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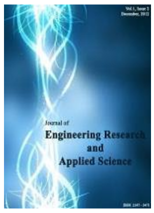

Evaluation of Transmission Line Fault Based on Various Mother Wavelets

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Abstract

Multi-resolution analysis and data feature extraction have received a lot of attention in signal processing. The time-frequency analysis method provides information on joint distribution in both the time and frequency domains and is a potent mathematical tool for analysing time-varying non-stationary signals. The Short-Time Fourier Transform (STFT) is one of the standard time-frequency distribution functions. However, the wavelet transform offers great frequency resolution at low frequencies and high time resolution at high frequencies, which offers constant, equally spaced time-frequency localisation. In this study, to extract the optimal feature vector, the single-phase ground short-circuit fault signal was obtained in the MATLAB environment. Two methods were applied to determine the most suitable wavelet family. The optimal resolution level was determined using Shannon entropy, while the Minimum Description Length (MDL) method was used to select the most suitable mother wavelet family. Accordingly, various wavelet families, including db8, sym5, coif5, bior1.3, and rbio3.1, were tested in discrete wavelet analysis. The results demonstrate that, when the high- and low-frequency components of the fault signal are analyzed in the feature vector extraction using the db8 wavelet, the similarity of the approximation coefficients to the main signal is not significantly affected. Moreover, the feature vector enables the most transparent and accurate identification of transient fault components, particularly in terms of the critical detail coefficients.

Keywords: *Discrete Wavelet Transform, fault diagnosis, Mother wavelet,time-frequency analysis.*

1. Introduction

For power system engineers, providing end users with continuous electricity is a challenging task. It is important to determine the type of fault and its exact location, even if the cause is uncontrollable. A fault is created when conductors come into contact with one another or the ground. The different types of faults are single line-to-ground (SLG), line-to-line (LL), double line-to-ground, and triple line (LLL). SLG, LL, and LLG faults are unbalanced, but LLL faults are balanced. High fault current flows through the power system network as a result of short circuits, causing overheating and mechanical stress on the system's components [2, 8]. It is important to analyse the causes of these faults for rapid system maintenance. This reduces expenses, saves time, and enhances power system stability and dependability [1]. A deeper comprehension of fault behaviour enables easier reactivation and faster transmission line repairs [10]. In this case, identifying and analysing faults requires the extraction of fault features.

Methods used in fault analysis including FT, SFT, Wavelet analysis, etc. FT does not include time information, but it does provide information about a signal's harmonic components. As a result, it is impossible to watch particular events take place at any one time. This basic problem makes Fourier transforms unsuitable for signals that are not stationary. For stationary signals, this is not a major issue. The application of wavelet transforms has solved this problem for nonstationary signals such as fault signal. The wavelet transform, in contrast to the Fourier transform, makes it possible to determine a signal's low-frequency and high-frequency components within each time interval. The composition of the energies of the first, second, and third detail signals—which are separated from the discrete wavelet transform of the differential current signal—determines the feature vector [5, 9]. This approach can be used to accurately analyse transient states and systems whose frequencies change over time.Wavelet series are a technique that can be used in a wide range of domains, such as signal processing, applied mathematics, and image and audio

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compression [3, 11]. Two methods are utilised to determine the optimal technique for wavelet analysis: Shannon entropy and Minimum Discription Length [7]. A wavelet function is chosen using the MDL data criterion. To determine the ideal level of resolution, the Shannon entropy-based criterion is applied. The entropy-based criterion determines the entropy of every subspace made up of detail coefficients ('d') and approximation coefficients ('a') at every DWT resolution level. It uses the optimal mother wavelet to determine the optimal level of resolution by comparing the entropy of a parent subspace with that of its offspring subspaces. According to the criterion, signal decomposition is not required if the entropy of a signal at a new level is greater than that of the previous level.

In this study, the fault signal (single-phase-to-ground short-circuit fault) was analysed using a discrete wavelet. In a 735 kV power transmission system with series compensation, a single-phase-to-ground short-circuit problem was examined using MATLAB. For the best wavelet analysis of the obtained fault signal, the proper decomposition level and wavelet family were chosen using Shannon entropy and the Minimum Description Length (MDL) technique. As a result, the MDL technique identified db8, sym5, coif5, bior1.3, and rbio3.1 as the most appropriate families, and Shannon entropy was used to produce resolution levels of 8, 2, 7, 9, and 10, respectively.The results showed that the db8 (Daubechies 8) wavelet is better suited for upcoming studies like classification because of its reduced noise level, higher energy/amplitude in the feature vector, and easier visibility of detail coefficients. As a result, a general assessment and a comparison assessment were conducted for each wavelet. Also it demonstrates that wavelet-based feature extraction is a reliable and effective computational method for analysing defect signals. This method could be expanded in future studies to categorise electromechanical system defects.

