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Wavelet-Based Transmission Line Fault Classification

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Abstract:-Accurately recognizing and categorizing faults is critical for ensuring a power system's dependability and stability. In a fault condition, the tripping action is heavily influenced by the voltage and current waveforms recorded at the relay position. As a result, a quick and precise analysis is necessary to find and characterize problems in power transmission lines. Various signal processing algorithms are employed to examine the voltage and current waveforms of defect signals. Using discrete wavelet-based signal analysis, this study seeks to detect and classify several forms of transmission line problems. The defect can be classified by inspecting the current waveform of the fault signals with the discrete wavelet transform. The discrete approximation coefficient of the wavelet function is employed as an indicator for defect identification and classification. The artificial neural network is used to classify different transmission line defects.

Keywords: - Fault, Wavelet Transform, Energy, ANN

I. INTRODUCTION

Numerous defects can disturb the regular flow of power through transmission lines, which are prone to many problems. When two or more conductors come into contact with the ground or each other, a fault will occur. Single line-to-ground faults, line-to-line faults, double line-to-ground faults, and three-phase faults are the four types of faults that can occur in three-phase transmission systems. Excessive currents and strains on power system components are caused by these errors, which can cause hazardous damage and have an impact on power quality. Determining problems is therefore essential for ensuring the system continues to operate with a regular power supply.

Due to the adoption of digital relaying, distance relays have experienced substantial improvements in fault detection recently. Fault detection must take signal processing into consideration. Prior to now, the main instruments for signal processing defect identification were Fourier analysis and Kalman filtering techniques. Wavelets [13], on the other hand, are a more recent mathematical method for signal processing that has grown in acceptance. Wavelet analysis [2] gives various fundamental functions with a broad functional form, in contrast to Fourier analysis, which depends on a single basis function. In wavelet transform (WT) [3], a suitable wavelet function, or "mother wavelet," is chosen and then examined using shifted and dilated variations of this wavelet. Wavelets have more customizable frequency and timing properties than Fourier methods.
Short-time Fourier Transform and Wavelet Transform are fundamentally different from one another in that the former employs short windows at high frequencies and long windows at low frequencies. Wavelet Transform's fundamental operations involve time compression or dilation rather than a change in the modulated signal's time-frequency. The higher frequency and time resolution of Wavelet Transform allows for more precise fault identification. The ANN [1] is used as a classification tool due to its fast output characteristics.

2. MATLAB/Simulink Model

The transmission line network has been developed into MATLAB Simulink. Figure 1 shows the developed Simulink model. The various faults such as LL, LG, LLG, LLL and LLLG [10] have been created and the various waveforms of voltage and current for the fault have been captured.

