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Deep Neural Network Based Transmission Line Fault Location Algorithm

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Abstract: The transmission lines form a very important component of the power system. Hence, they have to work reliably in transmitting the power. It has been observed that fault occurrence chances on transmission lines are more. Hence to make the network reliable there arises a need for detection and isolation of faults taking place at various locations of the line. In this paper a method using Deep Neural Network is being implemented for location of fault. The research work is carried out for a network consisting of two busesand 100 km length line and 132 kV as working voltage. The feature extraction is done using the Discrete Wavelet Transform (DWT) in combination with Principal Component Analysis (PCA). The features are used in training the neural network. The model works on feed forwardalgorithm. The network helps in locating the faults with higher accuracy.

Keywords: *Transmission lines; Fault; Wavelets; Principal Component Analysis; MATLAB/Simulink; NeuralNetwork; Decomposition Coefficients*

1. Introduction

High voltage transmission lines get exposed to a complicated environment over a extended period due to their considerable length. Regular short-circuits lead to a substantial impact on the system's stability. So studying fault localization based on measurement data has become crucial. There are various methods devised for fault location[1]. Travelling waves also help to identify the faults efficiently[2]. Wavelets and decomposition techniques are used in DWT based systems. SVM approaches, one of the classification strategies, also deals with the related issue [3]. The technique involving synchronous phasors does have a higher potential for locating faults. But the phasor measurement technique makes it costly [4]. Signal analysis techniques are based on Fourier and wavelet analysis [5]. For signal decomposition, the discrete wavelet transform (DWT) is used. The feature extraction technique also use the same methodology [6].

The comparison of features extracted with the help of Principal Component Analysis (PCA) is done with those obtained by Linear Discriminant Analysis (LDA). A comparison in respect of time consumed and other parameters is done [7].

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The non-stationary signals undergo the signal processing and fault investigation is carried out by neural network [8]. Deep neural networks make use of layers (called as input, hidden and output) connected to one another. Creating a sizable input dataset and using it to train the network are prerequisites for this method. Accuracy of the neural network increases with training. Deep neural networks' capacity for self-adaptation makes them a popular choice for defect categorization. The model, which was formed on thebasis of dataset generated from power system network model, detected the defects more accurately[9]. To determine the type of transmission line defect, deep learning models, namely ann and cnn, were employed. The performances of the two networks were contrasted [10]. Implementation of neural networks is done based on discrete wavelet transform and it provides better accuracy in classification implemented for microgrids [11]. SSAE neural network is implemented that hasgreater ability to extract features [12]. The wavelets extract the necessary features which are further worked upon by PCA to reduce their dimensionality [13]. The processing of signals is done automatically and deep learning technique classifies the faults for ten different cases [14]. The method employs 13 level DWT and features are selected from feed forward algorithm [15].

2. Method

As given in figure 1, the suggested power system consists of a transmission line that has 100 km length and voltage, 132 kV. At the receiving end, bus 2 is connected to the static load of 25 MW and 50 MVAR. The line, that will simulate various unsymmetrical faults, such as S-L-G(Single Line to Ground), L-L(Line to Line), L-L-G(Double Line to Ground) and three phase faults at various fault locations and fault resistance values, is linked to the fault simulating block.

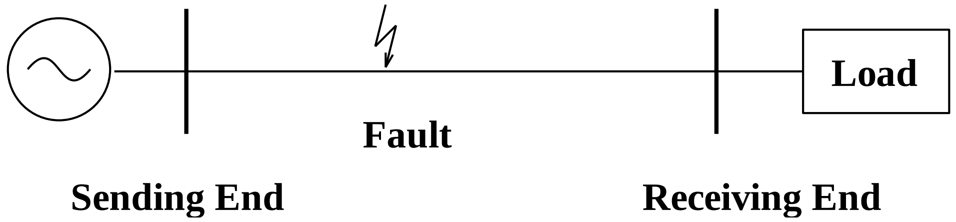

Fig 1. The two-bus system

Table 1 has the transmission line specifications in terms of positive sequence and zero sequence resistance, inductance and capacitance.

Table 1. The Specifications for Transmission Line

Variable	Value
Resistance (Positive Sequence)	100.039 Ω/km
Resistance (Zero Sequence)	0.1021 Ω/km
Inductance (Positive Sequence)	1.012e-3H/km
Inductance (Zero Sequence)	2.0281e-3H/km
Capacitance (Positive Sequence)	7.456e-9F/km
Capacitance (Zero Sequence)	4.4e-9F/km

Figure 2 shows the block diagram for the system that uses a neural network to locate the fault. The dataset is generated by performing simulations on the power system model in MATLAB. Feature extraction is done by Discrete Wavelet Transform at level 1 using Daubhechie's mother wavelet dB5. The Principal Component Analysis (PCA) is used for extracting features that are dominant. The features are input to the neural network model. The features are used to train and test the network.

