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Single-Ended Data Based Fault Type Identification in Transmission Line Using DNN

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Abstract: The transmission lines form a very crucial part of any power system network. Hence its reliability of power transmission is equally important. But The chances of fault occurrence probability on transmission lines are quite large. Hence to maintain the reliability of transmission there is a need to classify, detect and isolate the faults that will occur on the transmission line. In this paper the Deep Neural Network based technique is implemented for classifying and locating the fault. The system implemented is a two-bus power system network, the line being 100 km long and working voltage is 132 kV. The input dataset RMS values of voltage and currents corresponding to no fault condition and different fault types including different phases. The model gives results with best accuracy in classifying symmetrical as well as unsymmetrical faults providing an overall greater accuracy for the faults studied.

Keywords: *Faults, Wavelets, MATLAB/Simulink, Decomposition Coefficients*

1. Introduction

The increasing demand for electrical energy in industrial as well as domestic sector necessitates the development of good relaying and protection system. This definitely adds to the efficiency and reliability of the entire system. Various methods have been developed for fault detection and classification. The travelling wave-based methods, impedance techniques and the methods based on synchronized phasors are one of the few methods [1]. Line fault is identified by the traveling waves [2]. DWT based methods makes use of decomposition techniques and wavelets. SVM methods also addresses the similar problem and is one of the classification techniques [3]. The technique using synchronous phasor measurement has a high capability for locating faults. But the requirement of phasor measurement units makes it costlier [4]. Fourier and wavelet based methods are used for signal analysis [5].Deep neural networks are based on number of layers (input, output and hidden) connected to each other. The technique necessitates the formation of large input dataset and training the network with this dataset. Training the neural network improves its accuracy.

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2. Literature Review

Discrete wavelet transform (DWT) is employed for signal decomposition. The same technique is also used for feature extraction [6]. Thefeatures are extracted using Principal Component Analysis (PCA) and the results are compared with Linear Discriminant Analysis (LDA). The comparison is done with respect to time taken and other parameters [7]. The signal processing is used for signals that are non-stationary. The fault investigation is done by neural network [8]. The model classified the faults with greater accuracy and was based on dataset obtained by simulating the power system network.[9]. Two deep learning models, namely CNN and ANN models were used for detection of the defect type in the transmission line. The two networks were compared with respect to their performances [10]. The neural networks based on discrete wavelet transform were implemented and provided better amount of classification accuracy for the microgrids [11]. SSAE deep neural network based on higher ability to extract features is implemented [12]. The distinguishable features are being extracted from the wavelets. Further principal component analysis (PCA) is put to usefor the reducing dimensionality of data set, and the principal components represent signals of the networkthat are non-stationary [13]. The technique models a system to generate the automatic processing of signals and extract the features with the help of deep learning and classify ten types of faults in transmission lines [14].

3. Power System Network/Model

The proposed power system is a transmission line 100 km long with line voltage of 132 kV as shown in figure 1. The static load of MW and MVAR have been connected to the bus 2 at the receiving end. Fault simulating block is connected to the line that will simulate different unsymmetrical faults and symmetrical faults for different values of fault resistances and fault locations.

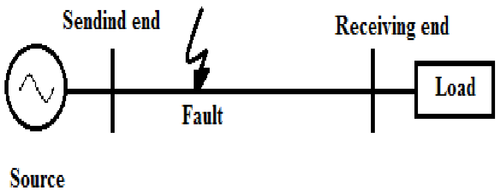

Fig. 1. A two-bus system

The system block diagram is shown in figure 2. The output of the DNN model will be the type of fault.

