

FAULT DETECTION AND CLASSIFICATION OF TRANSMISSION LINES USING ARTIFICIAL NEURAL NETWORKS WITH MULTIPLE DATASETS

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ABSTRACT

This paper concentrates on classifying and detecting faults in transmission lines, which play a crucial role in transporting electricity from generation to distribution stations. However, these lines are frequently affected by faults caused by human interference, weather conditions, ageing conductors, and the long distances involved in transmission. A transmission line rated at 11/132 kV, 100 MVA, and 50Hz was modeled in MATLAB/SIMULINK to gather data on voltage and current under fault conditions. Training was conducted on 143 fault scenarios using the backpropagation algorithm of an Artificial Neural Network. The individual phases were analysed and subjected to fault detection and classification. 90% of the data was used for training, while validation and testing used 5% each, respectively. 77.6% of the data was ideally classified with a Root Mean Square Error (RMSE) of 0.12348, while 22.4% of the remaining data was in a confusing state. Also, RMSE 0.00415 for fault identification was recorded, and 95% of the data were correctly classified at the fault location zone. At the same time, 5% of the data was in a confused state. The proposed model can facilitate quick and accurate localization and detection of faults on transmission lines, considering their type and severity. This model delivers valid results, is user-friendly, and executes with precision and speed. However, it has limitations, as the output results indicate that fault classification accuracy is poor. Incorporating machine learning algorithms could enhance the accuracy of fault classification.

Keywords: Backpropagation, Artificial Neural Network, fault detection, Fault localisation, fault classification

I. INTRODUCTION

The transmission line is a crucial component of the power system, connecting generating stations with distribution units. However, these networks are susceptible to unavoidable faults that cannot be managed through physical or human intervention but require advanced techniques. [1]. A fault in a power system is any abnormality or failure in current flow caused by human error, overload, environmental factors, or adverse weather conditions such as rain, wind, snow, and fog. These faults disrupt electricity flow, leading to short circuits, system instability, industrial load failures due to voltage drops in healthy feeders, blackouts, power loss, and economic disruptions. Therefore, it is crucial to implement effective measures for maximum transmission line protection. This can

be achieved using modern techniques for fault detection, classification, and localization, enabling quick and accurate line isolation to prevent system collapse. [2]. However, feedback from fault classification can significantly assist in detecting fault locations for fast clearing time to restore power [3].

Various types of faults occur in transmission lines, including short circuit faults. These faults happen when the load current is disrupted due to installation breakdowns caused by sparks across facilities, aging equipment, temperature changes, adverse weather, chemical pollution, or foreign objects like trees and animals on the lines. Other types of faults are phase and ground faults. A ground fault involves a connection between one phase conductor and the ground, while a phase fault involves two or

more phase conductors, either with or without ground involvement. Examples are as follows.

- i. Line-to-ground fault (L-G)
- ii. Line-to-line fault (L-L)
- iii. Three-line fault (L-L-L).

Faults are classified according to the severity of occurrence, and the most common faults are the L-L and L-G faults, while the most intense is the L-L-L and L-L-L-G faults.

Table 1 summaries the different types of faults and their percentage of occurrence in transmission line

Table 1: An overview of different kinds of faults

Types of faults	Symbol	% Occurrence	Severity
Line to ground	L-G	75-80%	Very less severe
Line to line	L-L	10-15%	Less severe
Double line to ground	L-L-G	5-10%	Severe
Three phases	L-L-L or L-L-L-G	2-5%	Very severe

II. PROTECTION OF TRANSMISSION LINE

The fault must be detected and classified for a transmission line to be fully protected. The location of the fault must be accurate for quick isolation of the line to save it from system collapse. Figure 1 provides a simplified overview of a network's fault correction flow. The input signal consists of high voltage, which is sent to the current and voltage signal acquisition stage to be converted between analogue and digital formats. The next stage is the data processing unit, which extracts the necessary information from the signal. The fault detection unit then ensures a reliable and rapid relaying operation. The primary protective relays for the transmission line include the overcurrent protection relay, directional overcurrent relay, distance relay, and pilot relay. These relays protect the line from both symmetrical and unsymmetrical faults. However, they do not offer complete protection due to the frequent occurrence of short-circuit faults in the distribution network. [4]. The fault locator and classifier section is used to locate the exact distance of the fault and determine the fault type and phase.

