Enhanced Transmission Line Protection Based on Discrete Wavelet Transform (DWT)

N.S. Ugwuanyi, T.C. Madueme

***Abstract:** In order to reduce damage of transmission line due to fault, reliable, high-speed, sensitive and dependable protection system is a primary requirement of today's interconnected power system. It is pertinent to not only detect faults at exactly their time of occurrence, but also to classify them for appropriate restorative decision to be made. In this paper, approach for the protection of transmission line which uniquely manipulates the coefficient energy of Wavelet Transforms to generate ratios that are used for both detection and classification of transmission line faults. The fault current signals generated by MATLAB/SIMULINK simulation have been analyzed using Daubechie-4 (d4) mother wavelet at 7th level decomposition with the help of Wavelet Toolbox embedded in MATLAB. The value of the coefficient energy of the current signals gives the indication of fault and no-fault conditions. Also, the coefficient energy ratios were calculated to help classify the faults. This approach was applied to 132Kv case study and ten classes of fault could be correctly identified and classified within fault duration of 0.01 seconds.*

***Index Terms:** Discrete Wavelet Transform (DWT), Transmission Line Protection, Multi-Resolution Analysis (MRA), Wavelet Energy ratio.*

I. INTRODUCTION

Transmission lines which run over several kilometres will have the chance for occurrence of fault. In order to reduce damage of transmission line due to fault, reliable, high-speed, sensitive and dependable protection system is a primary requirement of today's interconnected power system. It is pertinent to not only detect faults at exactly their time of occurrence, but also to classify them for appropriate restorative decision to be made. The use of digital relays has recorded great improvement in power system protection, however, since the 90's intelligent techniques are under investigation to increase reliability, speed and accuracy of existing digital relays based on Artificial Neural Network (ANN), Fuzzy Logic (FL), Fuzzy-Neuro and Fuzzy Logic-Wavelet based systems [2][3][4].

Various ANN protection schemes for single and/or double circuit transmission lines have been proposed by the researchers in [4][5][6]. The major advantage of ANN based protection scheme is its "intelligence" to find the internal similarity of different types of disturbances. The only concern is that one must train the network with a large data set, and one must select enough relevant training scenarios. Fuzzy logic on its own uses linguistic variables instead of numerical variables and so is much simpler than the neural network based techniques as well as the wavelet based Techniques. In the real world, measured quantities are real numbers (crisp). The operation principle of fuzzy logic controller is similar to human operator. It performs the same actions as a human operator does by adjusting the input signal looking at only the system output [7][8]. However, fuzzy algorithms cannot be guaranteed for wide variations in system conditions and are fairly accurate only under certain assumptions of fault distance, pre-fault power flow, fault resistance and line length.

Signal processing is one of the most important parts of the operation for fault detection. The fundamental frequency components of the post fault voltages and currents need to be extracted as quickly and accurately as possible for the quick response of a digital distance relay. The performance of Fourier analysis, Kalman filtering, least squares methods based algorithms and Finite impulse response (FIR) filtering based protection which were the main tools in signal processing for fault detection are limited for non-stationary signals [9],[10]. Wavelet approach is one of the new signal processing tools which is useful for power system transient analysis, since the conventional signal processing techniques have inherent disadvantages. Wavelet approach to transmission line protection entails the extraction of fault signals, analyzing with wavelet transformation, and consequently making decision for relevant operation of the protective relays.

II. ORIGINALITY

Many works have been published on the use of wavelet transform, for fault detection, location and classification [9-17] some involving combinations of Neural Network and Wavelet Transforms and other using other parameters of Wavelet Transformation. The authors of this work have considered that since the wavelet energy of a signal is unique, any variation in the line will automatically have equivalent variation in the wavelet energy and also will vary the ratio of the line voltages or current (since the energy is a measure of the distortion in the signal). These ratios could be normalized and used as index for fault detection. It has been suggested that wavelet be used to detect fault and while Neural network be used to classify it; however, for an interconnected system, the time for both analysis and detection is very paramount. It will certainly be easier for computer analysis, if just certain values pre-calculated are being manipulated than performing fresh calculations in different routes. Therefore, authors also considered that if a computer program has to manipulate just one input, the speed of operation will be increased when compared with having more than one parameters to evaluate,

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N. S Ugwuanyi, Department of Electrical/Electronic Engineering, Federal University Ndufu-Alike, Ikwo, E-mail: ugwuanyi.nnaemeka@funai.edu.ng
T.C. Madueme, Department of Electrical Engineering, University of Nigeria, Nsukka, E-mail: theophilus.madueme@unn.edu.ng

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Hence, the reason for manipulating the wavelet energy coefficient for both detection and classification. Although many works have been reported about using Wavelet transform technique to detect and classify fault, very few or none has been reported on the use of Wavelet Energy coefficient and its ratio only. This opens way for more tools for transmission line fault detection and classification.

