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Fault Detection and Classification in Transmission line using DWT and ANFIS Techniques

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Abstract: *This paper proposes Discrete Wavelet Transform (DWT) and Adaptive Neuro-Fuzzy Inference System (ANFIS) techniques for fault detection, classification and detection of faulty phase in the transmission line. The detection is done by computing the energy values and Standard Deviation (STD) of the phase currents using DWT. The features extracted by DWT are given as inputs to ANFIS to classify the type of fault and identify the faulty phase in the transmission line.*

Keywords: *Discrete Wavelet Transform (DWT), Adaptive Neuro-Fuzzy Inference System (ANFIS), Fault detection and classification, faulty phase, Transmission line.*

1. INTRODUCTION

Transmission lines are the vital links of the electric power system that enables the power transmission from the generating stations to distribution networks. Along with other electrical equipments transmission lines suffer from the unexpected electrical disturbances which affect the quality of power supplied to the loads and also cause instability in the power system [1]. The occurrence of any transmission line faults give rise to transient condition. The various types of faults that occur in the transmission lines are line to ground fault (L-G), double line to ground fault (L-L-G), double line fault (L-L), three phase fault and three phase to ground fault (L-L-L and L-L-L-G). Among these, line to ground faults are the most common followed by double line faults and three phase faults. It is adequate to determine the type of fault and the faulty phase in the transmission line. Fourier transforms techniques are used for the detection of the transmission line faults but these techniques give information about all frequencies that are present in the signals but does not provide information regarding the time at which these frequencies are present. Based on fault transients, several algorithms have been proposed for fault detection and classification. The wavelet transform gives information both in frequency and time domain. The wavelet analysis allows the decomposition of a signal into different levels of resolution called Multi Resolution Analysis (MRA). Reference [2] proposed an effective feature extraction using wavelet transform. Reference [3] showed that wavelet transform is used to capture high the high-frequency travelling waves for fault detection, classification and phase selection of faults. References [4], [5], [6] uses combined techniques such as Wavelet Transform and Artificial Neural Network (ANN) and Wavelet Transform with Fuzzy logic [10] for fault detection. Reference [7] uses combined techniques of wavelet multi resolution analysis and ANFIS for smart fault location in transmission lines. This paper uses Discrete Wavelet Transform (DWT) and Adaptive Neuro- Fuzzy Inference System (ANFIS) for fault classification and detection. DWT is used to extract the energy values and standard deviation of the current signals to detect the faults in the transmission line. The features extracted are given as input to the ANFIS to detect the type of fault and faulty phase. The simulations for different faults are simulated in MATLAB/SIMULINK environment. The features extracted are used to train ANFIS to determine the type of fault and faulty phase.

2. DISCRETE WAVELET TRANSFORM

Wavelet is a short duration wave. It is a mathematical basis function used to divide a given continuous time signal into different scale components. It allows the decomposition of a signal into different levels of resolution. The basic function is dilated at low frequencies and compressed at high frequencies, so that large windows are used to obtain the low frequency components and small windows are used to obtain to reflect discontinuities. In wavelet transform approximations are high scale, low frequency components and details are low scale, high frequency components of the signal. The original signal decomposes through two complementary filters and emerges as two signals. This decomposition is further iterated with successive approximations being decomposed in turn, so that one signal is broken down into many lower resolution components. This is called Multi Resolution Analysis (MRA). The wavelet resolution is shown in figure 1.

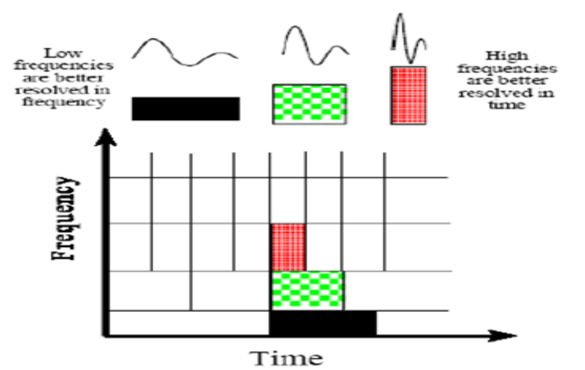

Fig. 1: Wavelet Resolution

Wavelet transform is divided into Discrete Wavelet Transform (DWT) and Continuous Wavelet Transform (CWT). Both DWT and CWT are continuous-time transforms. The DWT is preferred than CWT as CWT provides more information than required whereas DWT provides only the required information in both frequency and time domain. Daubechies wavelet is used in this paper. Daubechies 4 (db4) is used as mother wavelet and five level decomposition is used for extracting the energy values and standard deviation values as it is appropriate for power system fault analysis. The wavelet transform of a continuous signal x(t) is defined by,

$$\mathrm{WT(a,b)}=1/\sqrt{a}*\int_{\infty}^{\infty} X(t) * g\left(t-\frac{b}{a}\right) dt \qquad (1)$$