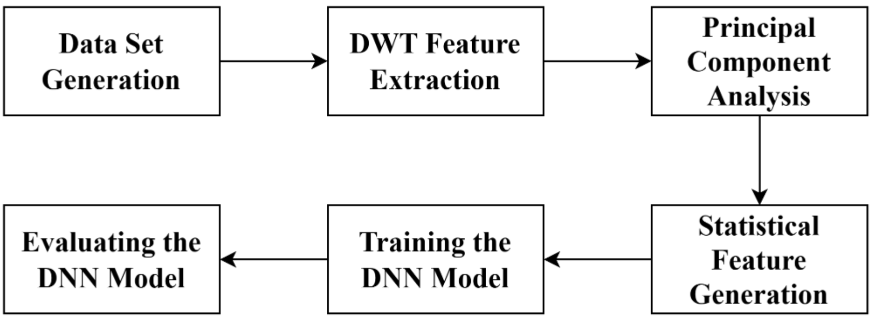

Fig 2. System Block Diagram

The power system is simulated in Matlab-simulink. The simulation is run to obtain prefault and post fault voltages and currents by creating faults at various locations. The obtained values are converted into the useful feature set using the discrete wavelet technique and principal component analysis. They help to reduce the dimensionality in time and space.

The process of transforming the original data into a new features set is called feature extraction. It aids in producing only pertinent or helpful features, reducing redundancy in the process. To extract the features, DWT and PCA are merged into a single method. Since the DWT transform preserves information in time as well as frequency domains, it is recommended over the FFT when obtaining the frequency components of a signal [16]. The linear dimensionality is decreased with PCA. It's employed to extract the salient characteristics [17]. The DWT and PCA are combined to enhance feature extraction procedure [18]. The actual data serves as the input, while features that most accurately reflect the input data serve as the output. It also lessens the intricacy of space and time. The parameters measured are three phase current magnitude, phase angle, and frequency, three phase voltage magnitude, phase angle and individual phase voltage magnitude. These are measured at the transmission line's transmitting terminals. The method used determines the fault location precisely for various faults using neural network [19]. The paper summarizes the use of DWT for locating the fault with the help of travelling wave technique for a hybrid system [20]. The method of ICA

(Independent Component Analysis) for fault location is implemented and compared with DWT [21].

Non-stationary signals are ones whose frequency composition varies over time. Signals in power systems transient state analysis are typically non-stationary. The wavelet transform is an effective method for examining signals that are non-stationary. According to wavelet transform theory, a sequence of wavelets can be formed from transient signals. This method has been used to power system research thus far for the analysis of various transient signals, particularly traveling waves of voltage and current.

Wavelets are produced by applying scale S and translation τ parameters to a mother wavelet $\psi(t)$.

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\psi\frac{(t-\tau)}{s} \tag{1}$$

Also, it is given as

$$\psi_{j,k}(t) = 2^{\frac{-j}{2}}\psi(2^{-j}t - k) \tag{2}$$

Scale and translation parameters are denoted by j and k, respectively. The wavelet is moved in the time domain by parameter k, and the amount of signal compression is adjusted by parameter j. The signal in DWT is broken down into approximations and details. Smaller frequencies are referred to as signal approximations, and smaller scales are referred to as signal details.

Daubhechie's mother db5 wavelet computes the level 1 discrete wavelet transform of input signal data. Figure 3 illustrates the stages involved in decomposition. It results in decomposition of signal into and detail and approximation coefficients [22].

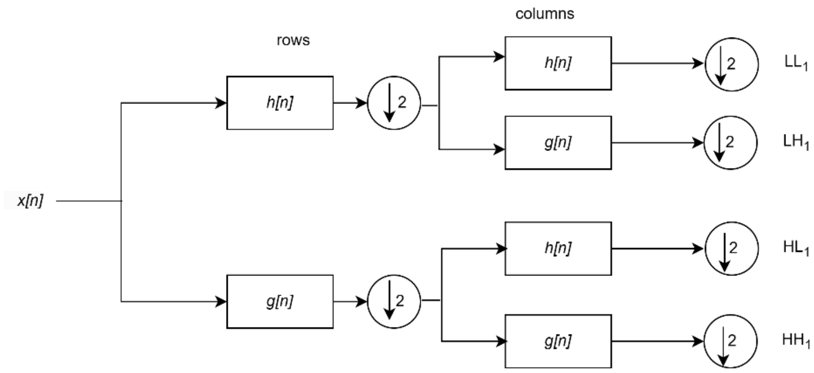

Fig 3. Two-Dimensional DWT

3. Results and Discussion

The dataset is generated by performing simulations on the power system model in MATLAB. Feature extraction is done by Discrete Wavelet Transform at level 1 using Daubhechie's mother wavelet dB5. The principal component analysis extracts the dominant features. The features are input to the neural network model. The simulation is run to obtain prefault and post fault voltages and currents by creating faults at various locations. The faults are simulated in MATLAB for every 1 km upto 100 km with the fault resistance values ranging from 0.25 ohm to 130

ohm. The faults types simulated are phase A-G, B-G, C-G, phases A-B, A-C, B-C, A-B-G and B-C-G along with no-fault condition. The parameters measured are three phase current magnitude, phase angle, and frequency, three phase voltage magnitude, phase angle and individual phase voltage magnitude. These are measured at the transmission line's transmitting terminals. Figure 4 illustrates how the three phase voltage waveforms for the specified power system network are obtained under typical operating conditions. Each phase's amplitude is the same.