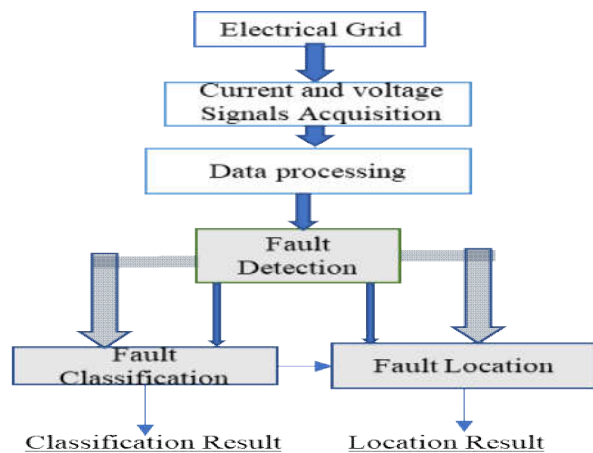


Figure 1: Fault location, detection and classification diagram

This paper explores the use of machine learning techniques for detecting and classifying faults due to their speed and accuracy. One such technique is the artificial neural network, which involves two main steps. The first step is modelling the network to extract fault cases from the transmission line using MATLAB/SIMULINK. The second step involves using the data obtained from these simulations to detect and classify the faults with the aid of a trained classifier. [5].

Recent literature focused on both conventional techniques which include the distance relay approach [4], [6]–[9], the use of mobile robot[10], [11], fuzzy logic approach [12], wavelet approach [13], [14], neuro-fuzzy technique[15], [16]. While the machine learning and artificial intelligent approach include Artificial neural network (ANN) [17]–[21], support vector machine SVM[1], [22], Decision tree (DT)[23]. These methods have been used with great success based on accuracy and precision, though there have been some drawbacks. Some techniques like wavelets are useful where time and frequency data are needed. However, it is sensitive to noise and harmonics, requires a high sampling rate and is time-consuming because getting a referred wavelet and the number of decompositions is done by trials. WT and ANN are predominantly used for fault detection and classification[24]. Many hybrid methods have been combined to produce good results, such as S-transform and ANN, and this method was used to detect and classify faults on transmission lines. Though the ANN and SVM have produced good results in identifying faults, it need a large volume of data for their training, which makes it complex to handle [25]. WT detects faults accurately and instantly, though it is difficult to differentiate between the various fault conditions[26]. Though most of these methods have been used in recent times, there have been some challenges, such as not being applicable for high-frequency signals and high computational complexity for Hilbert-Huang transform HHT [27]. Principal Component Analysis (PCA) in machine learning is a straightforward and efficient technique that reduces re-projection errors and is resistant to noise. However, when the number of dimensions exceeds the number of data points, the convergence matrix becomes very large, which can complicate the process of obtaining it. [28]. The methods previously discussed each have their limitations. Consequently, this paper seeks to improve upon these methods by offering enhanced techniques for fault detection, classification, and localization. A key observation is that many existing studies fail to provide a thorough explanation of fault localization, making it challenging to quickly isolate and address major repairs of faults.

Also, In discrete wavelet transform (DWT) and decision Tree (DT) [29], It has limited time resolution capability and low performance for high-performance fault. In wavelet and data mining [30], K- Nearest Neighbours (KNN) and Decision Tree (DT) fault locations are not measured. In [31], the S-transform technique, fault location and classification were not determined. Differential and Hibert-Huang transmission (HHT) technique is very expensive and have no-fault direction. Also, mathematical

morphology and the Recursive Least-square (RLS) method [32] have high calculation and technical standards that need an expert to implement. Another shortcoming from these techniques already explained was the inability to focus more on fault localisation. Localisation of fault assists in quick diagnosing and restoration of power during fault.

III. METHODOLOGY

ANN are prototypes that are derived from sensory systems. This model accepts many input parameters and returns a single output result [33]. Artificial neural networks, as computational models for human nervous systems, aid in establishing relationships

between any system's inputs and outputs.

