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A comparative analysis of different mother wavelets for fault detection and classification in the Nigerian 330 kV transmission network

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Abstract

Transmission line fault identification and classification are necessary to ensure the stable and reliable operation of the power systems. During a fault, power flow is disrupted, resulting in a transient condition. Tripping action on the transmission line is mainly dependent on current and voltage waveforms, which are sometimes obtained at the relay location. In order to identify and classify these transmission line faults in real time, fast and accurate analysis is required. Many researchers have deployed signal processing algorithms as tools to study the voltage and current waveforms of fault signals. This paper focuses on a discrete wavelet-based technique for fault detection and classification using the Nigerian 330 kV transmission network as a case study. Detailed coefficients of three-phase and ground currents were used to capture high-frequency transients generated at the instant of fault occurrence (0.4 s). A threshold value of 40 was selected, compared to 31.551 maximum coefficient at no-fault. Ten mother wavelets were comparatively evaluated using the maximum detail coefficient as the performance index. Simulation results show that while all wavelets successfully detected and classified faults, higher-order wavelets such as db4, db8, sym4, and sym8 provided improved stability, lower normal-condition baseline values, and superior fault discrimination. MATLAB/SIMULINK software is used to test the model system with the proposed approach, demonstrating fast response, computational simplicity, and suitability for real-time transmission line protection.

Keywords: Transmission Line; Fault Detection; Fault Classification; Discrete Wavelet Transform

1. Introduction

An electrical power system is a network designed to generate, transmit, and distribute electrical energy from the sending end to the receiving end. The modern electrical power system is divided into three major subsystems, namely: generation stations, transmission stations, and distribution stations. The most important subsystems in power systems are the transmission subsystem, which serves as a crucial link between the generation sections and distribution sections. These lines serve as a vital link between the generating unit and consumers to achieve the continuity of electric supply. The major factors that hamper the continuous flow of electricity are the occurrence of faults on the transmission lines, which result in power flow disruption, power losses, as well as very low transfer capability which give rise to a transient condition [1, 2]. For efficient operation and optimal utilization of the power system, as well as to ensure continuity of service, it is important that these faults on the transmission lines are detected, and classified in real time in order to be cleared promptly to minimize damage and system instability. Many researchers have proposed a variety of fault-finding methods based on the examination of current and voltage waveforms associated with the fault. Several methods include the Kalman-based algorithm, the Fourier-based algorithm, and the FIR filtering-based algorithm. The

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wavelet transform is one of the fault detection techniques that has been used recently. The wavelet transform is a useful technique for analyzing transient voltage and current signals in both the frequency and time domains.

2. Review of Related Works

2.1. Wavelet Transform Techniques for Signal Analysis

The wavelet transform (WT) is a mathematical tool used to analyze the faulty signals obtained from the transmission line or power systems in real time as well as the frequency domains. Wavelet transform (WT) provides a non- uniform division of the frequency domain that is used for short windows with high frequency and long windows with low frequency. The multiresolution analysis (MRA) algorithm is used to analyze fault signals in transmission lines by utilizing a particular frequency band. Transient voltages and current signals during the fault occurrences can carry high-frequency components, which are important information regarding the detection, classification, and location of faults on the transmission line or power systems.

For the discrete wavelet transform, the signal can be decomposed through a high-pass filter and a low-pass filter into an approximation with detail coefficients. Approximate coefficient is the smoothed version of the original signal; in contrast, the discrete coefficient is the high frequencies that make up the original signal. The approximate coefficients can also be decomposed into another high level of approximate and detail coefficients at the incoming signal of both high-pass filter and low-pass filter, where $\mathrm{B}_1, \mathrm{B}_2,$ and B_3 , represent the approximation coefficients (ApCo) of the decomposed signal at each level 1, 2, and 3. Similarly, $\mathrm{D}_1, \mathrm{D}_2,$ and D_3, represent the detail coefficients (DeCo) of the decomposed signal at each level 1, 2, and 3 as seen in Figure 1.