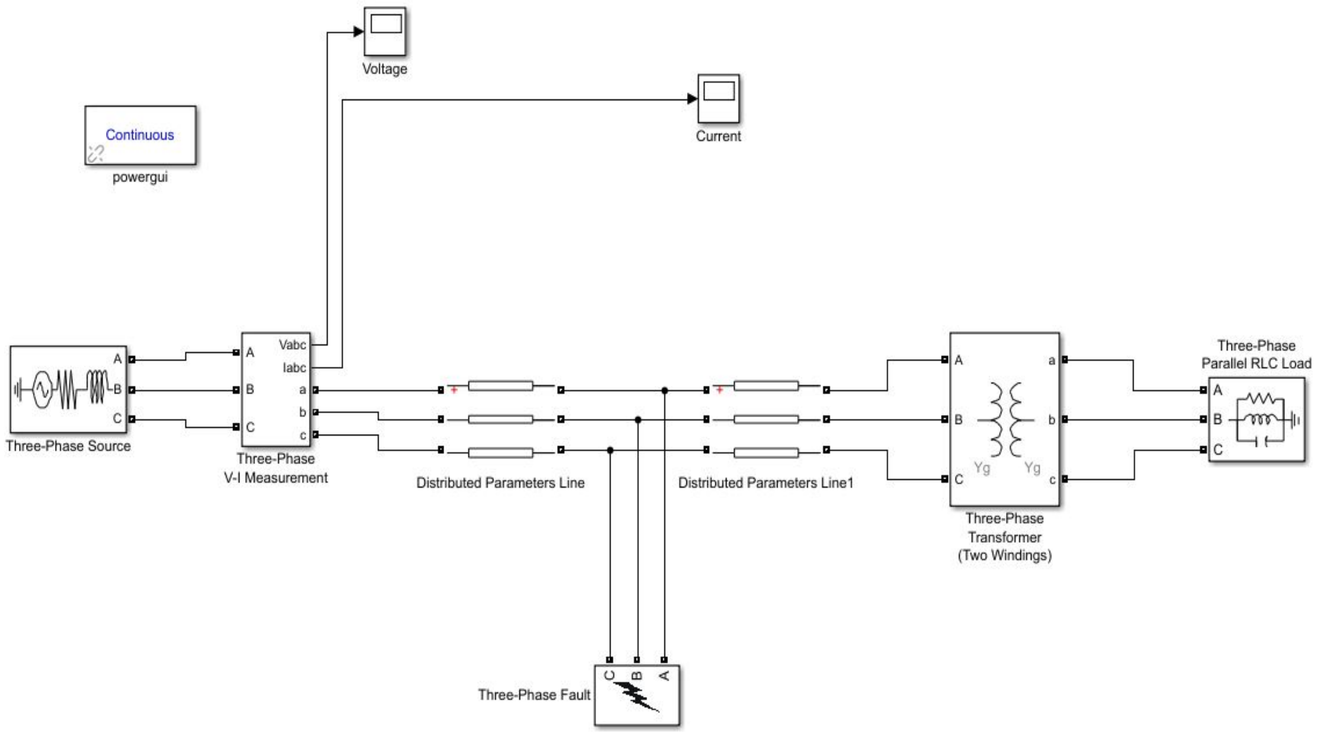

Fig.1 MATLAB Simulink model of transmission line

The transmission line model simulates with LL fault and the current waveform of the LL fault has been captured as shown inthe following figure 2.

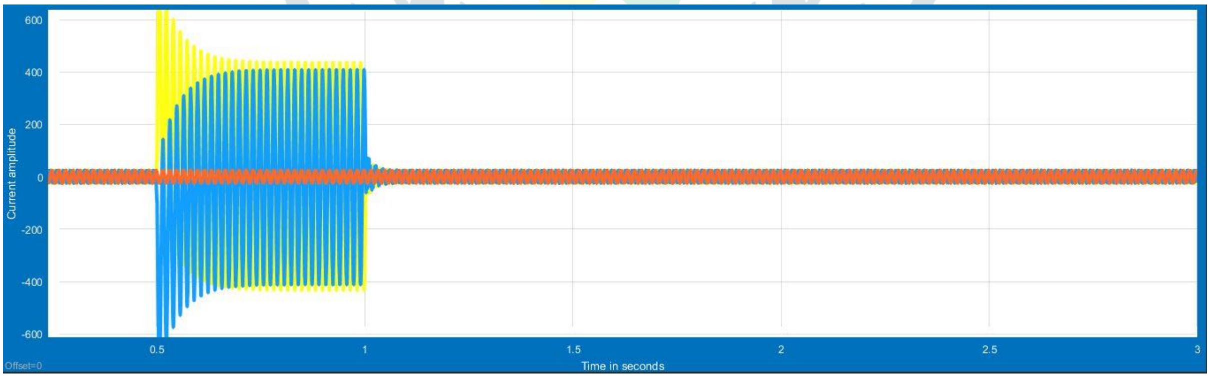

Fig.2 Current Waveform of LL fault

Then LG fault simulates and the Current waveform for the LG fault has been captured as shown in the following figure 3