2. Power System Model

The model [15] was implemented to study transient fault signals in a series-compensated 735 kV power transmission system. The system represents a 735 kV, 60 Hz, three-phase transmission network transferring power through two 300 km lines connecting buses B1, B2, and B3. A 300 MVA, 735/230 kV transformer at bus B2 supplies a 250 MW load, while six 350 MVA generators provide a total generation capacity of 1500 MW.

The transmission lines are series-compensated with 40% of their reactance and shunt-compensated using 330 Mvar reactors. Each series compensation unit includes a capacitor, a metal-oxide varistor (MOV), and a spark gap for protection. The system operates in discrete mode with a sampling time of 50 µs.

In a line-to-ground fault on line 1, the current rises to 10 kA, with the MOV dissipating 13 MJ without triggering the spark gap. In contrast, during a three-phase-to-ground fault, the MOV energy reaches 30 MJ, activating the spark gap and rapidly discharging the capacitor. Fault signals were analysed using wavelet transforms before breaker operation to extract feature vectors that represent key transient characteristics, such as frequency components and energy distribution.

The corresponding current waveforms of the system are shown in Fig. 1. According to Fig. 1, the fault occurs at t = 0.0167 s and is cleared at t = 0.9 s when the circuit breakers operate.

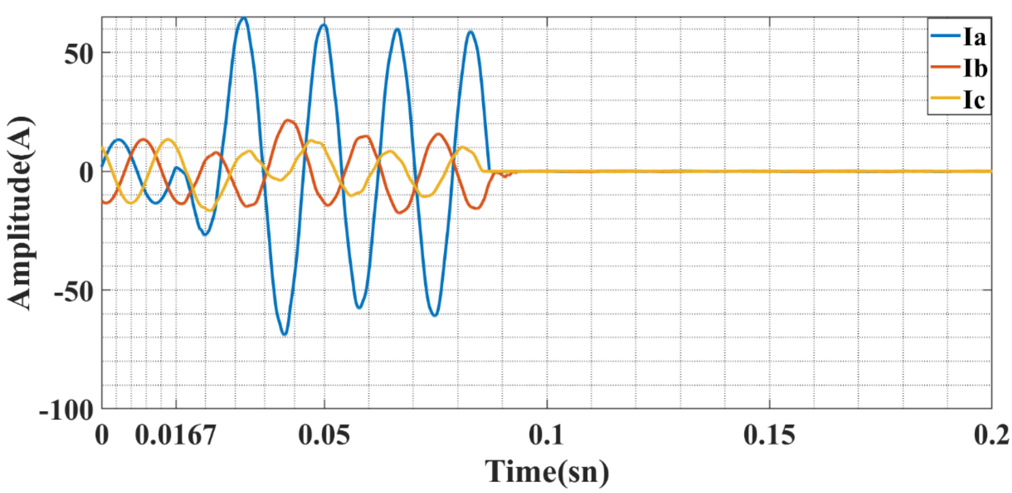


Figure 1. Currents of the system

3. Wavelet Transform Analysis

The objective was to extract a feature vector from the fault current of phase A, since the faults exhibited time-varying behavior. While signals are generally represented as functions of time, analyzing them in the frequency domain can provide valuable information. The FT converts a signal from the time domain to the frequency domain, revealing the frequencies present, but it does not indicate when these frequencies occur, making it suitable for time-invariant signals but insufficient for transient events. To address this, the STFT applies the transform within a moving time window, offering limited time–frequency information. However, the constant-length time interval derived by the window function is one of the method's drawbacks. Although a short temporal window offers adequate time resolution, the frequency resolution that results is inadequate. Frequency resolution will increase but time resolution will decrease if a larger temporal frame is chosen. Therefore, techniques where the window length is automatically adjusted to frequency should be employed if the objective is precise identification of distinct temporal events.Decomposition by WaveletTransform is a good way to solve the STFT method's resolution issues [14]. In the wavelet transform, the input signal is separated into detail coefficients (cD) and approximation coefficients (cA). These represent the high-frequency (y_high[n]) and low-frequency (y_low[n]) parts of the signal, respectively. The coefficients of each frequency band in the wavelet transform can be described mathematically as follows [4].