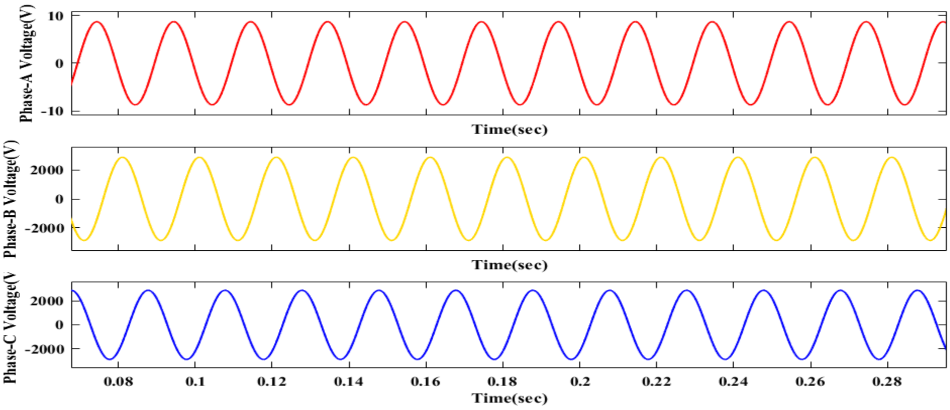

Figure 4. Prefault Three Phase Voltage Waveforms

The S-L-G fault is simulated with phase A as the faulted phase. In MATLAB, the simulation results are acquired. The voltage waveforms for each of the three phases during this fault are shown in Figure 5. It is observed that, in contrast to the other phases, the faulty phase's voltage drops to zero.

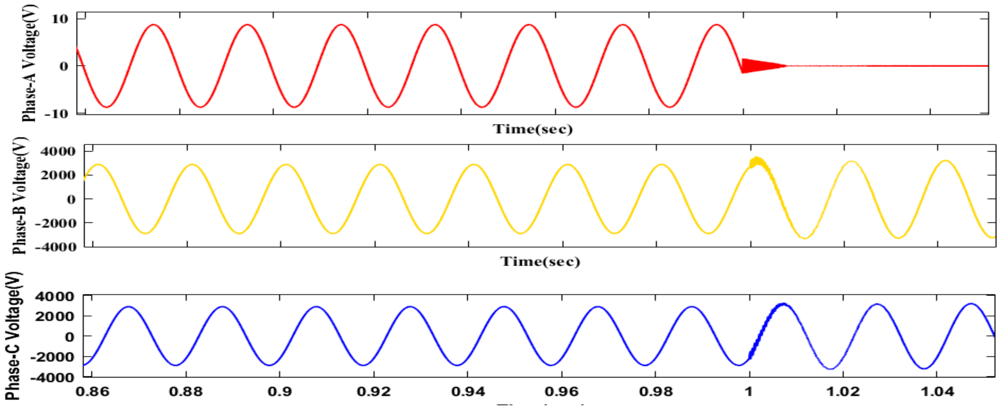

Fig 5. Three Phase Voltage Waveforms (A-G Fault)

The L-L fault is simulated with phase A and B as the faulted phases. The voltage waveforms for each of the three phases during this fault are shown in Figure 6. Phase-A and B voltages are shown to decrease and to be in phase.

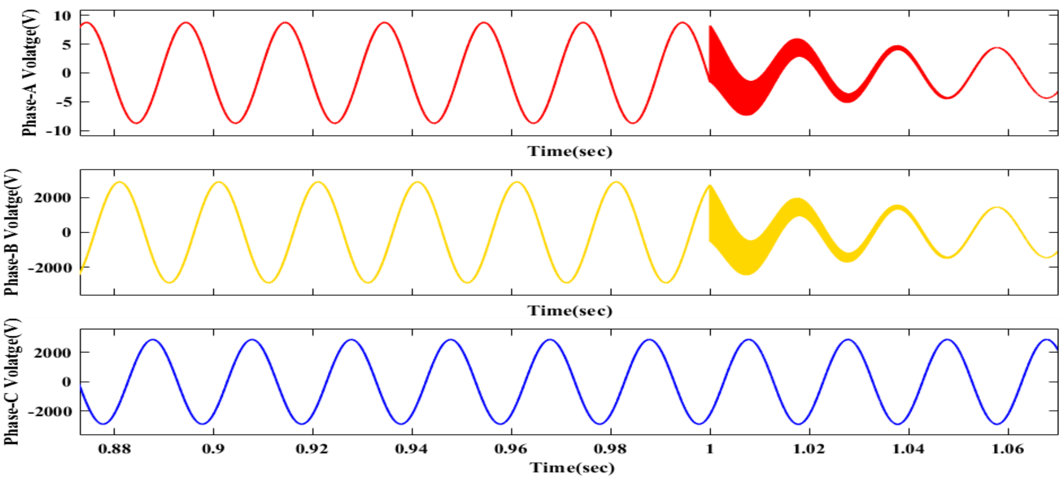

Fig 6. Three Phase Voltage Waveforms (A-B Fault)

The L-L-G fault is simulated with phase A and B as the faulted phases including ground. The voltage waveforms for each of the three phases during this fault are displayed in Figure 7. While phase-C voltage magnitude remains constant, phase-A and phase-B voltages are observed to decrease and to be in phase.