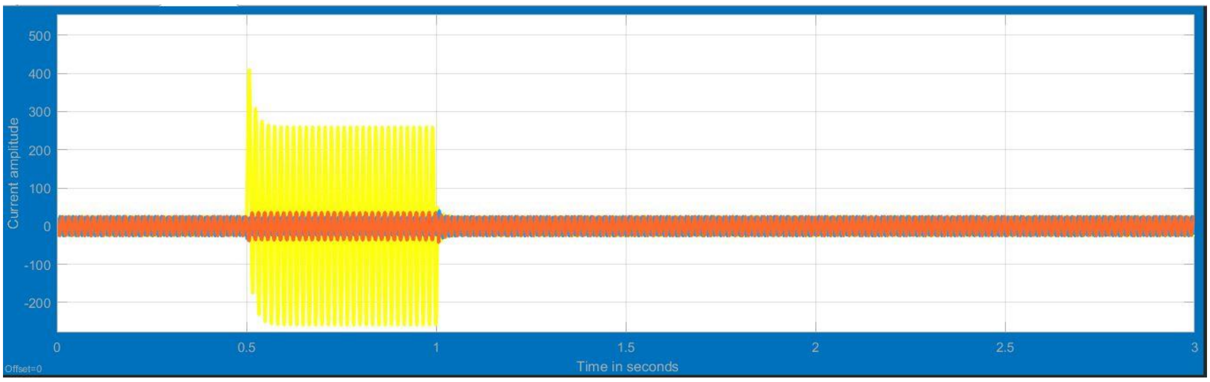

Fig.3 Waveform of LG fault

Figure 4 shows the Current waveform for the LLG fault

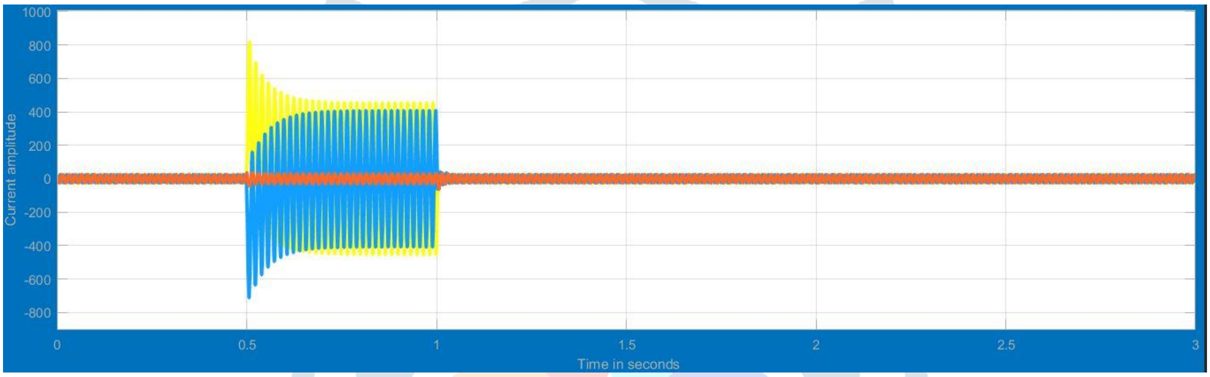

Fig.4 Waveform of LLG fault

Similarly, fault LLL simulates into MATLAB and following Waveform for LLL fault obtained

