TRANSMISSION LINE FAULT DETECTION AND CLASSIFICATION OF MULTI - DATASETS USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

This paper focuses on fault classification and detection in the transmission line, and these lines are instrumental in the transportation of electricity from the generation to the distribution station. However, faults always affect the line due to human interference, weather, ageing conductors, and long-distance transmission line. An 11/132 kV, 100 MVA, 50Hz transmission line was modelled using MATLAB/SIMULINK to extract faulty line voltage and current data. The training was carried out for 143 fault cases using the Artificial Neural network's backpropagation algorithm. The individual phases were analysed and subjected to fault detection and classification. A total of 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 Root Mean Square Error (RMSE) of 0.12348, while 22.4% of the remaining data was at 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 be helpful in fast and accurate localisation and detection of faults based on their types and severity on the transmission line. This model produces a valid result, easy to use, precision and speed in execution. However, this technique has limitations based on the output results, which show that fault classification produces poor accuracy; therefore, machine learning algorithms can improve this.

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

1. INTRODUCTION

The transmission line forms an integral part of the power system because it links the generating stations and the distribution units. However, these networks are prone to inevitable faults and cannot be controlled by physical or human intervention but by advanced technique [1]. A fault is any abnormality or failure of the current flow in a power system caused by human error, overload, environment, adverse weather conditions such as rain, wind, snow and fog. This fault has caused interruption in the flow of electricity, which has led to short circuits, loos of system stability, failure of industrial load due to drop in voltage of healthy feeders, blackout, loss of power and cripple economic activities. Therefore, adequate measures must be put in place to provide maximum protection of the transmission line. This can be achieved by a modern technique involving fault detection, classification, and localization for quick and accurate line isolation to prevent system collapse [2]. However, feedback gotten from fault classification can significantly assist in detecting fault location for fast clearing time to restore power[3].

Diverse categories of fault occur in transmission lines, some of which are short circuit faults. This type of fault occurs when the load current is interrupted due to installation breakdown due to spark gap across the facility, ageing equipment, temperature change, adverse weather condition, chemical pollution, and foreign objects like trees and animals on lines. Other types of faults include phase and ground faults. Ground fault involves one phase conductor and ground, while phase fault requires two or more phase conductors with or without ground. 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 fault.

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

Table: An overview of 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

1.2 PROTECTION OF TRANSMISSION LINE

For a transmission line to be fully protected, the fault must be detected and classified. The location of the fault must be accurate for quick isolation of the line to save it from system collapse. Figure 1 represents a simplified explanation of the flow of fault correction in a network. The input signal consists of high voltage sent to the current and voltage signal acquisition, which helps convert it to either analogue to digital or vice versa. The next stage is the data processing unit, which helps extract the data or signal the valuable information needed in the module. The fault detection unit provides a reliable and fast relaying operation. The dominant protective relays for the transmission line are the overcurrent protection relay, directional overcurrent relay, distance relay, and pilot relay. This Relay helps to shield the line against symmetrical and unsymmetrical faults. However, it does not guarantee full protection due to frequent short circuit faults at the distribution network. The fault locator and classifier section is used to locate the exact distance of fault and determine the fault type and phase.

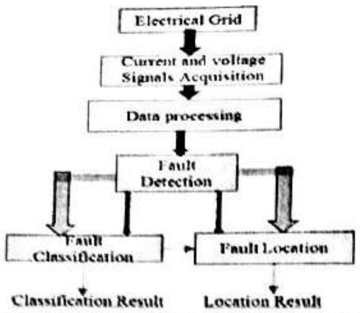

Figure 1: Fault location, detection and classification diagram

This paper is focused on the use of machine learning techniques in detecting and classifying faults due to their speed and accuracy. One of the machine learning techniques used is the artificial neural network technique. This technique is divided into two major parts, first is the modelling of the network to extract faults case from the transmission line using MATLAB/SIMULINK, the next is to detect and classify the faults using the data gotten from the simulations to detect and classify the fault with the help of a trained classifier.