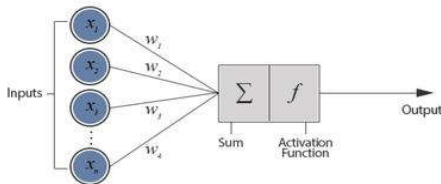


Figure 2. structure of ANN propagation

Neurons are the basic units in the nervous system where information is processed.

Incoming information takes the form of signals, which are transmitted between neurons via connection links. Each neuron has an internal action triggered by a bias or firing threshold, resulting in an activation function being applied to the weighted sum of the input signals to generate an output signal.

As shown in the diagram above, each connection link has a weight that multiplies the signal sent. When input signal $x_1, x_2, \dots, x_n$ reach the neuron through a connection link with associated weights $w_1, w_2, \dots, w_n$ respectively, the resulting input to the neuron called the net input, is the weighted sum $\sum_{i=1}^n w_i \cdot x_i$. if the firing threshold is b and the activation function is f then the output of the neuron is

$$y = f(\sum_{i=1}^n w_i \cdot x_i) \quad (1)$$

The method used here is the backpropagation algorithm, which is the generalisation of the delta rule. The delta rule for single-layer neural networks is generalised that, to update a weight w_{ik} when the learning input pattern x^q is represented, we need $\Delta w_{ik} = \delta_i^q \cdot x_k^q$. Because backpropagation employs the gradient descent method, the derivative of the square error function relating to the network's weight must be determined. The square function, assuming one output neuron, is $E = \frac{1}{2}(t - y)^2$ (2)

Where E represents the square error, t represents the target output for a training sample, and y represents the actual output neuron.

When differentiating, a factor of $\frac{1}{2}$ is used to cancel the exponent. Because the expression will later be multiplied by an arbitrary learning rate, making no difference if a constant coefficient is introduced now. For each neuron j , its output o_j is defined as

$$o_j = \varphi(\text{net}_j) = \varphi(\sum_{k=1}^n w_{kj} x_k) \quad (3)$$

The input net_j to a neuron is the weighted sum of previous neurons' outputs o_j . If the neuron is in the first layer after the input layer, the layer is simply the network's inputs x_j . The neuron has n input units. The variable w_{kj} The weight between neurons i and j . In general, the activation function φ is nonlinear and differentiable.

A. MODELLING OF 11/132 kV THREE PHASE TRANSMISSION LINE

A three-phase transmission line with specifications of 11/132 kV, 100 MVA, and 50 Hz is modelled using SIMULINK, as illustrated in Figure 3 below. The model incorporates transmission line parameters that are input into the system. Faults are introduced at various locations to measure the resulting faulty current and voltage. This generated dataset is then used as input data for training the neural network.

