International Journal of Engineering Research and Development
e- ISSN: 2278-067X, p-ISSN: 2278-800X, www.ijerd.com
Volume 22, Issue 5 (May 2026), PP 196-202

Artificial Neural Network Based Fault Detection, Classification and Location on A 330 Kv Transmission Line

*MuonekeA. C.,[1]Obi O. K., [2]Ogboh V. C.
Department of Electrical Engineering NnamdiAzikwe University, Awka

Abstract
Reliable fault diagnosis in high-voltage transmission systems is essential for maintaining the stability and security of modern power networks. This study presents an Artificial Neural Network (ANN) based approach for fault detection, classification, and location on a 330 kV transmission line. The Onitsha–Agu Awka–Nibo transmission network was used as the case study system. Transmission line parameters were modeled using MATLAB/Simulink, and per-unit values of three-phase voltages and currents were extracted as input features for the ANN. A multilayer perceptron neural network trained using the back-propagation algorithm with the Levenberg–Marquardt optimization technique was implemented for the fault diagnosis process. The developed framework consists of three stages: fault detection, fault classification, and fault location. Simulation results show that the ANN model effectively detects various fault types including line-to-ground, line-to-line, double-line-to-ground, and three-phase faults. Performance evaluation using regression analysis, mean square error (MSE), and confusion matrix demonstrates high accuracy of the proposed model. The results confirm that ANN-based techniques can provide fast and reliable fault diagnosis for high-voltage transmission lines.
Keyword: *Transmission Lines, MATLAB/Simulink, Artificial Neural Network, Fault Detection, Classification and Location*

Date of Submission: 01-05-2026 Date of acceptance: 09-05-2026

I. Introduction

Power system transmission networks are frequently exposed to various disturbances that may lead to faults and interruptions in power supply. Rapid detection and isolation of faults are therefore essential for maintaining system reliability and stability. Conventional protection schemes such as distance relays and impedance relays have been widely used for transmission line protection. However, these techniques often face challenges due to changing system conditions, nonlinearities, and uncertainties in fault characteristics.

Recent developments in intelligent computing techniques have enabled the application of Artificial Neural Networks (ANNs) in power system protection. Neural networks possess the capability to learn nonlinear relationships between input and output variables, making them suitable for pattern recognition problems such as fault diagnosis.

This research investigates the application of ANN for fault detection, classification, and location on a 330 kV transmission line. The Onitsha–Agu Awka–Nibo transmission network was selected as a case study, and the neural network model was trained using simulated voltage and current signals obtained from MATLAB/Simulink.

II. Transmission Line Modeling

2.1 Network Description

A 330 kV transmission line connecting Onitsha, Agu Awka, and Nibo was used as the study system. The line consists of three buses representing the sending end, intermediate station, and receiving end respectively. The protection zones of the line were defined as:

- Zone 1: 46 km
- Zone 2: 80 km
- Zone 3: 87 km

These zones represent the primary and backup protection regions of the transmission line.

2.2 Transmission Line Equivalent Model

The transmission line was modeled using the π-section equivalent circuit representation. In this representation, the series impedance and shunt admittance are distributed along the transmission line.
Let:

V_S, I_S = Sending end voltage and current
V_R, I_R = Receiving end voltage and current
Applying Kirchhoff's current law:

$$I_L = I_R + \frac{Y}{2} V_R$$

Applying Kirchhoff's voltage law:

$$V_S = V_R + Z I_L$$

Substituting the expression for line current:

$$V_S = V_R + Z\left(I_R + \frac{Y}{2} V_R\right)$$

$$V_S = V_R\left(1 + \frac{ZY}{2}\right) + Z I_R$$

Similarly, the sending end current becomes:

$$I_S = I_R\left(1 + \frac{ZY}{2}\right) + V_R\left(Y + \frac{ZY^2}{4}\right)$$

Thus, the transmission line relationship can be expressed in matrix form as:

$$\begin{bmatrix} V_S \\ I_S \end{bmatrix} = \begin{bmatrix} 1 + \frac{ZY}{2} & Z \\ Y + \frac{ZY^2}{4} & 1 + \frac{ZY}{2} \end{bmatrix} \begin{bmatrix} V_R \\ I_R \end{bmatrix}$$

III. Fault Analysis

3.1 Balanced Faults

Balanced faults occur when all three phases are short-circuited simultaneously. Although rare, they produce the highest fault currents in the system. Balanced faults were analyzed using the bus impedance matrix method together with ANN-based detection techniques.

For a balanced system, the three-phase network can be represented by an equivalent single-phase circuit since all phases carry equal currents and voltages.