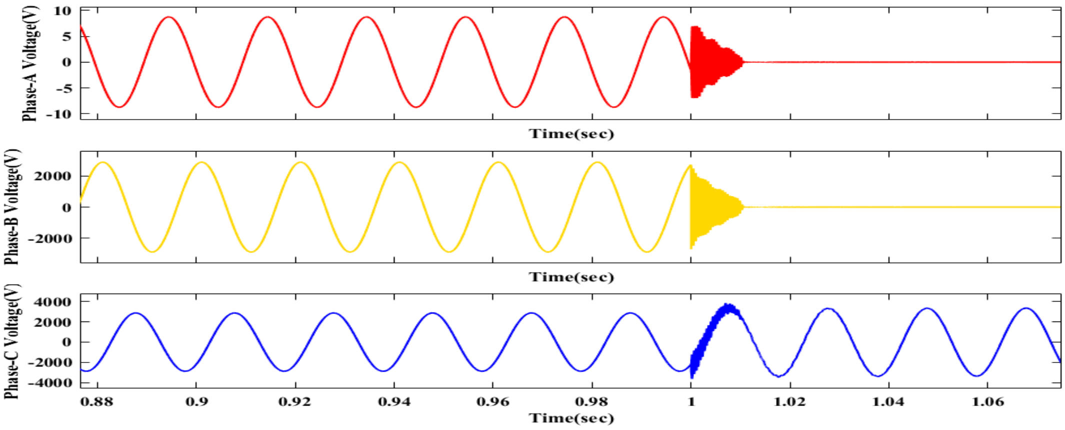

Fig 7. Three Phase Voltage Waveforms (A-B-G Fault)

The L-L-L-G fault is simulated with all the phases as the faulted phases. Figure 8 shows the voltage waveforms of all the three phases including ground. It is seen that the voltage for all phases becomes zero.

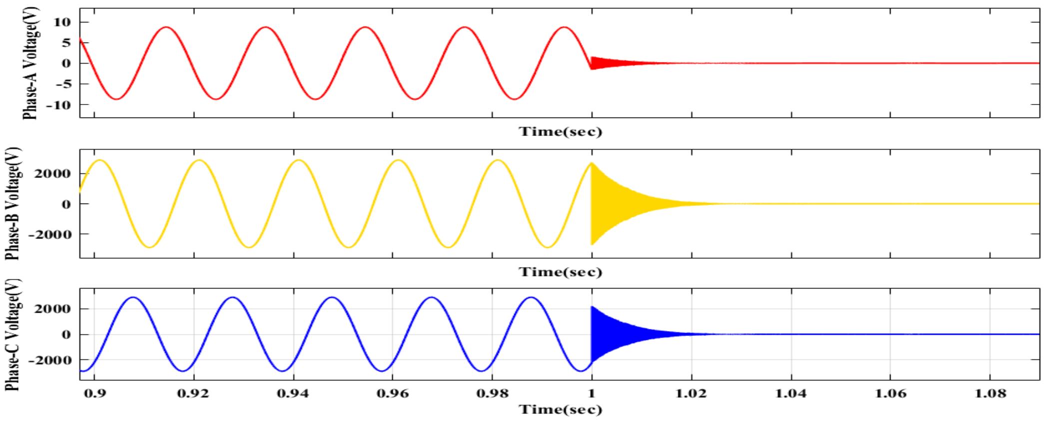

Fig 8. Three Phase Voltage Waveforms (A-B-C-G Fault)

3.1. Dataset Generation and Feature Extraction

Table 2 illustrates the detail and approximation coefficient maximum values for all the parameters.The twelve features for all given parameter are extracted with PCA and DWT as shown in table 2.

Table 2. Statistical Features

Statistical Features	I(A)	I(phase angle in Degrees)	f (Hz)	V(V)	Vph (phase angle in Degrees)	Va(V)	Vb(V)	Vc(V)
Contrast	2.48	2.41	2.3	2.38	2.22	2.25	2.38	2.49
Correlation	0	0	0	0	0.08	0.05	0.02	0.01
Energy	0.71	0.70	0.72	0.67	0.7	0.7	0.71	0.68
Homogeneity	0.88	0.88	0.88	0.87	0.88	0.88	0.88	0.87