$$yhigh_{[n]} = \sum_{t=-\infty}^{\infty} s[i]\, h[2n-i] \qquad (1)$$

$$ylow_{[n]} = \sum_{t=-\infty}^{\infty} s[i]\, g[2n-i] \qquad (2)$$

Here, i represents a sampled data point, and n is the total number of samples. The term $[i]$ refers to the discrete radar signal that includes noise, while $[2n-i]$ and $h[2n-i]$ are the low-pass and high-pass filters, respectively, which depend on the chosen mother wavelet function. Using these frequency filters, the wavelet transform allows the extraction of specific frequency bands from the original signal. Fig. 2. illustrates the x-level decomposition process of the N Hz signal into approximation coefficients (cA) and detail coefficients (cD).

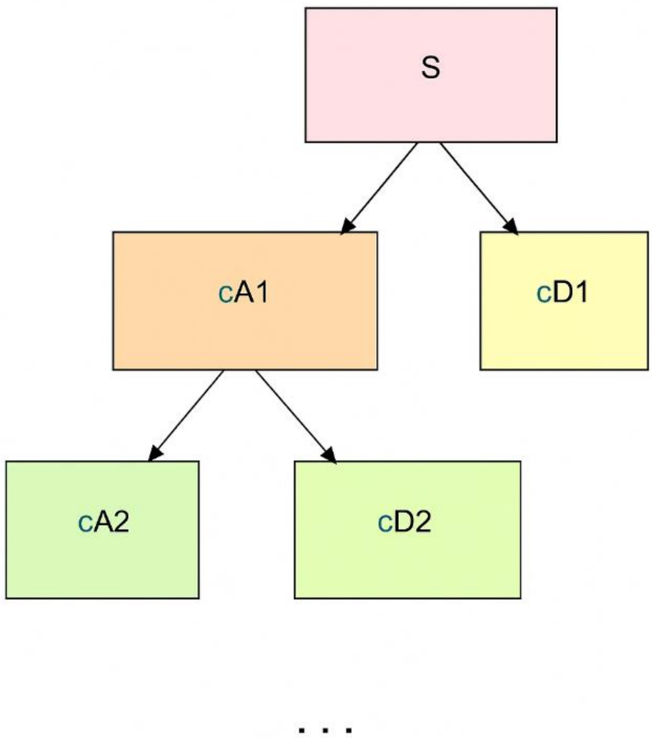


Figure 2. The decomposition process at the x level

The wavelet function is formed by scaling and shifting copies of the scaling function (x) and the mother wavelet function (x), which is a smooth function with compact support. Because there are many kinds of mother wavelet functions, choosing the most suitable one is very important to achieve the best performance — not only for denoising but also for other signal processing tasks. In the discrete wavelet transform, the coefficients represent how the signal is projected onto a set of basis functions created by translating and stretching the mother wavelet and scaling functions [6]. More specifically, the low-pass coefficients are linked to the scaling function, while the high-pass coefficients are linked to the mother wavelet function, as shown in Equations (3)–(5) [12].

$$\mathrm{g(h)} = (-1)^{\mathrm{n}}\mathrm{h}(1-\mathrm{n}) \quad (3)$$

$$\emptyset(x) = \sum_{n} h(n)\sqrt{2}\,\emptyset\,(2x-n) \quad (4)$$

$$\emptyset(x) = \sum_{n} g(n)\sqrt{2}\,\emptyset\,(2x-n) \quad (5)$$

Mother wavelets are of great importance in wavelet analysis because each wavelet can be suitable for different application areas. Therefore, selecting the right mother wavelet ensures a strong correlation between the signal and the optimal results [13]. For this purpose, the Wavelet function is chosen using the MDL data criterion. The best level of resolution is determined using the Shannon entropy-based criterion. At every DWT resolution level, the entropy-based criterion determines the entropy of each subspace made up of detail coefficients ('d') and approximation coefficients ('a'). It uses the optimal mother wavelet to determine the optimal level of resolution by comparing the entropy of a parent subspace with that of its children's subspaces [9]. As shown in Table 1, the best resolution level provides the highest correlation while keeping the dimensionality as low as possible compared to the other analyzed mother wavelets. Based on this evaluation, the selected mother wavelets and their corresponding decomposition levels are listed in Table 1: db8 at level 8, sym5 at level 2, coif5 at level 7, bior1.3 at level 9, and rbio3.1 at level 10.

