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ORIGINAL ARTICLE

Fault detection through discrete wavelet transform in overhead power transmission lines

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Abstract

Transmission lines are a very important and vulnerable part of the power system. Power supply to the consumers depends on the fault-free status of transmission lines. If the normal working condition of the power system is disturbed due to faults, the persisting fault of long duration results in financial and economic losses. The fault analysis has an important association with the selection of protective devices and reliability assessment of high-voltage transmission lines. It is imperative to devise a suitable feature extraction tool for accurate fault detection and classification in transmission lines. Several feature extraction techniques have been used in the past but due to their limitations, that is, for use in stationary signals, limited space in localizing nonstationary signals, and less robustness in case of variations in normal operation conditions. Not suitable for real-time applications and large calculation time and memory requirements. This research presents a discrete wavelet transform (DWT)-based novel fault detection technique at different parameters, that is, fault inception and fault resistance with proper selection of mother wavelet. In this study, the feasibility of DWT using MATLAB software has been investigated. It has been concluded from the simulated data that wavelet transform together with an effective classification algorithm can be implemented as an effective tool for real-time monitoring and accurate fault detection and classification in the transmission lines.

KEYWORDS

fault diagnosis, fault location, fault simulation, power system interconnection, transmission lines

1 | INTRODUCTION

The power transmission network is an important part of a power system and has a vital role in maintaining the continuity of electrical power to the customers.[1] The deregularization of the power sector has forced the utilities to provide uninterruptable power to their customers and resolve power quality concerns promptly.[2] The power companies are also looking at reducing the downtime of systems in case of any emergency or abnormal situation.[3] The practice of the power operators should be to minimize the fault clearance time so that the system can be brought back into its normal operating state within the minimum possible time.[4]

In case of any abnormal situation in transmission lines, detection and classification of faults must be as fast as possible so that protective devices can isolate the faulty section to safeguard and protect the power system from damages, such as outages, thermal loading, voltage, angular instability, and so forth.[5] Therefore need is to devise a solution that should be able to detect the fault quickly, precisely, and effectively. Faults in transmission can be symmetrical or unsymmetrical and classified as line-line, line-to-ground, three phase fault, and double line-to-ground fault having substantial impact on the performance of transmission lines.[6,7]

Fault analysis has an important association with the selection of protective equipment for the protection and system reliability assessment of extra high-voltage transmission lines. As fault occurs anywhere in the transmission network, the normal working condition of the system is disturbed. If the fault persists for a longer duration it may result in economic losses. Therefore, the fault analysis of 500 kV overhead transmission lines has an important role in ensuring the reliability of the power network in Pakistan. This research will pave the way for analyzing different faults so as to ensure minimum power interruption time, improve mean time to repair, improve time-related to energy not served, and reduce financial losses which is due to sustained power interruption because of faults in overhead transmission lines.

Fault classification in transmission lines needs complex mathematical modeling, signal processing techniques, and expert knowledge to extract features from the fault signal and categorize the type of fault through the implementation of a particular algorithm.[8] Several research reveal that certain fault classification algorithms, fault resistance, and fault inception angle, which are essential for exact feature extraction through a selection of suitable signal processing tools have not been considered.[9,10] In this study, the DWT has been analyzed to retrieve energy contents in the transient signal at variable parameters, such as changing the location of the fault, changing the fault inception angle, and changing values of fault resistance and ground resistance. These four parameters are not found in the previous work for calculating the energy in the fault signal**.** The fault in transmission lines creates disturbances and generates current and voltage transients, which are nonstationary in nature and need to be analyzed using time and frequency analysis techniques for fault analysis and diagnosis in power transmission lines.[11,12]

2 | LITERATURE REVIEW AND RESEARCH GAP ANALYSIS

2.1 | Feature extraction techniques used for fault detection in transmission lines

Various tools used and reported in the past literature for feature extraction from the fault signal with their respective merits and limitations are presented:

(1) Fourier Transform (FT)

FT actually breaks the input signal into smaller frequencies of different sinusoids.[13] This technique is very helpful and simple in nature if the signal is static in nature.[14] Conveying accurate information can be challenging for transient or nonstationary signals because certain features may be lost during the conversion from frequency domain to time domain.[15] Expression of FT for signal $x(t)$ is as under:

$$x(f) = \int_{-\alpha}^{-\alpha} x(t)e^{-j2\pi ft}dt = x(t), e^{2\pi ft}. \tag{1}$$

Which is the inner product of the signal $x(t)$ and the complex sinusoid $e^{-j2\pi ft}$.

(2) Fast Fourier transform (FFT)

FFT is a commonly used approach for feature extraction to convert time domain signal into frequency domain.[16] FFT with several other algorithms is used by the researchers for fault detection and classification in transmission lines.[17,18] The FFT is a useful tool for analyzing stationary signals, and when a signal is periodic, this can be analyzed using the discrete Fourier transform (DFT).[19] Given a sequence $x(k)$ of length N, the DFT is defined by.

$$X[n] = \sum_{k=0}^{N-1} x[k]e^{-\frac{j2\pi nk}{N}}, \quad n = 0, 1, 2, \dots N-1 = x[k], e^{j2\pi nk/N}. \tag{2}$$

The term$e^{-j2\pi nk/N}$ is a discrete-time sinusoid with frequency proportional to n.

(3) Continuous Wavelet Transform (CWT)

The CWT is a mathematical technique that is used for analyzing signals in both the time and frequency domains. Unlike the discrete wavelet transform (DWT), which decomposes the signal into discrete scales, the CWT uses a continuous range of wavelet scales to analyze the signal at different frequencies and time scales. The CWT is useful for detecting signals with variable frequency content

TABLE 1 Limitations of feature extraction techniques used for fault detection in transmission lines.

Feature extraction	Merits	Limitations
Fourier transform (FT)	Very beneficial and simplified in nature if the signal is in a static condition.	Information is lost while the signal transforms from the frequency domain into the time domain
Continuous wavelet transform (CWT)	It provides time and frequency localization of signal components, which allows for a more detailed analysis of the signal. Computationally efficient compared to other signal analysis techniques such as Fourier transform.	Sensitive to the choice of wavelet function, and selecting the appropriate wavelet can be a challenging task. CWT requires significant computational resources, especially when analyzing large data sets
Discrete wavelet transform (DWT)	It is a powerful tool for signal analysis and is mostly used for feature extraction from fault signals. Spectrum energy analysis of transient signal is detailed and continuous contrary to CWT.	Selection of mother wavelet and decomposition matters for feature extraction WT is affected by the sampling frequency
Stockwell transform (ST)	It combines the features of short time Fourier transform (STFT) and continuous wavelet transform (CWT) having the ability to localize signals during fault situations. DWT accurately identifies disturbances in transmission lines due to fault	Generation of S matrix from the signals (voltage and current) from each phase is complex in nature
Fast Fourier transform (FFT)	Its conversion in time and frequency domain for fault analysis in power transmission lines is easy. It provides an accurate assessment of stationary signals.	FFT does not provide information in the time domain whereas the computation of the faulty or transient signal is required in the frequency domain.
Wavelet packet transform (WPT)	It provides better time-frequency resolution than the Fourier transform and wavelet transform and also has high flexibility.	Computational complexity Difficulty in selecting the appropriate wavelet and decomposition level. Sensitivity to noise.

over time, making it a powerful tool for analyzing nonstationary signals.

