network model was constructed using MATLAB's `fitnet` function and trained with the Bayesian Regularization (BR) backpropagation algorithm (`trainbr`). The regression network was a single-hidden-layer multi-layer perceptron with 28 input neurons, 100 hidden neurons, and 1 output neuron. The BR framework was chosen for its ability to automatically determine an appropriate level of model complexity without requiring a separate validation set for early stopping.

Performance Metrics

Classifier performance was evaluated using accuracy, per-class precision, recall, and F1-score. These metrics are defined as:

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \quad \dots(4)$$

$$\text{Precision}_j = \frac{\text{TP}_j}{\text{TP}_j + \text{FN}_j} \quad \dots(5)$$

$$\text{Recall}_j = \frac{\text{TP}_j}{\text{TP}_j + \text{FP}_j} \quad \dots(6)$$

$$\text{F1-Score}_j = 2 \cdot \frac{\text{Precision}_j \cdot \text{Recall}_j}{\text{Precision}_j + \text{Recall}_j} \quad \dots(7)$$

$$\text{Macro-F1} = \frac{1}{12} \sum_{j=1}^{12} \text{F1}_j \quad \dots(8)$$

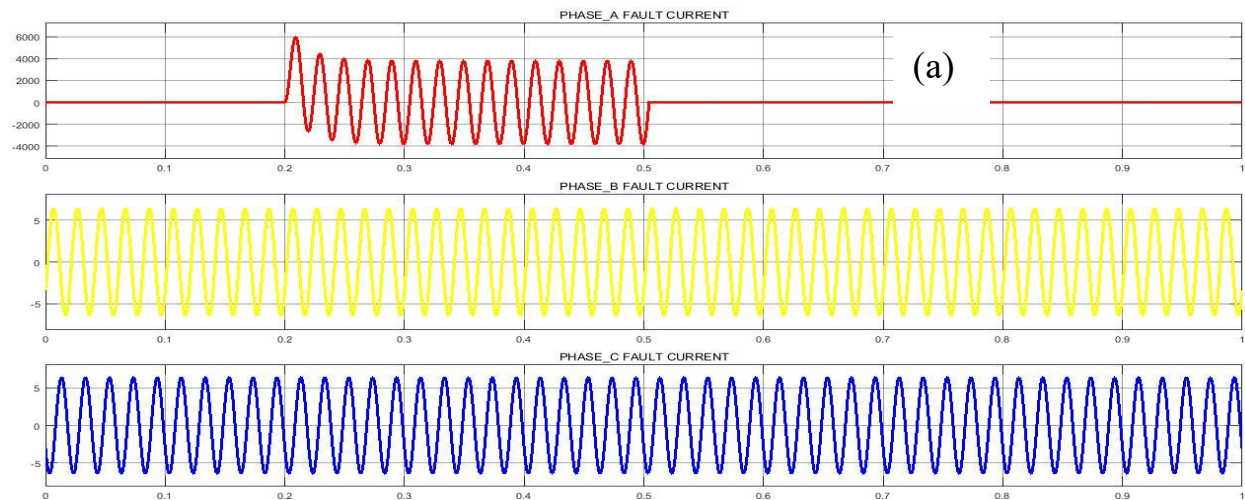
Where TP = True Positives, TN = True Negatives, FP = False Positives, FN = False Negatives, and Nc = 12 is the number of fault classes.

For regression performance, the coefficient of determination (R^2), mean squared error (MSE), and residual analysis were employed.

RESULTS AND DISCUSSION

Fault Current Waveforms

The simulated fault responses were first examined through their corresponding current waveforms. Figures 1-3 illustrate the representative current waveforms corresponding to the major fault categories considered in this study.