4. Discussion of the Results

In this study, the current signal of a single-phase-to-ground fault was analyzed using wavelet families as shown in Table 1. Each wavelet decomposition shows both the approximation (low-frequency) and detail (high-frequency) coefficients of the fault signal as shown in Figure 3.

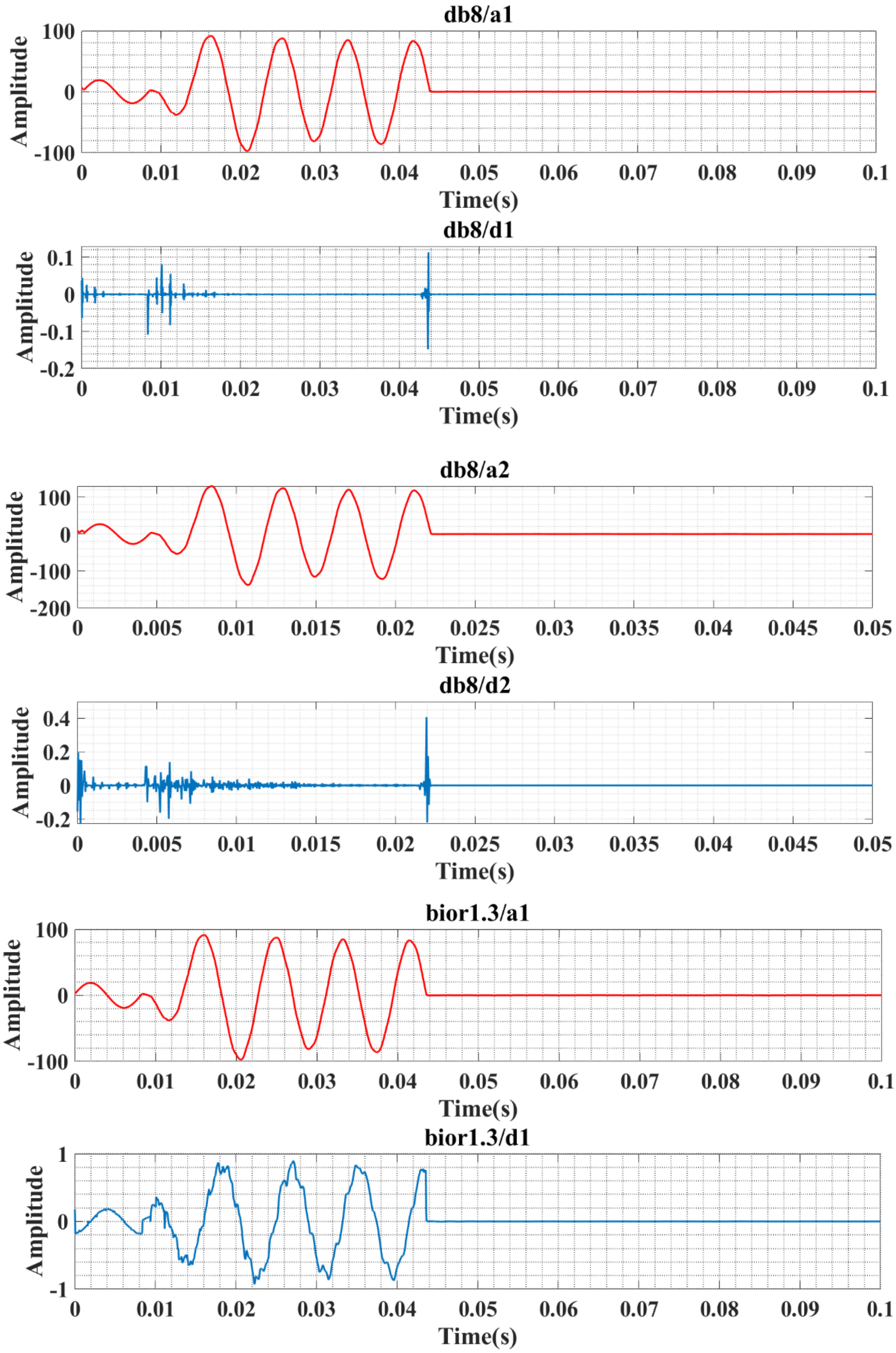
The detail coefficients are especially important because they clearly indicate the moment of the fault with strong high-frequency components. By observing the Fig.3, it can be seen that each wavelet family reacts differently to the transient part of the signal. The main goal is to determine which wavelet provides the best performance for feature vector extraction, based on clarity and noise level. According to Table 2 and the signal behavior, the db8 wavelet family gives the best performance for feature vector extraction.