(4) Short time Fourier transform (STFT)

Research has shown that the STFT is a more effective method for representing a signal in both the frequency and time domains. The STFT is able to overcome the limitations of the Fourier Transform in certain specific cases.[20] Among its drawbacks window sizing is an important consideration; once the specific size window is selected, it remains the same for all frequencies.[21] Long window does not localize short pulses in the time domain and also low frequencies can hardly be illustrated with a short window.[22,23] Equation of a signal $x(t)$ in STFT is given below:

$$X_{STFT}(f,\tau) = [x(t), w(t-\tau)e^{j2\pi ft}], \tag{3}$$

X_{STFT} is a function of both time (τspecifies where the window is nonzero) and frequency (f).

(5) Wavelet transform (WT)

WT has evolved as a features-extracting tool that overcomes the shortcomings of FT and STFT.[24] The WT is capable of providing error-free low-frequency and high-frequency data for long-time intervals, making it a flexible tool for frequency-time transformation with customizable window sizing.[25] The WT can analyze fault signals by breaking them down into detailed (cD) and approximate coefficients (cA). This decomposition provides enough information for detecting and classifying faults in transmission lines. Mathematically, a signal $x(t)$ can be expressed in WT as under:

$$W\tau, s(t) = \frac{1}{\sqrt{s}}\int_{-\infty}^{\infty} x(t)\Psi\left(\frac{t-\tau}{(s)}\right)dt, \tag{4}$$

m and τ are translating and scale factors. $\Psi(t)$ is the mother wavelet. Discrete wavelet transform is a type of WT in discrete form, which uses samples of data or discrete signals for analysis of fault signals because of the increasing use and demand of digital relaying in modern power systems, hence digital fault analysis methods rely on DWT.[26] The DWT of a signal $x(t)$ is defined as:

TABLE 2 Summary of the literature review.

Reference	Type of system (OH/UG/Hybrid)	Feature extraction techniques	Classification methods	Technique and system used	Fault inception angle and fault resistance are considered	Accuracy/precision
Nguyen and Liao[33]	Overhead	Current signals	AFNIS	EMTP/500 kV, 50 Hz, 200 miles	No parameter is considered	Less than 90%
Ngaopitakkul et al.[34]	Hybrid transmission lines	DWT	Decision-tree (DT)	PSCADEMTDC/MATLAB/500 kV/50 Hz, 207 km	No parameter is considered	80%
Singh et al.[35]	Overhead	DWT	SVM	PSCAD/EMTDC400 kV, 50 Hz, 128 km	No parameter is considered	90%
Alsafasfeh et al.[36]	Overhead	DWT	PCA	PSCAD, 220 kV, 50 Hz.	No parameter is considered	94.59%
Hasabe and Vaidya[37]	Overhead	DWT	ANN	MATLAB/SIMULINK220 kV, 50 Hz, 200 km	Fault resistance and length of the line are considered	Satisfactory
Rao and Naik[38]	Overhead	DWT	MRA	MATLAB/SIMULINK400 kV, 300 km, 50 Hz	Only fault inception angle is considered	High
Nayeripour et al.[39]	Overhead	Fuzzy-Wavelet, Singular Values	Fuzzy logic	MATLAB/SIMULINK, 154 kV, 50 Hz, 28 km, Simav & Demcri Turkey	Ground resistance and length are not considered	Not mentioned
Jamil et al.[40]	Overhead	3 phase input signals (voltages and currents)	ANN (FFNN & BPNN)	MATLAB/SIMULINK, 50 Hz, 400 kV, 300 km	Ground resistance and length are not considered	Satisfactory
Hosseini et al.[41]	Overhead	DWT	SVM & MLP	MATLAB/PSCAD/EMTDC, 50 Hz, 400 kV, 100 km	Only fault resistance is considered	99.62%
Jamil et al.[42]	Overhead	WT	Genetic algorithm (GA)	MATLAB, 300 km, 50 Hz, distance not mentioned	Only fault resistance is considered	93%
Suhail Khokhar et al.[43]	Overhead	DWT	PNN	PSCAD/EMTDC11 kV, U/G distribution system	Ground resistance and length are not considered	High
Patel[44]	Hybrid TL	Fast Discrete orthogonal S-transform (FDOST)	SVM	EMTP/ATP400 kV, 50 Hz, combined transmission line, 100 km (OH), 40 km (UG)	Fault resistance and fault inception angle are considered	99.53%
Gashteroodkhani et al.[45]	Hybrid	TT	SVM	230 KV, 60 Hz, 160 km (OH), 32 km (UG).	Fault inception angle & fault resistance are considered	98%

TABLE 2 (Continued)

Reference	Type of system (OH/UG/Hybrid)	Feature extraction techniques	Classification methods	Technique and system used	Fault inception angle and fault resistance are considered	Accuracy/ precision
Düzgün Akmaz et al.[46]	Overhead	FFT	ELM	ATP/EMTP/MATLAB 50 Hz, 380 kV, 600 km	Only Fault resistance is considered	99%
Rosle[47]	Overhead	-	ANN	MATLAB/SIMULINK 60 Hz, 735 kV, 600 km	Only fault resistance is considered	Satisfactory
Our proposed scheme	Overhead	DWT	Deep learning (proposed)	MATLAB/SIMULINK 50 Hz, 500 kV, 155 km	Fault inception angle, fault resistance, ground resistance, and length are considered for fault detection	99.9%

$$DWT(x,m,n) = \frac{1}{\sqrt{a_0^m}} \Sigma_m \Sigma_n x(k)\psi\left(\frac{k - nb_0 {a_0}^m}{a_0^m}\right), \tag{5}$$

where K, m, and n are integers. a_0^m and $nb_0{a_0}^m$ show scale known as dilation and time shift translation, and parameters b_0 and a_0 are constants.

(6) Wavelet packet transform (WPT)

WPT uses high-frequency data contained in the faulty signal. To analyze frequency contents, approximate and detailed coefficients are obtained through the decomposition technique.[27] The decomposition process takes a lot of time in calculation, so to minimize calculation burden the decomposition is performed up to four levels.[28] WPT has the capability to exhibit relatively better frequency resolution than DWT.[29] Mathematically, WPT is expressed as:

$$W_b^{n,a} = 2^{a/2} \int f(t)\psi_n(2^{-2}t - b)dt, \tag{6}$$

b and a represents wavelet position and scale. ψ^n denotes the mother wavelet.

(7) Stockwell transform (ST):

ST exhibits combined features of WT and STFT suitable for a transient signal, where the frequency of the signal increases with a decrease in window size.[30–32] ST possesses capabilities to deliver required information against characteristics of fault signal, that is, time, frequency, and phase angle; it is also prone to noise when used for feature extraction compared with other counterpart signal processing techniques. S transform for signal $x(t)$ is mathematically expressed as:

$$S(\tau, f) = \int_{-\alpha}^{\alpha} x(t)\frac{|f|}{\sqrt{2\pi}} e^{-(t-\tau)^2 f^2/2} e^{-j2\pi f t} dt \tag{7}$$

t and f specify time and frequency and T is control parameter used for Gaussian window adjustment. A comparative analysis of the mentioned featured extraction tools is shown in Table 1.

It is revealed that DWT is the most effective tool for analyzing the transient signal to extract its features for fault detection. DWT is able to handle the impacts of various parameters, such as fault inception angle, fault resistance, ground resistance, and fault location in fault detection for transmission lines. These parameters can affect the spectral energy needed for feature extraction from the fault signal, and in turn, affect the accuracy of fault detection. A summary of the literature review of the previous work carried out by the researchers is presented in Table 2; it highlights the details about feature extraction tools and fault classification techniques along with details of parameters considered by the researchers in their respective research work. Whereas this study considers all the parameters for fault detection against the previous work, which is lacking due to some or few parameters considered for fault detection. Considering all these parameters and analyzing faults through MATLAB/SIMULINK, this study reveals the validity of results in terms of identifying faulty phases using DWT as a feature extraction tool to achieve novel results.