Mean	0.01	0.01	0	0.01	0	0.01	0.01	0.01
Standard Deviation	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Entropy	1.36	1.28	1.48	1.5	1.5	1.58	1.46	0.5
RMS	0.18	0.18	0.18	0.18	0.18	0.18	0.18	0.18
Variance	0.03	0.03	0.03	0.03	0.03	0.03	0.03	0.03
Smoothness	0.91	0.91	0.91	0.89	0.83	0.91	0.91	0.9
Kurtosis	12.1	11.9	11.2	10.7	10.8	10.53	11.7	12
Skewness	1.84	1.79	1.59	1.5	1.63	1.62	1.91	1.84

3.2. Deep Neural Network

The type of neural network employed is Multi-Layer Perceptron. There are three or more layers in this kind of feedforward neural network: one input layer, one output layer, hidden layers and activation functions. Several Multi-Layer Perceptron topologies have been investigated for fault detection. The size oftraining data set, the networksize and thelearning algorithm used are some of the variables that determine the optimal architecture.

The implemented network is very well designed to generate optimum and accurate results for the input data. The hidden layers and their neurons are so chosen that optimum performance is achieved. The activation function also has considerable impact on accuracy in fault location. The layer graph showing the different layers of network is shown in figure 9. The different layers are connected in series having single input and output layer. There are ten distinct layers in the network. The figure depicts the network architecture, which has three completely connected layers and three layers with weights that can be learned.The deep learning network architecture is specified by the layer graph.

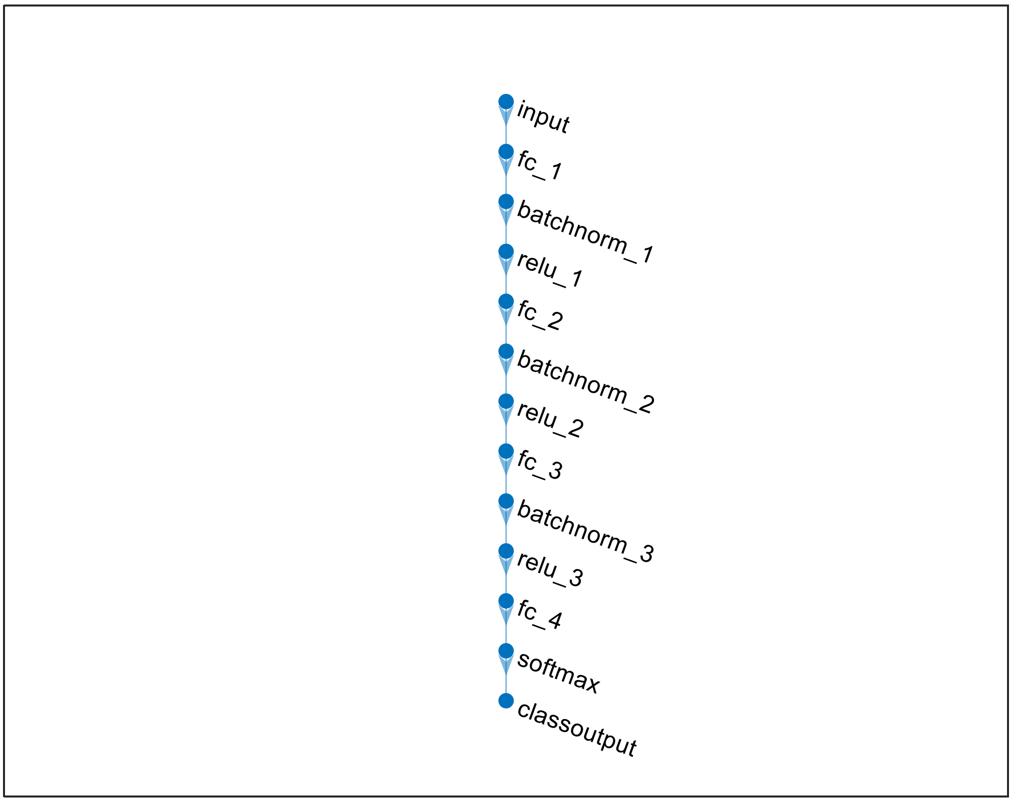

Fig 9. Layer Graph

Figure 10 and 11 shows the individual accuracy and loss plots respectively. The training options are created to train the network for thirty epochs.