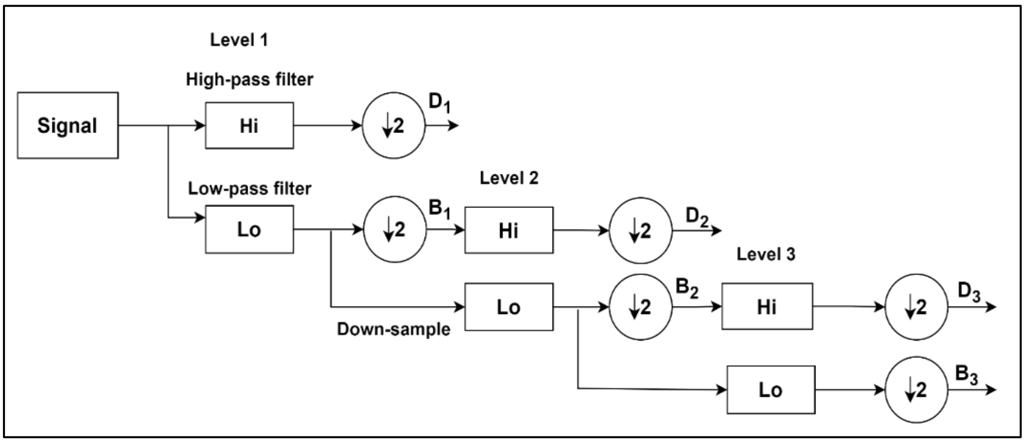

Figure 1 Signal decomposition of high and low pass filter

Wavelet analysis is based on the decomposition of a signal into scales using a wavelet analysis function called "Mother wavelet," which regulates their time width according to their frequency, causing low frequency wavelets to be wider and high frequency wavelets to contract. Fast transient disturbances at lower scales are detected by mother wavelets that are primarily localized in time, while the slow and long transient disturbances are detected by mother wavelets that are less localized in time. Due to this, the wavelet transform provides an excellent support for the analysis of signals that are not stationary and contain local transients. Several mother wavelets can be used in practice to detect and classify transmission line faults. Selecting the best mother wavelet requires one to take into consideration the different features of various mother wavelets. For better frequency resolution, smooth wavelets, such as the Symlet wavelet, are a better option suitable for high frequency resolution than wavelets with sharp steps, like the Haar wavelet. One of the most popular mother wavelets for a variety of power system applications is the Daubechies wavelet, which works best for detecting signals with low amplitude, short duration, rapid decay, and oscillation. The Daubechies four (db4) wavelet is employed for the classification and identification of transmission line faults. Because the Daubechies four (db4) wavelet is more localized, it can be used for quick and brief transient signal analysis. Examining the decomposed signal in both the time and frequency domains is made possible by one of the wavelet transform's greatest features, the time-frequency localization property. Wavelet decomposition comes in two forms, namely:

- Continuous Wavelet Transform (CWT)
- Discrete Wavelet Transform (DWT)

Continuous wavelet transform analyzes a signal with respect to continuous scales and time shifts, it also produces a detailed time frequency representation which is useful for identifying transient events and frequency variations within a signal, but major a limitation of CWT is that, it requires higher computational effort. In contrast, the Discrete wavelet transform uses specific discrete scales and positions implemented through filter banks to decompose a signal into approximation and detail components, making it computationally efficient and well-suited for real-time applications such as fault detection and feature extraction in power systems, unlike the continuous wavelet transform.

A discrete wavelet was employed in [3] as a signal analysis tool to identify and classify the type of transmission line faults. The coefficients of the discrete approximation of the db8 wavelets are used as an index for fault identification and classification. For testing the modelling of the transmission network, MATLAB/SIMULINK software was used, with simulation results obtained by applying the wavelet algorithm. [4], uses wavelet multiresolution analysis to detect and classify faults in transmission lines. Current signals data were collected at the local end of the transmission line, which uses only half a cycle of the post-fault data. The simulation result shows that all possible ten types of faults under different fault inception angles and fault resistances were detected and classified with reasonable accuracy. In [5], the discrete wavelet transform was used as a signal processing technique to classify and detect three-phase transmission line faults. Different types of faults were created in a two-bus system at different locations, and fault currents in all the phases were acquired. Detailed coefficients of each faulty signal were obtained through the application of DWT, which in turn are used in the algorithm to classify the fault in the transmission line. [6] deployed the discrete wavelet transform as a tool adopted to transform the fault signals in such a way that it can be translated to indicate and classify fault type. [7] uses multi-resolution analysis (MRA) to measure the sharp variation of voltage and current signals in faulty conditions. The extracted signals were obtained at both ends of the transmission line. Detailed coefficients of db3 and db4 were applied to the acquired time and frequency signal in order to measure the extracted signals' delivery in the time and frequency domain, with the result showing that the wavelet transform is more suitable for high impedance faults with high voltage transmission lines.