Recent literature focused on both conventional techniques which include distance relay approach ——, the use of mobile robot, fuzzy logic approach, wavelet approach, neuro-fuzzy technique. While the machine learning and artificial intelligent approach include Artificial neural network (ANN) ——, support vector machine SVM), Decision tree (DT). All these methods have been used with great success based on accuracy and precision, though there have been some drawbacks. Some of the techniques like wavelet are useful where time and frequency data is 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. 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 needs a large volume of data for its training, which makes it complex to handle. WT detects faults accurately and instantly, though it is difficult to differentiate between the various fault conditions. 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. Using principal component analysis PCA in machine learning is a simple and fast method that minimizes re-projection error and is immune to noise. However, the convergence matrix is always large if the number of dimensions is greater than the number of data points, making it difficult to obtain the convergence matrix. The various methods mentioned above have their setbacks; therefore, this paper aims to address them by providing better fault detection, classification, and localization methods. The main noticeable observation is inability of most of the papers to explain extensively fault localization thereby making it difficult to isolate or take on major repairs of fault within the shortest possible time. Also, In discrete wavelet transform (DWT) and decision Tree (DT). It has limited time resolution capability and low performance for high performance fault. In wavelet and data mining, K- Nearest Neighbours (KNN) and Decision Tree (DT) fault location are not measured. In, S-transform technique, fault location and classification were not determined. Differential and Hibert-Huang transmission (HHT) technique is very expensive and no-fault direction. Also, in mathematical morphology and Recursive Least-square (RLS) method has high calculation and technical standard which needs an expert to implement.

Another shortcoming from these techniques already explained was the inability to focus more on fault localization. Localization of fault assist in quick diagnosing and restoration of power during fault.

I. METHODOLOGY

Artificial Neural Networks are mathematical models derived from biological nervous systems. They are attractive as computation devices that can accept many inputs and learn solely from training samples. As mathematical models for biological nervous systems, artificial neural networks help establish relationships between inputs and outputs of any system.

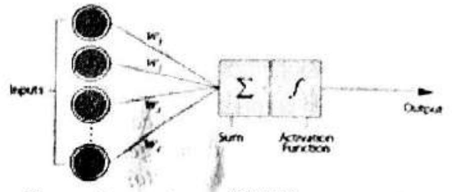

Figure 2 structure of ANN propagation

Neurons are the elementary units in a nervous system at which information processing occurs.

Incoming information is in the form of signals that are passed between neurons through connection links. Each neuron has an internal action, depending on a bias or firing threshold, resulting in an activation function being applied to the weighted sum of the input signals to produce an output signal.

As seen in the figure above, each connection link has a proper weight that multiplies the signal transmitted. When input signal x1, x2, ... xn reach the neuron through connection link with associated weights w1, w2, ... wn respectively, the resulting input to the neuron called the net input, is the weighted sum $\sum_{i=1}^{n} w_i x_i$ if the firing threshold is $\varphi(\sum_{i=1}^{n} w_i x_i)$

(1) The method used here is the back propagation algorithm, which is the generalisation of the delta rule. The delta rule for single-layer neural networks is generalised that, to update a weight $\Delta w^q ik = \delta_i^q . . x_k^q$. 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 $o_j = \varphi(net_j) = \varphi(\sum_{k=1}^{n} w_{kj} x_k)$

(3) The input net_i 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 comprising 11/132 kV, 100 MVA, 50 Hz is modelled using SIMULINK, as shown in figure 3 below. The model comprises transmission line parameters that are fed into the system. The fault is initiated at different locations to measure faulty current and voltage from the line. The dataset is generated and used as input data for the training of the neural network.