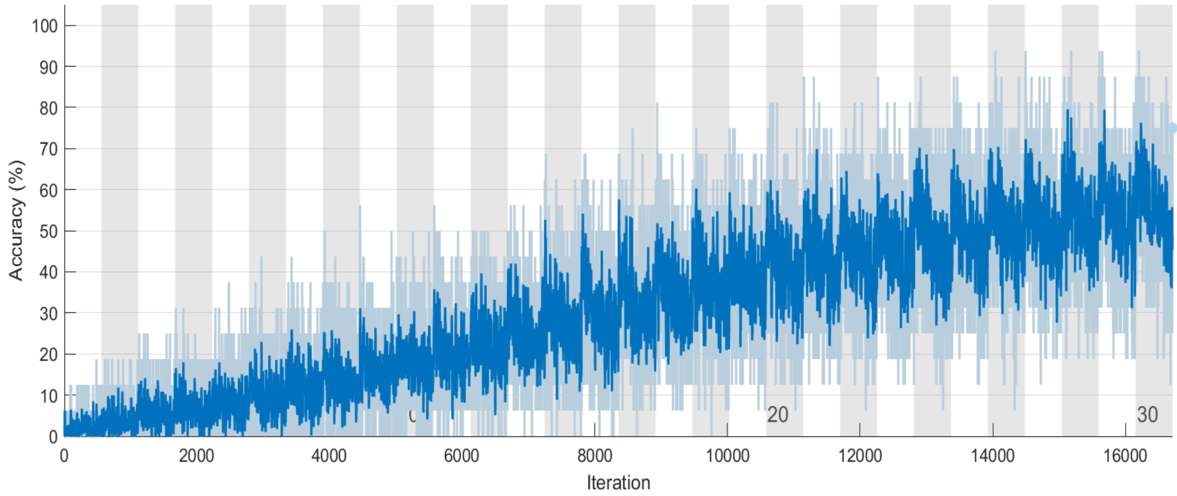

Fig 10. Plot of the Accuracy during training

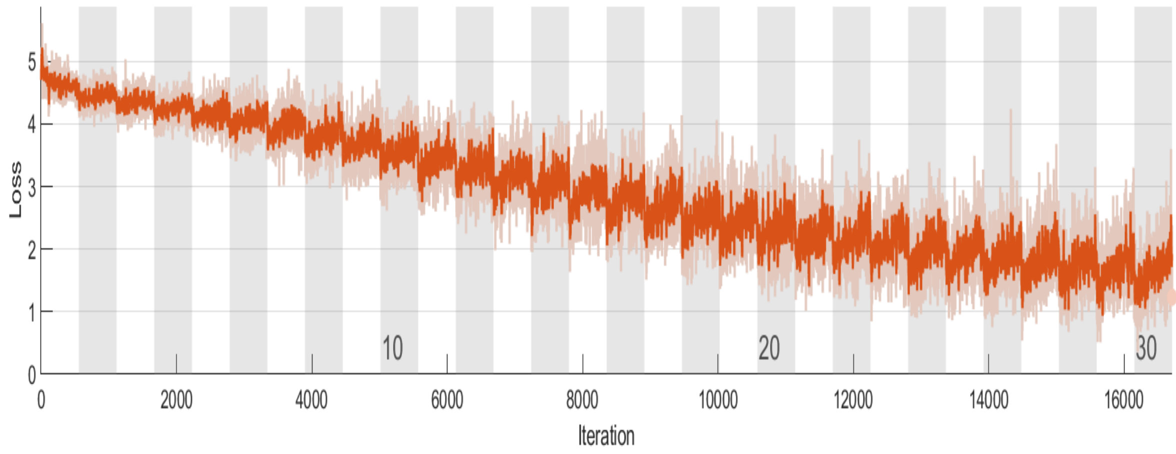

Fig 11. Plot of the Loss during training

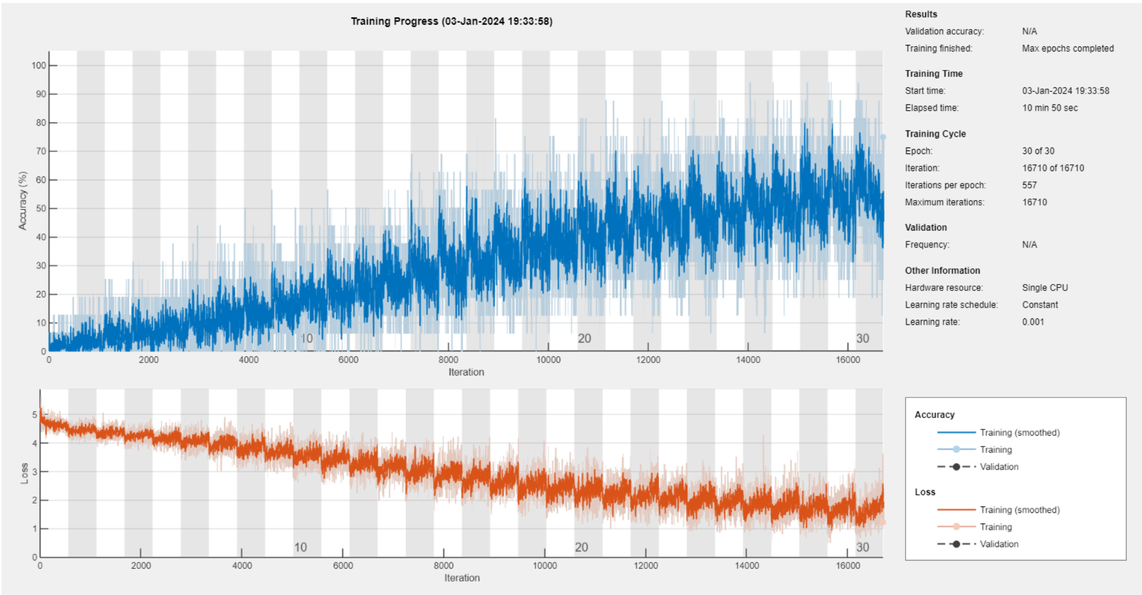

Fig 12. The Trained Plot

Figure 13 shows the scatter plot for SLG fault between phase A and ground. The mean square error and mean absolute error are observed as 0.0011 and 0.0253 respectively.