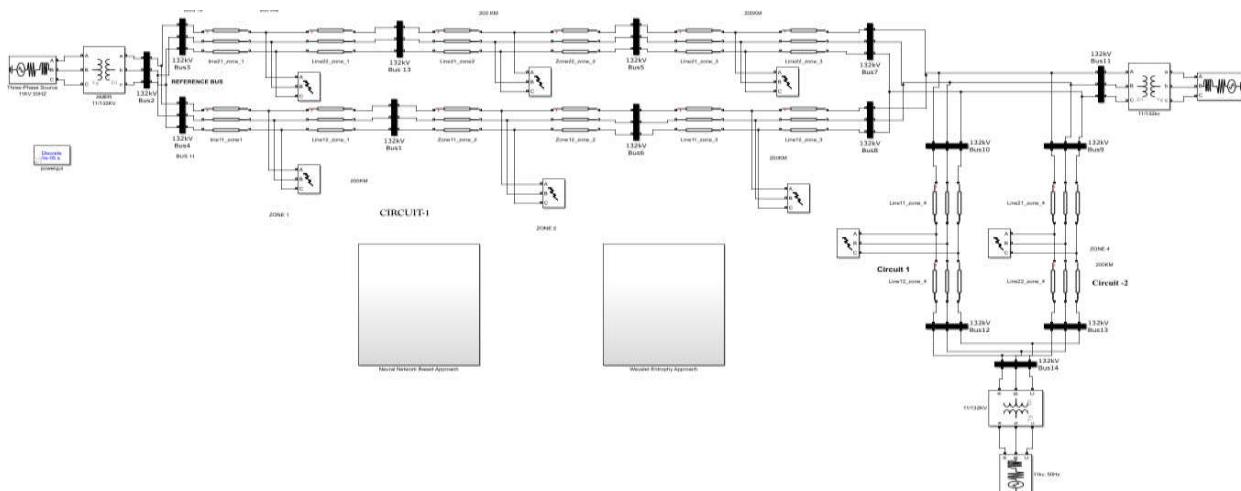


Figure 3. SIMULINK model for the proposed Transmission line

The transmission line model consists of three transmission lines operating on 11 /132 kV, 100 MVA, 50 Hz supply. Faults were applied in different locations to generate current, and voltage fault data were used to form a dataset for the ANN training.

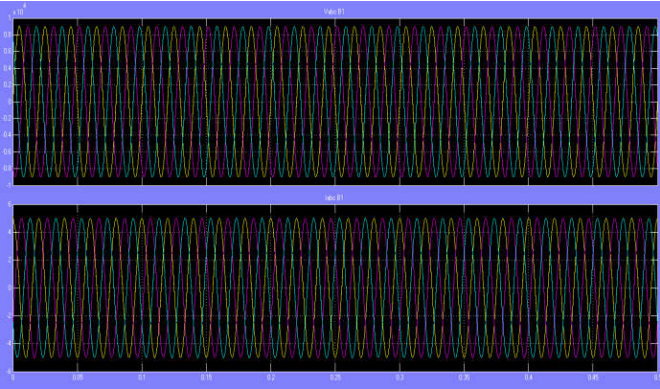


Figure 4. Three voltage and current waveforms were measured at bus bar 1 under normal conditions.

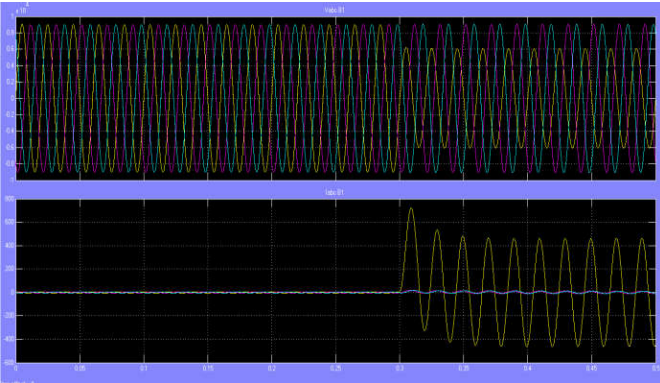


Figure 5. When the LG (AG) fault occurs in zone 1 on 20km from reference bus bar 1, three voltage and current waveforms are produced.

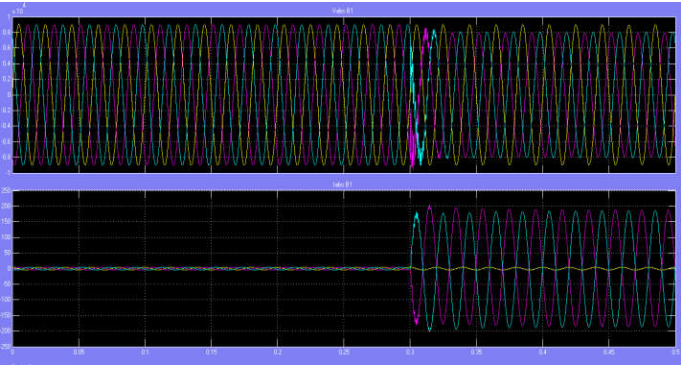


Figure 6. Three voltage and current waveforms are produced when the LLG (BCG) fault occurs in zone 2, 120 km from reference bus bar 1.