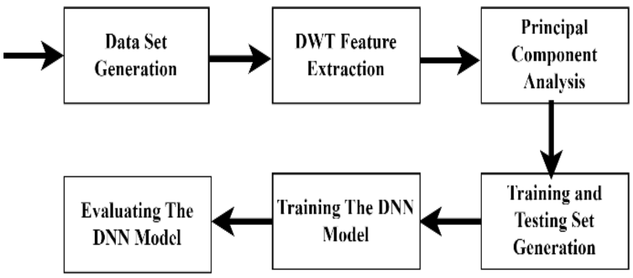

Fig. 2. System Block Diagram

The specifications of transmission line per km of length are given in table 1.

Table 1. The Specifications of Transmission Line

Variable	Value
Positive Sequence Resistance	100.0445 Ohms/km
Zero Sequence Resistance	0.1123 Ohms/km
Positive Sequence Inductance	1.011e-3 H/km
Zero Sequence Inductance	2.0191e-3 H/km
Positive Sequence Capacitance	7.469e-9 F/km
Zero Sequence Capacitance	4.4e-9 F/km

Figure 3 shows the current magnitude, phase and frequency waveforms for single line to ground fault. Figure 4 indicated the Voltages of the three phases for the same fault condition.

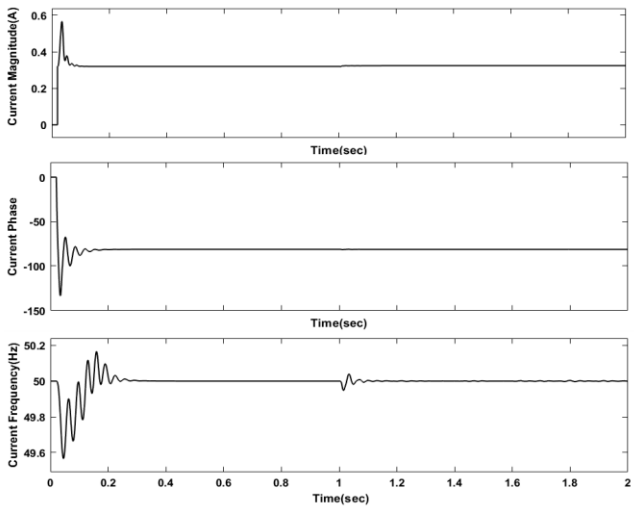

Fig. 3. Current Magnitude, Phase and Frequency Waveforms during Single Line to Ground Fault

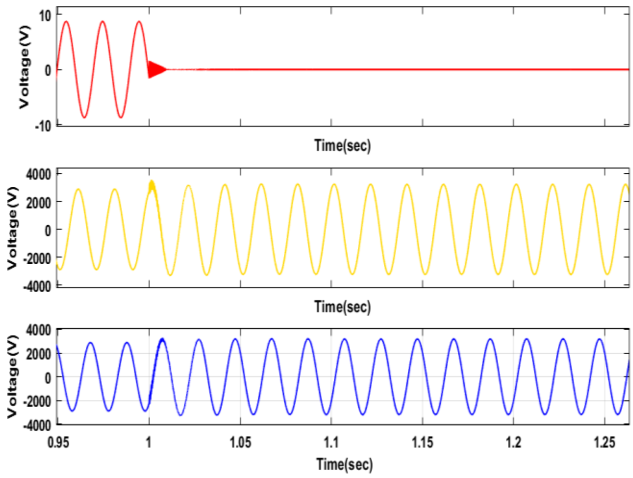

Fig. 4. Phase A, B and C Voltage Waveforms during Single Line to Ground Fault

4. Deep Neural Network

The proposed neural network is designed to produce optimum results for the given input dataset. The number of neurons and hidden layers are chosen to gain maximum performance. Also, the activation function plays a crucial role in accurate classification. The series network is shown in figure 4. It is a network that consists of different layers connected one after another with single input and output layer. It consists of 3 fully connected layers and three layers with learnable weights. The fully connected layers consist of neurons 64-32-9 and the activation functions are relu-relu-softmax. The z-score normalization is used to rescale the features.

