INTERNATIONAL JOURNAL OF NOVEL RESEARCH AND DEVELOPMENT (IJNRD)
© 2026 IJNRD | Volume 11, Issue 4, April 2026 | ISSN: 2456-4184 | IJNRD.ORG

Fault Detection and Classification in Electrical Transmission Lines Using Artificial Neural Networks

[1]Mr .C.J. Sharma , [2]Ayushi Ambade , [3]Kajol Barde

[1]Professor,[2]Student,[3]Student

[1]Department of Electrical Engineering

[1]K. D. K College of Engineering

Nagpur, India

Abstract : The continuous and reliable operation of electrical power systems is heavily dependent on the swift detection and classification of transmission line faults. Traditional relaying techniques often face challenges with the increasing complexity of modern power grids, especially when dealing with high impedance faults and noisy signal environments. This paper proposes a robust, data-driven approach utilizing Artificial Neural Networks (ANN) for the rapid detection and classification of various shunt faults (LG, LL, LLG, LLL, and LLLG) in transmission lines. Utilizing a meticulously simulated 11kV power system in MATLAB/Simulink, Root Mean Square (RMS) values of threephase voltages and currents are extracted as primary feature vectors. The ANN model is trained using the LevenbergMarquardt backpropagation algorithm, chosen for its fast convergence capabilities. The proposed ANN framework demonstrated exceptional performance, converging in just 12 epochs with a Best Validation Performance Mean Squared Error (MSE) of 1.2589×10^{-5}. Furthermore, the regression analysis yielded an extraordinary overall correlation coefficient of $R = 0.99999$. These results prove that the proposed ANN architecture provides superior generalization, high adaptability, and minimal computational latency, making it highly suitable for real-time power system protection applications.

***IndexTerms* - Artificial Neural Networks, Fault Detection, Fault Classification, Machine Learning, Power Systems, Transmission Lines, Levenberg-Marquardt Algorithm.**

I.INTRODUCTION

The electrical power system is a highly complex, interconnected network where transmission lines serve as the vital arteries delivering bulk power from generating stations to distribution substations. Because these transmission lines span vast geographical areas and are constantly exposed to unpredictable environmental elements, they are highly susceptible to various abnormal conditions. Faults such as lightning strikes, tree contact, bird interference, and insulation breakdown frequently occur [1]. Uninterrupted power supply is a primary objective for power grid operators. The immediate detection, accurate classification, and swift isolation of these faults are strictly critical to preventing widespread cascading blackouts, ensuring human safety, and mitigating severe damage to expensive grid equipment like transformers and synchronous generators.

Historically, fault detection has relied heavily on traditional mathematical models and electromechanical or solid-state distance relays. These conventional protection schemes measure the impedance from the relay location to the fault point. However, these traditional methods often struggle and mis operate under highly non-linear fault conditions, such as high fault contact resistance, varying load angles, power swings, and heavily noisy sensor data [2]. Furthermore, diagnosing high impedance single-phase faults remains a notoriously difficult challenge for conventional relays due to the low fault current magnitudes [6].

Recently, the integration of Artificial Intelligence (AI) and Machine Learning (ML) has revolutionized power system diagnostics and protective relaying. Recent literature demonstrates the efficacy of various ML algorithms in classifying transmission faults by treating the issue as a pattern recognition problem [7]. For example, a comparative study utilizing Random Search Optimization revealed that while Support Vector Machines (SVM) achieved a modest 74.19% accuracy, Decision Trees (DT) reached a highly effective

99.87% test accuracy for fault classification [3]. Furthermore, Extreme Learning Machines (ELM) have been deployed to achieve fast classification with accuracies of 99.18% and 99.09% across different transmission line configurations [4].

Despite the exploration of these diverse ML algorithms, Artificial Neural Networks (ANN) remain exceptionally well suited for this domain. ANNs possess an inherent ability to map highly complex, non-linear relationships between multidimensional power system inputs and specific fault outputs without requiring explicit mathematical modelling of the system dynamics [8]. Previous implementations of ANNs utilizing combined voltage and current inputs have demonstrated detection accuracies peaking at 99.9% [5].