3 | RESEARCH METHODOLOGY

Fault signals considering various parameters, that is, fault inception angles, fault resistance, fault resistance, and ground resistance are generated in transmission lines using DWT as a feature extraction tool, which has been widely used by researchers for fault detection due to its inherent characteristics to overcome effects of noise in detection of fault and understating information in both time and frequency domain.[48,49] The methodology used in this work can be understood from the following steps and flow chart, as shown in Figure 1.

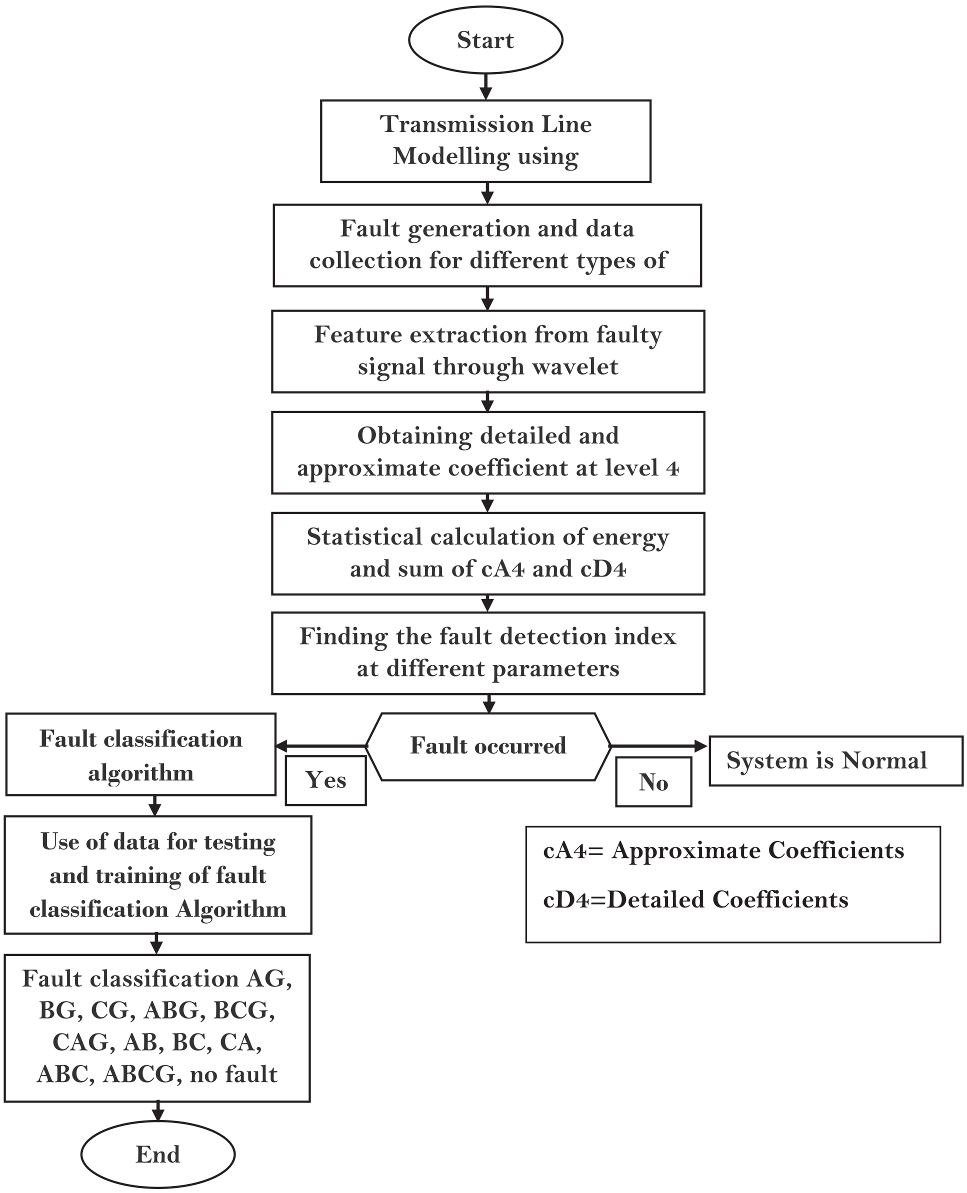

FIGURE 1 Flow chart showing the process of feature extraction from fault signal for fault detection and fault classification in transmission lines.

- MATLAB/SIMULINK has been used for modeling and simulation due to its characteristics, such as high accuracy, reliability, easiness of implementation, and fastness.
- Use of MATLAB code to find out DWT coefficients.
- Obtaining detailed and approximate coefficients at level 4 to obtain the fault index value.
- Differentiate between fault and normal state of the system based upon fault index value compared to a suitable threshold value.

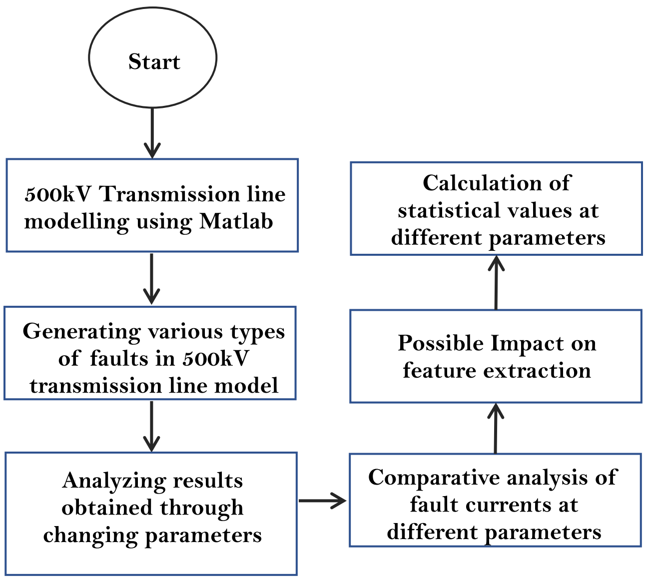

FIGURE 2 Block diagram showing the process of feature extraction from the fault signal.

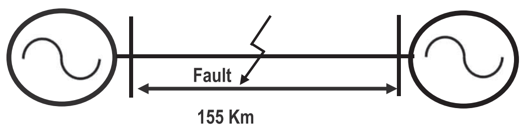

FIGURE 3 Single line diagram of the 500 kV transmission line (Jamshoro-New Karachi, Pakistan).

3.1 | Single-line diagram of proposed research work for fault detection

A single-line diagram of a transmission line under study along with length and sources is shown in Figures 2 and 3, based upon real data of an operational section of a 500 kV transmission line between Jamshoro-New Karachi, Sindh, Pakistan. Table 3 describes the total length of the 500 kV transmission line section under study along with normal power handling capacity per circuit, thermal loading of power in MW, type, and configuration of the conductor. Table 4 details the electrical parameters of a source and line parameters of an existing 500 kV transmission line between Jamshoro-New Karachi (Sindh, Pakistan), along with the conventional frequency used in the national grid of Pakistan. The fault duration window is 1 s used for fault simulation. A MATLAB model of the same 500 kV transmission line circuit of 155 km length between Jamshoro-New Karachi, Sindh, Pakistan, has been developed. The model comprises two sections, each having a distance of 100 and 55 km, respectively, at different parameters as mentioned in Table 5.