In [8], the wavelet transform and support vector machine were used for the detection and classification of transmission line faults. Similarly, [9, 10] uses combinations of wavelet transform and support vector machine to detect and classify HIF in a power distribution network. The extracted waveform from faulty cases obtained with DWT was fed into the SVM to train the system for accurate detection and classification of HIF. Also, wavelet transform, and Artificial Neural Networks (ANN) for transmission line fault detection and classification are presented in [11, 12, 13].

The effectiveness of the wavelet analysis is largely influenced by the choice of the mother wavelet [14]. The choice of the appropriate mother wavelet depends on the nature of the signal and on the type of information to be extracted from the signal. This paper evaluates ten different mother wavelets, such as: Haar, Daubechies, Symlets, Coiflet, Biorthogonal Splines, Reverse Biorthogonal Splines, Meyer, Fejér–Korovkin, Higher-Order Daubechies, and Higher-Order Symlets families, in order to select the most suitable wavelet applied for fault detection and classification by using the analysis of maximum coefficients of phase currents with fault-induced transients.

3. Materials and Method

3.1. Transmission Line Model

To implement the wavelet, transform for transmission line fault detection and classification, a simple or complex power system network is required. In this research, the Nigerian 50 Hz, 330 kV transmission network, specifically the 72 km double-circuit line connecting Calabar to Ikot Ekpene, is modeled in MATLAB/Simulink software. The line parameters are modeled to reflect the actual operational characteristics of the Nigerian 330 kV system. The parameters from Table 1 are used to create the model in Simulink in Figure 2. This model generates fault data of single-line to ground, double-line to ground, and three-phase to ground fault.

Table 1 System Parameters of the Proposed Model

System components	Parameters/units	Value
Phase to phase voltage	voltage(kV)	330
Source resistance Rs	Ohms(Ω)	0.8929
Source inductance	H	16.58x10−3
Fault resistance Ron	Ohms(Ω)	0.01

Ground resistance Rg	Ohms(Ω)	0.01
Snubber resistance Rs	Ohms(Ω)	1.0x10−6
Fault capacitance Cs	F	infinite
Switching time	seconds	0.8

