

Wavelet fuzzy logic framework for digital protection of a double-circuit transmission line

RAJIB SADHU^{1*} , RIMI PAUL² 

¹*Department of Electrical Engineering, University Institute of Technology
Burdwan University
Burdwan-713104, India*

²*Department of Electrical Engineering, Aliah University
Kolkata-700160, India
e-mail: {[@gmail.com](mailto:*sadhu.rajib/rimipaul.au)}*

Abstract: Fault classification and location identification are prime apprehensions in power system distance relaying. A digital protection scheme for a double-circuit transmission line based on fuzzy logic is presented in this paper. The discrete wavelet transform (DWT) and discrete Fourier transform (DFT) have been used for analyzing the measured voltage and current signals at the relaying point. This paper proposes an algorithm that combines the discrete wavelet transform (DWT) with fuzzy logic to identify various types of faults. Here, the two mother wavelets, i.e. Daubechies and discrete Meyer (Dmey), have been employed in the DWT domain to measure post-fault currents at a single end of the line. The standard deviation of DWT coefficients has been used in this case. The combined DWT-fuzzy scheme has been tested across various fault types and conditions, including fault resistance, location, and inception angle (FIA). The combination of DFT and fuzzy logic is used to identify fault locations in overhead transmission lines for different fault conditions. The DFT estimates the phasors of voltage and current signals to calculate apparent impedance. This apparent impedance is then analyzed using fuzzy logic to locate faults. The proposed combined DWT-Fuzzy scheme accurately classifies faults under various conditions, including fault resistance, fault location, and fault inception angle variations. This method achieves a fault location error rate of less than 0.5% in most test cases.

Key words: digital protection, discrete Fourier transform (DFT), discrete wavelet transform (DWT), fault classification and localization, fuzzy logic

Nomenclature

ADC	Analog-to-digital converter
ANN	Artificial neural network
DFT	Discrete Fourier transform
Db4	Daubechies-4 wavelet

Dmey	Discrete Meyer wavelet
DWT	Discrete wavelet transform
FFT	Fast Fourier transform
FI	Fault index
FIR	Finite impulse response
FIS	Fuzzy inference system
HVDC	High voltage direct current
IIR	Infinite impulse response
ML	Machine learning
MRA	Multiresolution analysis
MF	Membership function
SD	Standard deviation
TL	Transmission line

1. Introduction

Faults disrupt the continuous flow of power, making it essential to detect, classify, identify faulty phases, and locate faults for effective protective schemes. This enhances distance relay performance and improves the reliability of the transmission structure [1]. Fault analysis enables prompt fault clearing and power supply restoration with minimal disruption. An intelligent fault-recognizing scheme for a microgrid employed DWT combined with an ensemble bagged decision tree (EBDT) [2]. Researchers used the energy of the DWT detail coefficients to extract input features from the electrical signals. Researchers also employed a combination of wavelet transform (WT) and an artificial neural network (ANN) for the same purposes in [3, 4]. Usman *et al.* reported only the ANN method for faults in smart meters or advanced metering infrastructure (AMI) connected to the distribution network [5]. A WT-ANN technique is also employed in [6] to locate faults on a double-circuit TL, in which WT is applied to the signals at one end. Yousaf *et al.* employed deep learning (DL), including long short-term memory (LSTM), and ensemble machine learning (ML) techniques to classify faults [7]. A combined fuzzy logic and support vector regression (SVR) approach was utilized for fault detection in voltage source converters (VSCs) in HVDC networks. This method uses fuzzy logic to generate a composite signal from voltage, current, power, and impedance [8]. After applying a bandpass filter in the 200–250 Hz range and calculating the RMS values, the processed signal is used to train the SVR model [8]. A fault is detected when the deviation between the estimated and original signal