3.2 | MATLAB model of the 500 kV transmission line based on actual parameters for fault detection and classification

A MATLAB model of the transmission line has been built using MATLAB version 2020 as shown in Figure 4 relevant parameters in each block are adjusted like line parameters in section blocks, the setting of fault type in fault block along with a change of fault inception angle, fault resistance, ground resistance and location of transmission line in source, fault, and transmission line section blocks, respectively. Thus the process of simulation is initiated and continued till all possible combinations of selected values of

TABLE 3 Data of model under review (500 kV Jamshoro-New Karachi Circuit).

S #	Name of circuit	Length in km	Approx. loading capacity/circuit	Thermal loading	No of string	Types of conductor
1	500 kV Jamshoro-New Karachi (Sindh, Pakistan)	155	1700 MW	2750 MW	1st 29 km: 43 units/string 29–85 km: 40 units/string 85–126 km: 33 units/string 126–155 km: 30 units/string	Greely/Drake (AAAC) (Quad bundle)

TABLE 4 System data and line parameters of 500 kV transmission line between Jamshoro-New Karachi.

S #	Entity	Parameters	Value
1	Generator (source)	Line voltage Vs (RMS)	25 kV, Y-g, $X/R = 7$, phase angle = 0°
2	Frequency		50 Hz
3	Transmission line	Length of line = 155 km Positive sequence impedance/Ohms per phase/km = 0.0185 + j0.2767 Zero sequence impedance/Ohms per phase/km = 0.231 + j0.7892	
4	Fault	Fault duration	0.1 s

TABLE 5 Parameters variation used in MATLAB/Simulink model.

S #	Model parameter	Training data
1	Fault location (km)	5, 15, 25, 35, 45, 55, 65, 75, 100, 110, 120, 130, 140, 150, 155
2	Fault resistance (ohms)	3, 6, 9, 12, 15, 18, 21, 23, 25, 27, 29, 31, 34, 37, 39, 41
3	Ground resistance (ohms)	0, 2, 3, 4, 5, 10, 12, 14, 16, 18, 21, 24, 27, 30, 33, 36, 39, 41
4	Fault inception angle (degrees)	0, 10, 20, 30, 40, 50, 60, 70, 80, 90, 110, 120, 130, 180, 210, 220, 240, 260, 280

parameters considered are completed for all different types of faults as mentioned in Table 6.

The fault signals, that is, currents contains high frequency component that need to be analyzed for fault detection in transmission lines.[50,51] The previous research reveals that wavelets are effectively used for analyzing transients in the fault signals.[52] Use of multi-resolution analysis (MRA) as the tool which decomposes the original signal into approximate and details, that is, to low frequency signal and high frequency through wavelet transforms.[53] To obtain approximate and detailed coefficients the signal is passed through a high pass and low pass, detailed process showing how does detailed and approximate coefficients are obtained is shown Figure 5.

A sampling frequency of 20 kHz has been used in this research work as it provides a number of benefits, such as more accurate fault detection and identification, the ability to capture high-frequency components of fault signals, and reduced risk of aliasing. For MRA analysis, the signal is passed through high pass and low pass filters for disseminating it further into two for obtaining detailed and approximate coefficients, the cycle is repeated, and the signal is decomposed further until it arrives at the predicted level. Mother wavelet Db4 has been chosen for level 3 decomposition due to its proven feature extraction characteristics, the original frequency of the fault signal is captured by detail coefficients (cD) D1, D2,

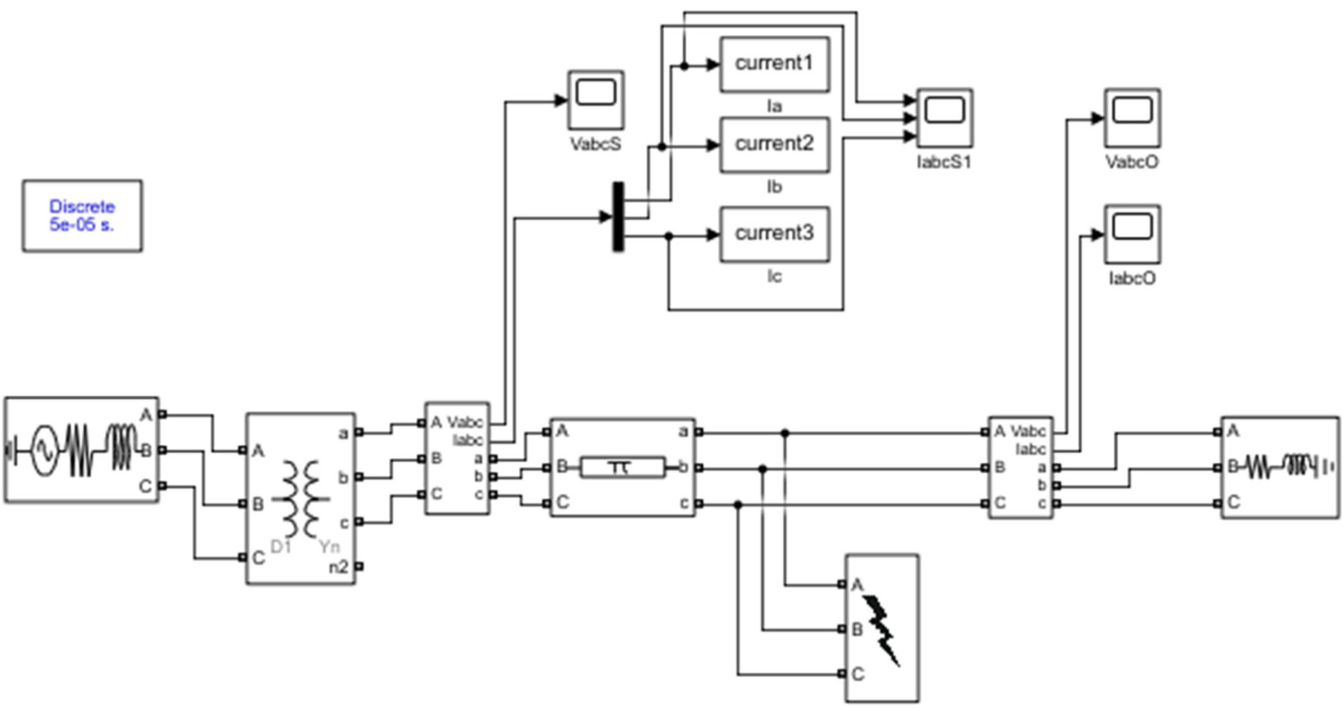

FIGURE 4 MATLAB model of 500 kV transmission line (155 km) between Jamshoro-New Karachi Pakistan.

TABLE 6 Nomenclature of different types of faults.

S #	Fault type	Notation
1	Phase A to ground	A-G
2	Phase B to ground	B-G
3	Phase C to ground	C-G
4	Phase A to Phase B	A-B
5	Phase B to Phase C	B-C
6	Phase C to Phase A	C-A
7	Phases A, B and ground	A-B-G
8	Phases B, C and ground	B-C-G
9	Phases C, A and ground	C-A-G
10	Phases A, B & C	A-B-C
11	Phases A, B, C and ground	A-B-C-G

D3, D4 and approximate coefficient (cA) up to level A4. This helps in extracting useful information from the original signal into different frequency bands.[54] The information of the original signal can be reconstructed by adding up those wavelet signals at the same sample point.[55–57] The wavelet toolbox in MATLAB is the tool for wavelet analysis; Figures 6 and 7 explain the whole decomposition process.