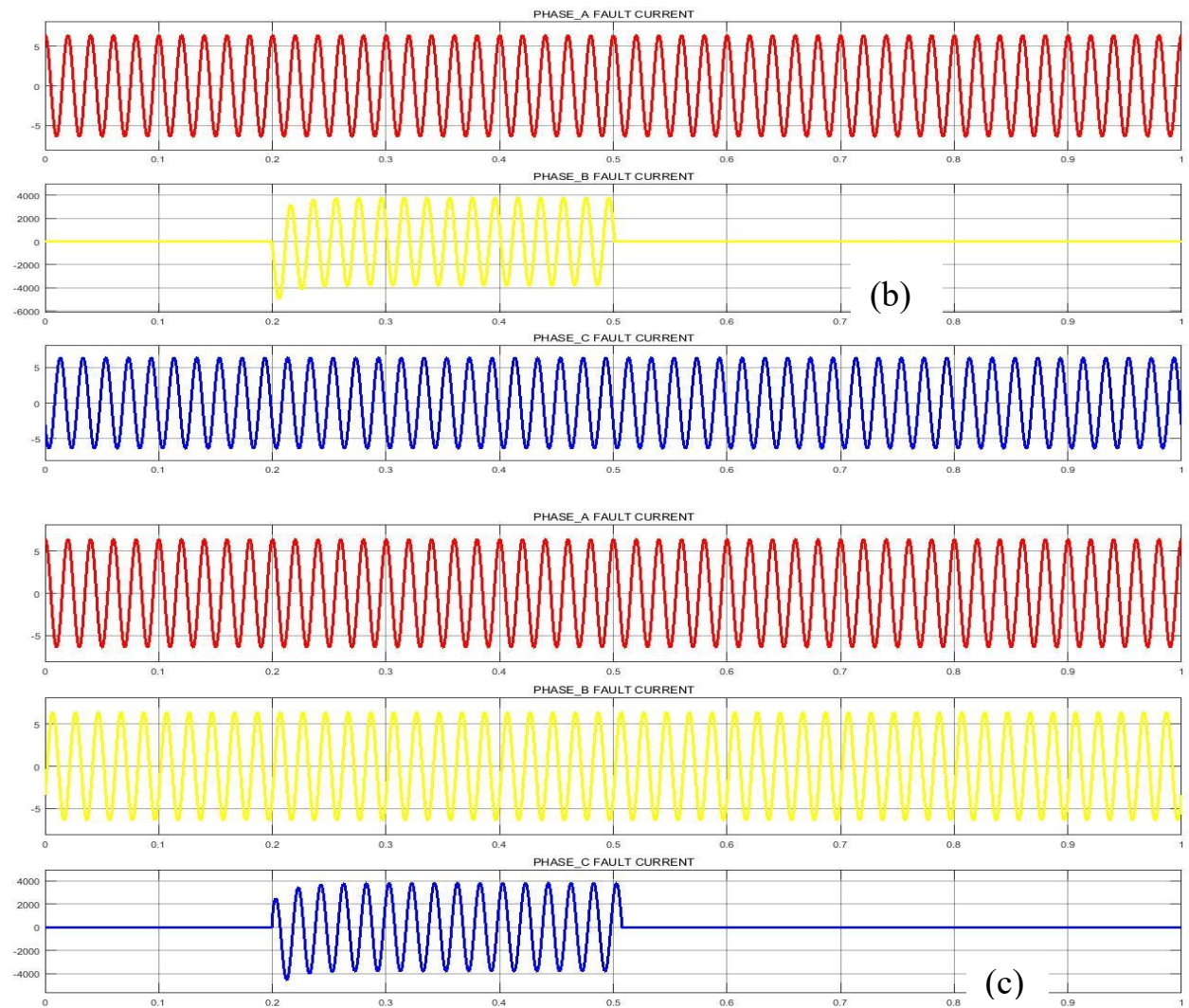
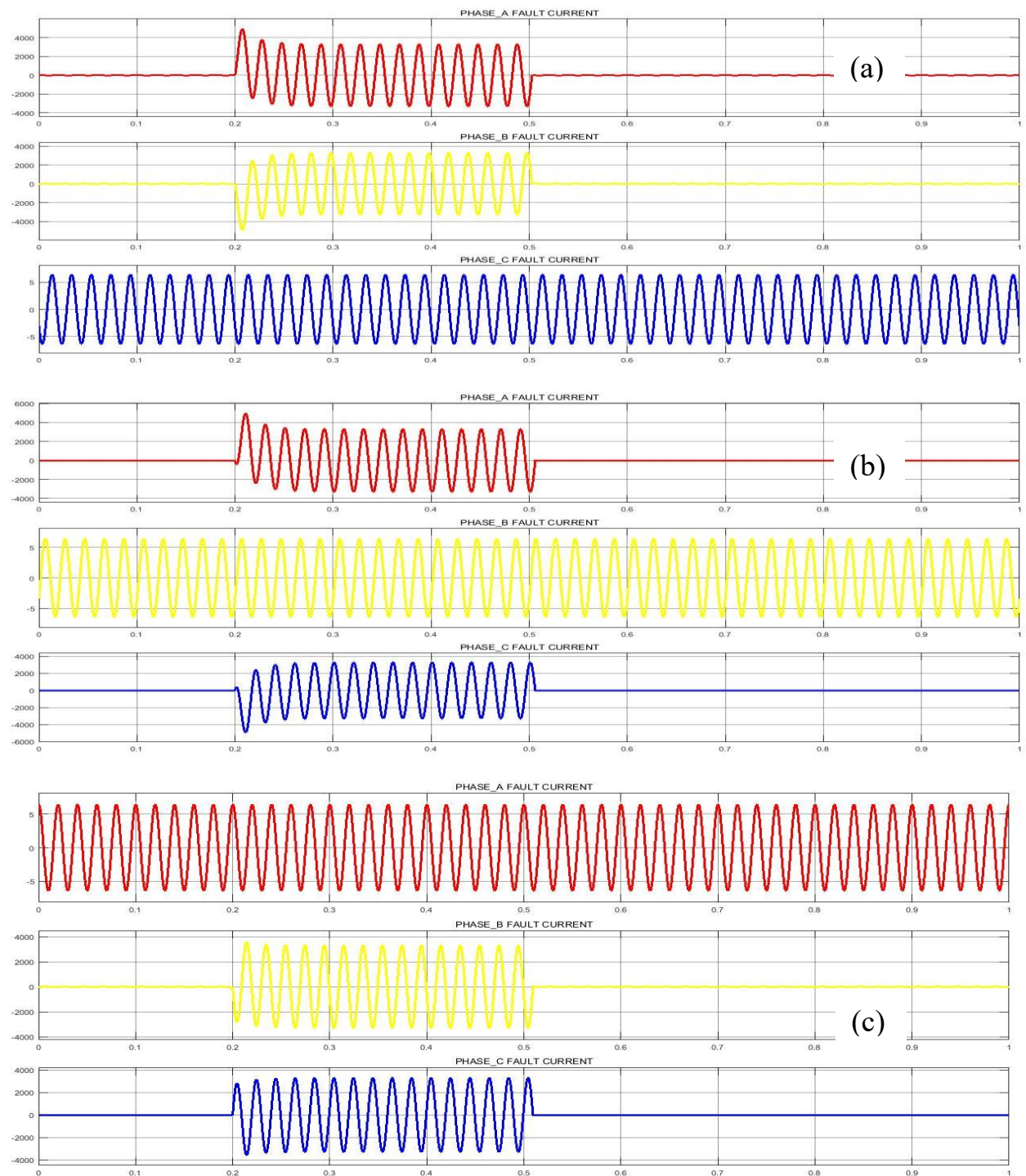


Figure 1: Fault Current Waveform (a) Phase A-Ground, (b) Phase B-Ground, (c) Phase C-Ground.