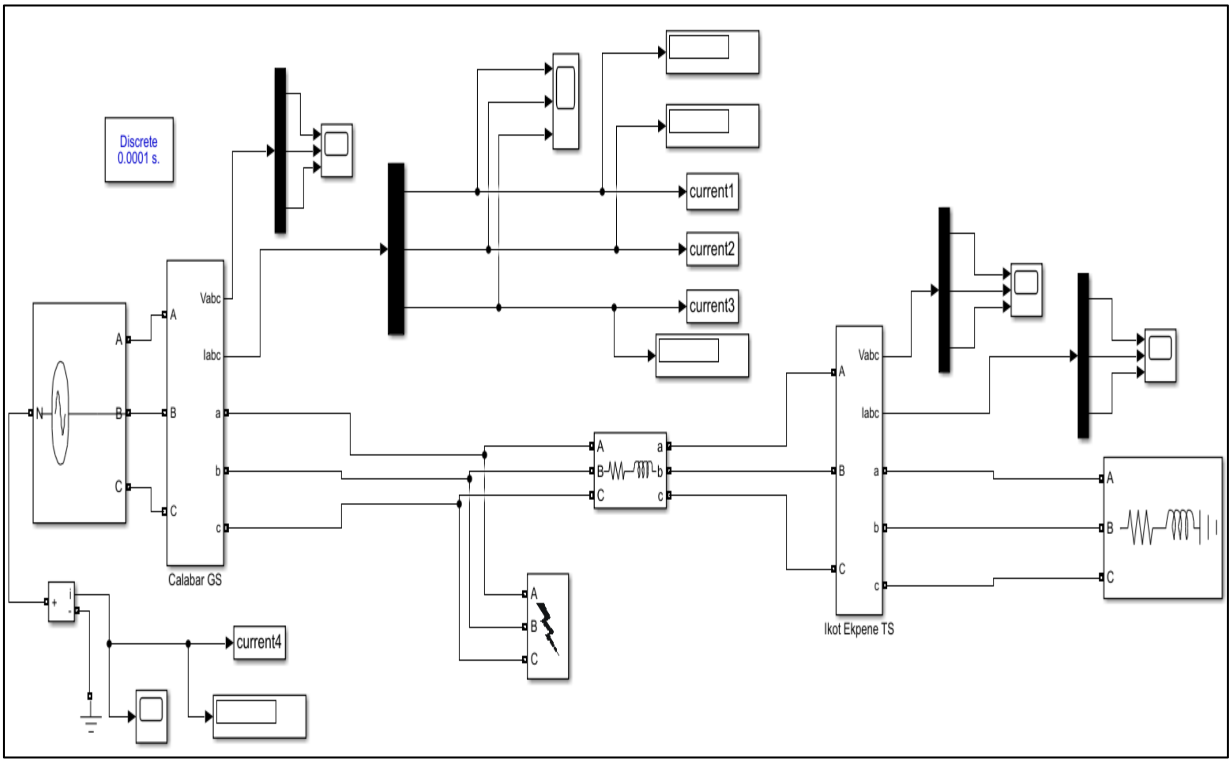

Figure 2 MATLAB Simulation diagram of power system network

As seen in Figure 2, all three-phase currents are represented separately with the help of a demultiplexer. In addition to neutral current, all three-phase currents are connected to the workspace block, and these currents can be easily applied with the wavelet transform in the workspace. Ten discrete mother wavelet families, such as Haar, Daubechies, Symlets, Coiflets, Biorthogonal Spline Wavelets, Reverse Biorthogonal Spline Wavelets, Discrete Meyer, Fejér–Korovkin, Higher-Order Daubechies, and Higher-Order Symlets, are used in this MATLAB programming. The maximum value of each coefficient of each phase current and neutral current was obtained in all twelve fault cases.

4. Results and Discussion

The simulation results obtained from the power system model in Figure 2, under different operating conditions, are presented in Figures 3 and 4. The graphs show the waveform to validate the absence of a fault and the presence of a fault in the transmission network. Under the no-fault state, the waveform is sinusoidal and has no distortion due to noise or fault, so the resultant waveform is standard.