exceeds a pre-set threshold [8]. Distance relaying techniques use impedance measurements at the fundamental frequency to locate and classify faults using sampled voltage and current data, independent of fault resistance. A fuzzy-neural network was employed to estimate fault location and identify faults for distance relaying [9]. A combined fuzzy logic and ANN-based fault classification technique using phase components of voltage and current is also described in [10]. In ANN, the selection of transfer functions, number of hidden layers, number of neurons, and training algorithms are important aspects to achieve good performance. Similarly, for other machine learning classifiers, a large amount of labelled data is required for training. To address the challenges of computationally expensive training of an ANN, the need for expert domain knowledge, and the large data storage requirements in the cloud for deep neural network-based systems, the proposed scheme of [11] uses only fuzzy logic. This approach accurately identifies ten types of possible short-circuit faults. Also, this promising approach can classify and locate faults using a new threshold-based fault index (FI) within the DFT framework [12]. Various hybrid schemes, including machine learning-wavelet transform (WT) [1–4], deep learning-WT [7], fuzzy-ML [8, 9], fuzzy logic-discrete Fourier transform [12], etc., have been employed in transmission lines for detecting faults and their location. Fuzzy logic is a simple and rule-based structure [12–14]. A Fuzzy inference system (FIS) is used with measured positive-sequence voltage for locating faults in [12]. A fuzzy-logic-based fault classification method for an HVDC system, utilizing voltage and current measurements along with chromatic monitoring, is introduced in [13]. Rana *et al.* [14] also employed fuzzy logic for fault detection, identification, and location in an electric distribution network. A fault detection and classification technique for a unified power quality conditioner (UPQC)-compensated distribution line is discussed in [15] and was developed using normalized current measurements in MATLAB simulations. The Fuzzy expert system-based fault location identification for cross-country and evolving faults in extra high voltage (EHV) transmission lines is presented in [16]. Here, if-then logic and Mamdani-type FIS are used in MATLAB. Series fault classification using fuzzy logic and the fundamental component of the current of a six-phase transmission line is described in [17]. A digital distance-protection scheme for TLs, based on analysing measured electrical signals using the WT as an MRA [18], can detect faults at the relay location. For fault classification in an IEEE 5-bus system, the Daubechies-4 (Db4) wavelet is used by the researchers in [19]. Here, the wavelet transform has been utilized to decompose the faulty phase current signals to obtain the detail coefficients. In the wavelet transform, the choice of wavelet and level of decomposition greatly affects the system performance [20]. Shalby *et al.* [21] demonstrated energy concentration for optimal decomposition level, whereas authors in [22] used the MDL technique to determine the optimal mother wavelet.

Motivated by the above literature, this paper introduces a combined Fuzzy, DWT, and DFT scheme to detect, classify, and locate electrical faults in a double-circuit transmission line. Among the various methods discussed in the literature, fuzzy logic stands out as less complex, does not require labelled data for training, and is often more accurate than alternative approaches. As a result, fuzzy rules have been employed for online fault classification and location

identification using the MATLAB/Simulink platform. Here, the MDL technique has been used to identify the optimal wavelet from the Daubechies series. The performance of the Daubechies wavelet has been compared to the discrete approximation of the Meyer wavelet (Dmey). The researcher applied a Dmey wavelet to obtain statistical features from leakage current [23], denoising signals [24], etc. Here, the Dmey wavelet has been used to classify ten types of faults, and its performance has been compared with other cases.

The contribution of this paper is as follows:

- The fault classification and location identification method uses a realistic approach for the processing of measured voltage and current signals. To fully digitize the system, voltage and current signals have been processed through digital signal conditioning tools before applying the discrete wavelet transform (DWT) and the discrete Fourier transform (DFT).
- The fault classification performance of the combined DWT-Fuzzy technique using two different wavelet filters, Db4 and Dmey, has been tested and compared.
- The method for identifying fault locations relies on calculating the apparent impedance of distance relay logic using the fundamental frequency components of voltage and current signals. Therefore, additional signal-processing units are unnecessary for distance relays when implemented in a digital distance protection system.

The rest of the paper has been organized as follows. The proposed fault classification and location identification system has been explained in Section 2. In Section 3, the experimental results have been discussed, and conclusions are presented in Section 4.

2. Proposed fault classification and location identification system

The power system considered for fault classification and location identification is shown in Fig. 1. It represents a 132 kV double-circuit transmission line, 200 km long, fed by two three-phase 50 Hz sources at both ends. The short-circuit capacity (SCC) of each source is 6 000 MVA, and the angle difference between them is 20°. Various types of faults occur at different locations along the transmission line between buses B₁ and B₂. The voltage and current at bus B₁ are used for measurement. The wavelet transform-fuzzy (WT-fuzzy)-based fault classification and DFT-fuzzy-based fault location identification techniques have been discussed in cases 1 and 2, respectively.