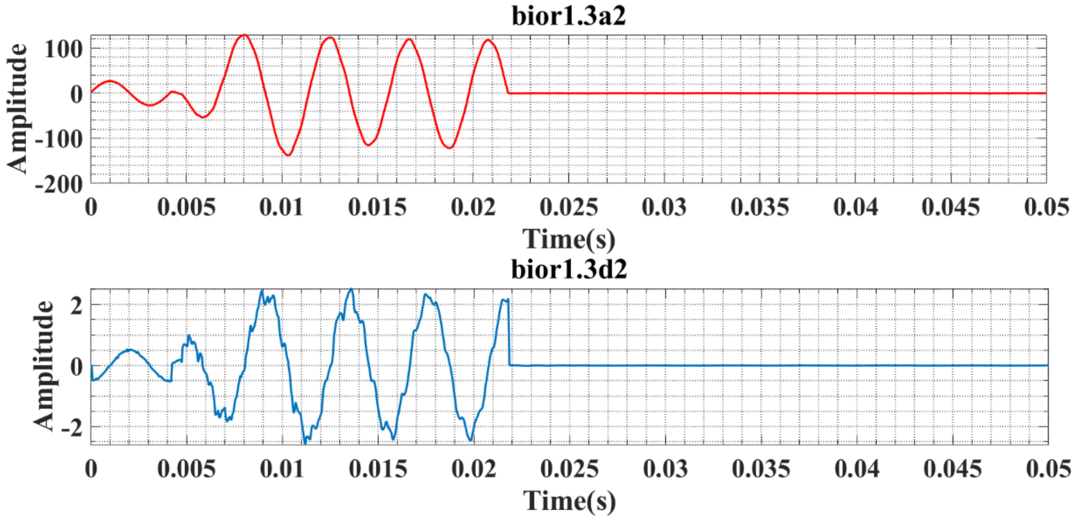
It provides a clear separation of transient fault components and compactly represents the energy of the signal. Therefore, db8 is the most suitable wavelet for accurate and efficient fault detection in this analysis. Other wavelets such as sym5 also give reasonable results but with less energy concentration. coif5, bior1.3, and rbio3.1 show weaker detection feature capability due to their lower sharpness and higher noise sensitivity.