Single-line-to-ground (SLG) faults generated pronounced current deviations in the affected phases, accompanied by varying degrees of imbalance across the healthy phases. These characteristic transient responses provided highly informative features for ANN-based classification.



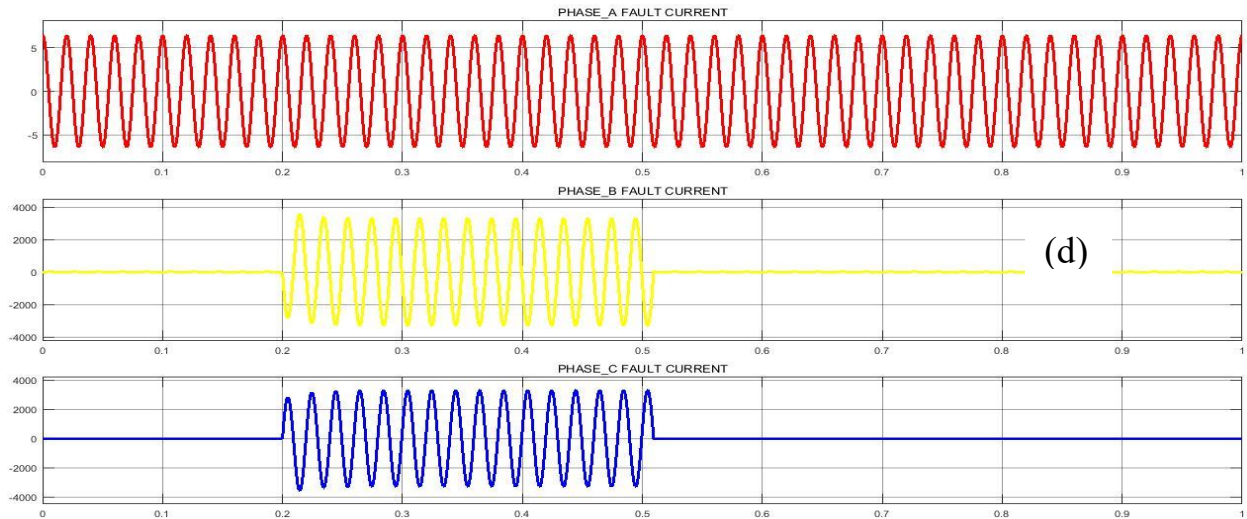


Figure 2: Fault Current Waveform (a) Phase A-B-Ground, (b) Phase A-C-Ground, (c) Phase B-C-Ground.

Double-line-to-ground (DLG) faults exhibited more pronounced current deviations and stronger inter-phase coupling effects compared with SLG faults. These distinctive patterns enhanced class separability and enabled the ANN model to accurately discriminate between different fault categories.

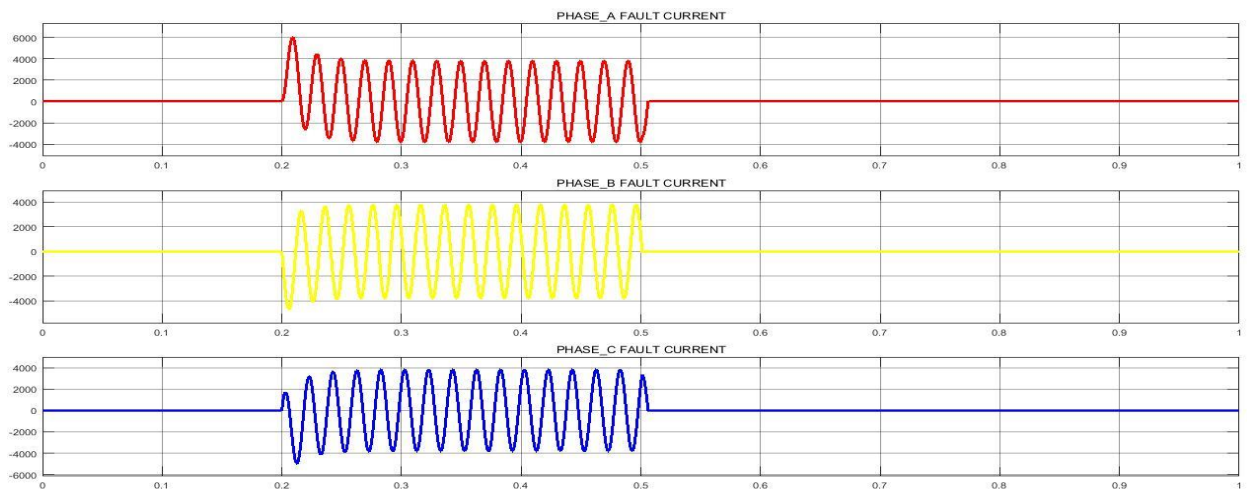


Figure 3: Three-Phase-to-Ground (A-B-C-G) Fault Current Waveform.