Where a and b are the scaling and translational parameters and g is the mother wavelet function.The discrete wavelet transform is defined as,

$$\mathrm{DWT(m,k)}=\frac{1}{\sqrt{a0^m}} * \sum_n X(n) g(k-na0^m/a0^m) \qquad (2)$$

Where g[n] is the mother wavelet, the scaling and translation parameters a and b are functions of an integer parameter m, $a=a0^m$ and $b=na0^m$.

In this paper, the process of feature extraction consists on finding the distinctive waveform parameters with significant information that can represent the fundamental characteristics of the problem. The standard deviation (STD) of the coefficients, in each frequency band, is chosen to be extracted and is used as the input data to train ANFIS. The STD of the output signal is obtained by the equation shown below. This feature provides information about the level of variation of signal frequency distribution.

$$\mathrm{STD}=\sqrt{(1/(n-1)\sum_{i=1}^{n}(x_i \quad -1/n(\sum_{i=1}^{n} x_i \quad)^2)} \qquad (3)$$

where "x" is the data vector and "n" is the number of elements in that data vector.

The energy values are given by the sum of the square of details and approximations obtained by the decomposition. Since five level decomposition is used, the energy value of the current signal is given by the equation,

$$\mathrm{Energy}=\sum D1^2 +\sum D2^2 +\sum D3^2 +\sum D4^2 + \sum D5^2 + A52 \qquad (4)$$

The energy values and standard deviations are obtained for normal condition and for other fault types. It is seen that the energy values and standard values during fault condition deviates from the values obtained during normal condition. If the A-G fault occurs the energy value and standard deviation of phase A alone deviate from the energy value and standard deviation of phase A during normal condition.

3. ADAPTIVE NEURO FUZZY INFERENCE SYSTEM

Based on the theory given in [8], ANFIS is used to detect the type of fault and faulty phase in the transmission line from the features extracted using wavelet MRA.

ANFIS is an intelligent adaptive data learning technique that utilises the FIS to model any system from its input-output data. The FIS model developed by Takagi-Sugeno-Kang, which is known as Sugeno model, is given in [9]. From the input-output data, ANFIS adjusts the membership functions (MFs) using least square method for linear systems and the back propagation descent method for nonlinear systems in [9].

The ANFIS detection model has three inputs, standard deviation values of the three phases A, B and C represented by SDA, SDB and SDC respectively and one output (type of fault with faulty phase). The input data is generated by the applying the DWT analysis on the current signals obtained for various fault conditions and for various fault resistances. The output is obtained such that, each fault type is assigned a particular value. The ANFIS is trained with generated inputs and assigned output. The table 1 shows the assigned output for different fault types and faulty phase.

Table 1

S. No	Fault type	Assigned output
1	No fault	0
2	A-G	0.1
3	B-G	0.2
4	C-G	0.3
5	A-B-G	0.4
6	A-B	0.5
7	B-C-G	0.6
8	B-C	0.7
9	A-C-G	0.8
10	A-C	0.9
11	A-B-C	1
12	A-B-C-G	1.1

The network is trained for the input-output data set with a MATLAB ANFIS editor, which adjusts the MFs directly based on the data set. ANFIS is an adaptive data learning technique that utilises the FIS to automatically model the fault classification system from its input-output data.

Three variables with triangular MFs are generated for each input variable. Because ANFIS is chosen to use Sugeno class models the outputs are constant. 12 rules have been formulated using FIS and 48 input-output data are used for training ANFIS, considering the fault resistances of 10, 20, 50 and 100 ohms for each type of fault. The obtained ANFIS structure for trained data is shown in the figure 2.