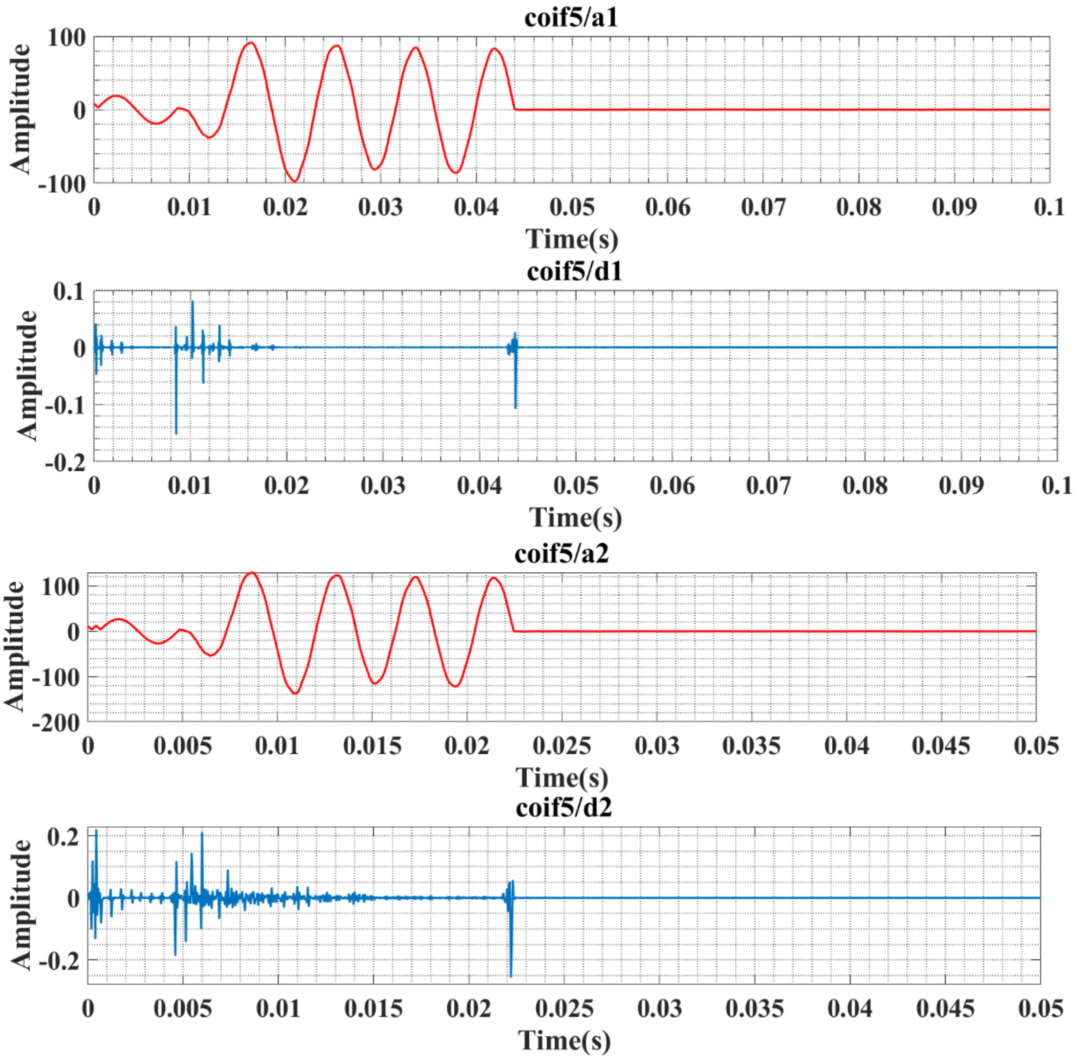
Overall, using db8 allows better identification of the fault characteristics and improves the reliability of the wavelet-based feature extraction process.

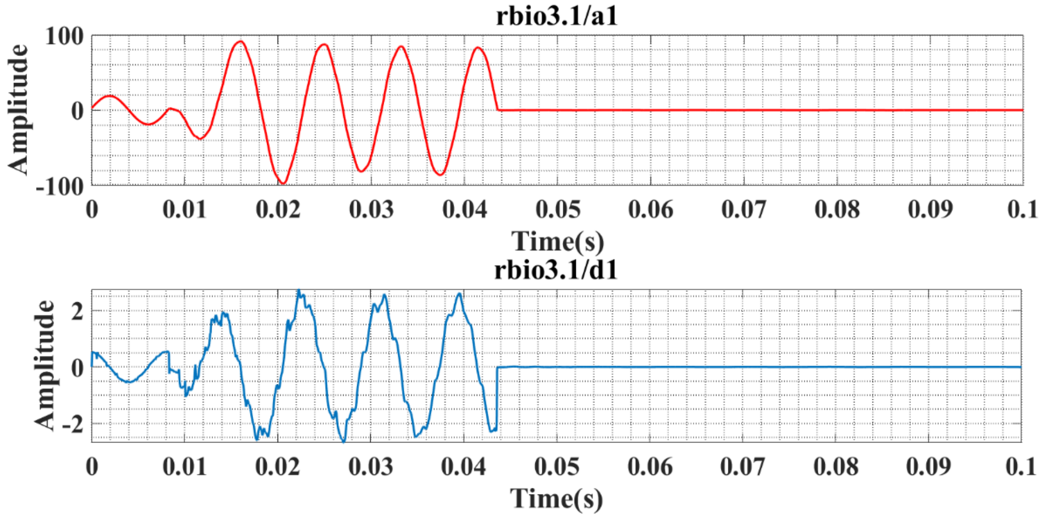
Table 1. MDL and Entropy results for the fault signal