2.1. Case 1: Wavelet fuzzy-based fault classification technique

A flowchart for the wavelet-fuzzy-based fault classification technique is shown in Fig. 1. At first, the three-phase (3- ϕ) and ground current signals are taken from a 132 kV 3- ϕ power system. The current signal is then processed through a signal conditioning block for the DWT. Next, the standard deviation (SD) values of the 3rd-level detailed coefficients of DWT are calculated. SD values have been used as input to the fuzzy system for fault classification.

The wavelet-fuzzy-based fault classification technique has been unfolded through the following steps.

2.1.1. Signal conditioning

The block diagram of the signal conditioning module for the DWT has been shown in Fig. 2. The DWT cannot directly decompose analog current signals because it operates on discrete-time signals. Therefore, signal conditioning [19] is used to convert the analog signal into a suitable discrete form before applying the DWT. Detailed steps for signal conditioning are illustrated in the flowchart in Fig. 1. The signal conditioning process typically involves the following steps:

- **Analog filtering** [25]: A low-pass filter minimizes the effects of noise and restricts frequencies beyond the specific band of frequency. Here, the Butterworth filter has been used to remove high frequencies existing on the input signal.
- **Analog-to-digital conversion (ADC)** [25]: The filtered analog signal has been sampled and quantized by an ADC to produce a discrete-time digital signal. This conversion process utilizes zero-order hold and quantizer blocks.

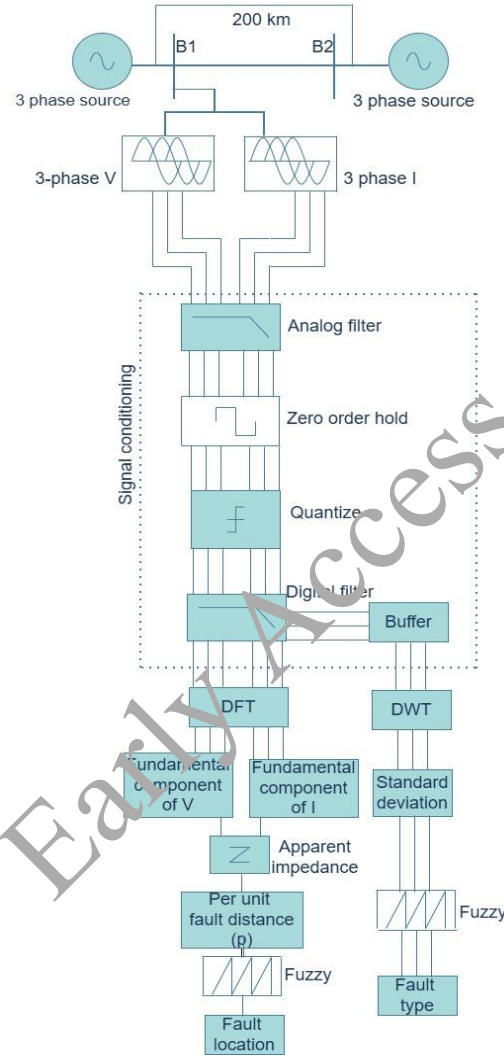


Fig. 1. Flow chart for fault classification and location identification system

- **Digital filtering [25]:** Additional filtering may be performed in the digital domain to further refine the signal or isolate specific frequency components. IIR filters are not used in digital protection because group delay cannot be specified in these filters. For this reason, FIR filters are preferred over IIR filters for modeling digital relays.

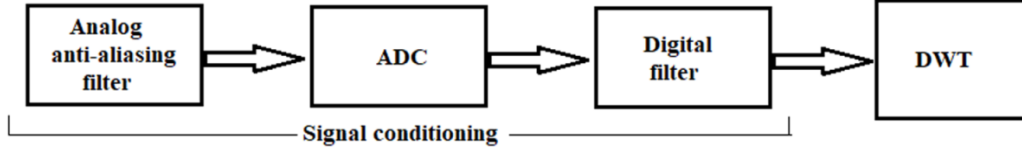


Fig. 2. Block diagram of the signal conditioning module for DWT

- **Buffering [26]:** A buffer stores the digitized data temporarily to ensure smooth, synchronized input for DWT processing.