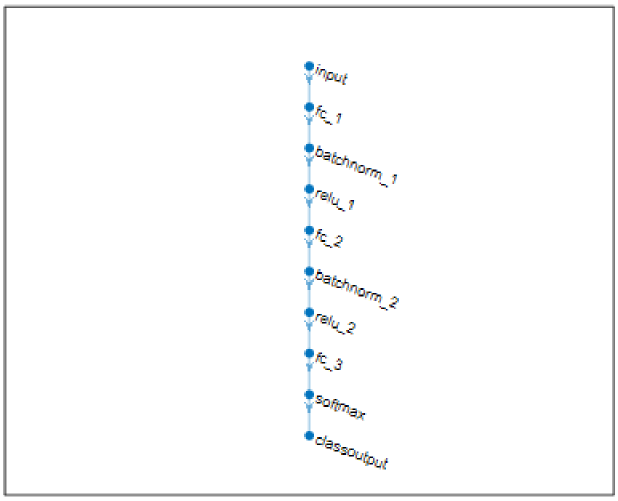

Fig. 5. Layer Graph

5. Dataset Generation

The data set consists of a table of 11152 rows and 97 columns. The rows show the number of samples and the column shows the statistical features and targets. The 96 columns are the statistical features representing the magnitude, phase and frequency of overall current, magnitude and phase of overall voltage and voltages of individual phases (RMS values). The last column represents the target/label/fault type. nine target labels, corresponding to no fault condition and different fault types including different phases. The labels (2 to 11) are the fault types phase A-G, phase B-G, phase C-G, phase A-B, phase A-C, phase B-C, phases A-B-G, phases B-C-G and label 1 is for No Fault condition. The phases are designated as A, B and C. The fault distance is measured from the sending end of transmission line.

6. Feature Extraction/ Dataset Generation

Feature extraction is the process of generating a new set of features from the original data. It helps to generate only the relevant/useful features and thereby decreasing redundancy. A combined technique using DWT and PCA is used to extract the features. DWT transform is used to obtain the frequency components of signal and is preferred over FFT since it retains information in time as well as frequency domain [16]. PCA reduces the linear dimensionality. It is used to extract the dominant features [17]. The combination of PCA and DWT is used to improve the feature extraction process [18]. The input is the original data and the output is in form of features that best represents the input data. Also, it reduces the complexity in time and space. The input features taken are overall current magnitude, phase and frequency, overall voltage magnitude and phase. The input voltages and currents are measured at the sending terminals of transmission line.

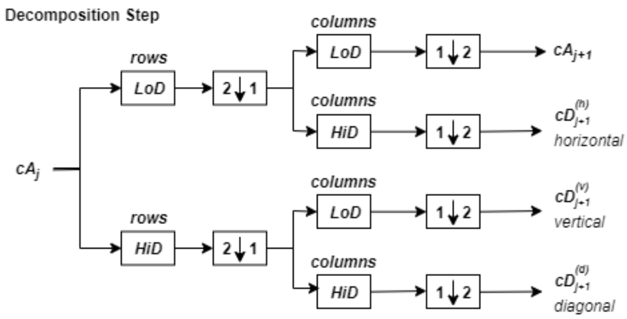

Fig. 6. Two-Dimensional DWT [19]

Discrete wavelet transform (DWT) of the input test signal data is computed at level 1by Daubhechies mother db5 wavelet. The decomposition steps are shown in figure 6. It shows the approximation coefficients and detail coefficients. The level 2 approximate and detail coefficients of frequency are obtained as shown in figure 7 and 8 respectively.