III. WAVELET TRANSFORMATION

Wavelets are mathematical functions that cut up data into different frequency components and then study each component with a resolution matched to its scale. Wavelets are oscillating transforms of short duration amplitude decaying to zero at both ends. Wavelet transforms converts amplitude versus time signal to scale versus time signal. Wavelet analysis is particularly efficient where the signal being analyzed has transients or discontinuities, such as the post-fault voltage/current waveform. The wavelet functions are created from a single characteristic shape, known as the mother wavelet function, by dilating and shifting the window. A mother wavelet is a function that oscillates, has finite energy and zero mean value. The spectacular feature of Wavelet transform is its ability to change scale of observation to study different scales. The wavelet can be expanded to a coarse scale to analyze low frequency, long duration signal and can be shrunk to fine scale to analyze high frequency, short duration features of a signal.

Wavelet transform can be continuous or discrete. For a continuous input signal, the time and scale parameters are usually continuous, and hence the obvious choice is continuous wavelet transform (CWT). On the other hand, the discrete WT can be defined for discrete-time signals, leading to discrete wavelet transform (DWT) [11].

Continuous Wavelet Transform (CWT) is defined as:

$$\mathrm{CWT}(x,a,b) = \frac{1}{|\sqrt{a}|}\int_{-\infty}^{+\infty} x(t)\Psi^{*}a,b\left(\frac{t-b}{a}\right)\,dt \quad \dots (1)$$

Where x(t) is the signal to be analyzed, Ψ(t) is the mother wavelet while $\Psi_{a,b}(t) = \frac{1}{\sqrt{a}}\Psi\left(\frac{t-b}{a}\right)$ represents its dilated and translated version.

a is scale factor (dilation) and b is a time shift (translation). Large and low scales are respectively correspondence with low and high frequencies, and * stands for complex conjugation. The constant $\frac{1}{\sqrt{a}}$ is used to normalize the energy and ensure that the energy of $\Psi_{a,b}(t)$ is independent of dilation level.

The choice of a mother wavelet is flexible provided that it satisfies the following conditions [12].

$$\int_{-\infty}^{+\infty} \boldsymbol{\Psi(t)\,dt = 0} \quad \dots\dots\dots\dots\dots\dots\dots\dots(2)$$

The DWT of a signal is defined as [10]:

$$\mathrm{DWT}(x,m,n) = \frac{1}{\sqrt{a_0^m}}\left(\sum_n X(n)\Psi^{*}\left[\frac{k-na_0^m b_0}{a_0^m}\right]\right)\dots(3)$$

Here, the scaling and shifting parameters **a** and **b** in equation (1) are replaced by their digital counterparts, a_0^m and $na_0^m b_0$ respectively; k, m, n being elements of positive integers. The most frequently used selections of a_0 and b_0 are, by [12], $a_0 = 2$ and $b_0 = 1$.

IV. WAVELET DECOMPOSITION AND MULTI-RESOLUTION ANALYSIS (MRA)

Multi-resolution analysis (MRA) is one of the tools of Discrete wavelet transform, which decomposes original signal typically non-stationary signal into low frequency signal called Approximations and high frequency signal called Details, with different levels or scales of resolution, using a mother wavelet. In wavelet analysis, the original signal is decomposed into its constituent wavelet sub-bands or levels each level representing that part of the original signal occurring at that particular time and in that particular frequency band. MRA designed to produce good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. In MRA, the signal is passed through a series of high-pass filters, also known as wavelet functions, to analyze the high frequencies and it is passed through a series of low-pass filters, also known as scaling functions, to analyze the low frequencies; and also the resulting signal downsampled. The approximations are the high-scale, low-frequency components of the signal and contain more useful information about the original signal. The details on the other hand are the low-scale, high-frequency components and contain information about the fault.