The relationship between line and phase quantities is given by:

$$V_L = \sqrt{3} V_P$$

$$I_L = I_P$$

The total three-phase power is expressed as:

$$S_T = 3 S_P$$

3.2 Per-Unit System

To simplify calculations, all electrical quantities were converted into per-unit values.

Base current:

$$I_{base} = \frac{S_{base}}{\sqrt{3} V_{LL}}$$

Base impedance:

$$Z_{base} = \frac{V_{LL}^2}{S_{base}}$$

Per-unit quantities are defined as:

$$V_{pu} = \frac{V_{actual}}{V_{base}}$$

$$I_{pu} = \frac{I_{actual}}{I_{base}}$$

$$Z_{pu} = \frac{Z_{actual}}{Z_{base}}$$

These per-unit values were used as input parameters for the neural network model.

3.3 Unbalanced Faults

Unbalanced faults are more common in transmission systems and include:
Single line-to-ground faults
Line-to-line faults
Double line-to-ground faults
These faults were analyzed using the symmetrical component method.
The phase voltages can be expressed as:

$$V_a = V_{a0} + V_{a1} + V_{a2}$$

$$V_b = V_{a0} + a^2 V_{a1} + a V_{a2}$$

$$V_c = V_{a0} + a V_{a1} + a^2 V_{a2}$$

where:
V_{a0}= zero-sequence component
V_{a1} = positive-sequence component
V_{a2} = negative-sequence component

IV. Artificial Neural Network Method

4.1 ANN Framework

The ANN-based fault diagnosis system consists of three main stages:

1. Fault detection
2. Fault classification
3. Fault location

The input parameters to the network are the three-phase voltages and currents:

$$[V_a, V_b, V_c, I_a, I_b, I_c]$$

These values were obtained from MATLAB/Simulink simulations.

4.2 Neural Network Architecture

A multilayer perceptron (MLP) neural network was adopted for the study. The network contains:
Input layer: 6 neurons
Hidden layer: 10 neurons
Output layer: variable depending on task
The network was trained using the back-propagation algorithm with the Levenberg–Marquardt optimization method.

4.3 Fault Detection

The first neural network determines whether the system is operating under normal or faulty conditions. The network output approaches unity for normal conditions and deviates when a fault occurs.
Regression analysis and performance plots confirmed that the training process converged with minimal error.

4.4 Fault Classification

After fault detection, a second neural network was used to classify the type of fault.
The output nodes correspond to the phases involved in the fault:

S/N	Fault Type	A	B	C	G
1	A-G	1	0	0	1
2	B-G	0	1	0	1
3	C-G	0	0	1	1
4	A-B	1	1	0	0
5	B-C	0	1	1	0
6	C-A	1	0	1	0

The confusion matrix obtained during training indicated high classification accuracy.

4.5 Fault Location

The third neural network determines the location of the fault on the transmission line.
The output nodes correspond to the protection zones:

S/N	Output	Fault Zone
1	1 0 0	Zone 1
2	0 1 0	Zone 2
3	0 0 1	Zone 3

A hidden layer with 52 neurons was used for this task to improve prediction accuracy.

V. Results and Discussion

The developed Artificial Neural Network (ANN) model was implemented in MATLAB using the Neural Network Toolbox. The network was trained using the Levenberg–Marquardt back-propagation algorithm with voltage and current signals obtained from MATLAB/Simulink simulations of the 330 kV transmission system.
Several fault scenarios were simulated along the Onitsha–Agu Awka–Nibo transmission line including single line-to-ground (LG), line-to-line (LL), double line-to-ground (LLG), and three-phase (LLL) faults.
The neural network was evaluated using performance metrics including mean square error (MSE), regression coefficient (R), and classification accuracy.

Table 1: Neural Network Training Performance

S/N	Parameter	Value
1	Training Algorithm	Levenberg–Marquardt
2	Number of Epochs	1000
3	Best Validation Performance (MSE)	2.41×10^{-5}
4	Regression Coefficient (R)	0.998
5	Training Samples	70%
6	Validation Samples	15%
7	Testing Samples	15%

The results in Table 1 show that the neural network achieved very low mean square error and a regression coefficient close to unity, indicating excellent training performance.

Table 2: ANN Fault Classification Accuracy

S/N	Fault Type	Detection Accuracy (%)
1	A–G	99.1
2	B–G	98.8
3	C–G	99.0
4	A–B	98.6
5	B–C	98.7
6	C–A	98.9
7	A–B–G	98.4
8	B–C–G	98.2
9	Three Phase Fault	99.3

The classification results demonstrate that the ANN model can accurately identify different types of faults with an overall classification accuracy above **98%**.