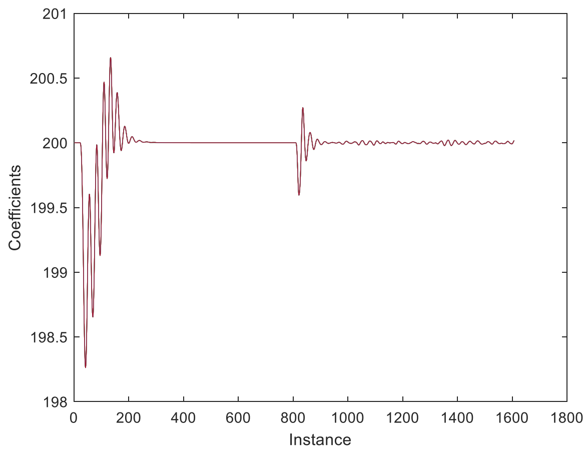

Fig. 7. Level 2 Approximate Coefficients of Frequency

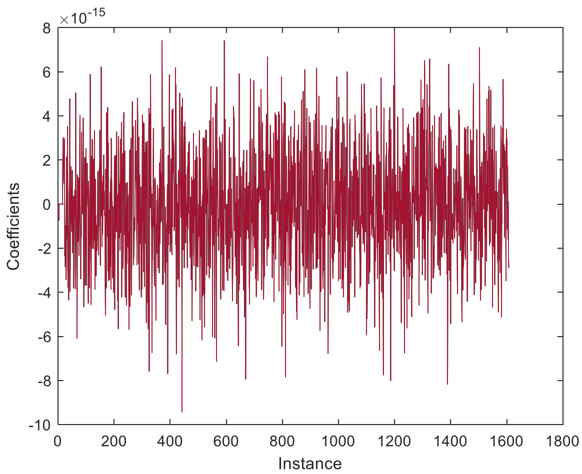

Fig. 8. Level 2 Detail Coefficients of Frequency

Total twelve statistical features with respect to every parameter are extracted using DWT and PCA as follows [6, 20]. The values are indicated in table 2 and figure 9.

1. Energy: The energy of a discrete-time signal over a finite interval $-N \leq n \leq N$ is given by

$$E_N = \sum_{n=-N}^{N} |x(n)^2| \tag{1}$$

2. Standard Deviation: It computes the standard deviation of all values in a given array.
3. Mean: It is the mean of elements of vector or the matrix
4. Kurtosis: The kurtosis of a distribution is defined as

$$k = \frac{E(x-\mu)^4}{\sigma^4} \tag{2}$$

where μ: mean of x, σ: the standard deviation of x, and $E(t)$: the value of quantity

5. Skewness: Skewness is an indication of asymmetry of data.

$$s = \frac{E(x-\mu)^3}{\sigma^3} \tag{3}$$

6. Entropy: Entropy indicates the information contain in the signal.

$$\sum_{i,j} |i-j|^2 \, p(i,j) \tag{4}$$

7. Contrast: It is a measurement of the overall intensity contrast between the pixel and neighbouring pixel
8. Correlation: It reveals a pixel's correlation with its neighbours over the entire image.

$$\sum_{i,j} \frac{(i-\mu i)(j-\mu j)p(i,j)}{\sigma i \sigma j} \tag{5}$$

9. Homogeneity: It is used to gauge how well the distribution of GLCM pieces matches the diagonal.

$$\sum_{i,j} \frac{p(i,j)}{1+|i-j|} \tag{6}$$

10. Variance: The variance is defined as follows for a vector A containing N observations (scalar).

$$V = \frac{1}{N-1} \sum_{i=1}^{N} |A_i - \mu|^2 \tag{7}$$

μ: mean of A.