If $c_0(n)$ represent the original discrete-time signal to be decomposed into approximations (smoothed version of the original signal) $c_1(n)$ and details $d_1(n)$, then they are defined as:

$$c_1(n) = \sum_k h(k-2n)c_0(k) \dots\dots\dots\dots\dots\dots(4)$$

$$d_1(n) = \sum_k g(k-2n)c_0(k) \dots\dots\dots\dots\dots\dots(5)$$

Where h (n) and g (n) are the associated filter coefficients that decompose c 0 (n) in to c 1 (n) and d1(n) respectively. That means in first stage decomposition the original signal is divided into two halves of frequency bandwidth. The next higher scale decomposition is now based on the signal c 1(n). The decomposed signal at scale 2 is given by:

$$c_2(n) = \sum_k h(k-2n)c_1(k) \dots\dots\dots\dots\dots\dots(6)$$

$$d_2(n) = \sum_k g(k-2n)c_1(k) \dots\dots\dots\dots\dots\dots(7)$$

The decomposition process can be iterated, with successive approximations being decomposed in turn, so that one signal is broken down into many lower-resolution components. In the first decomposition, signal is decomposed into d1 and c1, the frequency band of d1 and c1 is fs/2– fs, and 0 - fs/2 respectively where the sampling frequency is fs. In the second decomposition step the c1 is decomposed to give c2 and c2. The frequency band of c2 detail level 2 components is fs/4– fs/2, and A2 approximation level 2 is 0–fs /4. As the fault signals contain the high amount of harmonic components, The energy of the signal increases at the occurrence of fault. The energy of the detailed coefficient is computed by equation (8).

$$\boldsymbol{E_w} = \sum_{k=1}^{n_w} [\boldsymbol{d_w(k)}]^2 \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (8)$$

Where $d_w(k)$ is the k^{th} wavelet coefficient within the w^{th} window and $\boldsymbol{n_w}$ is the window length, computed as

$$n_w = \frac{n_s}{2}$$

Where n_s is the number of samples within one cycle of the fundamental frequency of 50 Hz.

Let us state clearly here that while the formulars are the key player of the Wavelet transform, the authors used the graphical user interface (GUI) available in WAVEMENU Matlab to achieve the results. That is to say that the authors set the parameters and the results were automacally extracted from the screen.

V. PROPOSED METHOD

In order to detect and classify fault, the wavelet energy coefficients of the three phase currents, their ratios and the total ratio are calculated under normal condition and fault conditions as:

Wavelet energy coefficients under normal conditions: $\boldsymbol{E_n\,abc}$ (i.e $\boldsymbol{E_n a}$, $\boldsymbol{E_n b}$ & $\boldsymbol{E_n c}$).

Wavelet energy coefficients ratios of the three phase currents under normal condition:

$\boldsymbol{R_n a : R_n b : R_n c \equiv E_n a : E_n b : E_n c}$ **(i.e** dividing through by the smallest coefficient energy)

Total ratio under normal condition:

$$\boldsymbol{R_n T = R_n a + R_n b + R_n c}$$

Wavelet energy coefficients under fault conditions: $\boldsymbol{E_f\,abc}$ **(i.e** $\boldsymbol{E_f a}$, $\boldsymbol{E_f b}$ & $\boldsymbol{E_f c}$)

Wavelet energy coefficients ratios of the three phase currents under fault condition:

$\boldsymbol{R_f a : R_f b : R_f c \equiv E_f a : E_f b : E_f c}$

Total ratio under normal condition:

$$\boldsymbol{R_f T = R_f a + R_f b + R_f c}$$

Whenever $\sum \boldsymbol{E_f\,abc} > \sum \boldsymbol{E_n\,abc}$, fault is detected.

The algorithm is summarized in flow chart in figure 1 below.