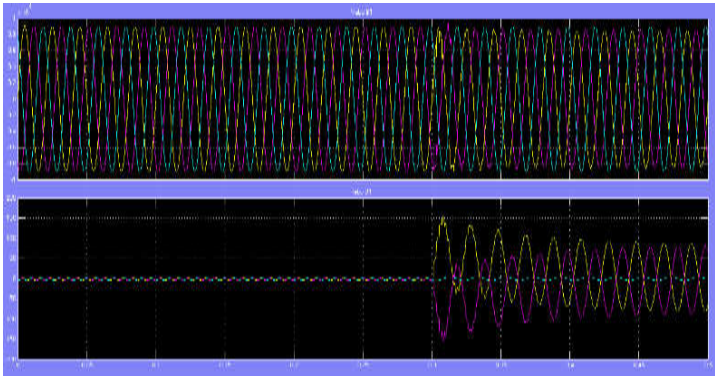


Figure 7. Three voltage and current waveforms are produced when the LL (AB) fault occurs in zone 3 on 285 km from reference bus bar 1.

IV. RESULTS AND DISCUSSION

- A. The ANN training for fault classification and zone identification was carried out using two different neural network structures, though both networks received the same input data. The training parameters from bus bar 1 included positive sequence three-phase active and reactive power, actual active power, individual currents, and phase voltage. The training process covered 143 distinct fault cases, simulated across three transmission line zones. Each phase of the transmission line was tested at ten different fault locations with three types of unsymmetrical faults and two types of symmetrical faults. Each simulation of the transmission line lasted one second, with each fault event lasting 0.3 seconds. For all fault simulations, the fault resistance and ground resistance were set to 0.001 ohms.
- ANN TRAINING FOR FAULT CLASSIFICATION*

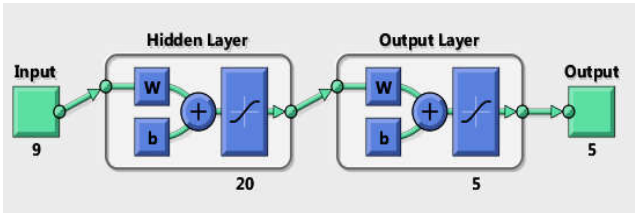


Figure 8. Configuration of a neural network for fault classification training

Results			
	Samples	MSE	%E
Training:	129	9.35256e-2	18.60465e-0
Validation:	7	1.23484e-1	42.85714e-0
Testing:	7	1.79064e-1	71.42857e-0

Figure 9. Training of neural network for fault classification

Out of 143 fault sample case data sets, 129 data samples were used for training, accounting for 90% of the data used for training. A 5% dataset was used for validation and testing. A neural network takes 28 epochs to train for fault classification,

and the mean square error becomes a minimum of 0.12348, as shown by the green line in Figure 9.