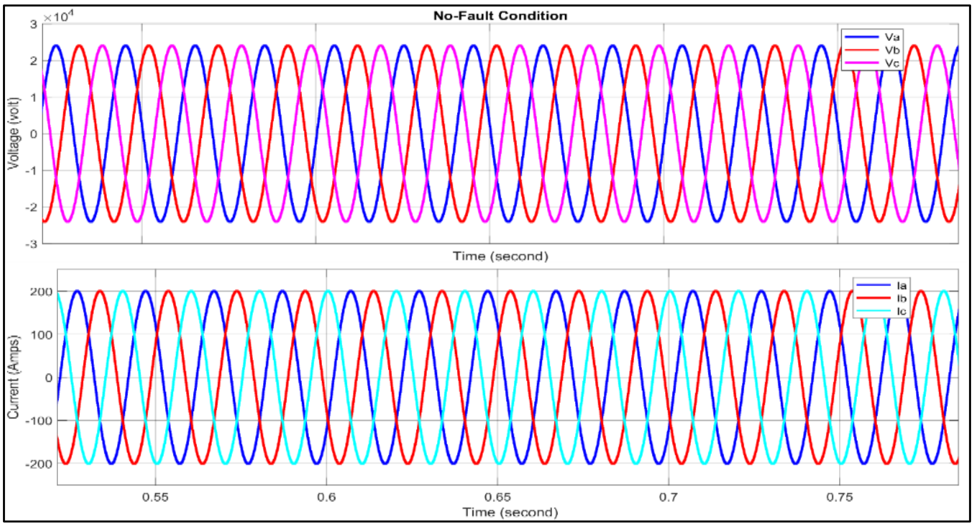

Figure 3 Simulation result of three-phase to ground at no fault condition

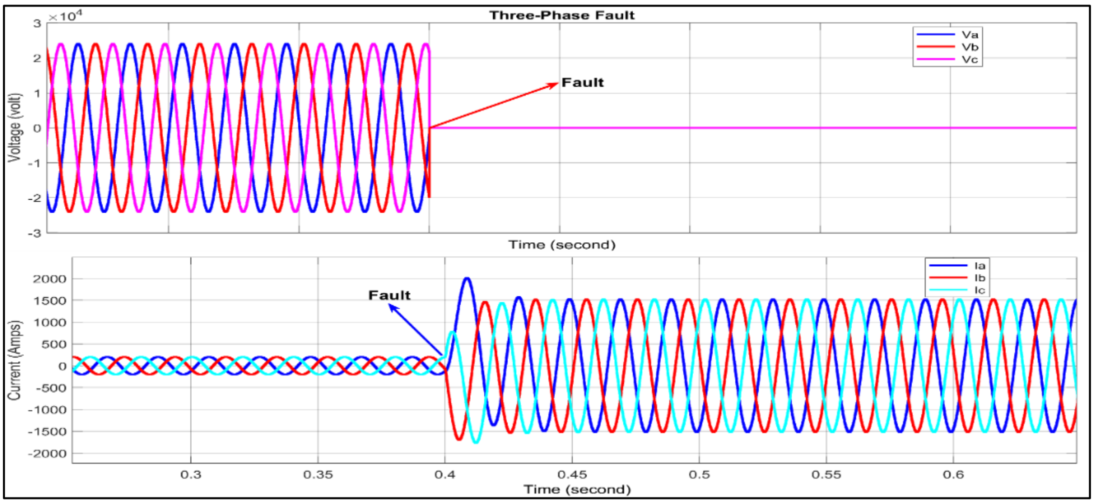

Figure 4 Simulation result of three-phase to ground at fault condition

Figure 4 shows the presence of a fault in the transmission line; the fault current becomes abnormally high, while the fault voltage decreases to zero.

4.1. Detail Coefficient Based Fault Detection

The effectiveness of the wavelet transform for transmission line fault detection was evaluated using the decomposition of phase current signals obtained from the modeled 330 kV Nigerian transmission network in Figure 2. Under normal operating conditions, the maximum detail coefficients for all selected mother wavelets remained very small, thereby establishing a stable reference threshold. At the instant of fault occurrence, a significant rise in detail coefficients was observed, as seen in Table 2. The rise in detail coefficients reflects high-frequency transient components introduced by the disturbance. For single line-to-ground faults, only the affected phase and ground experience a rise in coefficient magnitudes, while healthy phases remain near threshold values. It continues like this in all 12 simulated cases with 10 mother wavelets. These observations validate the suitability of first-level detail coefficients as a reliable and efficient indicator for real-time transmission line fault detection.

Table 2 Comparison Table of Different Mother Wavelet

Fault type	**Maximum coefficient of each phase at different Mother Wavelet**			
	Phase A	Phase B	Phase C	Ground G
	Haar Wavelet Family			
a-g	2.9926e+05	31.551	31.549	2.9923e+05
b-g	31.547	8.3956e+06	31.552	8.3955e+06
c-g	31.55	31.549	8.0963e+06	8.0963e+06
a-b	8.6948e+06	8.6948e+06	31.552	0.0810
a-c	7.7971e+06	31.551	7.7971e+06	0.0839
b-c	31.55	1.6492e+07	1.6492e+07	0.0029
a-b-g	5.996e+06	1.1394e+07	31.551	5.3975e+06
b-c-g	31.549	1.6592e+07	1.6392e+07	1.9949e+05
a-c-g	4.9985e+06	31.55	1.0596e+07	5.597e+06
a-b-c	5.9848e+05	1.6791e+07	1.6193e+07	1.8992e-11
a-b-c-g	5.9848e+05	1.6791e+07	1.6193e+07	3.2927e-09
No fault	31.536	31.549	31.549	4.9741e-13
	Daubechies Wavelet Family (db4)			
a-g	1.5329e+05	13.547	0.8626	1.5327e+05
b-g	14.407	2.7353e+06	0.8603	2.7353e+06
c-g	14.407	13.545	2.6378e+06	2.6378e+06
a-b	2.8328e+06	2.8328e+06	0.8618	0.0264
a-c	2.5403e+06	13.546	2.5403e+06	0.0274
b-c	14.408	5.3731e+06	5.3731e+06	0.0015
a-b-g	1.9535e+06	3.7121e+06	0.86156	1.7585e+06
b-c-g	14.408	5.4056e+06	5.3406e+06	1.0218e+05
a-c-g	1.6286e+06	13.546	3.4521e+06	1.8235e+06
a-b-c	3.0656e+05	5.4706e+06	5.2756e+06	9.7051e-12
a-b-c-g	3.0656e+05	5.4706e+06	5.2756e+06	3.3156e-09
No fault	14.407	13.546	0.86104	4.9344e-13
	Symlets Wavelet Family (sym4)			
a-g	88045	11.722	0.4951	88037
b-g	12.024	5.295e+06	0.4938	5.295e+06
c-g	12.024	11.722	5.2434e+06	5.2434e+06
a-b	5.3465e+06	5.3465e+06	0.4947	0.0524
a-c	5.1919e+06	11.722	5.1919e+06	0.0529
b-c	12.024	1.0538e+07	1.0538e+07	0.0008
a-b-g	3.5987e+06	7.0944e+06	0.49456	3.4956e+06