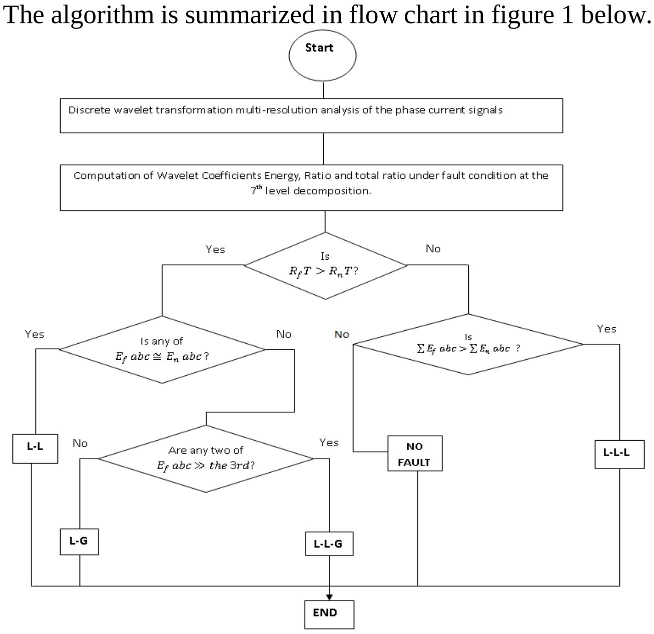

Figure 1: Flow Chart for the Algorithm

In order to reduce the computational burden the sampling frequency should not be too high but should be high enough to capture the information of fault. The sampling time considered in the analysis is 80µs, which corresponds to a sampling frequency of 12.5 kHz, and the total number of wavelet levels considered is 11.

Therefore 1st level detail output corresponds to a frequency band of 6.25-12.5 kHz. Down sampling by two at each succeeding level will lead to a 7th level output corresponding to a frequency band of 97-195 Hz. This implies that it includes 2nd and 3rd Harmonics components which are predominant in case of transmission line faults. Therefore, 7th level decomposition is used for analysis even though the first decomposition level of the DWT contains highest frequency components. The fault duration is 0.01seconds and the wavelet toolbox in MATLAB has been used for DWT operation. Daubechies wavelet Db4 is used as mother wavelet since it has good performance results for power system fault analysis.

VI. TESTING

This approach is applied to a Nigerian 132Kv line running from new Haven to Otukpo. The single line diagram of a power system case study is shown in Figure 1 and the parameter values of the power system are shown in Table 1.

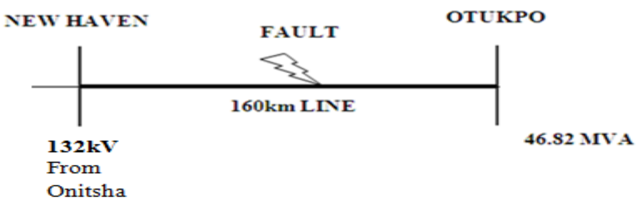

Fig.2: Single Line Diagram of the Power System Case Study

Table 1: Parameter Values of the Power System

Components	Parameters
Frequency	50**Hz**
Source voltage	132**kV**
Transmission line Impedance	R1 = 0.135074 **Ω/km** R0 = 0.303094 **Ω/km** X1 = 0.270124 **Ω/km** X0 = 0.86961 **Ω/km**
Capacitance	C1 = 0.0240500e-7 **F/km** C0 = 0.0069003e-6 **F/km**
Line Load	46.82 **MVA**
Line Length	160**km**

Source: New Haven Power Station (Nigeria)

VII. RESULTS AND DISCUSSION

Normal Condition

The coefficient energy and ratios of these signals at the level 7 decomposition are presented in Table 2. The results obtained at no fault conditions are used as threshold for fault detection

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FAULT TYPE		A-G	B-G	C-G
WAVELET COEFFICIENT ENERGY ($x10^{-5}$)	A	6.42	1.479	1.802
	B	1.773	5.736	1.635
	C	1.666	1.652	6.469
WAVELET COEFFICIENT ENERGY RATIO	A	3.8535	1	1.1021
	B	1.0642	3.8783	1
	C	1	1.117	3.9566
TOTAL RATIO R_fT		5.9177	5.9953	6.0587
SUM OF COEFFICIENT ENERGY		9.86E-05	8.87E-05	9.91E-05