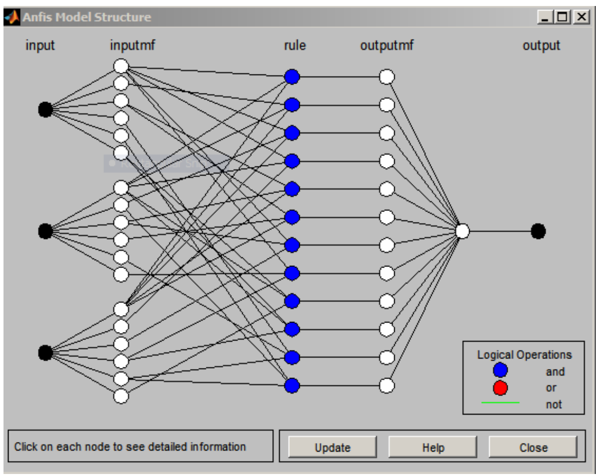

Fig. 2: ANFIS structure developed in MATLAB for fault classification.

The fault classification using ANFIS is shown in figure3.

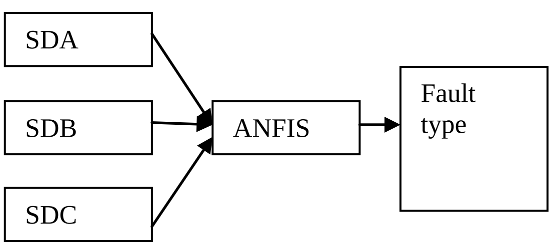

Fig.3. Fault classification using ANFIS

4. METHODOLOGY

The process of fault detection and classification approach is done by creating the power system model. The current signals for normal and various fault conditions are obtained for different fault resistances. The obtained current signals are transformed using DWT. The energy values and standard deviation values obtained using DWT are used to train ANFIS. The fault resistances and fault type are changed to develop different training data. The process of fault detection and classification is shown in figure 4.

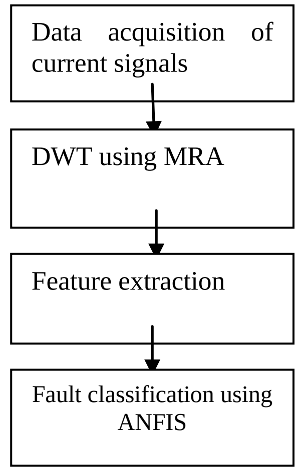

Fig. 4: Process of fault detection and classification

5. SYSTEM STUDIED

In order to verify the proposed techniques, the IEEE 9 bus system model is simulated using MATLAB/SIMULINK for normal condition and for various fault conditions. The power system model for IEEE 9 bus transmission system is shown in the figure5.

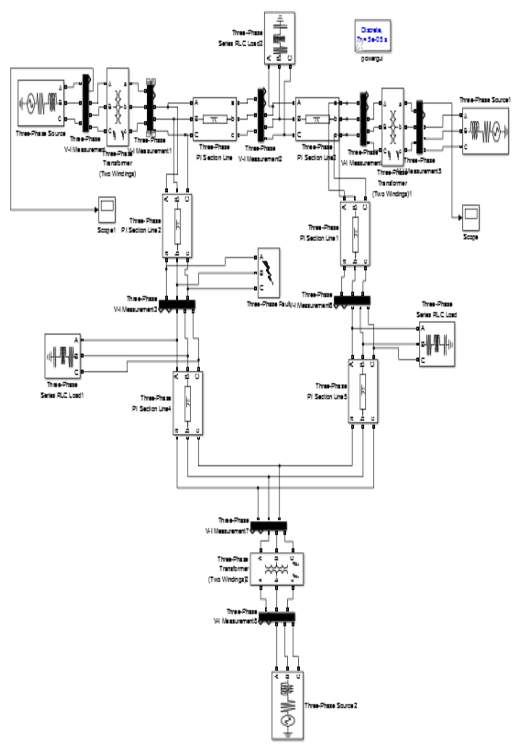

Fig. 5: Simulation model for IEEE 9 bus system.

The IEEE 9 bus system is modelled and analysed for different fault conditions. It consists of three generators, three transformers, three loads and six transmission lines. The system data for IEEE 9 bus system is shown below in table 2.

Table 2: IEEE 9 bus system data

Blocks	No of blocks	Parameters	Values
3Φ voltage source	3	Voltage (rms)	16.5KV 18KV 13.8KV
Transformer (Yg)	3	Voltage (rms)	16.5/230KV 18/230 KV 230/13.8KV
3Φ series RLC load	3	Power	125MW, 50MVAR 90 MW, 30MVAR 100MW, 35MVAR
3Φ transmission line π model	6	Length	150km each

The different types of single line to ground faults, different double line faults with or without ground and three phase faults with or without ground are simulated and analysed.