2.1.2. Discrete wavelet transform (DWT)

The DWT [27] is a powerful technique for analyzing transient phenomena, especially those associated with transmission line faults. DWT-based filters with down-sampling operations separate the original signal into approximation and detail levels or scales [22]. Once the signal is in a clean, digitized form, the DWT can be effectively used to decompose it into time-frequency components for analysis, such as in power quality monitoring, fault detection, or signal compression. In this proposed method, Db4 is used as the mother wavelet in the DWT.

2.1.3. Calculation of standard deviation

Standard deviation (SD) σ is defined in (1):

$$\sigma = \sqrt{\sum (D_3 - \mu_D)^2 / M}, \quad (1)$$

where: D_3 is the 3rd-level detail coefficients, μ_D is the mean of the 3rd-level detail coefficients and M is the number of detail coefficients.

In Fig. 1, the third (3rd)-level detail coefficients of the DWT are output to the standard deviation block, which calculates the standard deviation of the 3rd-level detail coefficients of the DWT.

This SD (σ) value is taken as the fault index (FI). If the SD of wavelet 3rd-level detail coefficients of any phase is greater than the threshold (Th) value ($\sigma > Th$), then a fault has been detected on that particular phase. The output of this block is then sent to the fuzzy block to identify the fault types.

2.1.4. Fuzzy logic controller for fault classification

A fuzzy inference system (FIS) is the essential element of any fuzzy logic system. The main feature of the fuzzy logic design process is to develop the input and output membership functions [17]. Fuzzy logic uses fuzzy set theory, if-then rules, and a fuzzy reasoning process to find the output corresponding to the inputs [12]. Fuzzy logic has been used here for the detection and classification of all symmetrical and unsymmetrical faults. This decision-making tool can determine different fault types.

Steps for determining fault types using fuzzy logic and SD values are described below: -

- Step 1: The calculated SD values have been used as a fault index and input to the fuzzy inference system.
- Step 2: Fuzzy logic toolbox has been used for developing the logic for the classification of faults. Triangular membership functions (MF) have been used as input and output variables for every phase.
- Step 3: Simple if-then fuzzy rules have been used here. If $\sigma > Th$ value in any phase, then a fault is detected on that particular phase. Four input variables are the σ values of the three-phase and ground currents. The output variables are the logical displays that give binary outputs based on fault types. For converting σ values of currents to logical outputs, two if-then fuzzy rules have been added for every phase and ground. For example, if σ values of phase B and ground are higher than Th , and lower than Th for phase A and phase C, then a B-G fault is detected. Similarly, for other fault types, σ values corresponding to phases will be higher than Th .
- Step 4: The display connected to the faulty and healthy phases will show the binary values 1 and 0, respectively. In this way, faults can be classified by using FIS.

The pre-processing module of Fig. 1 aims to extract the distinctive features of the input signals, reduce the fuzzy logic structure, and improve the performance.

2.2. Case 2: DFT–fuzzy-based fault location identification technique

A flow chart for fault location identification using DFT and fuzzy logic has also been shown in Fig. 1. The functions of the blocks are as follows:

2.2.1. Isolation and frequency scaling of the analog signal

For the extraction of the fundamental frequency component of the voltage and current, signal conditioning is essential [25]. For this purpose, the DFT has been used here instead of the DWT. The DFT employs the same signal conditioning blocks as the DWT, eliminating the need for buffering. This removal of buffer hardware reduces costs, providing benefits for this method. For the use of digital relays, voltage and current signals are generally scaled down to convenient levels by instrument transformers [28].

2.2.2. Discrete fourier transform (DFT)

The DFT is used to compute the magnitude and phase angle of waveforms in the discrete domain. For computing the DFT, the fast Fourier transform (FFT) is the best computation method [25]. The FFT is very useful in calculating the magnitude and phase angle of a specific number or band of frequencies. Here, The DFT has been used to calculate the fundamental frequency components of the voltage and current signals at the time of the fault. Least squares error (LSE) and Walsh function algorithms are popular DFT-based phasor estimation techniques used in numerical relays [25]. Here, the Walsh function algorithm has been utilized.