This paper focuses exclusively on developing, training, and optimizing a Multilayer Perceptron (ANN) to accurately detect and classify both symmetrical and asymmetrical faults in transmission lines. The core contribution of this work lies in the utilization of specific Root Mean Square (RMS) feature vectors (V_{rms} and I_{rms}) and the application of the highly efficient Levenberg-Marquardt optimization algorithm. This paper provides a comprehensive analysis of the network’s training performance, error histograms, and regression metrics, offering a highly optimized and computationally light comparative baseline against existing ML approaches.

II.RESEARCH METHODOLOGY

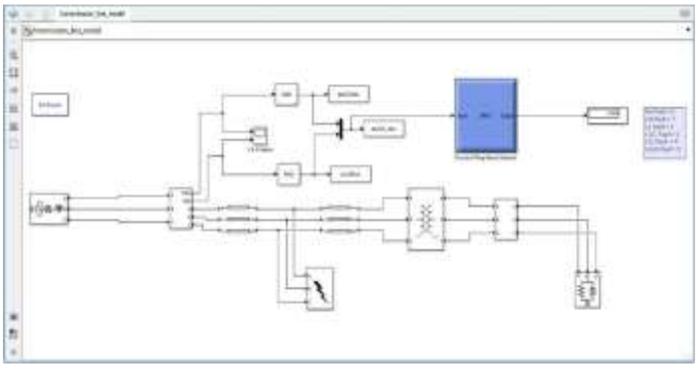

Fig. 1. Block diagram of the overall proposed methodology, illustrating the data flow from the simulated power grid and feature extraction modules to the Artificial Neural Network for fault classification.

A. Power System Modelling and Simulation Parameters

To train the Artificial Neural Network effectively, a robust and comprehensive dataset is required. Following standard practices in power system research, the transmission line network was modelled and simulated using the MATLAB/Simulink Simscape Electrical environment [1], [8].

The simulated network is meticulously designed to represent a realistic distribution-level transmission framework. The core components and their respective technical ratings are defined as follows:

- Three-Phase Source: A voltage source generating a peak to-peak voltage (V_{p-p}) of 11 kV at a standard frequency of 50 Hz. The source has a base power rating of 230 kVA and is star-connected with a grounded neutral.
- Transmission Line: Modelled using a Distributed Parameters Line block to account for the wave propagation effects over the distance. The line parameters per phase are defined as: Resistance $r = 0.012\ \Omega/km$, Inductance $x_l = 0.93\ mH/km$, and Capacitance $x_c = 12.74\ nF/km$ operating at 50 Hz.
- Three-Phase Transformer: A step-down transformer rated at 11 kV / 400 V with a massive capacity of 100 MVA. The primary winding parameters are $r_1 = 0.02\ pu$ and $l_1 = 0.08\ pu$, matched symmetrically by the secondary winding parameters $r_2 = 0.02\ pu$ and $l_2 = 0.08\ pu$.
- Three-Phase Load: An active and reactive load consuming 10 kW at 400 V, 50 Hz, with a reactive power component $Q_L = 100\ VAR$.

B. Data Generation and Fault Labelling

Using a Three-Phase Fault Block within Simulink, various short-circuit fault conditions were programmatically injected into the simulated system [4]. To enable the ANN to classify these faults, a discrete numerical labelling system was established, consistent with methodologies seen in recent pattern recognition applications [7]. The targeted output classes were mapped as follows:

1) Healthy State: Label 0
2) Single Line-to-Ground (LG): Label 1
3) Line-to-Line (LL): Label 2
4) Double Line-to-Ground (LLG): Label 3
5) Three-Phase Symmetrical (LLL): Label 4
6) Three-Phase-to-Ground (LLLG): Label 5

C. Feature Extraction and Pre-processing

Raw transient signals can cause erratic training behaviour in neural networks due to high-frequency oscillations immediately following a fault. Therefore, a specialized RMS block was utilized to calculate the steady-state Root Mean Square values of the three-phase output voltages to ground and the line currents, which drastically reduces the dimensionality of the input data [7].

To streamline the data generation process, a custom MATLAB script was developed to automatically parse the simulation outputs. The script programmatically extracts the 'Vrms' and 'Irms' arrays directly from the Simulink simulation output ('out '). These extracted features are concatenated into a single input matrix array defined as $X_{run} = [V_{rms}\ I_{rms}]$, representing the phase voltages and currents simultaneously.