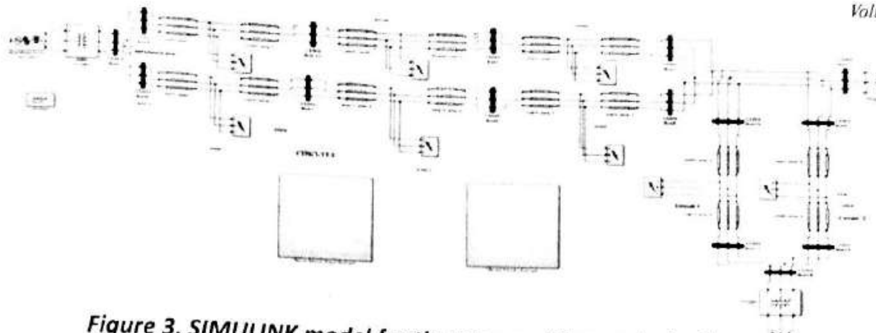

Figure 3. SIMULINK model for the proposed Transmission line

he 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.

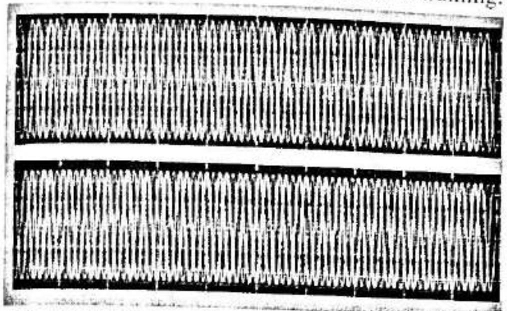

Figure 4. Three voltage and current waveforms were measured at bus bar 1 under normal conditions.

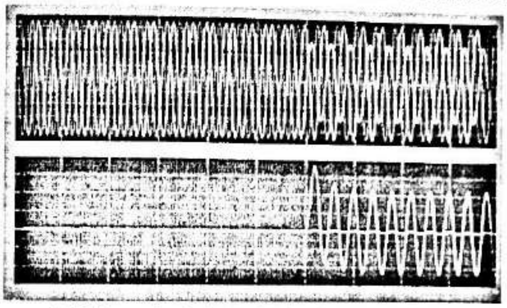

Figure 5. When the LG (AG) fault occurs in zone 1 on 20km from reference bus bar 1, three voltage and current waveforms are produced

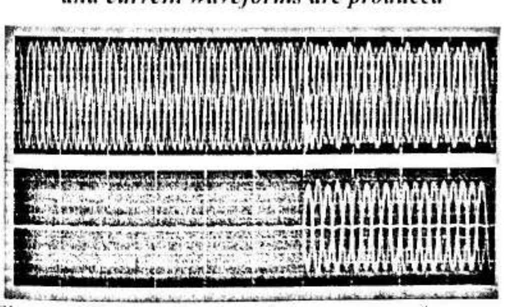

Figure 6. Three voltage and current waveforms are produced when the LLG (BCG) fault occurs in zone 2, 120 km from reference bus bar 1.

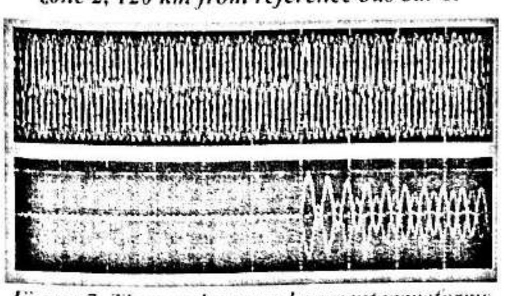

Figure 7. Three voltage and current waveforms are produced when the LL (AB) fault occurs in zone 3 on 285 km from reference bus bar 1

This paper is focused on the use of machine learning techniques in detecting and classifying faults due to their speed and accuracy. One of the machine learning techniques used is the artificial neural network technique. This technique is divided into two major parts, first is the modelling of the network to extract faults case from the transmission line using MATLAB/SIMULINK, the next is to detect and classify the faults using the data gotten from the simulations to detect and classify the fault with the help of a trained classifier

3.0 Training Of The Artificial Neural Network

The training of ANN for fault classification and fault zone identification is carried out for the two separate neural network structures are utilized. Still, the input of both networks is the same. The bus bar 1 measurement parameters used are positive sequence three phases active and reactive power, actual active power, each current and phase voltage was used for the training. The training was carried out for 143 fault cases. These fault cases simulate in three zones of the transmission line. Total three unsymmetrical and two symmetrical fault cases simulate each transmission line phase at different ten fault locations. Always transmission line simulates for 1 second of simulation time, and each fault event takes 0.3 seconds. During that fault, resistance becomes 0.001 ohms and ground resistance 0.001 ohms for all types of fault simulation.