2.2.3. Apparent impedance calculation

The discrete voltage and current signals have been initially transformed into their direct and quadrature components. The first harmonic components of the voltage and current signals are used to calculate impedance. Then, using the impedance calculation formula, the impedance $Z = \frac{V}{I}$ has been calculated as a quotient of voltage and current phasors. The DFT can extract the magnitude and phase angle of the fundamental frequency component of voltage and current signals [25]. This can be represented as $V \angle \theta$ and $I \angle \alpha$.

So, impedance

$$Z \angle \phi = V \angle \theta / I \angle \alpha, \quad (2)$$

where: the phase angle between voltage and current is $\phi = \theta - \alpha$. Based on the detected faults by the DWT-fuzzy fault classifier, the impedance measurement block can measure apparent impedance for single-line to ground (L-G), double-line (L-L), and triple-line (L-L-L) faults by using the equations of (3), (4), and (5), respectively. The impedance measurement block consists of subsystems that determine the apparent impedance for different types of faults.

For a single line-to-ground (A-G) fault, the apparent impedance is

$$Z_{AP} = V_A / (I_A + 3KI_0), \quad (3)$$

where line zero sequence current compensation factor $K = (Z_0 - Z_1)/3Z_1$, and zero sequence current $I_0 = (I_A + I_B + I_C)/3$.

a. For a double line to ground fault and a double line fault

$$Z_{AP} = (V_A - V_B) / (I_A - I_B), \quad (4)$$

b. For a triple line fault

$$Z_{AP} = V_A / I_A, \quad (5)$$

where, V_A is the voltage at phase A; V_B is the voltage at phase B; and I_A is the current at phase A; I_B is the current at phase B. Thus, the apparent impedance logic varies with the type of fault. The measured apparent impedances can be used to draw an apparent impedance trajectory in the case of a mho-type digital distance relay.

2.2.4. Per-unit fault distance measurement for fault location identification

The steady value of apparent impedance can be calculated by using (3), (4), and (5) for L-G, L-L, and L-L-L faults, respectively. Apparent impedance is represented as Z_{AP} . Generally, for distance relays, the Z_{AP} value is extracted after being scaled down by the current transformer (C.T.) and the potential transformer (P.T.). In that case, the true value of the apparent impedance should be incorporated into the C.T. and P.T ratios (C.T.R. and P.T.R.), as in (6).

$$Z_{APT} = Z_{AP} \cdot \frac{P.T.R}{C.T.R} \quad (6)$$

To find the distance (p) in per unit (p.u.), the impedance value must be converted to a p.u. value.

$$Z_{APT(p.u)} = Z_{APT} / Z_B, \quad (7)$$

where, Z_B is the base value of the line impedance per-unit distance of the fault location from the relaying point,

$$p = Z_{APT(p.u)} / Z_{1(p.u)}, \quad (8)$$

where Z_1 is the positive sequence impedance of the line and it can be expressed in per unit by $Z_{1(p.u)} = Z_1 / Z_B$.

Using fuzzy logic, the p -value of the original distance of fault location can be calculated.

For finding the percentage (%) of error [6] for fault location identification, the formula used is as follows,

$$\% \text{ Error} = \frac{\text{Actual location} - \text{Estimated location}}{\text{Line length}} \times 100. \quad (9)$$

2.2.5. Fuzzy logic controller for fault location identification

To locate faults, the Mamdani method of the fuzzy inference system (FIS) is utilized. A total of eight membership functions is employed here. Gaussian-type membership functions are preferred over triangular or trapezoidal membership functions because they offer a more accurate representation of faults. This accuracy is due to the smoothness of the Gaussian curve, which ensures that the function is non-zero at all points [26]. The Gaussian fuzzy membership function (GFMF) is symmetrical and is quite popular in fuzzy logic for its accuracy, as applied to the protection of power systems [29]. GFMF depends on two parameters, i.e., b is the mean, and γ is the standard deviation of the Gaussian function [26]. The GFMF block implements an MF based on a symmetric Gaussian function, as shown in (10).

$$f(x, \gamma, b) = e^{-(x-b)^2 / 2\gamma^2}, \quad (10)$$

where γ is the standard deviation of the Gaussian function and b is the mean of the Gaussian function.

Steps for finding fault location using the FIS technique are as follows:

- i. A fuzzy interface system with 8 Gaussian membership functions has been created in MATLAB. The range of input is from 0 to 1, as p.u. distance of the fault location from the relaying point (p) has been taken as input. The range of output is from 0 to 200, as “distance” has been taken as output. Eight rules are added one after the other. The rules are like:
 - If input is MF1 then output is MF1.