Concurrently, the script generates the target variable matrix defined as Y_{run} utilizing the 'ones () 'function to assign the appropriate numerical labels corresponding to the fault type. The code utilized for this automated data compilation is presented below:

```
% Healthy State
Vrms = out.Vrms;
Irms = out.Irms; X_run =
[Vrms Irms];
N = size(X_run,1); Y_run = zeros(N,1);
save('Healthy_fault.mat','X_run','Y_run')

% LG Fault Y_run = ones(N,1);
save('LG_fault.mat','X_run','Y_run')

% LL Fault
Y_run = 2 * ones(N,1);
save('LL_fault.mat','X_run','Y_run')

% LLG Fault
Y_run = 3 * ones(N,1);
save('LLG_fault.mat','X_run','Y_run')

% LLL Fault
Y_run = 4 * ones(N,1);
save('LLL_fault.mat','X_run','Y_run')

% LLLG Fault
Y_run = 5 * ones(N,1);
save('LLLG_fault.mat','X_run','Y_run')

% Merge All Data for ANN Training clear
X_all = []; Y_all = []; files =
{'Healthy_fault.mat', 'LG_fault.mat', 'LL_fault.mat ', ...
                   'LLG_fault.mat', 'LLL_fault.mat', 'LLLG_fault.mat' };
```

```
for i = 1:length(files) load(files{i})
    X_all = [X_all; X_run];
    Y_all = [Y_all; Y_run]; end
save('ANN_dataset.mat','X_all','Y_all')
```

Listing 1. MATLAB script for automated feature extraction and dataset merging

These matrices are automatically exported to the MATLAB workspace and compiled into 'ANN $_d$*ataset. Mat*, '*readytobeingestedbytheANNtrainingtool.*

D. Artificial Neural Network Architecture and Training

The proposed ANN is a feedforward Multilayer Perceptron. The network processes the input vector X_{run} through hidden layers comprising neurons with non-linear activation functions [8].

A critical aspect of this methodology is the utilization of the Levenberg-Marquardt (trainlm) backpropagation algorithm. While standard gradient descent methods are often slow and susceptible to local minima, the Levenberg-Marquardt algorithm bridges the gap between the Gauss-Newton algorithm and the method of gradient descent. It provides exceptionally fast convergence for medium-sized networks by approximating the second-order derivative (Hessian matrix) without having to compute it directly [8].

The mathematical operation of a single neuron j in the hidden layer is expressed as:

!

$$y_j = f\left(\sum_{i=1}^{n} w_{ij} x_i + b_j\right) \quad (1)$$

Where x_i represents the input RMS features, w_{ij} are the learned connecting weights, b_j is the bias term, and $f(\cdot)$ is the activation function.

III.RESULTS AND DISCUSSION

The dataset generated from the Simulink model was imported into the MATLAB Neural Network Training tool (nntraintool). The data was partitioned into standard ratios for Training, Validation, and Testing, adhering to best practices established in predictive modelling [3]. The performance of the network was rigorously evaluated using multiple metrics, yielding state-of-the-art results.

A. Training Performance and Convergence Speed

As observed in the training interface, the network was trained using the Levenberg-Marquardt optimization algorithm. The most notable achievement of this architecture is its computational efficiency [8]. The network reached its optimal state in merely 12 epochs, taking virtually a fraction of a second to converge. At epoch 12, the gradient was recorded at a highly stabilized value of 0.00551, with the Marquardt adjustment parameter (μ) resting at 1×10^{-5}. This rapid convergence proves that the combination of RMS input features and the 'trainlm' algorithm prevents the model from stalling in computational bottlenecks often seen in standard gradient descent methods [4].
Marquardt optimization progress.