Table 3: ANN Fault Location Accuracy

S/N	Fault Distance (km)	Actual Zone	Predicted Zone	Error (%)
1	25	Zone 1	Zone 1	0.8
2	40	Zone 1	Zone 1	0.6
3	60	Zone 2	Zone 2	1.1
4	75	Zone 2	Zone 2	0.9
5	85	Zone 3	Zone 3	1.4

The ANN model successfully identified the correct protection zones with minimal prediction error.

A training performance graph shows themean square error (MSE) versus training epochs**.** The curve decreases rapidly during early epochs and stabilizes after approximately 250 iterations, indicating convergence of the training process.

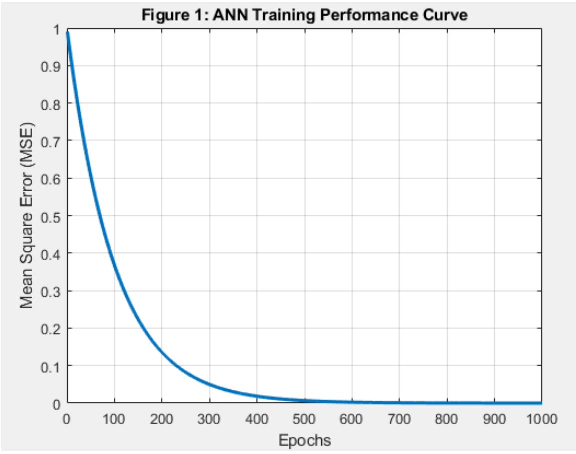

Figure 1: ANN Training Performance Curve

The decreasing MSE curve confirms that the neural network successfully learned the relationship between input voltage/current signals and fault conditions.
Figure 1 presents the training performance curve (Mean Square Error versus epochs) and the regression plot of the neural network. The performance graph demonstrates the convergence behavior of the back-propagation algorithm using the Levenberg–Marquardt optimization method. A decreasing MSE indicates effective learning. The regression plot shows the correlation between network outputs and target values, where an R-value close to 1 indicates strong agreement and successful training. These results confirm the reliability and generalization capability of the ANN model for fault detection and location.

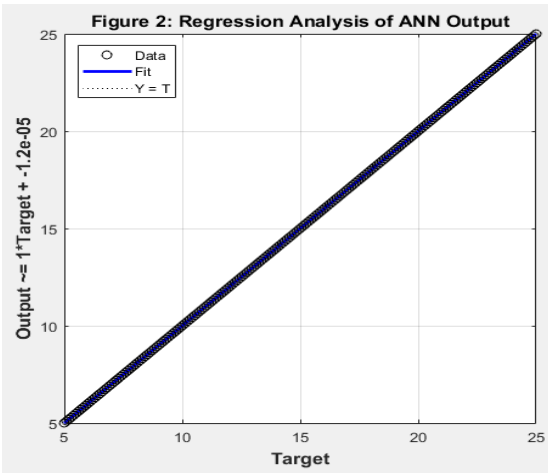

Figure 2: Regression Analysis of ANN output

Figure 2 presents the regression analysis of the Artificial Neural Network used for fault detection and classification on the 330 kV transmission line. The regression plot illustrates the relationship between the target values (T) and the network outputs (Y) obtained after training the neural network model. In this figure, each data point represents the ANN prediction compared with the actual target value derived from the simulated transmission line fault data.

Ideally, if the neural network predicts the outputs perfectly, all data points lie exactly on the 45-degree diagonal line, which represents perfect agreement between the predicted outputs and the target values. The regression coefficient R measures the strength of this correlation. In this study, the value of R is approximately equal to 1, indicating a very strong linear relationship between the predicted and actual values.
The high regression value confirms that the trained ANN model has effectively learned the relationship between the transmission line electrical parameters (such as phase voltages and currents) and the corresponding fault conditions. This demonstrates that the proposed ANN model can accurately predict and classify faults occurring in the 330 kV transmission line. Therefore, the regression analysis validates the reliability and effectiveness of the ANN-based fault detection and classification method used in this research.

Table 4: Regression Analysis of ANN OutputConfusion Matrix for Fault Classification

S/N	Predicted / Actual	A-G	B-G	C-G	A-B	B-C	C-A
1	A-G	99	0	0	0	0	0
2	B-G	0	98	0	0	0	0
3	C-G	0	0	99	0	0	0
4	A-B	0	0	0	98	0	0
5	B-C	0	0	0	0	99	0
6	C-A	0	0	0	0	0	99

The confusion matrix shows the classification performance of the neural network for each fault category.