b-c-g	12.024	1.0556e+07	1.0521e+07	58691
a-c-g	3.4269e+06	11.722	6.9569e+06	3.53e+06
a-b-c	1.7608e+05	1.059e+07	1.0487e+07	5.5578e-12
a-b-c-g	1.7608e+05	1.059e+07	1.0487e+07	3.4929e-09
No fault	12.024	11.722	0.49426	4.6914e-13
Coiflet Wavelet Family (coif3)				
a-g	80815	7.9118	0.4551	80807
b-g	8.1151	4.7506e+06	0.4539	4.7506e+06
c-g	8.1151	7.9118	4.7052e+06	4.7052e+06
a-b	4.7959e+06	4.7959e+06	0.4547	0.0471
a-c	4.6599e+06	7.9118	4.6599e+06	0.0475
b-c	8.1151	9.4558e+06	9.4558e+06	0.0008
a-b-g	3.2275e+06	6.3643e+06	0.4546	3.1368e+06
b-c-g	8.1151	9.4709e+06	9.4406e+06	53871
a-c-g	3.0763e+06	7.9118	6.2434e+06	3.167e+06
a-b-c	1.6162e+05	9.5011e+06	9.4104e+06	5.0973e-12
a-b-c-g	1.6162e+05	9.5011e+06	9.4104e+06	3.6196e-09
No fault	8.1151	7.9118	0.45433	4.7213e-13
Biorthogonal Spline Wavelet Family (bior3.5)				
a-g	74888	6.6183	0.4215	74881
b-g	7.0387	2.0989e+06	0.4204	2.0989e+06
c-g	7.0387	6.6172	2.0625e+06	2.0625e+06
a-b	2.1737e+06	2.1737e+06	0.4212	0.0206
a-c	2.0626e+06	6.6179	2.0626e+06	0.0209
b-c	7.0391	4.125e+06	4.125e+06	0.0007
a-b-g	1.499e+06	2.8484e+06	0.42102	1.375e+06
b-c-g	7.0388	4.1479e+06	4.125e+06	49920
a-c-g	1.3751e+06	6.6178	2.7501e+06	1.3993e+06
a-b-c	1.4977e+05	4.1978e+06	4.1251e+06	4.753e-12
a-b-c-g	1.4977e+05	4.1978e+06	4.1251e+06	2.7165e-09
No fault	7.0383	6.6175	0.42076	3.9818e-13
Reverse Biorthogonal Spline Wavelet Family (rbio3.5)				
a-g	2.4568e+05	21.712	1.3836	2.4565e+05
b-g	23.091	2.335e+06	1.38	2.335e+06
c-g	23.092	21.708	2.2975e+06	2.2975e+06
a-b	2.4988e+06	2.4988e+06	1.3824	0.0229
a-c	2.3794e+06	21.71	2.3794e+06	0.0234
b-c	23.093	4.513e+06	4.513e+06	0.0024