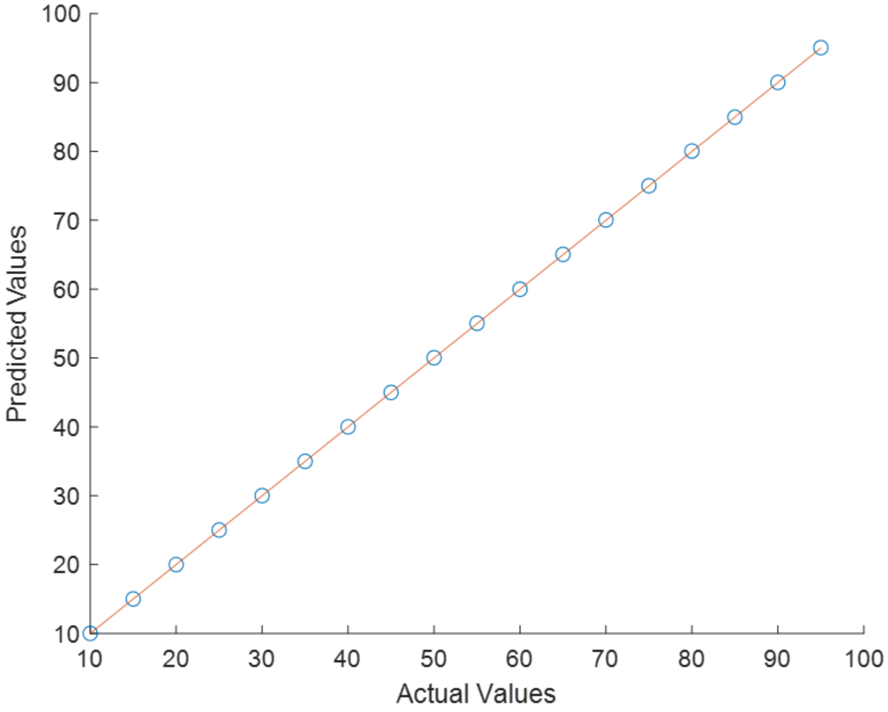

Fig 13. Scatter Plot for SLG (A-G) Fault

Figure 14 shows the scatter plot for LL fault between phase A and C. The mean square error and mean absolute error are observed as 6.3453e-04 and 0.0253 respectively.

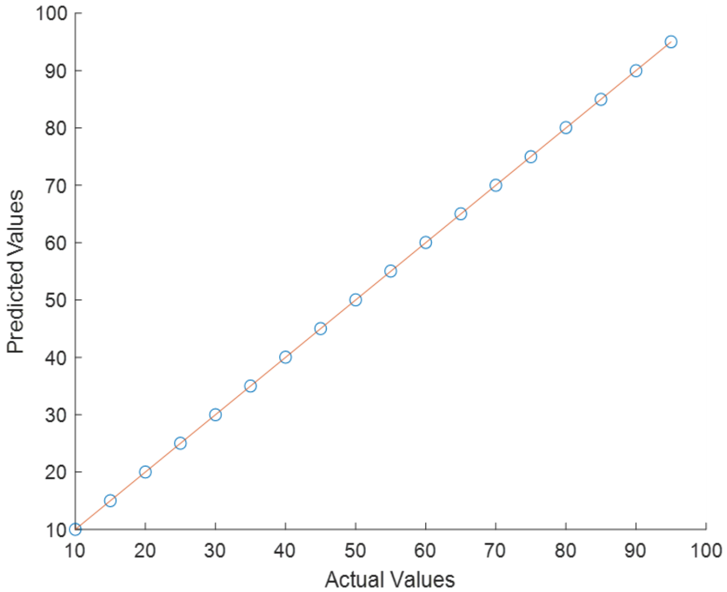

Fig 14. Scatter Plot for LL (A-C) Fault

Figure 15 shows the scatter plot for LLG fault between phase A, C and ground. The mean square error and mean absolute error are observed as 5.0089e-04 and 0.0180 respectively.