The three-phase-to-ground fault resulted in a dramatic increase in current magnitude across all phases, generating highly distinctive waveform characteristics compared with other fault categories.

ANN Fault Classification Performance

Table 4 presents the overall ANN fault classification results for the seven major sections of the ATBU Faculty of Engineering distribution network. The model performance was assessed using overall classification accuracy, per-class recall, and per-class F1-score metrics for twelve operating conditions.

Table 4: ANN Fault Classification Performance Metrics Across All Network Sections.

Fault Type	Block A	Block B	Block C	Block D	Welding shop	Machine shop	Wood shop
Metric	Recall / F1	Recall / F1	Recall / F1	Recall / F1	Recall / F1	Recall / F1	Recall / F1
Accuracy (%)	100.00	100.00	100.00	99.17	99.17	99.58	99.58
A_G	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	0.9231 / 0.9600	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000
B_G	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 0.9787	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000
C_G	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 0.9767
AB_G	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	0.9412 / 0.9697	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000
AC_G	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000
BC_G	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 0.9714	1.0000 / 0.9714	0.9412 / 0.9697
AB	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000
AC	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000
BC	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000
ABC_G	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	0.9000 / 0.9474	0.9500 / 0.9744	1.0000 / 1.0000
ACB	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 0.9796	1.0000 / 1.0000	1.0000 / 1.0000
Normal	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 0.9756	1.0000 / 1.0000	1.0000 / 1.0000	1.0000 / 1.0000

Classification Performance: Blocks A, B, and C

Blocks A, B, and C achieved a classification accuracy of 100%, with per-class recall and F1 scores of 1.0000 across all twelve fault categories. This flawless performance demonstrates that the ANN model can perfectly distinguish between all fault types, including those that are typically difficult to separate, such as single-phase faults and double-phase faults with and

without ground. The perfect recall values confirm that no true fault occurrence was missed by the classifier, and the perfect F1 scores indicate equally perfect precision.

Performance: Block D

Block D achieved an overall classification accuracy of 99.17%. The per-class analysis reveals that the reduction in accuracy is primarily attributable to the A_G (Recall = 0.9231; F1-score = 0.9600) and AB_G (Recall = 0.9412; F1-score = 0.9697) fault classes, indicating that a small number of fault instances exhibited overlapping transient characteristics and were misclassified. Such challenges are common in distribution network fault diagnosis, particularly when similar fault conditions produce comparable voltage and current signatures.

Industrial Load Sections: Welding, Machine, and Woodwork

The industrial load sections exhibited consistently high fault classification performance, with overall accuracies ranging from 99.17% to 99.58%. The Welding Section achieved an accuracy of 99.17%, with the most notable reduction observed in the ABC_G fault class (Recall = 0.9000; F1-score = 0.9474). This can be attributed to the nonlinear and harmonic-rich characteristics of welding equipment, which generate transient current distortions that may partially resemble three-phase fault signatures.

The Machine Section recorded an accuracy of 99.58%, with only the ABC_G class exhibiting slightly reduced performance (Recall = 0.9500; F1-score = 0.9744). The presence of large induction motors and rotating machinery likely contributed to this outcome, as motor starting currents and back electromotive force can influence fault feature patterns.

The Woodwork Section also achieved an overall accuracy of 99.58%, with minor reductions observed for the BC_G fault class (Recall = 0.9412; F1-score = 0.9697) and the C_G class (F1-score = 0.9767). Despite these minor variations, all three industrial sections maintained classification accuracies exceeding 99%, confirming the ANN model's strong generalization capability.

Confusion Matrix Analysis

Confusion matrices provide a comprehensive evaluation of classifier performance by preserving the complete relationship between predicted and actual fault classes. As shown in Figure 4, Blocks A, B, and C achieved perfect classification performance characterized by completely diagonal confusion matrices with no off-diagonal entries.