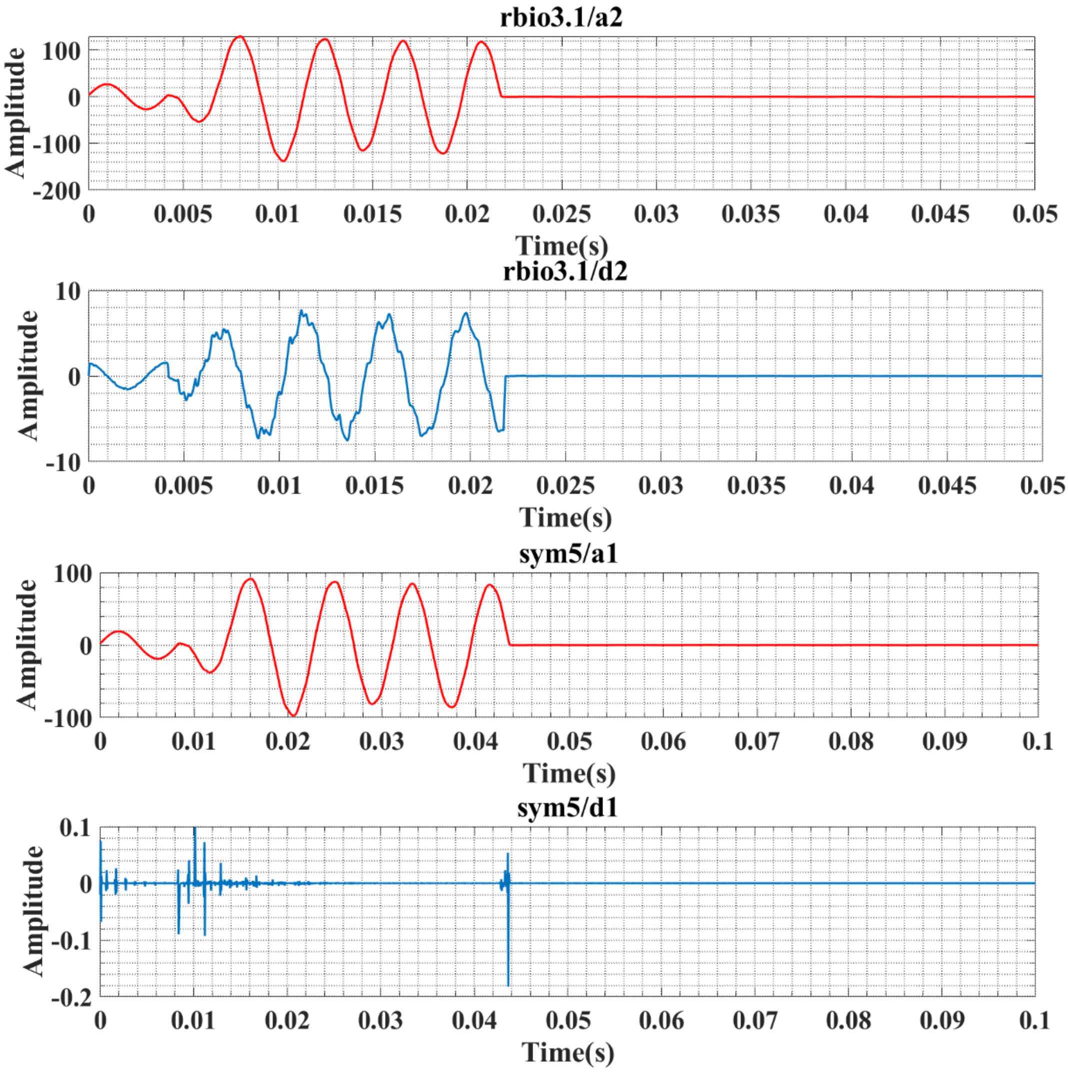
Filter	Decomposition level
db8	8
sym5	2
coif5	7
bior1.3	9
rbio3.1	10


db8/a1
Amplitude
Time(s)
db8/d1
Amplitude
Time(s)
db8/a2
Amplitude
Time(s)
db8/d2
Amplitude
Time(s)
bior1.3/a1
Amplitude
Time(s)
bior1.3/d1
Amplitude
Time(s)


bior1.3a2
Amplitude
Time(s)
bior1.3d2
Amplitude
Time(s)


coif5/a1
Amplitude
Time(s)
coif5/d1
Amplitude
Time(s)
coif5/a2
Amplitude
Time(s)
coif5/d2
Amplitude
Time(s)