3.1 Ann Training For Fault Classification

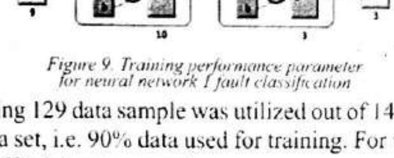

Figure 8. Neural network configuration for fault classification training

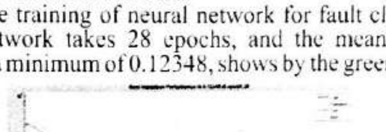

Figure 9. Training performance parameter for neural network I fault classification

For training 129 data sample was utilized out of 143 fault sample cases data set, i.e. 90% data used for training. For validation and testing, a 5% dataset was used.

During the training of neural network for fault classification, a neural network takes 28 epochs, and the mean square error becomes a minimum of 0.12348, shows by the green line in figure 9

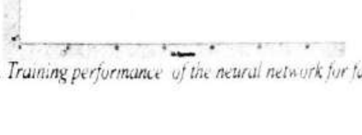

Figure 10. Training performance of the neural network for fault classification

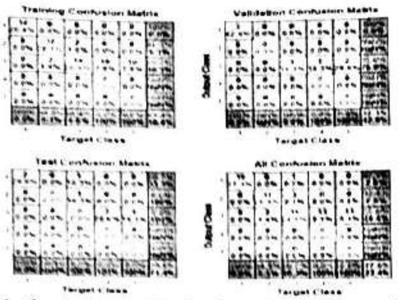

Figure 11. Confusion matrix for the training of neural network 1 for fault classification

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

ANN TRAINING FOR FAULT ZONE IDENTIFICATION

Results

	Samples	MSE	%E
Training:	129	2.92287e-2	4.65116e-0
Validation:	7	4.34676e-3	0
Testing:	7	1.28641e-3	0

Figure 12. Neural network configuration for fault zone ide

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 13. Training performance parameter for neural network 2 fault zone identification.

During the neural network training for fault zone identification, a neural network takes 77 epochs. The mean square error becomes a minimum of 0.004156, shown by the green line in figure 13, which is about 0.4156%. Figure 14 shows that 95 % of data classify the fault zone perfectly, and the remaining fault case data do not classify using neural network 1. It means that for the remaining 5 % data set, the neural network was confused to classify the fault zone.

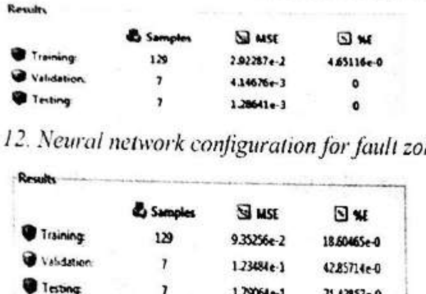

Figure 14. Training performance of neural network 2 for fault zone identification

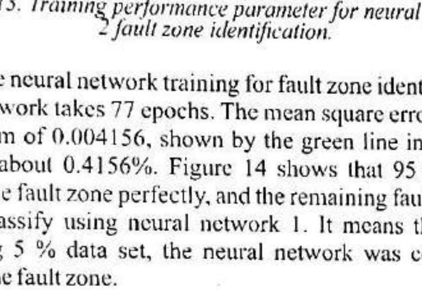

Figure 15. Confusion matrix for training of neural network 2 for fault zone identification

CONCLUSION

This paper has analysed different types of fault in transmission lines and how this fault affects the output of electricity delivered to the end-users. Fault classification, detection, and localization have also been discussed, emphasising the use of Artificial Neural Network to classify fault. Fault data was collected from a modelled transmission line network, fault current and voltage was used as input in training the neural network. The result from the ANN training shows that this method is used to classify and detect a fault with 95% accuracy, and the technique is easy to use without tedious mathematical models. This can be seen in the confusion matrix result obtained from the ANN algorithm.

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