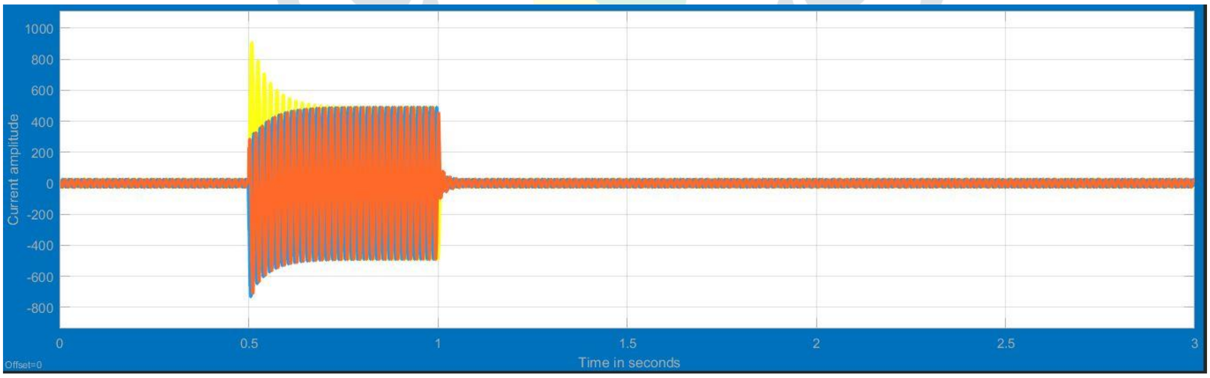

Fig.5 Waveform of LLL fault

3 .Wavelet Decomposition

By breaking down power signals into various frequency ranges using a number of low-pass and high-pass filters, the wavelet transform is an efficient signal-processing tool that can be used to detect abnormal operating circumstances. This makes it possible to perform a time-frequency multi-resolution analysis, which is very helpful for detecting any abrupt changes in electrical parameters including voltage, phase, current, and frequency. The mother wavelet basis function for defect identification in this investigation is the dB5 wavelet [13]. The signal is often split into a set of coefficients that correspond to the approximation (low-frequency or "a") and detailed (high-frequency or "d") bands. The detail coefficients give information about the high-frequency content or abrupt changes in thesignal, whereas the approximation coefficients provide information about the signal's general behaviour. It is possible to find any irregularities or problems in the power system by examining these coefficients.

Continuous wavelet decomposition and separate wavelet decomposition are the two types of wavelet decomposition. Continuous wavelet decompositions are applied to constant time signals, whereas a discontinuous wavelet decomposition [3] applies to discrete-time signals. A variant of the wavelet decomposition that uses many filters as opposed to a single wavelet transformation is Wavelet Package Decomposition. For analyzing signals with a complex frequency content, it is useful. The wavelet decomposition of LG fault signals is shown into the following figure 6.

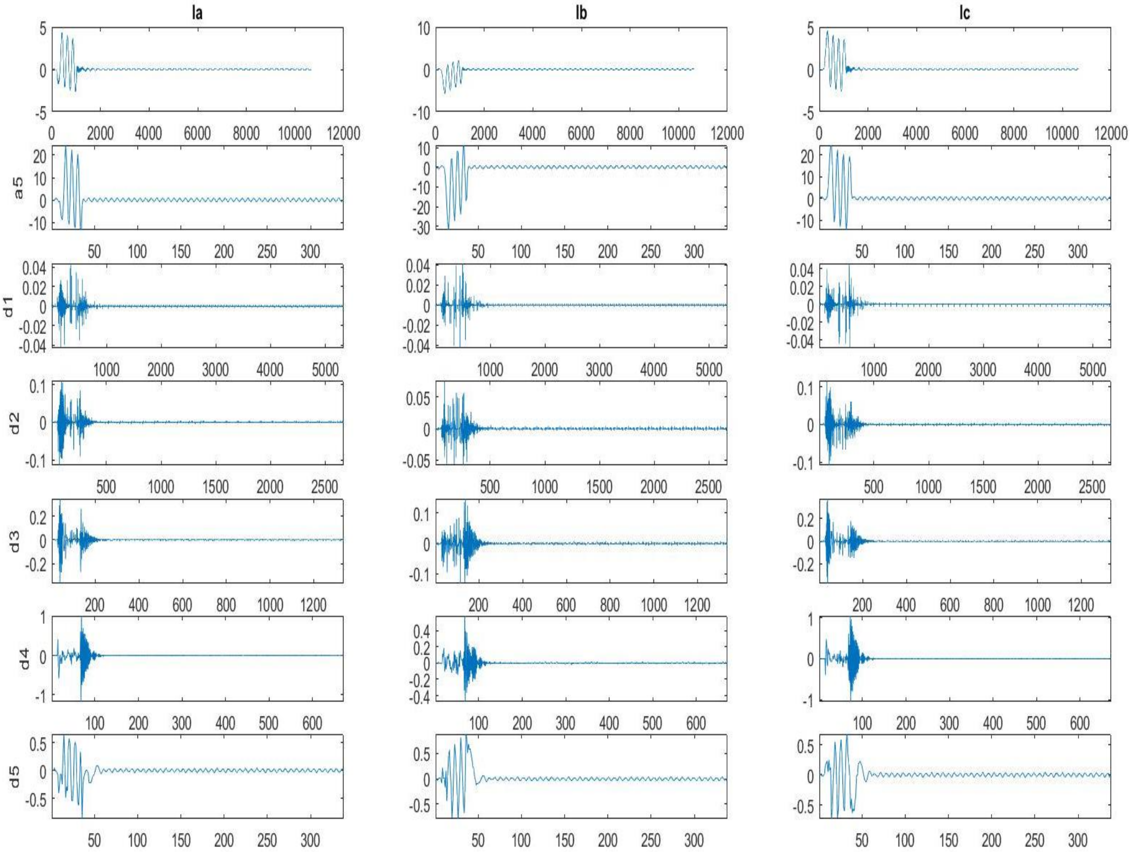

Fig.6 Wavelet Decomposition for LG Fault

Similar decomposition of the various faults has been carried out.