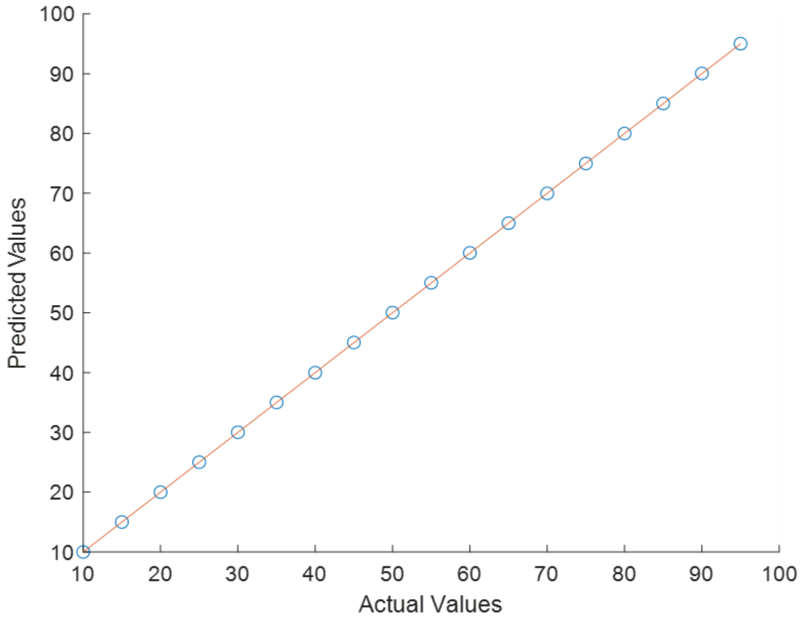

Fig 15. Scatter Plot for LLG (A-C-G) Fault

Figure 16 shows the scatter plot for LLLG fault between all the phases and ground. The mean square and mean absolute error are 9.1327e-04 and 0.0254 respectively.

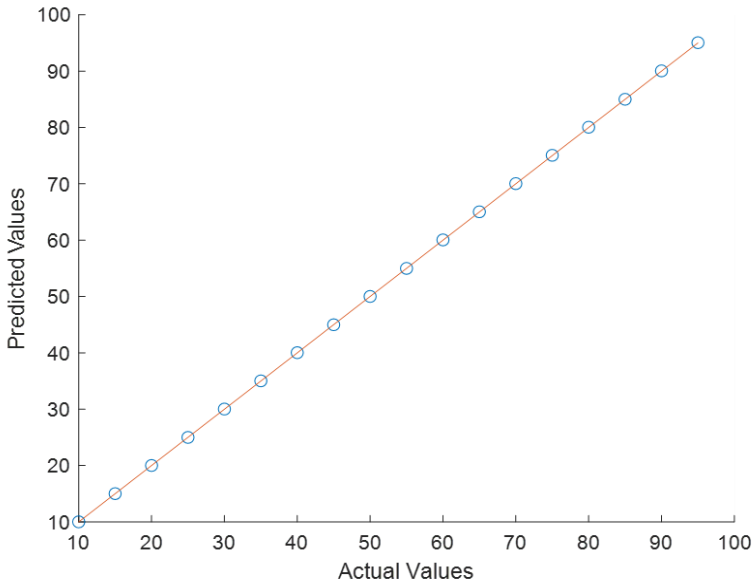

Fig 16. Scatter Plot for LLLG (A-B-C-G) Fault

Table 3 shows the fault locations in km given by the neural network against the actual fault locations for S-L-G, L-L, L-L-G and L-L-L-G fault types and table 4 gives the mean square error (MSE) and mean absolute error (MAE).

Table 3. Test Results the DNN for Fault Locations

Actual Fault Location (kms)	S-L-G Phase A-G	L-L Phase A-C	L-L-G Phase A-C-G	L-L-L-G Phase A-B-C-G

10	10.0075	10.0075	10.005	10.0075
15	15.0113	15.0075	15.0075	15.0133
20	19.995	20.01	20	20.01
25	25.0188	25.0188	25.0188	24.9937
30	30.015	29.9925	30.015	30.0255
35	34.9913	35	35.0087	35.0262
40	40	40.03	39.99	40.03
45	45.0012	45.0122	45.0377	44.9888
50	50.0375	50.025	50.0375	50.0125
55	55.0412	55.0412	55.0275	54.9862
60	59.985	60.03	60.03	60.045
65	65.0487	65.0325	65	65.0325
70	70.0525	70	69.9825	70.035
75	75.0187	74,9813	74.9813	75.0563
80	80.06	80.06	80	80.04
85	84.9788	84.9788	85.0212	85
90	90.0225	89.9775	90.045	90.045
95	95.0713	95.0238	95.0238	95.0475

Table 4. Mean Square Error (MSE) and Mean Absolute Error (MAE) in Testing the Model

Type of Fault	MSE	MAE
S-L-G Phase A-G	0.0011	0.0253
L-L Phase A-C	6.3453e-04	0.0205
L-L-G Phase A-C-G	5.0089e-04	0.0180
L-L-L-G Phase A-B-C-G	9.1327e-04	0.0254

4. Conclusion

This paper implements a multilayer perceptron Deep Neural Network fault location algorithm.The feature extraction using the Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA) reduces the redundancy in feature selection. In power transmission lines, neural networklocates the faults for different faults and fault resistances. The network is implemented and the transmission line is modelled and simulated using MATLAB/SIMULINK. The network is tested for various fault location and fault resistance values. For the fault locator, a minimum of mean square error (MSE) of 5.008e-04 is obtained for L-L-G fault and a maximum of 0.0011 is obtained for S-L-G fault. The findings obtained are determined to be extremely satisfactory. Therefore, it has been demonstrated that the DNN is a useful tool for investigating transmission line faults.

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