From the fault analysis and the values of the coefficients obtained analytically, it has been cleared that either the fault is in phase(s) with or without ground, the values of coefficient (spectral energy content) are seen quite high in faulty lines as compared to healthy lines. The following formula is used for extracting spectral energy from the signal using WT[58]:

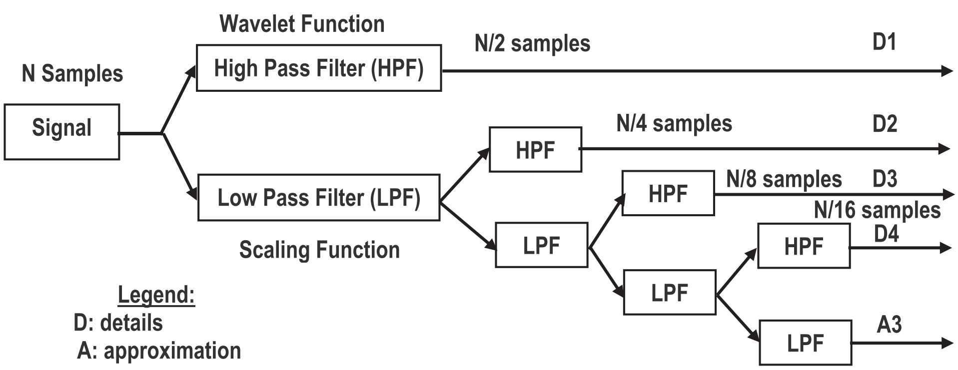

FIGURE 5 Multiresolution analysis (MRA) in DWT for feature extraction.

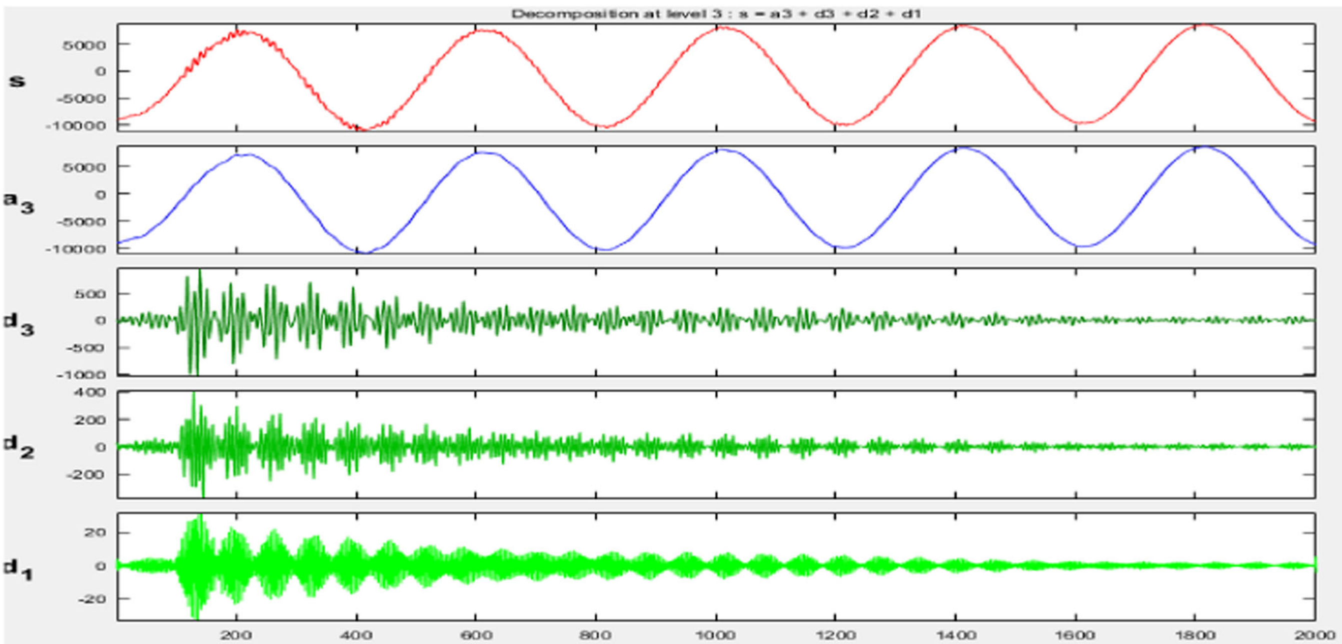

FIGURE 6 Three-level DWT decomposition of a faulty phase current.

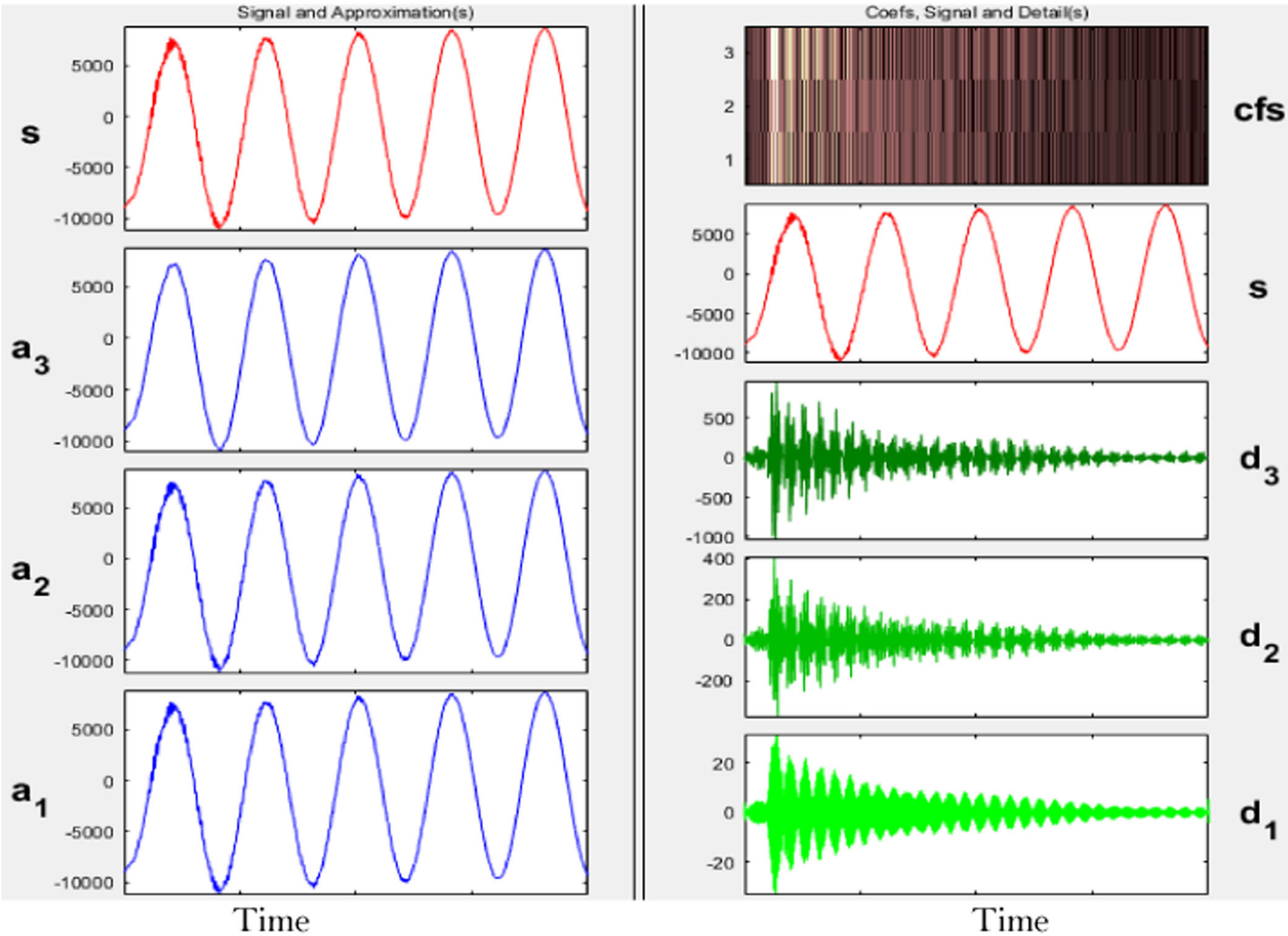

FIGURE 7 Three-level DWT-based decomposition of phase current, showing approximate (cA) and detailed coefficients (cD) for feature extraction from fault signal.