4. ENERGY LEVELS FOR DIFFERENT FAULTS

In this work, a crucial step is the wavelet transform energy determination. The voltage and current signals are provided as input to the transform, and the five-level detail composition has been carried out for the various faults using the db5 wavelet.

$$E=\frac{1}{T}\int_0^T t^2 dt = \sum_{n=0}^{N} |V[N]^2|$$

Where T = Periods N= length of the entire signal and V[n] =FT of the signal.

Similarly, the energy is calculated for other phases. The energy calculation has been tabulated into the following table 1.

Table 1: Energies of various faults

	LG_AG	LG_BG	LG_CG	LL_AB	LL_BC	LL_CA	LLG_ABG	LLG_BCG	LLG_CAG	LLL	LLL	LLL
EIa_I1	7.69E-03	5.80E-04	0.001524031	4.64E+03	0.001061097	0.030137528	0.030299625	4.64E+03	4.64E+03	2.85E-02	2.85E-02	2.85E-02
EIa_I2	0.04042	0.002695511	0.013287824	1.40E+04	0.002890532	0.352423039	0.162406666	1.40E+04	1.40E+04	0.27583158	0.275831578	0.27583158
EIa_I3	0.23962	0.01581832	0.131717987	3.30E+04	0.005552105	2.203302554	0.901387968	3.30E+04	3.30E+04	1.49280878	1.492808777	1.49280878
EIa_I4	0.82975	0.155174473	0.424704307	1.19E+05	0.019097866	6.036064672	2.089325902	1.19E+05	1.19E+05	8.43615541	8.436155409	8.43615541
EIa_I5	4.68457	0.511495895	1.214041161	9.21E+04	0.184118739	21.12860711	8.938112388	9.21E+04	9.21E+04	5.45949565	5.459495654	5.45949565
EIb_I1	0.00168	0.007113466	0.001608376	0.02183549	0.022139741	3.46E-04	0.037584665	1.41E+03	1.41E+03	0.02257934	0.022579343	0.02257934
EIb_I2	0.01498	0.024027314	0.013469833	0.185744328	0.135293113	0.001089456	0.150800846	4.13E+03	4.13E+03	0.07781766	0.077817661	0.07781766
EIb_I3	0.1529	0.080597613	0.129935865	1.129527544	0.527300106	0.003203961	0.931456848	4.11E+03	4.11E+03	0.28188603	0.281886031	0.28188603
EIb_I4	0.45748	0.662432598	0.422505456	2.613237567	3.993586988	0.009935148	2.510030721	2.00E+04	2.00E+04	2.25257515	2.25257515	2.25257515
EIb_I5	1.05485	3.930155723	1.21662583	19.23412607	12.95797251	0.126141969	11.97092055	9.19E+04	9.19E+04	8.53905831	8.53905831	8.53905831
EIc_I1	1.72E-03	4.92E-04	0.007394054	2.35E-04	0.019921975	0.03111923	0.015153929	5.18E+03	5.18E+03	0.03325721	0.033257213	0.03325721
EIc_I2	0.01563	0.002236161	0.038523005	9.14E-04	0.126316309	0.355028133	0.013030015	1.56E+04	1.56E+04	0.23399834	0.233998341	0.23399834
EIc_I3	0.15429	0.01454066	0.2054886	0.002285013	0.503838921	2.231051475	0.106311227	3.50E+04	3.50E+04	1.54049185	1.540491855	1.54049185
EIc_I4	0.15429	0.152586043	0.963563334	0.008586672	3.82440252	6.140474611	0.604106172	1.30E+05	1.30E+05	10.2945214	10.29452139	10.2945214
EIc_I5	0.98116	0.502571041	3.276589194	0.150548103	12.35313648	22.19747572	1.823734507	1.28E+05	1.28E+05	6.85965466	6.859654661	6.85965466

This calculated energy has been given as input to the Artificial neural network [8] for the classification of the faults. variation of hidden layers changes into Epoch, and various network combinations need to be carried outfor the classification of the faults.the following figure 7 shows the classification of faults with the good accuracy of 91.1%.