11. RMS: For the input x, it calculates the root mean square value

$$\sqrt{\frac{1}{N} \sum_{n=1}^{N} |x_n|^2} \tag{8}$$

Table 2. Statistical Features

Statistical Features	I (A)	I phase angle (Degrees)	f (Hz)	V (V)	V phase angle (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

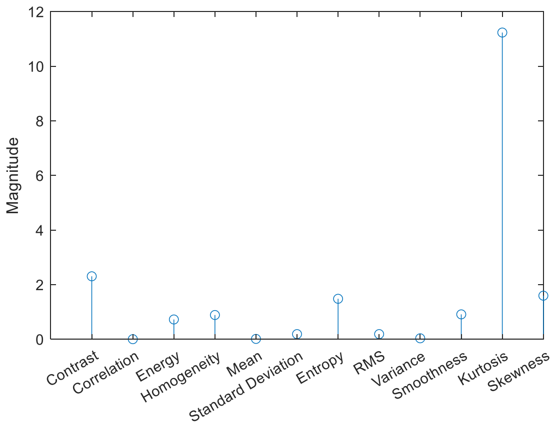

Fig. 9. Statistical Features of Frequency

7. Results And Discussion

The MATLAB Simulink model is used for simulating 10 different fault types that includes symmetrical and unsymmetrical faults along with no fault condition. The faults are simulated for every 1 km upto 100 km with the fault resistances ranging from 0.25 ohm to 130 ohm. Figure 10 shows the accuracy and loss in training.

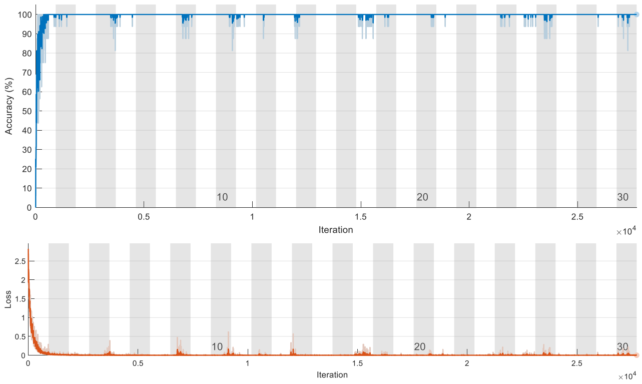

Fig. 10. Accuracy and Loss in Training

Another neural network is developed for classifying the faults. Confusion matrix shows that the accuracy obtained by the classifier is 100% as shown in fig.9.

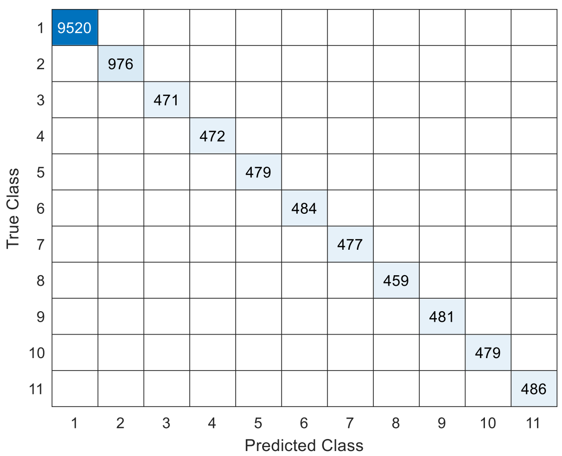

Fig. 11. Confusion Matrix for Fault Classification

Table 3 shows the accuracy results for different types of faults. The accuracy obtained for each type of fault is 100%. It is obtained with the help of confusion matrix as in figure 11.

Table 3. The Specifications of Transmission Line

Fault Type	Accuracy
No Fault	100
A-G	100
B-G	100
C-G	100
A-B	100
A-C	100
B-C	100
A-B-G	100
B-C-G	100
A-C-G	100
A-B-C-G	100

8. Conclusion

A fault classification method using a multilayer perceptron deep neural network is implemented in this paper. It locates and classifies in power transmission lines. MATLAB/SIMULUNK is used to model and simulate the transmission line and the implement the neural network. Ten different types of faults are classified for various fault locations and fault resistances. A Mean Square Error of 2.12e-9 is obtained for fault locator and accuracy of 100% for fault classifier. The results are found to be very satisfactory for both classifier and locator. Hence the DNN is proved to be an efficient tool for transmission line fault investigation.

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