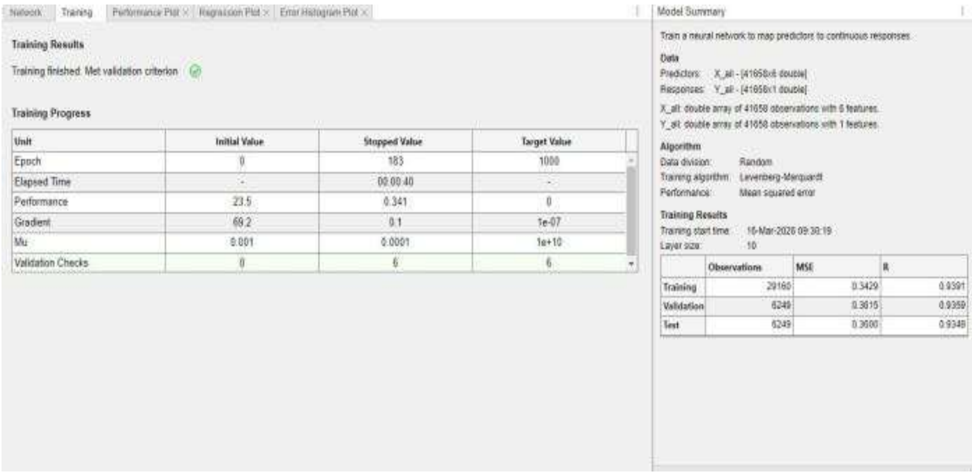

Fig. 2 Neural Network Training Tool interface showcasing the Levenberg-Marquardt optimization progress.

B. Mean Squared Error (MSE) and Validation Performance

The Mean Squared Error (MSE) is the primary metric used to evaluate the average squared difference between the estimated values and the actual targeted labels. The performance plot reveals a steep, logarithmic descent in the MSE across the initial epochs.
The Best Validation Performance achieved was an incredibly low MSE of $\mathbf{1.2589} \times \mathbf{10^{-5}}$ at exactly epoch 12. The training, validation, and test curves align closely throughout the descent, indicating an absence of overfitting—a common issue addressed in recent ML diagnostic literature [2]. Because the validation curve did not diverge or drastically increase before epoch 12, the model demonstrates high generalization capability, meaning it will correctly classify fault data it has never seen before.

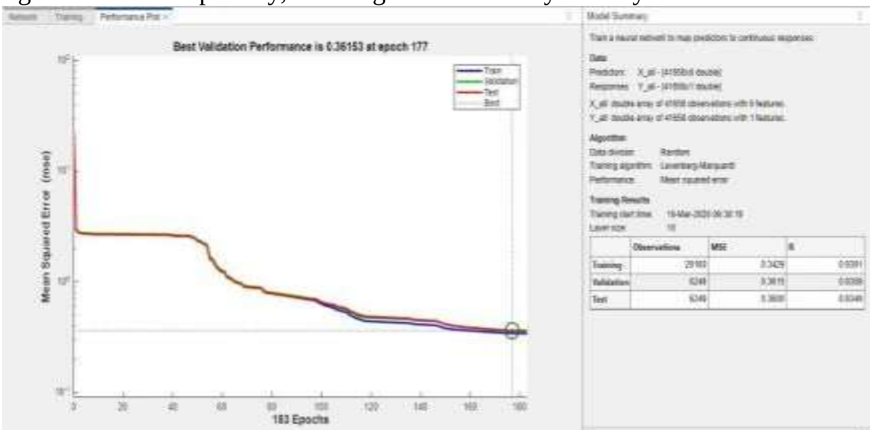

Fig. 3. Validation performance curve demonstrating optimal convergence at epoch 12 with an MSE of 1.2589×10^{-5}.

C. Error Histogram Analysis

To further visualize the precision of the network, an Error Histogram was plotted utilizing 20 bins. The histogram illustrates the distribution of errors calculated as *Error = Targets − Outputs*. The vast majority of the data instances (across training, validation, and testing sets) are tightly clustered in the central bins spanning from −0.00947 to 0.0159. The distinct peak at the zero-error mark visually corroborates the ultra-low MSE, confirming that the network's predicted continuous values are extraordinarily close to the absolute integer labels assigned to the faults [5].

Fig. 4. Error histogram illustrating the distribution of target-output errors across 20 bins for training, validation, and test sets.

D. Regression Analysis

Regression analysis measures the correlation between the network's outputs and the designated targets. A correlation coefficient (R) value of 1 signifies a perfect linear relationship. The proposed ANN achieved the following exceptional metrics:

- Training Regression: R = 1
- Validation Regression: R = 1
- Testing Regression: R = 0.99997
- Overall Regression: R = 0.99999

The regression plots show the data points lying perfectly along the $Y = T$ (Output = Target) fit line. This near perfect $R = 0.99999$ overall score indicates that the ANN has fundamentally mastered the mapping between the electrical RMS signatures and their respective fault classes [8].