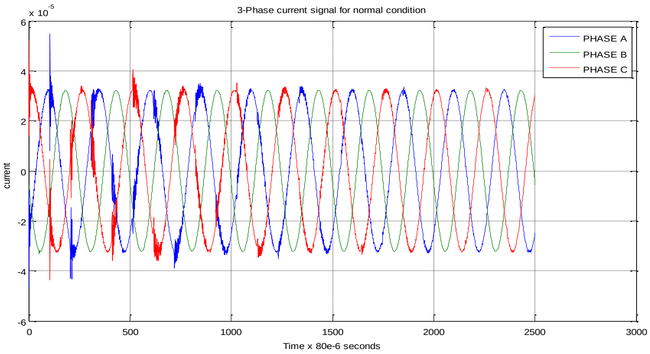

Fig. 3: Three Phase Current Signals at No Fault Condition

Table 2: Wavelet Coefficient Energy and Ratios of three Phase Normal Condition

NORMAL CONDITION		NORMAL
WAVELET COEFFICIENT ENERGY ($x10^{-5}$)	A	0.1559
	B	0.1328
	C	0.1737
WAVELET COEFFICIENT ENERGY RATIO	A	1.173
	B	1.000
	C	1.3080
TOTAL RATIO R_nT		3.4819
SUM OF COEFFICIENT ENERGY		0.4624e-5

Single Line to Ground Fault

It is clear from Table 3 that the sum of coefficient energy during this condition is greater than that found under normal condition, hence, transmission line Fault occurred. In order to investigate the type of fault, we check the total ratio of the coefficient energy. From Table 3, it is seen that the total ratio is greater than that calculated under normal condition. Therefore the fault cannot be three phase fault. If no coefficient energy of any phase is same as under normal condition and no two coefficient energies are extremely greater than the remaining third phase (as is the case here), then the fault must be a L-G fault. In a case of phase A to ground fault for instance, it is seen from Table 3 that the coefficient of phase B and C changed just very slightly compared to change in Phase A (all in relative to the normal). This implies that the fault occurred on phase A.

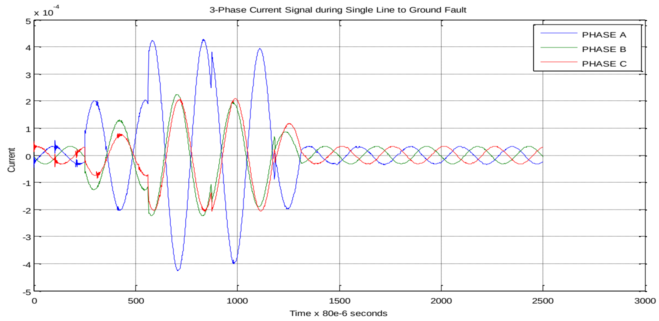

Fig.4: Three Phase Current Signals at L-G fault Condition

Double Lines to Ground Fault

From Table 4, the coefficient energy ratio is greater than that of normal condition, hence, cannot be a three phase fault. If none of the phases has its coefficient energy equal to that of normal and there exist two phases whose coefficient energies are very far greater than the remaining phase (as is the case here), then the fault is a 2L-G type and the two phases whose energies are very high in relative to normal are involved in the fault.

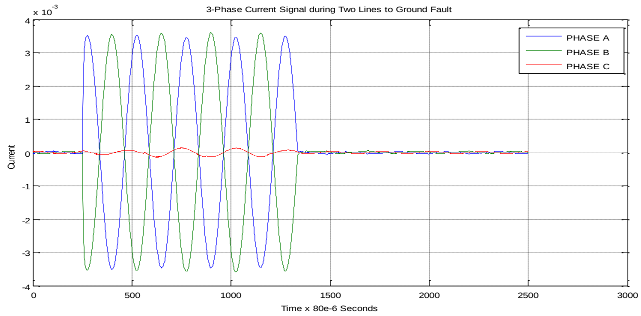

Fig.5: Three Phase Current Signals at 2L-G fault Condition

Table 4: Wavelet coefficient Energy and Ratios of three phase 2L-G fault

FAULT TYPE		AB-G	BC-G	AC-G
WAVELET COEF. ENERGY ($x10^{-5}$)	A	667.1	0.7654	638.8
	B	700.9	620.2	0.6856
	C	0.786	653.3	607
WAVELET COEF. ENER. RATIO	A	848.7277	1	931.74
	B	891.7303	810.29	1
	C	1	853.54	885.34
TOTAL RATIO R_fT		1741.458	1664.83	1818.09
SUM OF COEF. ENERGY		1.37E-02	1.27E-02	1.25E-02

Line to Line Fault

From Table 5 it is seen that sum of energies and the coefficient energy ratio are greater than that calculated under normal condition; confirming a non 3-phase fault has occurred.

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Since one of the phases has coefficient energy equal to that calculated during normal condition for the same phase, the fault is classified as L-L and the two phases whose energies are different from normal indicate the phases involved in fault.