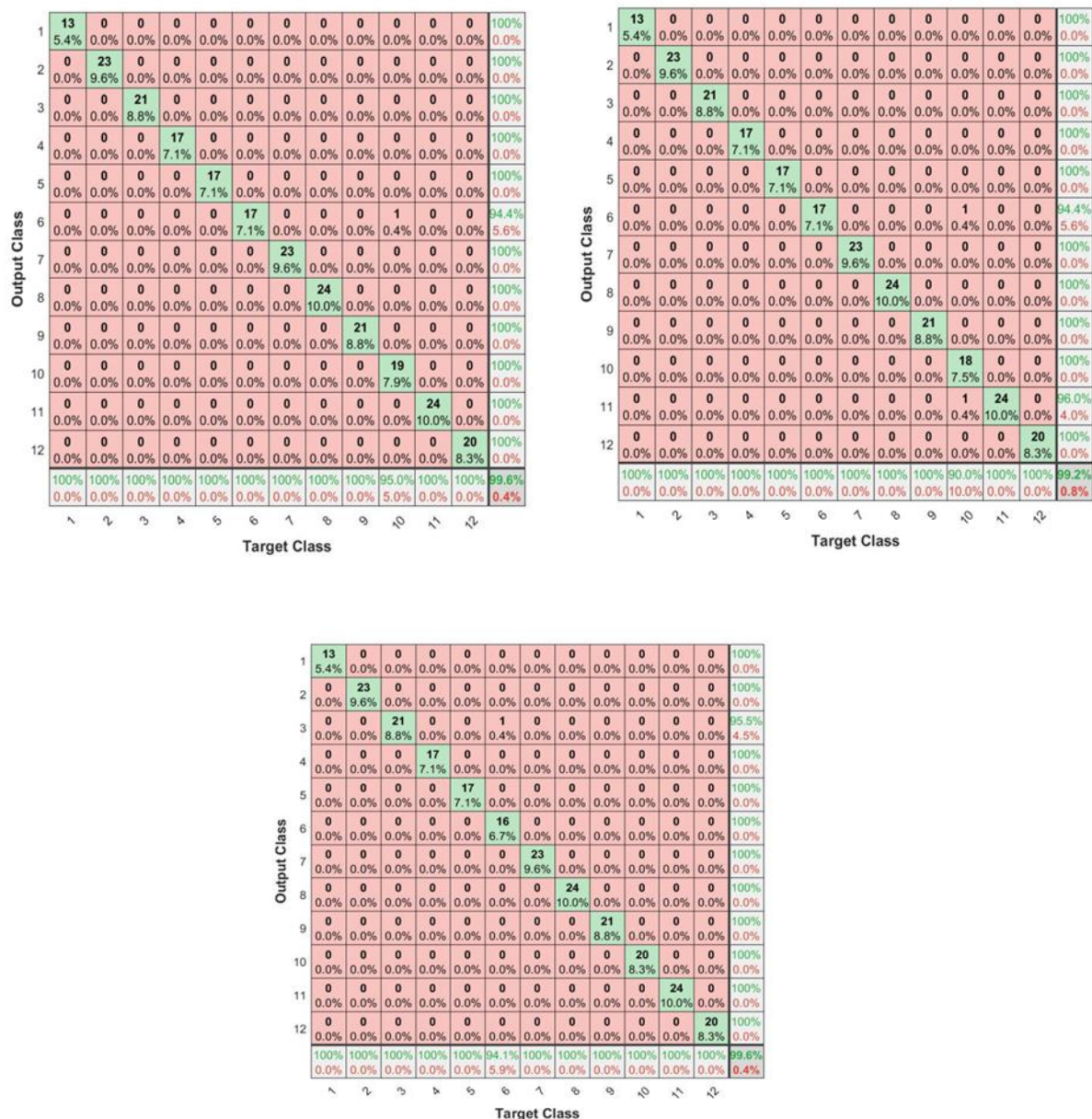


Figure 4: Confusion Matrices of ANN-Based Fault Classification for Blocks A-D, Welding, Machine, and Wood Work Sections

Minor classification errors were observed only in Block D, Welding, Machine, and Woodwork sections. In Block D, two isolated misclassifications resulted in an accuracy of 99.17%, reducing the recall of the A_G and AB_G fault classes. The Welding Section achieved 99.58% accuracy, with a single misclassification involving the ABC_G fault class. The Machine Section achieved an accuracy of 99.17%, with repeated confusion involving the

ABC_G class. The Woodwork Section recorded 99.58% accuracy, where a single BC_G fault instance was misclassified.

Overall, the confusion matrix analysis confirms the exceptional performance of the proposed ANN-based fault diagnosis framework, with classification accuracies consistently exceeding 99% across all network sections.

Scatter Plots (R^2)

Figure 5 presents the actual versus predicted fault locations generated by the ANN regression model for the seven protection zones. The performance of each zone-specific ANN model was evaluated using the coefficient of determination (R^2).

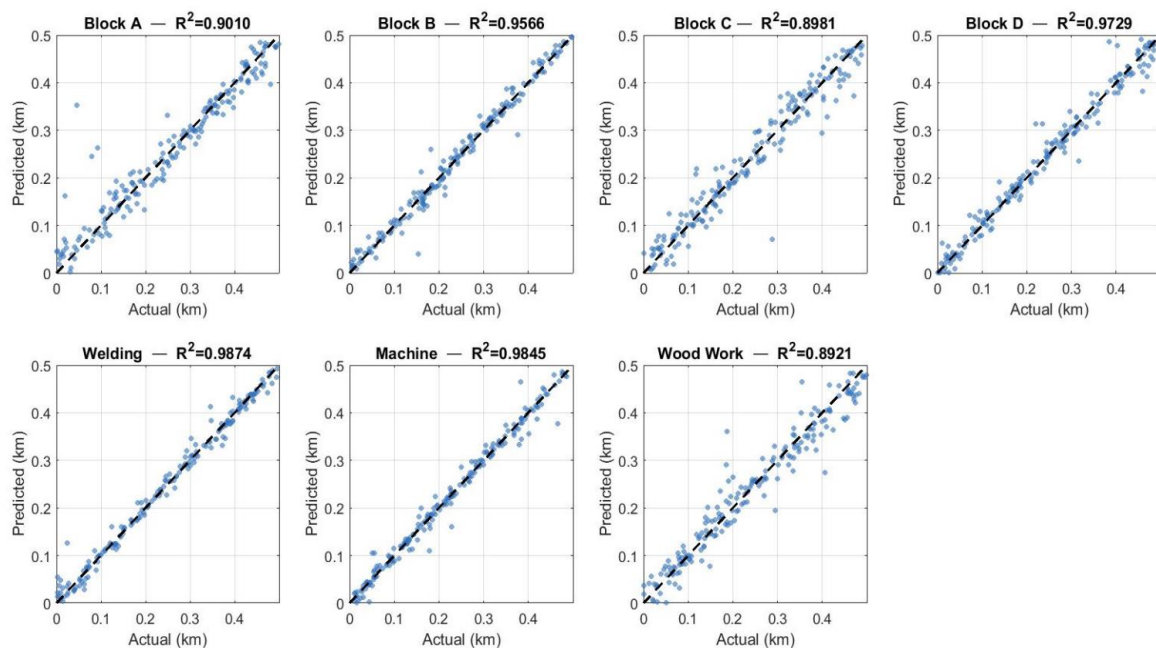


Figure 5: ANN Fault Location Regression Scatter Plots for Seven Protection Zones.