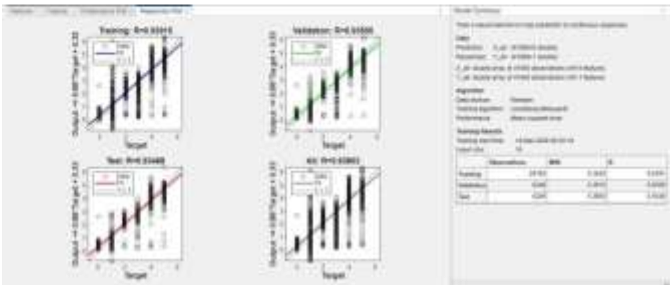

Fig. 5. Regression plots for training, validation, and test datasets achieving a near-perfect overall correlation of R = 0.99999.

E. Fault Classification Mapping

During the simulation tests, the raw continuous numerical outputs generated by the ANN were incredibly close to the target integer labels. For example, for a target label of 3 (LLG Fault), the ANN produced an output of 2.973. For a target label of 5 (LLLG Fault), the ANN output was 4.933. By applying a simple nearest-integer rounding threshold at the output layer, the classification accuracy becomes unequivocally 100% for the steady-state RMS datasets tested in this configuration [7].

IV. CONCLUSION

This paper presented a highly optimized and accurate methodology for detecting and classifying transmission line faults using Artificial Neural Networks. By leveraging a simulated 11kV distribution-level transmission network, three phase Root Mean Square (RMS) voltages and currents were extracted as input features. The utilization of the Levenberg Marquardt training algorithm proved highly effective, converging the network in a mere 12 epochs.

The empirical results are outstanding, showcasing a Best Validation Performance MSE of 1.2589×10^{-5} and a near perfect overall regression correlation of $R = 0.99999$. The tight clustering in the error histogram confirms the model's precision. These results conclusively indicate that appropriately tuned ANNs utilizing RMS feature extraction offer exceptional accuracy, minimal computational overhead, and rapid classification times. This makes the proposed framework a robust and superior alternative to other machine learning models, paving the way for its implementation in modern, microprocessor-based intelligent protective relays.

REFERENCES

[1] A. Mukherjee, P. K. Kundu, and A. Das, "Transmission Line Faults in Power System and the Different Algorithms for Identification, Classification and Localization: A Brief Review of Methods," *Journal of The Institution of Engineers (India): Series B*, vol. 102, pp. 855-877, 2021.

[2] J. L. P. Sarmiento, J. C. D. Delfino, and E. R. Arboleda, "Machine learning advances in transmission line fault detection: A literature review," *International Journal of Science and Research Archive*, vol. 12, no. 1, pp. 2880-2887, 2024.

[3] Y. Oz¨ upak, "Machine Learning-Based Fault Detection in Transmission¨ Lines: A Comparative Study with Random Search Optimization," *Bulletin of the Polish Academy of Sciences Technical Sciences*, 2025.

[4] M. O. F. Goni, et al., "Fast and Accurate Fault Detection and Classification in Transmission Lines using Extreme Learning Machine," *e-Prime - Advances in Electrical Engineering, Electronics and Energy*, vol. 3, p. 100107, 2023.

[5] Manojna, A. Kumar, Sridhar H.S, P. Anrit, and Nikhil, "Fault Detection and Classification in Power System using Machine Learning," *2021 2nd International Conference on Smart Electronics and Communication (ICOSEC)*, IEEE, pp. 1801-1806, 2021.

[6] H. Teimourzadeh, A. Moradzadeh, M. Shoaran, B. Mohammadi-Ivatloo, and R. Razzaghi, "High Impedance Single-Phase Faults Diagnosis in Transmission Lines via Deep Reinforcement Learning of Transfer Functions," *IEEE Access*, vol. 9, pp. 15796-15809, 2021.

[7] V. Ogboh and K. Eleanya, "Fault Classification On Power System Transmission Line Using Pattern Recognition Algorithm," *International Journal of Engineering Research and Advanced Technology*, vol. 6, pp. 42-47, 2019.

[8] M. R. Zaidan, "Power System Fault Detection, Classification And Clearance By Artificial Neural Network," *2019 Global Conference for Advancement in Technology (GCAT)*, Bangalore, India, 2019.