$$E_j(k) = \sum_{n=20(k-1)+1}^{20k} cD_j(n)^2, k = 1, 2, 3 \ldots \quad (8)$$

where E is the spectral energy, n, k, j and detailed coefficients (cD) is the coefficient number, window's number, and the wavelet decomposition level and the magnitude of the coefficient for the details from WT, respectively. Each spectral energy data contains the energy during a certain window length.[59]

Fault impedance affects phases and ground mode energies $E = WTC^2$ which is less when fault impedance is high and vice versa. Energy content distinguishes between the normal and faulty phases.[16] Fault inception angle at which fault transients occur in voltage and current are square sinusoidal functions of the wavelet coefficients.[60] Tables 7, 8, and 9 show the magnitude of coefficients for various fault types at different variables, that is, fault resistance, ground resistance, fault inception angle, and lengths at which fault occurs in transmission lines.

4 | SIMULATION RESULTS AND ANALYSIS

The fault current during each fault generated using variable parameters, as specified in Table 4 (see Section 3.1), is shown in output waves in Figures 8 and 9. Following is the summary of the final findings in the context of the behavior of fault current and subsequent energy contents in the transient signal, Table 10. Since the MATLAB model has been simulated by changing the various parameters. From the simulated results, it has been observed that by incorporating the mentioned parameters and their variation, it is understood that:

- The fault resistance affects high impedance faults (HIFs) since phases and ground mode energies $E = WTC^2$ peaks are smaller in high resistance faults than low impedance faults, which result in smaller wavelet energies.

TABLE 7 Maximum values of coefficients in different phases and ground according to the type of fault at fault resistance $R_f = 0.001$ ohm, ground resistance $R_g = 0.01$ ohm, fault inception angle (FIA) = 30^0, and length at which fault occurred = 10 km.

Type of fault	Max coeff of Ph A	Max coeff of Ph B	Max coeff of Ph C	Max coefficient of ground
AG	1005.10	0.00	0.00	311.44
BG	0.00	275.78	0.00	1700.70
CG	0.00	0.00	695.53	275.78
AB	14882.00	1698.70	0.00	0.00
BC	0.00	1421.00	13179.00	0.00
AC	1734.10	0.00	1698.70	0.00
ABG	14700.00	2311.10	0.00	364.33
BCG	0.00	2089.20	12916.00	526.50
ACG	2148.20	0.00	2308.00	85.79
ABC	11056.00	1731.80	7650.80	0.00
ABCG	11053.45	1729.23	7647.65	23.58
NO fault	0.00	0.00	0.00	0.00

TABLE 8 Maximum values of coefficients in different phases and ground according to the type of fault at fault resistance $R_f = 5$ ohm, ground resistance $R_g = 1$ ohm, fault inception angle (FIA) = 45^0, and Location of fault at length = 50 km.

Type of fault	Max coeff of Ph A	Max coeff of Ph B	Max coeff of Ph C	Max coeff of ground
AG	0.24	0.00	0.00	0.16
BG	0.00	1.03	0.00	0.17
CG	0.00	0.00	0.21	1.13
AB	0.07	0.44	0.00	0.00
BC	0.00	1.12	0.11	0.00
AC	0.68	0.00	0.13	0.00
ABG	0.24	1.03	0.00	0.33
BCG	0.00	1.12	0.15	0.24
ACG	0.239	0.00	0.14	1.12
ABC	0.237	1.118	0.137	0.00
ABCG	0.234	1.037	0.124	0.19
No fault	0.00	0.00	0.00	0.00

TABLE 9 Maximum values of coefficients in different phases and ground according to the type of fault at fault resistance $R_f = 10$ ohm, ground resistance $R_g = 2$ ohms, fault inception angle (FIA) = 90^0, and location of fault at length = 100 km.

Type of fault	Max coeff of Ph A	Max coeff of Ph B	Max coeff of Ph C	Max coeff of ground
AG	2.56	0.0	0.0	0.8872
BG	0.0	2.0636	0.0	0.40
CG	0.0011	0.0011	0.3231	2.251
AB	0.28	0.87	0.00	0.00
BC	0.00	2.23	0.34	0.00
AC	1.36	0.00	0.22	0.00
ABG	0.32	2.06	0.00	0.24
BCG	0.00	2.25	0.32	0.41
ACG	0.18	0.00	0.68	2.23
ABC	0.33	2.07	0.24	0.00
ABCG	0.41	2.25	0.32	0.32
No fault	0.00	0.00	0.00	0.00

- The faults involving ground resistance can also cause incorrect signal measurement data
- The fault inception angle affects the severity of the fault-initiated traveling waves.
- As the impedance is proportional to the distance between the fault point and the relay, the relay indirectly indicates the distance and location of the fault.

Besides the results, variation of the fault current can also be measured in the form of energy content in the transient signal as its fault index compared with certain threshold values is considered fixed for relative comparison. Based upon the net energy content of the faulty phase(s) with or without ground, it is easy to distinguish between faulty and healthy states of the power transmission network. This validates that even with changing variables, feature extraction from the fault signal is not affected. Therefore it is concluded that DWT is robust and variations of input parameters in the MATLAB model do not affect the energy of the signal during the fault.

As discussed earlier, the energy contents in the fault signal also vary in accordance with the change in fault inception angle, which is helpful for the accurate detection of fault by extracting features from the fault signal. Figure 10 helps to understand the behavior of