a-b-g	1.775e+06	3.2225e+06	1.382	1.5317e+06
b-c-g	23.092	4.5609e+06	4.5404e+06	1.6377e+05
a-c-g	1.6409e+06	21.71	3.1179e+06	1.5567e+06
a-b-c	4.9133e+05	4.6701e+06	4.595e+06	1.5479e-11
a-b-c-g	4.9133e+05	4.6701e+06	4.595e+06	5.1455e-09
No fault	23.09	21.709	1.3812	6.606e-13
Discrete Meyer Wavelet Family (dmey)				
a-g	75163	6.7737	0.4234	75156
b-g	7.0647	4.3659e+06	0.4223	4.3659e+06
c-g	7.0647	6.7737	4.313e+06	4.313e+06
a-b	4.4188e+06	4.4188e+06	0.4231	0.0431
a-c	4.2602e+06	6.7737	4.2602e+06	0.0437
b-c	7.0651	8.6789e+06	8.6789e+06	0.0007
a-b-g	2.9811e+06	5.8564e+06	0.42295	2.8754e+06
b-c-g	7.0648	8.6966e+06	8.6613e+06	50104
a-c-g	2.8049e+06	6.7737	5.7155e+06	2.9106e+06
a-b-c	1.5032e+05	8.7318e+06	8.6261e+06	4.7617e-12
a-b-c-g	1.5032e+05	8.7318e+06	8.6261e+06	3.7596e-09
No fault	7.0643	6.7737	0.42269	4.7144e-13
Fejér–Korovkin Wavelet Family (fk6)				
a-g	1.8109e+05	11.305	7.6781	1.8108e+05
b-g	11.737	5.0807e+06	7.6787	5.0807e+06
c-g	11.737	11.305	4.8996e+06	4.8996e+06
a-b	5.2618e+06	5.2618e+06	7.6787	0.0489
a-c	4.7185e+06	11.305	4.7185e+06	0.0508
b-c	11.737	9.9803e+06	9.9803e+06	0.0018
a-b-g	3.6286e+06	6.895e+06	7.6785	3.2664e+06
b-c-g	11.737	1.0041e+07	9.9199e+06	1.2072e+05
a-c-g	3.0249e+06	11.305	6.4121e+06	3.3871e+06
a-b-c	3.6217e+05	1.0161e+07	9.7992e+06	1.1416e-11
a-b-c-g	3.6217e+05	1.0161e+07	9.7992e+06	3.673e-09
No fault	11.737	11.305	7.678	4.4116e-13
Higher-Order Daubechies Wavelet Family (db8)				
a-g	90233	9.8482	0.2530	90233
b-g	10.101	4.9129e+06	0.2531	4.9129e+06
c-g	10.101	9.8482	4.8227e+06	4.8227e+06
a-b	5.0031e+06	5.0031e+06	0.2531	0.0482
a-c	4.7324e+06	9.8482	4.7324e+06	0.0491

b-c	10.101	9.7356e+06	9.7356e+06	0.0009
a-b-g	3.3956e+06	6.6107e+06	0.25305	3.2151e+06
b-c-g	10.101	9.7656e+06	9.7055e+06	60155
a-c-g	3.0948e+06	9.8482	6.3701e+06	3.2753e+06
a-b-c	1.8047e+05	9.8258e+06	9.6453e+06	5.8084e-12
a-b-c-g	1.8047e+05	9.8258e+06	9.6453e+06	3.5465e-09
No fault	10.101	9.8482	0.25305	4.2714e-13
Higher-Order Symlet Family (sym8)				
a-g	60431	8.2839	0.3403	60425
b-g	8.4968	4.9375e+06	0.3394	4.9375e+06
c-g	8.4968	8.2839	4.8787e+06	4.8787e+06
a-b	4.9963e+06	4.9963e+06	0.3401	0.0488
a-c	4.8199e+06	8.2839	4.8199e+06	0.0494
b-c	8.4968	9.8163e+06	9.8163e+06	0.0006
a-b-g	3.3701e+06	6.6226e+06	0.33994	3.2525e+06
b-c-g	8.4968	9.8359e+06	9.7967e+06	40284
a-c-g	3.1741e+06	8.2839	6.4658e+06	3.2917e+06
a-b-c	1.2086e+05	9.8751e+06	9.7575e+06	3.8338e-12
a-b-c-g	1.2086e+05	9.8751e+06	9.7575e+06	3.6461e-09
No fault	8.4968	8.2839	0.33973	4.6196e-13