6. SIMULATION RESULTS

Considering the line 2 of the IEEE 9 bus system the waveforms during normal and various fault conditions are obtained.

6.1. Without fault

During normal condition the three phase current waveform is obtained as shown in the figure 6.

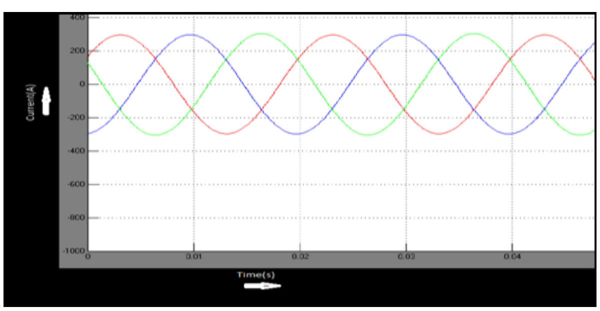

Fig. 6: Without fault

6.2. L-G faults

The L-G faults that occur in transmission system are A-G, B-G and C-G faults. A line to ground fault of fault resistance 10 ohms is applied to line 2 in ‘A’ phase of the transmission line. The waveform as shown in figure 7 is obtained.

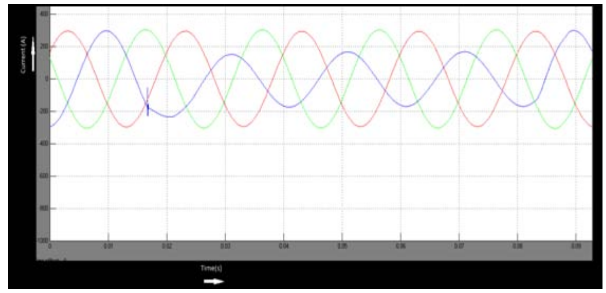

Fig. 7: A-G fault

6.3. L-L faults

The L-L faults that occur in transmission system are A-B, B-C and A-C faults. A double line fault of fault resistance 10 ohms is applied in the phases A and B of the transmission line. The waveform as shown in the figure 8 is obtained.

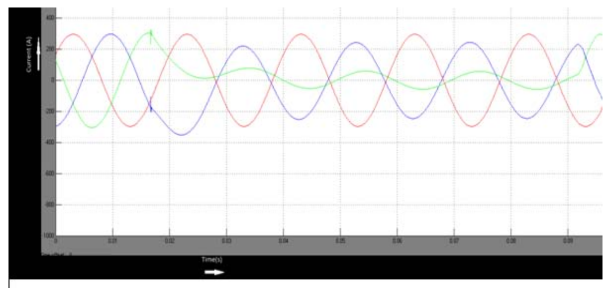

Fig.8. A-B fault

6.4. L-L-G faults

The L-L faults that occur in transmission system are A-B-G, B-C-G and A-C-G faults. A double line to ground fault of fault resistance 10 ohms is applied in the phases A and B of the transmission line. The waveform as shown in the figure 9 is obtained.

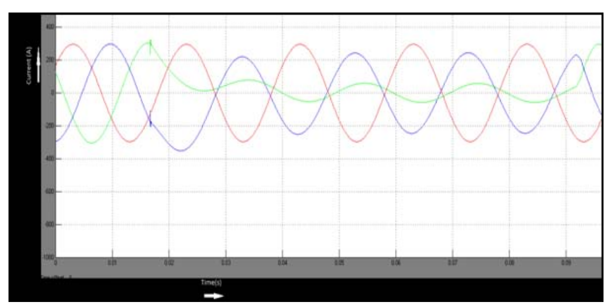

Fig.9. A-B-G fault

6.5. Three phase faults

Three phase faults in transmission system are A-B-C faults and A-B-C-G faults. The simulation results for both A-B-C and A-B-C-G faults of fault resistance 10 ohms applied in line 2 of the test system are obtained as shown in figures 10 and 11 respectively.