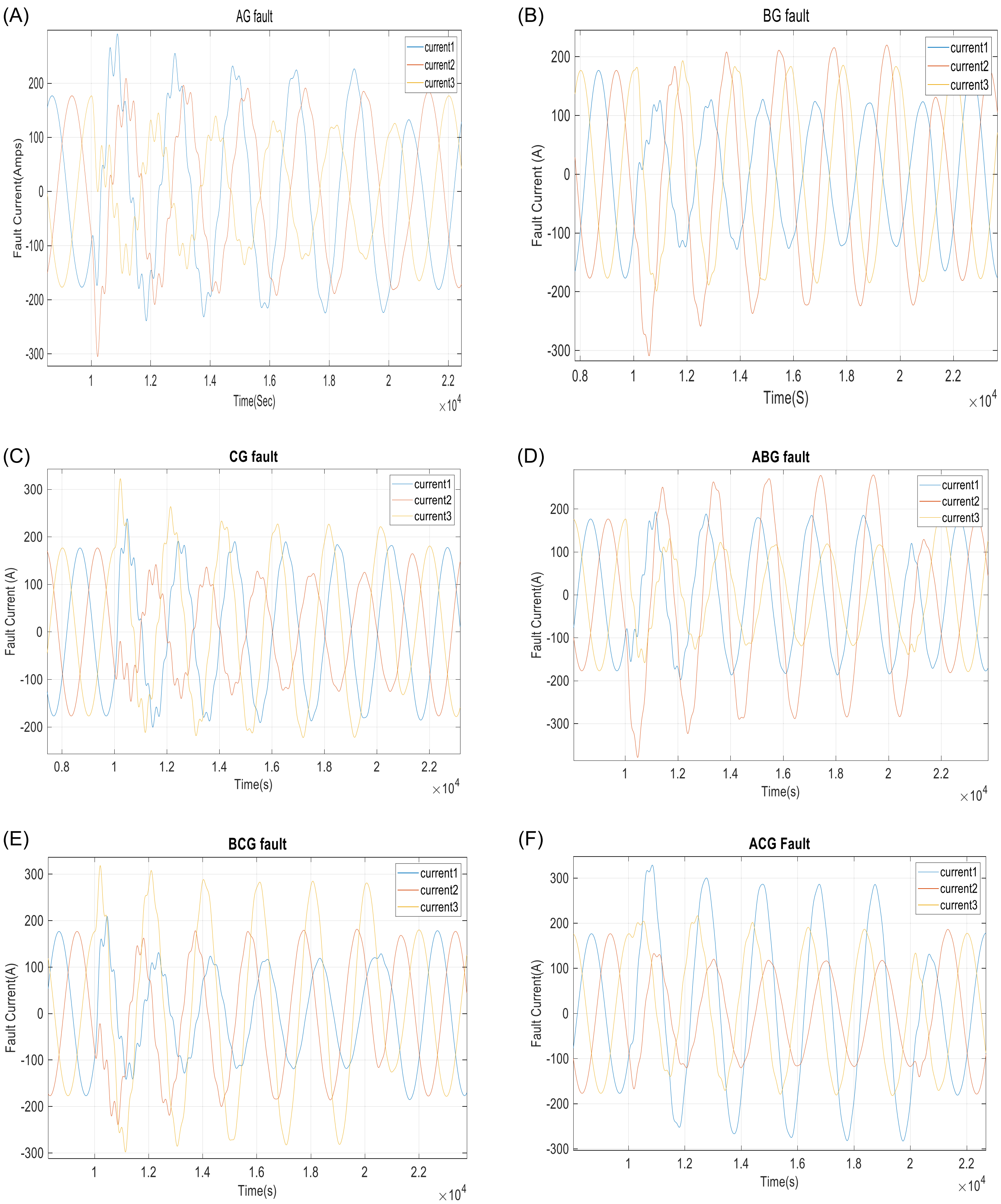

FIGURE 8 Current waveforms during AG, BG, CG, ABG, BCG, and ACG faults. (A) Current waveform during AG fault. (B) Current waveform during BG fault. (C) Current waveform during CG fault. (D) Current waveform during ABG fault. (E) Current waveform during BCG fault. (F) Current waveform during ACG fault.

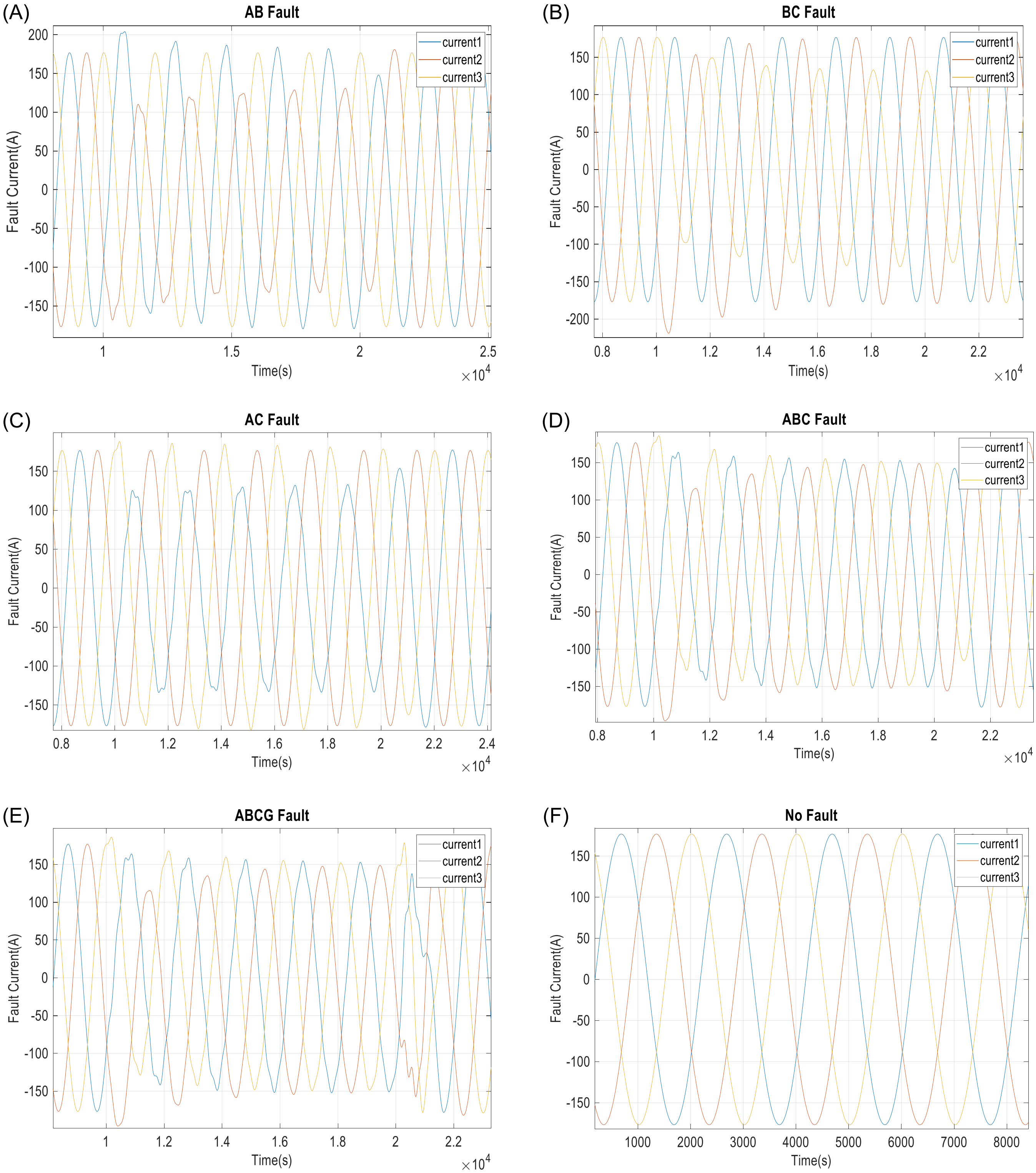

FIGURE 9 Current waveforms during AB, BC, AC, ABC, ABCG, and no-fault condition. (A) Current waveform during AB fault. (B) Current waveform during BC fault. (C) Current waveform during AC fault. (D) Current waveform during ABC fault. (E) Current waveform during ABCG fault. (F) Current waveform during no-fault condition.

TABLE 10 Summary of the simulation results.