rbio3.1/a1
Amplitude
100
0
-100
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Time(s)
rbio3.1/d1
Amplitude
2
0
-2
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Time(s)


rbio3.1/a2
Amplitude
100
0
-100
-200
0
0.005
0.01
0.015
0.02
0.025
0.03
0.035
0.04
0.045
0.05
Time(s)
rbio3.1/d2
Amplitude
10
0
-10
0
0.005
0.01
0.015
0.02
0.025
0.03
0.035
0.04
0.045
0.05
Time(s)
sym5/a1
Amplitude
100
0
-100
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Time(s)
sym5/d1
Amplitude
0.1
0
-0.1
-0.2
0
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
Time(s)

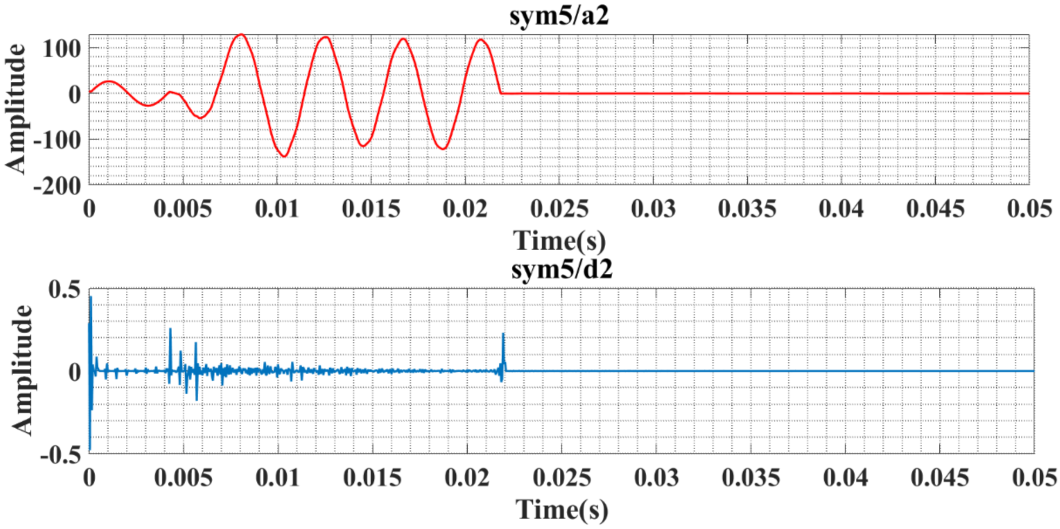


Figure 3. Decomposition of the sample fault current using the optimal wavelet family at the first and second levels

Table 2. Comparison of Wavelet Families for Fault Signal Feature Extraction

Wavelet Family	Fault Visibility	Noise Level	Suitability for Feature Extraction
db8	Very good (sharp and clear transients)	Low	Best – highly suitable
sym5	Good, smooth signal with clear start and end of fault	Low	Suitable
coif5	Moderate, fault visible but energy spread wider	Medium	Partially suitable
bior1.3	Moderate, amplitude changes less consistent	Low	Partially suitable
rbio3.1	Weak, fault components too smoothed	Low	Not suitable

5. Conclusions

This study involves the wavelet analysis of a single-phase-to-ground short-circuit fault occurring in a 735 kV electrical distribution section with series compensation. The Minimum Description Length criterion was used for optimal mother wavelet detection to adequately analyze the fault signal, while the optimal decomposition level was used for Shannon entropy. The results show that db8, sym5, coif5, bior1.3, and rbio3.1 were identified as the most suitable prices, with the order of price levels being the eighth, second, seventh, ninth, and tenth. Subsequently, the most effective wavelets for fault detection were not used in the basis decomposition for a two-level time-frequency analysis, which allows for an overall assessment.

The obtained results demonstrate that the db8 wavelet provides sharp detail coefficients with minimal noise, providing the most accurate and accurate detection of transient fault components. While the sym5 wavelet also demonstrated satisfactory performance, coif5, bior1.3, and rbio3.1 were less effective due to their stronger smoothing properties and lower energy consumption.

Overall, the results showed that the db8 wavelet was more effective in extracting feature vectors for precise fault detection. This would significantly contribute to the reduction in efficiency in the future due to potential fault lights and similar issues.

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