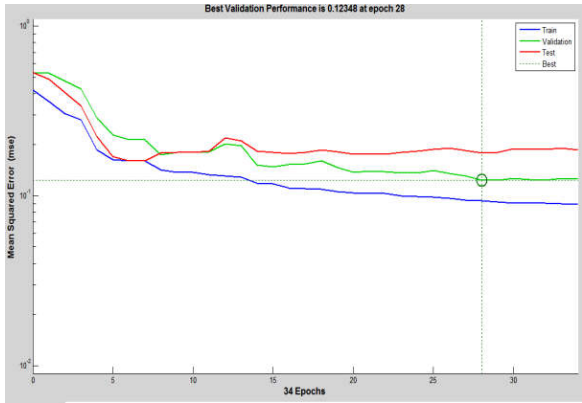


Figure 10. The neural network's training performance for fault classification

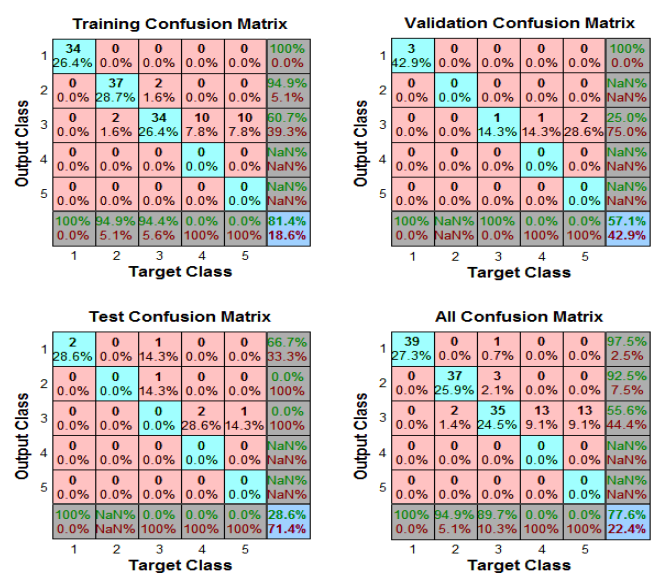


Figure 11. Confusion matrix for neural network training for fault classification.

Figure 10 shows that 77.6 percent of the data perfectly classify the fault, while the remaining fault case data do not classify using neural network 1. This means that the data set neural network was confusing for classifying the fault for the remaining 23% of the cases.

B. TRAINING OF ARTIFICIAL NEURAL NETWORKS FOR FAULT ZONE IDENTIFICATION

In the neural network training for fault zone identification, the neural network required 77 epochs to complete. The mean square error reached a minimum value of 0.004156, as indicated by the green line in Figure 14, which corresponds to approximately 0.4156%. Figure 15 demonstrates that 95% of the data was accurately classified into fault zones, while Neural Network 1 failed to classify the remaining 5% of the fault cases. This indicates that the neural network struggled to accurately

classify the fault zones for this 5% of the dataset.

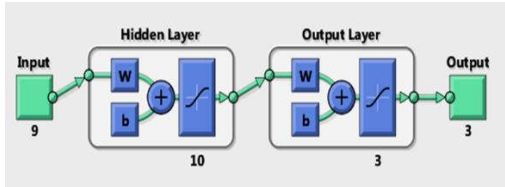


Figure 12. Neural network configuration for fault zone identification

Results			
	Samples	MSE	%E
Training:	129	2.92287e-2	4.65116e-0
Validation:	7	4.14676e-3	0
Testing:	7	1.28641e-3	0

Figure 13. Training performance parameter for neural network fault zone identification.

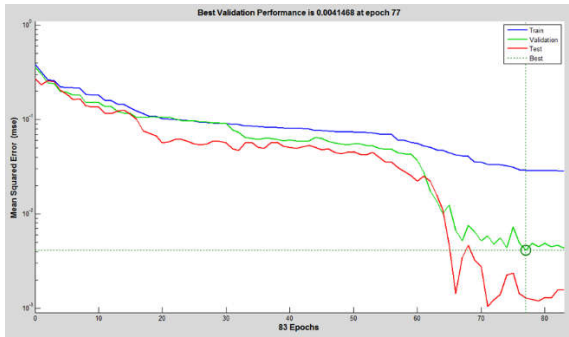


Figure 14. The neural network's training performance for fault zone identification.

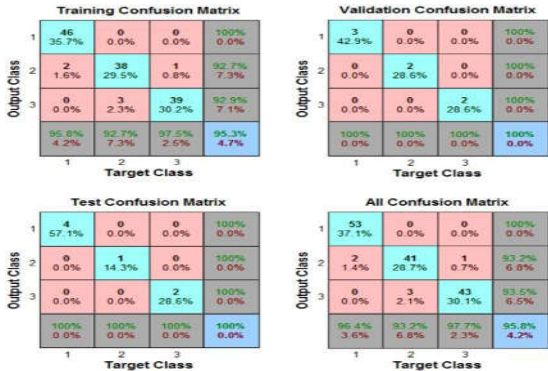


Figure 15. Confusion matrix for neural network training for fault zone identification.

V. CONCLUSION

This paper has examined various types of faults in transmission lines and their impact on the electricity delivered to end-users. It has also discussed fault classification, detection, and localization, highlighting the use of Artificial Neural Networks (ANN) for fault classification. Fault data was gathered from a modelled transmission line network, using fault current and voltage as inputs to train the neural network. The results from the ANN training indicate that this method can classify and detect faults with 95% accuracy. Additionally, the technique is

user-friendly and does not require complex mathematical models, as demonstrated by the confusion matrix results obtained from the ANN algorithm..

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