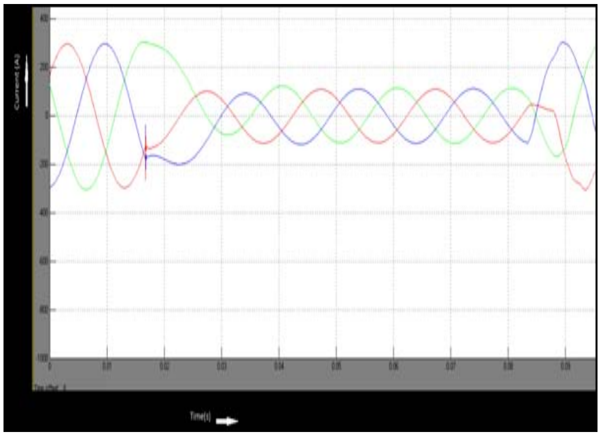

Fig. 10: A-B-C fault

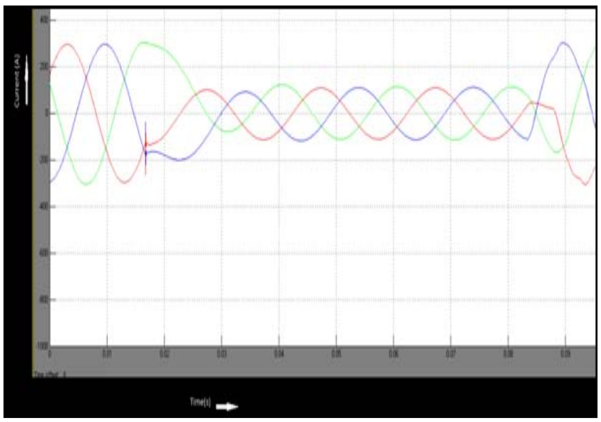

Fig. 11: A-B-C-G fault

7. DWT RESULTS

The DWT waveforms for the phases A, B and C during A-B-G fault are shown in the figures 12, 13 and 14 respectively. The DWT waveforms for normal and other fault types can also be obtained by DWT analysis.

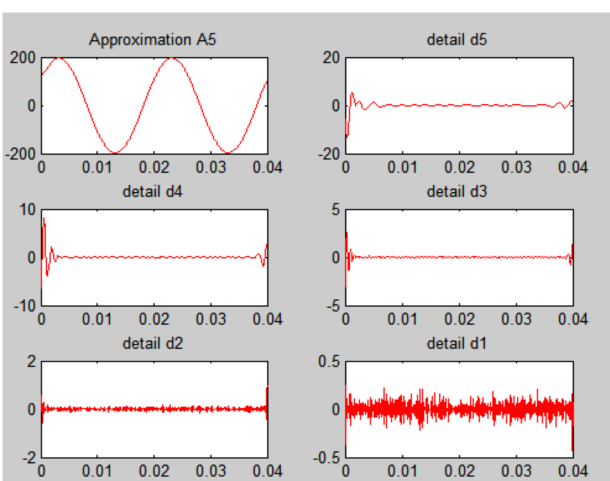

Fig. 12: DWT of phase A

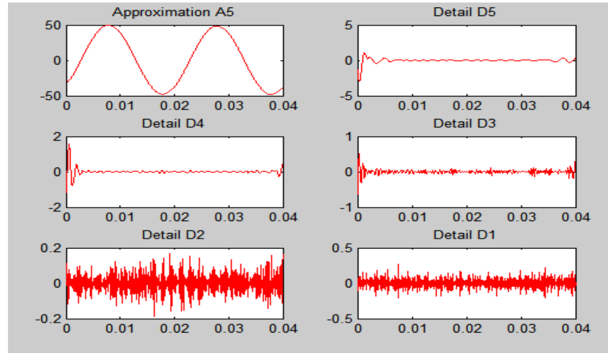

Fig. 13: DWT of phase B

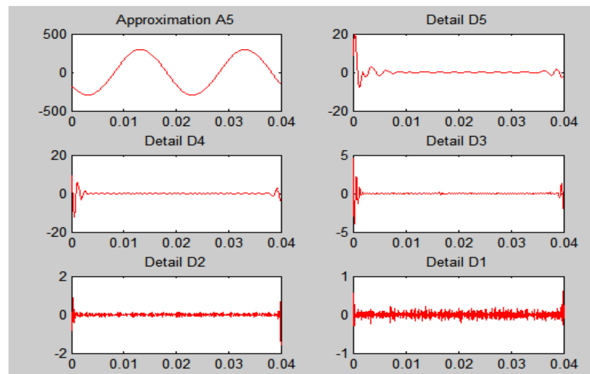

Fig. 14: DWT of phase C

The energy values and standard deviation obtained by DWT analysis for different types of faults for the fault resistance of 10 ohms is shown in the table3.