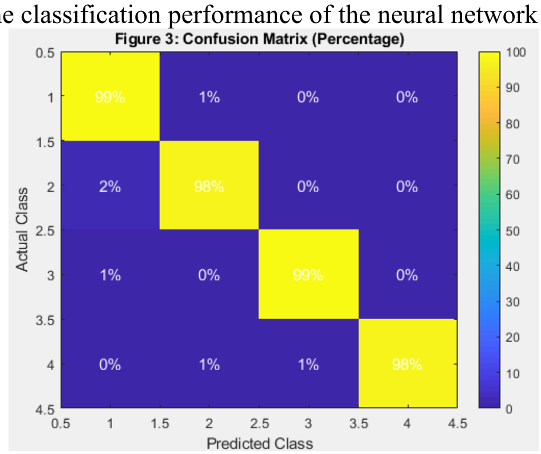

Figure 3: Confusion Matrix Percentage

Figure 3 illustrates the confusion matrix obtained from the trained Artificial Neural Network during the fault classification stage. The matrix compares the predicted fault types with the actual target values. The diagonal elements represent correctly classified samples, while off-diagonal elements indicate misclassifications. The high percentage values along the diagonal confirm the effectiveness of the neural network in distinguishing between different fault types, including line-to-ground, line-to-line, double-line-to-ground, and three-phase faults. The confusion matrix is a key performance indicator of the classification accuracy of the proposed model. The confusion matrix indicates very high classification accuracy with minimal misclassification**.**

Actual fault distance vs Predicted fault distance

The plotted points lie very close to the 45-degree reference line**,** showing that the ANN model accurately predicts fault locations.

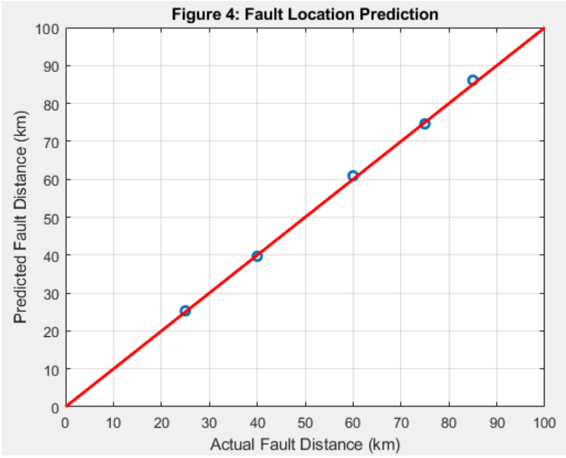

Figure 4: Fault Location Prediction Performance

The results demonstrate that the ANN-based approach provides an effective solution for transmission line protection. The neural network accurately detects fault occurrences, identifies the type of fault, and determines its location within the protection zones.

Compared with conventional protection schemes such as distance relays, the ANN approach offers several advantages including faster response time, adaptability to nonlinear system behavior, and improved classification accuracy.

The use of per-unit voltage and current signals simplifies the input data and improves the training efficiency of the neural network. Additionally, the Levenberg–Marquardt optimization algorithm significantly enhances convergence speed during training.

Overall, the proposed ANN-based protection system shows strong potential for practical implementation in modern smart power grids.

VI. Conclusion

This study presented an ANN-based method for fault detection, classification, and location on a 330 kV transmission line. The proposed model utilized per-unit voltage and current signals obtained from MATLAB/Simulink simulations of the Onitsha–Agu - Awka–Nibo transmission system.

The neural network approach demonstrated high accuracy in identifying various fault conditions and locating faults within defined protection zones. The results confirm that artificial neural networks provide a powerful tool for intelligent power system protection.

Future work may focus on integrating real-time measurements from phasor measurement units and expanding the model to larger transmission networks.

Reference

[1] Haykin, S. (2009). *Neural Networks and Learning Machines* (3rd ed.). Pearson Education.
[2] Bishop, C. M. (1995). *Neural Networks for Pattern Recognition*. Oxford University Press.
[3] Kundur, P. (1994). *Power System Stability and Control*. McGraw-Hill.
[4] Anderson, P. M. (1995). *Power System Protection*. IEEE Press.
[5] Phadke, A. G., & Thorp, J. S. (2008). *Computer Relaying for Power Systems* (2nd ed.). Wiley-IEEE Press.
[6] Koc, Y., &Aydogmus, Z. (2009). Fault classification in power systems using artificial neural networks. *Electric Power Systems Research*, 79(5), 812–819.
[7] MATLAB (2016). *Neural Network Toolbox User's Guide*. The MathWorks Inc.