S #	Type of fault	Conclusion
1	Phase A to ground fault	During the AG fault in the transmission line, there seems an abrupt rise in the fault current in phase A, as shown in Figure 8A.
2	Phase B to ground fault	During the fault in phase B with ground (BG) in the transmission line, the raised value of current in phase B is shown in Figure 8B.
3	Phase C to ground fault	Under the CG fault (fault in phase C with respect to ground) the variation in the amplitude of current in phase "C" during the fault is shown in Figure 8C.
4	Line to Line with ground fault (ABG)	Under the ABG fault, an abrupt rise of fault current in phases A and B is noted, which has been shown in Figure 8D.
5	Line to Line with ground fault (BCG)	Under BCG fault, as shown in Figure 8E, fault has occurred in two phases, that is, B & C with an abrupt rise of fault current in respective phases B and C.
6	Line to Line with ground fault (ACG)	Under double line to ground fault, as shown in Figure 8F, fault has occurred in phases A & C of the transmission line with respect to ground; it is observed that fault current in faulty phases attained their normal values.
7	Line to Line fault (AB)	Under an unsymmetrical fault that has occurred in between phases A and B, the magnitude of fault current in respective phases is quite high, which can be seen as shown in Figure 9A.
8	Line to Line fault (BC)	During the double phase fault between phase B and phase C fault, the rise of current is shown in respective faulty phases, as shown in Figure 9B.
9	Line to Line fault (AC)	Under the AC fault, a fault has occurred in between phases A and C, the wave output in Figure 9C shows the variation of fault current in those faulty phases.
10	Symmetrical fault ABC	Under the symmetrical fault ABC, the behavior of current in each phase is shown in Figure 9D, which shows an amplitude variation of current in each phase of the transmission line.
11	Symmetrical fault ABC with ground	Under the ABCG fault, amplitude variation in current in each phase of the transmission line has been observed, as shown in Figure 9E.
12	No fault	Under normal conditions (no-fault situation), when there is no fault in the transmission line, no variation in phase current has been observed, as shown in Figure 9F, hence the normal state of the power system is maintained.

fault waveforms at different FIAs $= 0°, 10°, 20°, 30°, 40°, 60°, 70°, 80°,$ and $90°$ to further evaluate its impact on DWT for obtaining statistical data to train fault classification algorithm.

5 | CONCLUSION

This study explores various feature extraction tools based on advanced signal processing techniques for real-time monitoring of fault identification in transmission lines. The focus is on the use of DWT, which has unique characteristics for accurately extracting features from fault signals to detect faults in overhead power transmission lines. The flexibility and time-frequency localization properties of wavelets have made them widely used in electrical power systems. The discrete wavelet transform is proven to distinguish between healthy and faulty phases under different fault conditions. The results show that fault signals analyzed using the DWT are not affected by changing parameters, such as fault inception angle, fault resistance, ground resistance, and transmission line length. Therefore, the health of the power system can be assessed by distinguishing fault index values. It is further suggested to investigate the effect of noise on the feature extraction from the fault signal on DWT along with other parameters.

AUTHOR CONTRIBUTIONS

All authors contributed equally to accomplish this study. In addition, all authors read and approved the final manuscript.

CONFLICT OF INTEREST STATEMENT

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data will be available upon request to the corresponding author.

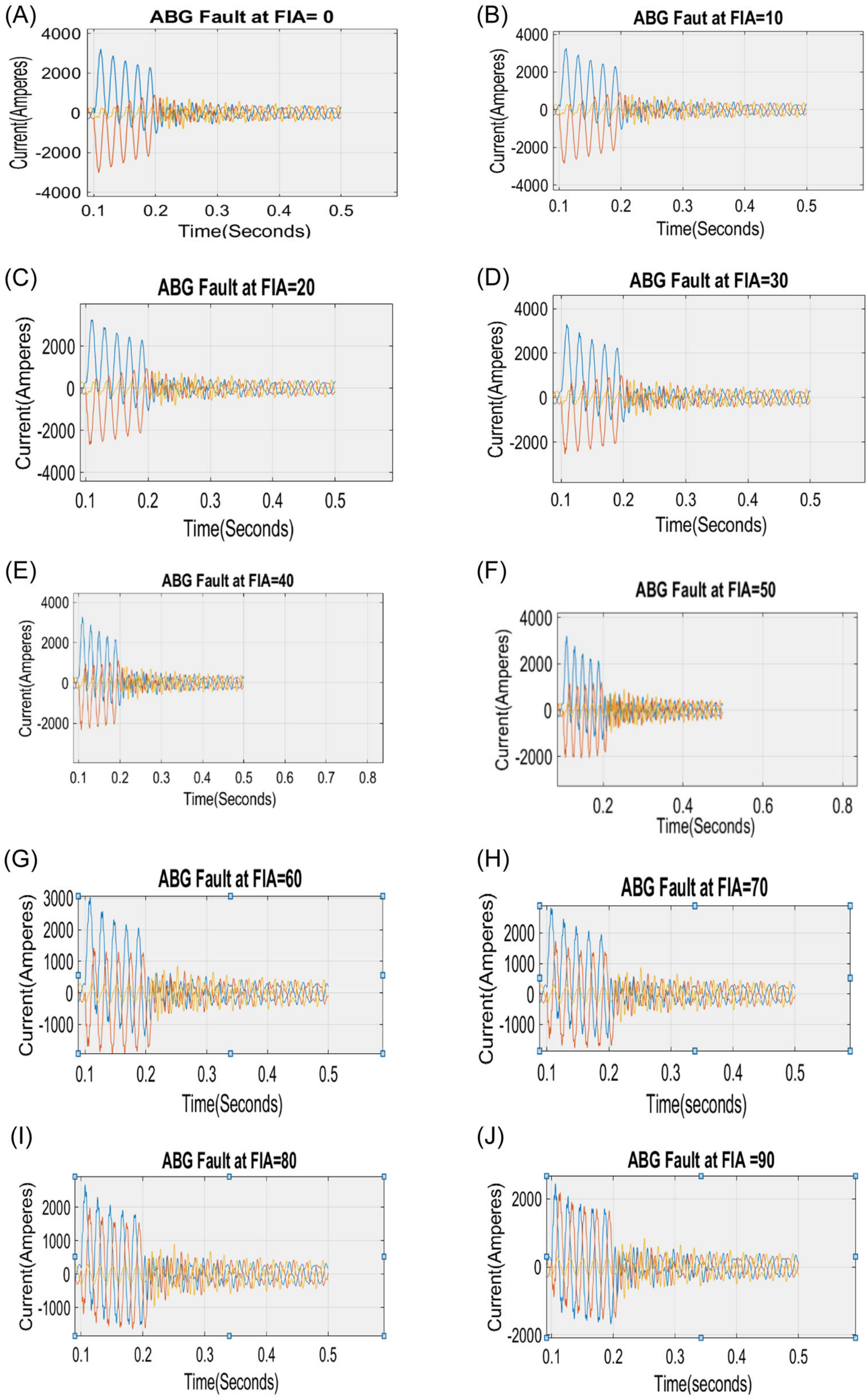

FIGURE 10 Transient response of fault signal during unsymmetrical fault, that is, ABG at different fault inception angles. (A) and (B) Transient response of fault signal at FIA = 0° and 10° during ABG fault. (C) and (D) Transient response of fault signal at FIA = 20° and 30° during ABG fault. (E) and (F) Transient response of fault signal at FIA = 40° and 50° during ABG fault. (G) and (H) Transient response of fault signal at FIA = 60° and 70° during ABG fault. (I) and (J) Transient response of fault signal at FIA = 80° and 90° during ABG fault.

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