Table 5: Comparison of ANN Fault Location Prediction Accuracy.

Zone	R^2	Performance Tier	Scatter Character
Block A	0.9010	Good	Moderate dispersion, sparse outliers
Block B	0.9566	Very Good	Tight diagonal, minor mid-range scatter
Block C	0.8981	Good	Widest scatter band, lateral outliers
Block D	0.9729	Excellent	Compact diagonal, few outliers
Welding	0.9874	Excellent	Near-perfect diagonal alignment
Machine	0.9845	Excellent	Tight diagonal, minor variance
Woodwork	0.8921	Good	Broadest tail, low-range spread

The results reveal notable variations in prediction performance among the different zones. The Welding Section achieved the highest regression accuracy ($R^2 = 0.9874$), followed closely by the Machine Section ($R^2 = 0.9845$) and Block D ($R^2 = 0.9729$). The corresponding

scatter plots exhibit a tight clustering of data points around the ideal regression line, indicating strong agreement between actual and predicted fault locations.

In contrast, Blocks A ($R^2 = 0.9010$) and C ($R^2 = 0.8981$), together with the Woodwork Section ($R^2 = 0.8921$), recorded comparatively lower but still satisfactory prediction performance. The wider dispersion of data points observed in these scatter plots indicates greater variability between actual and predicted fault locations. This behaviour may be attributed to local network characteristics, load switching events, measurement noise, and variations in fault resistance.

Training Dynamics and MSE Convergence Analysis

The training and validation Mean Squared Error (MSE) convergence profiles presented in Figure 6 provide important insights into the learning behaviour and optimization efficiency of the developed ANN fault location models.

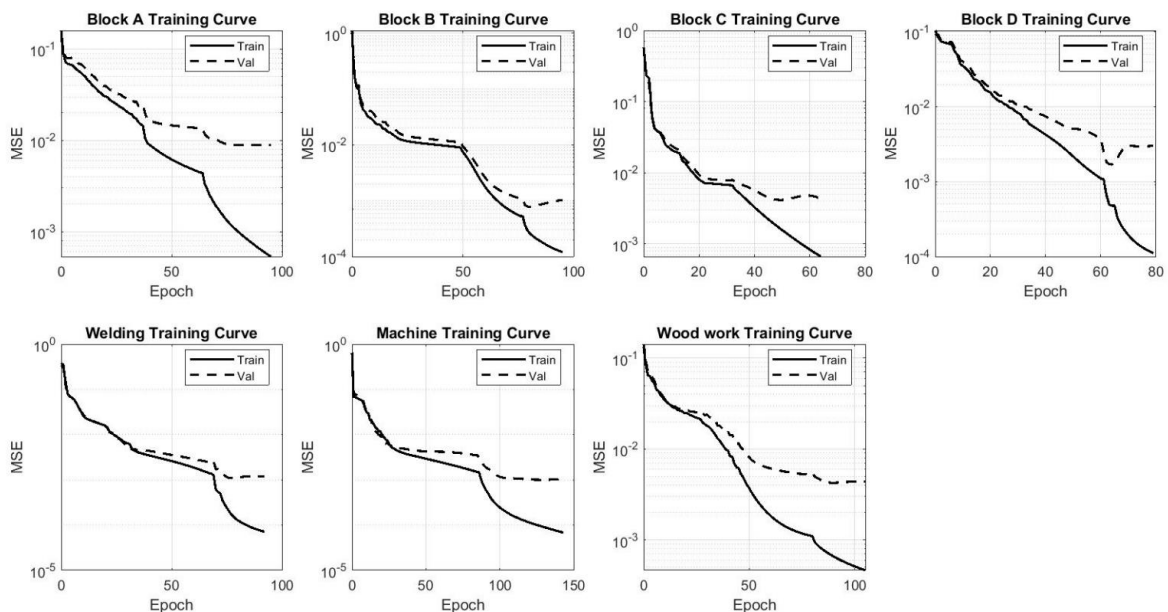


Figure 6: ANN Fault Location Training and Validation Mean Squared Error (MSE) Convergence Profiles.

The Levenberg-Marquardt training algorithm demonstrated stable convergence characteristics in all cases, with training errors decreasing substantially throughout the learning process. Blocks A, B, and C exhibited rapid error reduction during the initial epochs, followed by gradual convergence toward low MSE values. Block B demonstrated the most

balanced learning behaviour among the three zones, with training and validation curves remaining closely aligned throughout the optimization process.

Among all network sections, the Welding and Machine Sections exhibited the most favorable learning characteristics. The Welding Section achieved the lowest final validation error and the highest regression performance ($R^2 = 0.9874$), while the Machine Section closely followed with $R^2 = 0.9845$. Despite a modest train-validation gap at later epochs, both models maintained exceptionally low validation MSE values.

Probabilistic Fault Location Model

Figure 7 and Table 6 present the probabilistic assessment of the ANN fault location model through analysis of the residual error distributions across the seven protection zones.