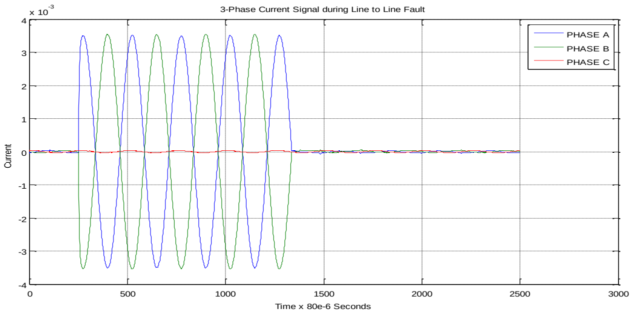

Fig.6: Three Phase Current Signals at L-L Fault Condition

Table 5: Wavelet Coefficient Energy and Ratios of three phase L-L fault

FAULT TYPE		A-B	B-C	A-C
WAVELET COEFFICIENT ENERGY ($x10^{-5}$)	A	677.8000	0.1563	628.300
	B	689.9000	631.000	0.1333
	C	0.1740	642.200	617.200
WAVELET COEFFICIENT ENERGY RATIO	A	3895.4023	1.0000	4713.4284
	B	3964.9425	4037.1081	1.0000
	C	1.0000	4108.7652	4630.1575
TOTAL RATIO R_fT		7861.3448	8146.8733	9344.5859
SUM OF COEFFICIENT ENERGY		1367.8740e-5	1273.3563e-5	1245.6333e-5

<u>Three Phase Fault (L-L-L)</u>

From table 6, the summation of coefficient energy is higher than that of normal while the total ratio is less than that of normal. This classifies the fault as L-L-L fault. It can be noticed that the coefficient energies of all phases were greatly changed.

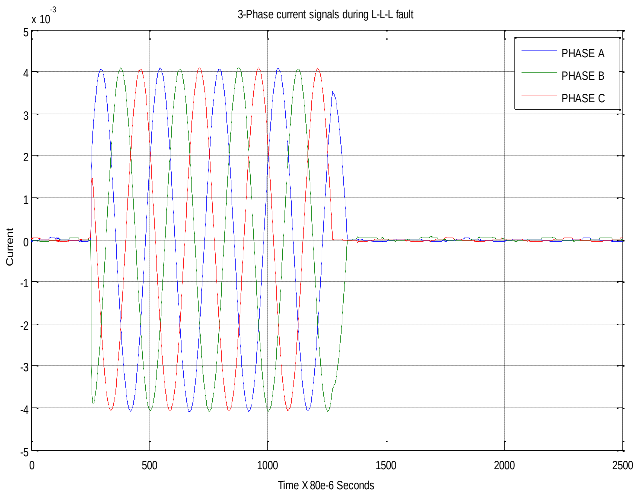

Fig.7:Three Phase Current Signals at L-L-L fault Condition

Table 6: Wavelet Coefficient Energy and Ratios of three Phase L-L-L fault

FAULT TYPE		ABC
WAVELET COEFFICIENT ENERGY ($x10^{-5}$)	A	885.6000
	B	898.3000
	C	832.7000
WAVELET COEFFICIENT ENERGY RATIO	A	1.0635
	B	1.0788
	C	1.0000
TOTAL RATIO R_fT		3.1423
SUM OF COEFFICIENT ENERGY		2616.2e-5

VIII. CONCLUSION

The ability of wavelet transform to extract information from transient signals simultaneously in time and frequency domain has been skilfully employed in this paper to detect and classify transmission line faults. With the approach presented in this work, ten classes of fault (A-G, B-G, C-G, A-B, B-C, A-C, AB-G, BC-G, AC-G & ABC) could be correctly identified and classified within 0.01 seconds of fault duration. All types of fault have been identified and classified by investigating the coefficient energies and coefficient energy ratios of the current signals. From the results, the coefficient energy and the total ratios were found to be increasing as the severity of the fault increases, except for L-L-L fault whose total ratio would be less than that calculated under normal condition

It is concluded that a fault occurs whenever the sum of the coefficient energies of the phase currents is greater than the sum of coefficient energies calculated during pre-fault condition of the line.

Therefore, the use of both coefficient energy and coefficient energy ratio precisely and reliably detects and classifies transmission line faults. However, further research will consider higher voltages to for more validations of results.

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