- If input is MF2 then output is MF2, and so on.
 - ii. One FIS with the GFMF has been placed in a MATLAB/SIMULINK model to collect the per-unit distance (p) from the system.
 - iii. The FIS will convert this per-unit value into the corresponding fault location in km using fuzzy logic.
- Input and output variables for the GFMF are shown in Fig. 3.

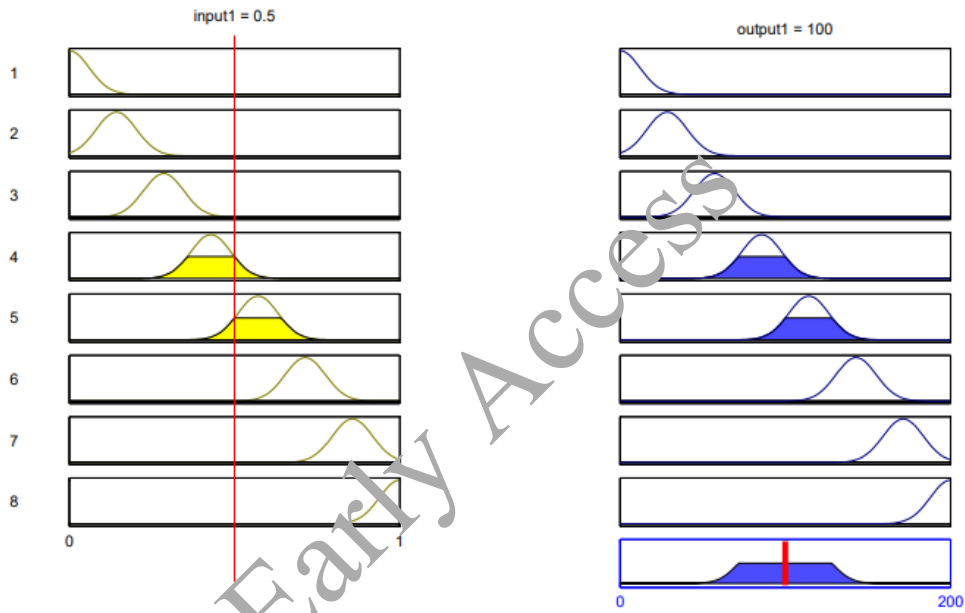


Fig. 3. Fuzzy input and output membership functions for fault location identification

The value of per-unit distance (p) has been taken as input, and the corresponding distance of the fault location as output is in km. For example, if input is 0.5, then fault location output is 100 km.

3. Results and discussion

3.1. Visualization of different faults

An automatic fault classification and location identification technique for a double-circuit transmission line using fuzzy logic has been presented here. The algorithm's performance has been tested under specific conditions to determine its practical suitability. The changes in three-phase currents for L-G and L-L faults have been shown in Fig. 4 and Fig. 5, respectively. At the

time of fault occurrence, the value of the faulty phase current increases. After a fault occurs, the graph will deviate from its normal position.

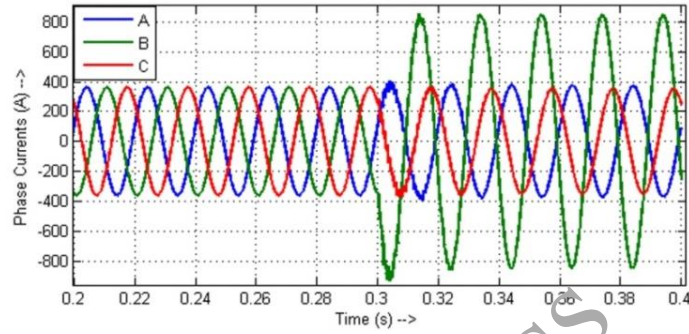


Fig. 4. Current signal for L-G fault (B-G fault)