4.2. Comparison for Fault Detection

A comparative evaluation of ten mother wavelets was conducted based on the maximum detail coefficient during various fault conditions, as seen in Table 2. Although all wavelets successfully detected faults in the transmission network. It was observed that the Haar wavelet exhibited the highest peak magnitudes, indicating strong sensitivity to abrupt signal variations. In contrast, higher-order wavelets such as db8 and sym8 demonstrated lower normal condition thresholds while maintaining substantial peak magnitudes during faults. These provide a more balanced, smooth signal, reduced noise sensitivity, and consistent discrimination across all fault types. Consequently, Daubechies db4 and Symlet sym4 wavelets are recommended for fault detection in the modeled 330 kV Nigerian transmission network.

4.3. Detail Coefficient-Based Fault Classification

To accurately classify the various faults, such as single-phase to ground fault (L-G), two-phase fault (L-L), two-phase to ground fault (L-L-G), and three-phase faults (L-L-L or L-L-L-G) along the transmission line, fault signals are simulated and analyzed using the modeled system in Figure 2. A deterministic threshold-based decision logic derived from the maximum detail coefficients of the three-phase currents and ground current. As presented in the simulation results shown in Table 2, the highest coefficient recorded under no-fault condition was 31.551 from a Haar wavelet family; therefore, a threshold value of 40 was selected to ensure reliable discrimination between healthy and faulty states. The classification algorithm compared the maximum detail coefficients of Phase A, given by letter (m), Phase B, given by letter (n), Phase C, given by letter (p), and Ground, given by letter(q), against the predefined threshold. A phase was considered to be faulty if the corresponding coefficient exceeded 40, while values below this threshold indicated a healthy condition. Based on this logic, different fault types in the transmission network were accurately identified. In a case where m, n, p, and q all exceeded 40, the condition was classified as a three-phase-to-ground fault. If m, n, and p exceeded 40 while q remained below 40, the condition was classified as a three-phase fault. For double line-to-ground faults, only the affected phases and ground that exceeded the threshold were classified. Similarly, for line-to-line faults, only the two involved phases that exceeded 40 were classified, while the ground remained below the threshold. Single line-to-ground faults were classified when only one phase and ground exceeded the threshold, as seen in Table 2. The proposed rule-based classifier demonstrated fast execution and clear decision boundaries, making it suitable for real-time protection implementation.

4.3.1. Comparison for Fault Classification

The threshold-based classification algorithm was applied across all ten mother wavelets to evaluate their fault discrimination capability. All mother wavelets successfully identify fault types, as their detail coefficients showed distinct magnitude patterns for different fault categories, as seen in Table 2. However, differences were between faulty and healthy conditions. For instance, the Haar wavelet produced the highest coefficient magnitudes, but its relatively higher baseline value under normal conditions reduced the margin between healthy and fault thresholds. Higher-order wavelets, such as db4, db8, smy4, and sym8, on the other hand, provide lower normal-condition coefficients while still producing significantly high magnitudes during faults. As a result of this, a threshold value of 40 was selected, they by improving the classification reliability and reduces the possibility of false triggering. Mother wavelets such as fk6, dmey, and coif3 demonstrated consistent and dependable discrimination performance. While all mother wavelets could accurately classify faults, db4, db8, sym4, and sym8 showed superior robustness, stability, and threshold separation, making them more suitable for use in the Nigerian transmission network model at 330 kV.

5. Conclusion

The various mother wavelet techniques for transmission of line fault, detection and classification have been compared in this paper. The use of detail coefficients proved highly effective in capturing fault-induced transients, which enables accurate fault detection with a clear threshold margin above the healthy condition. The rule-based threshold classifier techniques reliably distinguish between single line-to-ground, line-to-line, double line-to-ground, three-phase, and three-phase-to-ground faults. Comparative analysis carried out using ten mother wavelets revealed that although all wavelets achieved correct fault identification, higher-order wavelets, particularly db8 and sym8, offered superior performance due to better signal smoothness, reduced noise sensitivity, and wider separation between healthy and faulty states. The result also shows that the proposed techniques are accurate, computationally efficient, and suitable for real-time and practical implementation in contemporary transmission line protection schemes.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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