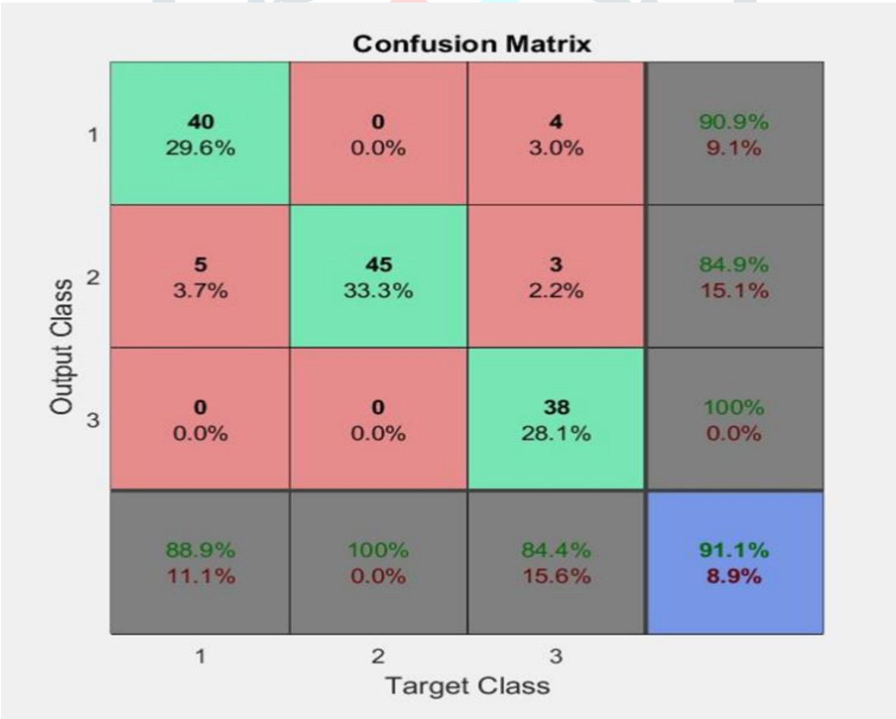

Fig.7ANN classification matrix

The flow chart of the proposed technique is as shown into the following figure 8 [9]

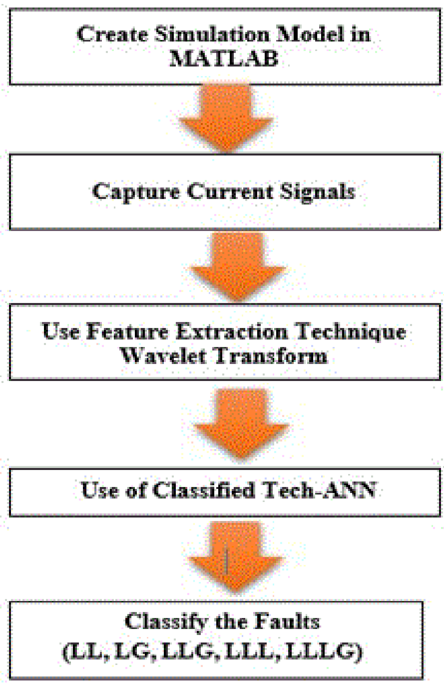

Fig.8 Flow chart

Conclusion: -This paper suggests classifying and identifying various failure types in a multibus power network using a wavelet analysis-based approach. All of these issues can be effectively categorized using discrete wavelet analysis. However, larger systems are needed to assess the usefulness of the strategy in order to achieve a high degree of accuracy, which may require the implementation of additional intelligent classification algorithms. Effectively, all potential electrical faults on the transmission line are categorized by the proposed work.

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