Table 3: Standard Deviation and Energy values at various conditions for the IEEE 9 bus system for the fault resistance of 10 ohms

S. No	Power system disturbance	Energy values	Standard deviation
1	No fault Phase A Phase B Phase C	 3.7e7 3.6e7 3.5e7	 37.6 37.9 36.1
2	A-G fault Phase A Phase B Phase C	 1.3e7 3.8e7 3.6e7	 26.4 37.6 37.4
3	B-G fault Phase A Phase B Phase C	 3.6e7 1.5e7 3.8e7	 37.54 25.1 36.5
4	C-G fault Phase A Phase B Phase C	 3.6e7 3.5e7 1.3e7	 37.7 37.6 20.7
S. No	Power system disturbance	Energy values	Standard deviation

5	A-B fault Phase A Phase B Phase C	 1.5e6 1.0e6 3.7e7	 24.3 6.0 37.7
6	A-B-G fault Phase A Phase B Phase C	 2.0e6 1.1e6 3.7e7	 24.3 8 36.5
7	B-C fault Phase A Phase B Phase C	 3.5e7 2.3e7 1.3e6	 37.5 30.7 8.9
8	B-C-G fault Phase A Phase B Phase C	 3.7e7 1.5e7 1.0e6	 37.8 24.1 10
9	A-C fault Phase A Phase B Phase	 5.7e6 3.6e7 1.3e7	 26.4 37.3 24.1
10	A-C-G fault Phase A Phase B Phase C	 6.1e6 3.7e7 2.1e6	 26.1 37.5 31.4
11	A-B-C fault Phase A Phase B Phase C	 9.3e6 7.7e6 4.1e6	 24.1 19.4 14
12	A-B-C-G fault Phase A Phase B Phase C	 9.2e6 6.2e6 4.1e6	 24.1 16.2 14.1

Similarly the energy values and standard deviation values are obtained for different fault resistances like 20, 50 and 100 ohms. It is observed that as the fault resistance increases the energy values and standard deviation obtained for different fault conditions approaches close to the energy values and standard deviation obtained during normal condition.

8. ANFIS RESULTS

The features extracted are trained to ANFIS to classify the fault type and faulty phase. The simulation model for ANFIS using Fuzzy toolbox in MATLAB/SIMULINK is shown in the figure 15 with three inputs and single output. When the B-G fault is applied the output is displayed as 0.2 as given by the table 1.

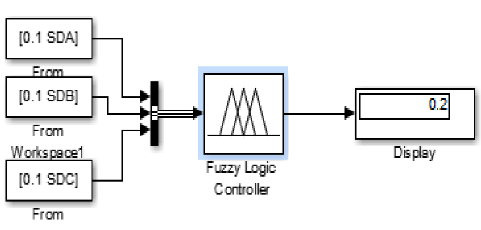

Fig. 15: Simulation model for ANFIS

After training ANFIS using Sugeno type function in ANFIS editor, the obtained ANFIS structure is obtained as shown in the figure 2. The output of ANFIS for different faults is shown in the table 4,

Table 4

S. No	Power system disturbance	Standard deviation	Output
1	Normal condition Phase A Phase B Phase C	 37.6 37.9 36.1	 0
2	A-G fault Phase A Phase B Phase C	 26.4 37.6 37.4	 0.1
3	B-G fault Phase A Phase B Phase C	 37.54 25.1 36.5	 0.2
4	C-G fault Phase A Phase B Phase C	 37.7 37.6 20.7	 0.3
5	A-B fault Phase A Phase B Phase C	 24.3 6.0 37.7	 0.5
6	A-B-G fault Phase A Phase B Phase C	 24.3 8 36.5	 0.4
7	B-C fault Phase A Phase B Phase C	 37.5 30.7 8.9	 0.7
8	B-C-G fault Phase A Phase B Phase C	 37.8 24.1 10	 0.6
S. No	Power system disturbance	Standard deviation	Output
9	A-C fault Phase A Phase B Phase	 26.4 37.3 24.1	 0.9
10	A-C-G fault Phase A Phase B Phase C	 26.1 37.5 31.4	 0.8
11	A-B-C fault Phase A Phase B Phase C	 24.1 19.4 14	 1.0
12	A-B-C-G fault Phase A Phase B Phase C	 24.1 16.2 14.1	 1.1

Similarly the ANFIS is trained for the different fault resistances by extracting the features using DWT analysis.

9. CONCLUSION

In this paper accurate detection, classification of fault and identification of faulty phase are performed using DWT and ANFIS techniques. However this method is valid till the fault resistance of 100 ohms because as the fault increases the features extracted during various fault conditions approaches close to the features extracted during normal condition. The application of DWT and ANFIS can further be extended in the smart fault location in transmission lines.

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