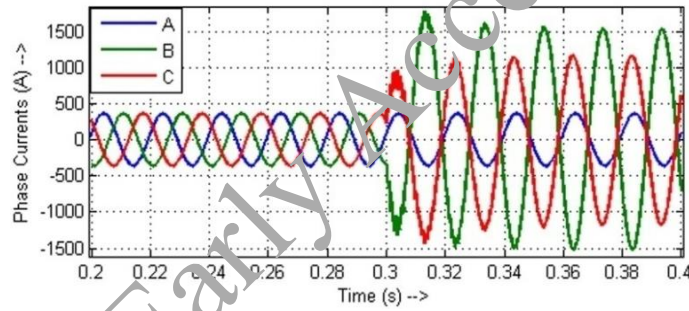
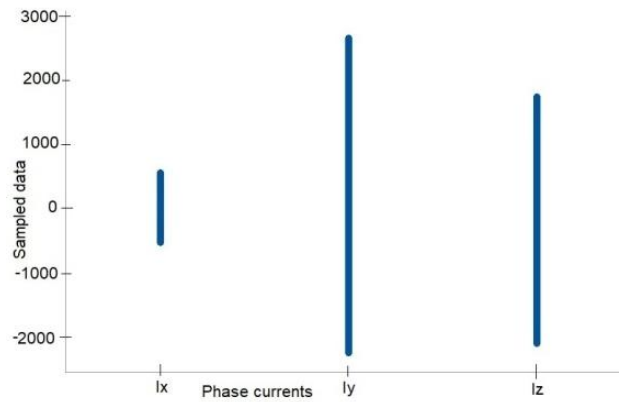


Fig. 5. Current signal for L-L fault (B-C fault)

In Fig. 6, individual plots of L-L (B-C) and L-G (B-G) faults have been used to visualize the fault types easily.



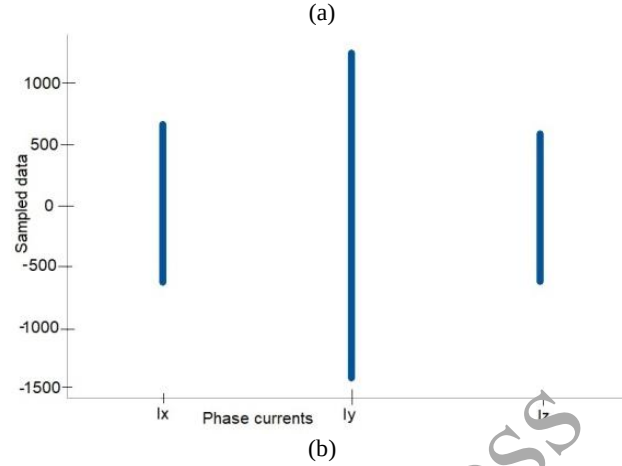


Fig. 6. The individual plots for the L-L (a); and L-G faults (b)

In the case of an L-L fault, the length of the straight-line indicating currents I_y and I_z of B and C phases, respectively, will increase to show the fault occurrence on those phases. But in that process, after data collection, visualization of the faults is possible, which is time-consuming.

3.2. Results for DWT-fuzzy based fault classification

Here, all results are described using SD values. The 3rd-level detail coefficient output of the DWT has been taken for the SD. SD values for different fault types are shown in Table 1.

Table 1. Standard deviation values for different fault types ($R_f = 1$, FIA = 60°, FL = 150 km)

Fault types	Standard deviation (A)				Logical display			
	P1	P2	P3	N	P1	P2	P3	N
F1	928	404	415	799	1	0	0	1
F2	412	930	392	793	0	1	0	1
F3	382	394	926	791	0	0	1	1
F4	1 720	1 424	410	0.011	1	1	0	0
F5	408	1 724	1422	0.011	0	1	1	0
F6	1 435	410	1 692	0.011	1	0	1	0
F7	1 718	1 425	410	742	1	1	0	1
F8	408	1 728	1425	754	0	1	1	1
F9	1 433	410	1695	746	1	0	1	1

F10	1 761	1 823	1 826	0.0001	1	1	1	0
------------	-------	-------	-------	--------	---	---	---	---

Three types of single-line to ground (L-G) faults have been represented as F1 (A-G), F2 (B-G), and F3 (C-G) in Table 1. Similarly, double-line (L-L) and double-line to ground faults have been represented as F4 (A-B), F5 (B-C), F6 (A-C), F7 (AB-G), F8 (BC-G), and F9 (AC-G). A three-phase symmetrical (LLL) fault has been represented as F10. Three-phase currents I_A , I_B and I_C are denoted as P1, P2 and P3, respectively. The ground current I_g is denoted by N . For L-G faults, faulty phases and ground currents (N) show high SD values. For L-L faults, faulty phases show high SD values, but SD values for N are nearly zero.