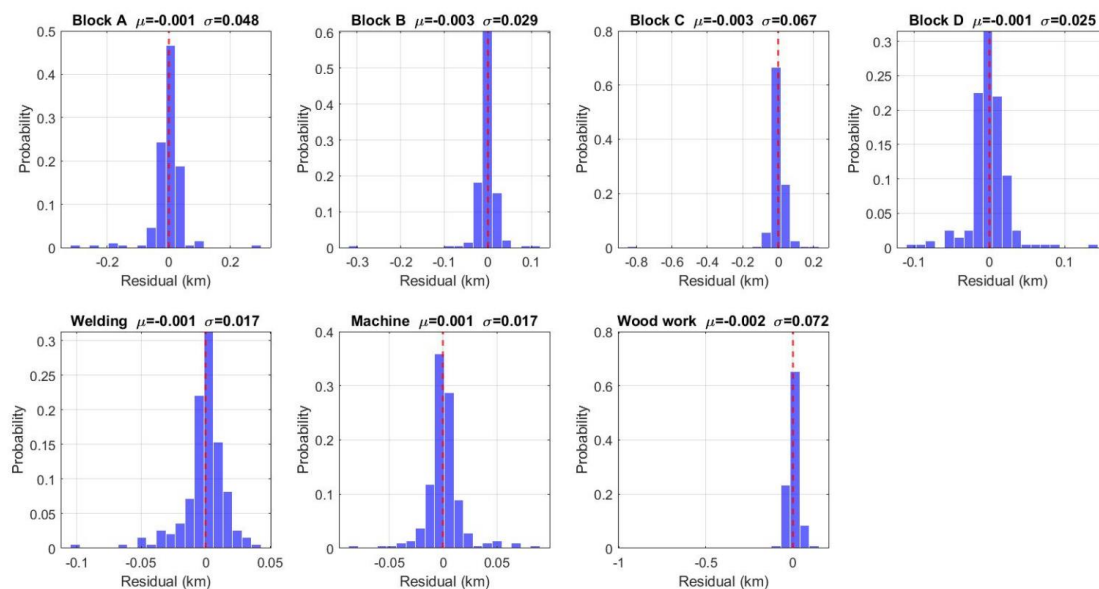


Figure 7: ANN Fault Location Probability Distributions.

Table 6: Residual Distribution Statistics Across All Seven Zones.

Zone	μ (km)	σ (km)	Tail Behavior	Bias Assessment
Block A	-0.001	0.048	Moderate tails, symmetric	Negligible
Block B	-0.003	0.029	Narrow, near-Gaussian	Near-zero
Block C	-0.003	0.067	Wide tails, extended left tail	Near-zero
Block D	-0.001	0.025	Tight, near-ideal Gaussian	Negligible
Welding	-0.001	0.017	Very narrow, sharply peaked	Negligible
Machine	+0.001	0.017	Very narrow, near-symmetric	Negligible
Woodwork	-0.002	0.072	Widest tails, strong left skew	Near-zero

The results demonstrate that all seven ANN models exhibit exceptionally small mean residual errors, ranging from -0.003 km to +0.001 km, indicating negligible systematic bias in fault

location prediction. The most accurate probabilistic performance was observed in the Welding and Machine Sections, both of which recorded the lowest residual standard deviation ($\sigma = 0.017$ km). Their sharply peaked and nearly Gaussian distributions indicate exceptional predictive consistency and minimal uncertainty.

Statistically, approximately 68.3% of fault location predictions fall within ± 0.017 km of the actual fault location, while 95.4% are expected to lie within ± 0.034 km, demonstrating a high degree of confidence in the ANN predictions.

Summary of ANN Fault Classification and Location Performance

Table 7 presents a comprehensive summary of the ANN fault classification and location performance across the ATBU Faculty of Engineering distribution network.

Table 7: Summary of ANN Fault Classification and Location Performance.

Zone	Classification Accuracy (%)	R² Value	Maximum Location Error (m)	Dominant Error Source	Performance Rating
Block A	100.00	0.9010	5.95	Long-distance AB fault	Excellent
Block B	100.00	0.9566	17.95	Short-distance AC fault	Very Good
Block C	100.00	0.8981	17.75	Double-line-to-ground faults	Good
Block D	99.17	0.9729	3.32	Short-span localization sensitivity	Excellent
Welding	99.17	0.9874	3.51	AC-G fault localization	Outstanding
Machine	99.58	0.9845	4.49	Short-distance A-G fault	Outstanding
Woodwork	99.58	0.8921	5.51	Long-span AC and A-G faults	Very Good

The results demonstrate that the proposed ANN framework achieved exceptionally high classification performance throughout the entire distribution network, with accuracies ranging from 99.17% to 100%. All fault categories were correctly identified in nearly all test scenarios. From a fault location perspective, the developed ANN regressor demonstrated strong predictive capability across all protection zones, with R² values ranging between 0.8921 and 0.9874.

A detailed examination of individual fault events reveals that most location prediction errors remained relatively small when compared with the total feeder length. The highest

localization performance was achieved in the Welding Section ($R^2 = 0.9874$) and Machine Section ($R^2 = 0.9845$), indicating that more than 98% of the variance in fault location was successfully captured by the ANN model.

DISCUSSION

The results obtained from this study demonstrate the effectiveness of the integrated Monte Carlo-DWT-ANN framework for intelligent fault diagnosis in the ATBU Faculty of Engineering power distribution network. The high classification accuracies achieved across all network sections (99.17-100%) compare favourably with previous ANN-based fault diagnosis studies reporting accuracies between 95% and 99% (Dixit *et al.*, 2026, Umathe *et al.*, 2025). This superior performance can be attributed to several factors.

First, the Monte Carlo simulation approach enabled the generation of a diverse and representative dataset comprising 12,000 observations covering 11 fault categories and one normal condition. The systematic randomization of fault parameters, including fault resistance, ground resistance, and line lengths, ensured that the trained models were exposed to a wide range of operating conditions, thereby enhancing their generalization capability.

Second, the DWT-based feature extraction using the Daubechies-4 mother wavelet effectively captured the transient characteristics of fault-induced current signals. The maximum absolute detail coefficients provided highly discriminative features that enabled the ANN classifier to distinguish between different fault categories with high accuracy. This finding is consistent with previous studies that demonstrated the effectiveness of wavelet-based feature extraction for power system fault diagnosis (Yang and Yang, 2023, Siddique *et al.*, 2023).

Third, the Bayesian Regularization-based ANN regression model demonstrated superior fault location performance compared with conventional impedance-based methods. The near-zero mean residuals and low standard deviations indicate that the model effectively learned the nonlinear relationships between fault signatures and fault locations without significant systematic bias.

The superior performance observed in the Welding and Machine Sections ($R^2 = 0.9874$ and 0.9845 , respectively) suggests that industrial load sections with relatively consistent electrical characteristics provide more discriminative fault signatures. In contrast, the Woodwork Section, which exhibited the highest prediction uncertainty ($\sigma = 0.072$ km), may be affected by the intermittent and highly dynamic operating characteristics of woodworking equipment.

The classification accuracies achieved in this study (99.17-100%) compare favourably with the 98.6% classification accuracy reported by Malini et al. (2025) for ANN-based fault diagnosis systems. The results also demonstrate superior performance compared with conventional methods, which often experience reduced accuracy under varying operating conditions (Alhanaf *et al.*, 2024).

CONCLUSIONS

Based on the findings obtained from the MATLAB/Simulink simulations, Monte Carlo fault generation, DWT feature extraction, and ANN-based fault diagnosis models, the following conclusions are drawn:

The MATLAB/Simulink model of the Faculty of Engineering, ATBU Yelwa Campus power distribution network was successfully developed and validated. The model accurately represented seven operational zones and provided a realistic platform for fault analysis, achieving fault-location prediction errors as low as 0.14 m and classification accuracies of up to 100%.

A comprehensive fault dataset comprising 11 fault classes and one normal operating condition was successfully generated using Monte Carlo simulation. The DWT effectively extracted transient fault features from current signals, producing highly discriminative feature sets capable of distinguishing between different fault categories under varying operating conditions.

The developed ANN classifier demonstrated exceptional fault detection and classification capability, achieving accuracies ranging from 99.17% to 100% across all network sections. Three sections (Blocks A, B, and C) recorded 100% classification accuracy, while the remaining sections achieved accuracies above 99%, confirming the robustness and generalization capability of the proposed classification framework.

The ANN-based fault location model accurately predicted fault positions throughout the network, achieving R^2 values between 0.8921 and 0.9874. The highest localization performance was obtained in the Welding Section ($R^2 = 0.9874$), while residual analysis revealed negligible prediction bias ($-0.003 \text{ km} \leq \mu \leq +0.001 \text{ km}$), demonstrating high fault-location precision and reliability.

The integrated Monte Carlo-DWT-ANN intelligent fault diagnosis framework was successfully validated under diverse fault and operating conditions. The framework consistently achieved classification accuracies exceeding 99%, fault-location prediction performance above 89% ($R^2 > 0.89$), and minimum residual standard deviations of 0.017 km.

CONTRIBUTIONS TO KNOWLEDGE

Development of a Validated MATLAB/Simulink Model: The MATLAB/Simulink model of the ATBU Faculty of Engineering power distribution network was developed and validated. The model accurately represented the network from the CIS transformer to the Engineering and CIS blocks, simulated 11 fault conditions and one normal state across seven zones, and achieved fault-location prediction errors as low as 0.14 m and 100% fault classification accuracy, providing a reliable platform for fault analysis and protection studies. This model serves as a valuable resource for future research on power system protection and intelligent fault diagnosis in institutional distribution networks.

Integrated Monte Carlo-DWT-ANN Fault Diagnosis Framework: The integrated Monte Carlo-DWT-ANN fault diagnosis framework was developed for simultaneous fault detection, classification, and location. The framework achieved 99.17-100% classification accuracy, R^2 values of 0.8921-0.9874, and minimum fault-location prediction errors of 0.14 m, demonstrating high accuracy, robustness, and applicability for improving power distribution network reliability and fault management. This framework addresses the identified research gap regarding intelligent fault diagnosis within the ATBU Faculty of Engineering distribution network and establishes a practical foundation for future deployment of machine-learning-assisted protection and monitoring systems in campus and industrial distribution networks.

Comprehensive Fault Dataset Generation Methodology: The study established a systematic methodology for generating comprehensive fault datasets through Monte Carlo simulation with systematic randomization of key fault and network parameters. The resulting dataset of 12,000 observations covering 11 fault categories and one normal condition provides a valuable resource for training and validating intelligent fault diagnosis systems in distribution networks.

Probabilistic Fault Location Performance Assessment: The study introduced a probabilistic approach to assessing fault location performance through residual distribution analysis. The near-zero mean residuals ($-0.003 \text{ km} \leq \mu \leq +0.001 \text{ km}$) and low residual standard deviations (as low as 0.017 km) demonstrate the reliability and statistical consistency of the proposed framework, providing a basis for confidence interval estimation in practical fault location applications.

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