The SD values of P2 (B phase current) and N are 930 A and 793 A, respectively, for the B-G (F2) fault. But the SD values of P1 and P2 are 412 A and 392 A, respectively; these values are lower compared to the SD value of P2. For the L-L fault, B-C (F5) is considered, where the SD values of P2 and P3 are 1 728 A and 1 425 A, respectively, and N is 0.011 A, which is nearly zero. The SD value of P1 is 408 A. In other types of faults, faulty phases show higher SD values than the healthy phases. For a symmetrical L-L-L (F10) fault, all A, B, and C phases have given higher SD values. In that case, SD values for P1, P2 and P3 are 1 761 A, 1 823 A, and 1 826 A, respectively.

Fuzzy logic is used here for the classification of fault types. Four different displays are connected to P1, P2, P3, and N . These displays show a binary number, i.e., if it shows 1, the phase is faulty, and it is zero for healthy phases. In Table 1, with the occurrence of the F2 fault, the display connected with P2 shows 1, the display connected with N shows 1, and the other displays show 0. Like the F2 fault, when the F1 fault occurs, the displays connected with P1 and N show 1, and this has been maintained for other cases too. Here, different fault cases are considered to test this logic, such as L-L fault, i.e., F6 fault, and L-L-G fault, i.e., F7 fault. This logical table is matched with the corresponding SD values of Table 1.

The fuzzy logic-based fault classification method has also been tested for faults in different locations, fault resistance (R_f), and fault incipient angle. This method performed with the same accuracy for those various fault conditions.

SD values for faults in different locations have been shown in Table 2.

Table 2. Standard deviation values for B-G (F2), B-C (F5), B-C-G (F8), and A-B-C (F10) faults with varying fault location ($R_f = 1$, FIA = 60°)

Fault Location (km)	F2 (A)				F5 (A)			
	P1	P2	P3	N	P1	P2	P3	N
25	365	4 202	436	4 161	405	6 984	6 678	0.036
50	386	2 348	422	2 279	404	4 276	3 889	0.035
100	401	1 282	408	1 188	405	2 403	2 048	0.022

150	412	930	392	793	408	1 724	1 422	0.011
175	432	840	377	652	405	1 492	1 148	0.005

Fault location (km)	F8 (A)				F10 (A)			
	P1	P2	P3	N	P1	P2	P3	N
25	405	6 984	6 678	4 161	6 694	6 991	7 008	0.000 1
50	404	4 276	3 889	2 279	4 427	4 803	4 821	0.000 1
100	405	2 403	2 048	1 188	2 832	2 896	2 905	0.000 1
150	408	1 728	1 425	754	1 761	1 823	1 826	0.000 1
175	405	1 492	1 148	652	1 522	1 602	1 614	0.000 1

The variations of SD values have been examined with different fault locations: B-G (F2), B-C (F5), B-C-G (F8), and A-B-C (F10) faults. It was observed that SD values for faulty phases are very high for faults near bus B₁, and comparatively lower for far-end faults from bus B₁. The SD values of P2 (B phase current) and N are 4 202 A and 4 161 A, respectively, for the F2 fault at 25 km. The SD values of P1 and P3 are 365 A and 436 A, respectively. Whereas the SD values of P2 and N are 840 A and 652 A, respectively, for the F2 fault at 175 km. For the F5 fault at 25 km, the SD values of P2 and P3 are 6984 A and 6 678 A, respectively. Whereas the SD value of P1 is 405 A. For the F5 fault at 175 km, the SD values of P2 and P3 are 1 492 A and 1 148 A, respectively. Similar results are shown in Table 2 for LLG and LLL faults.

SD values for F2, F5, F8, and F10 faults with varying fault resistance (R_f) have been shown in Table 3.

Table 3. Standard deviation values for F2, F5, F8, and F10 faults with varying R_f (FIA = 60°, FL = 150 km)

R_f (Ω)	F2 (A)				F5 (A)			
	P1	P2	P3	N	P1	P2	P3	N
1	412	930	392	793	408	1 724	1 422	0.011
10	410	928	392	751	408	1 693	1 401	0.011
20	410	894	390	722	408	1 612	1 388	0.011
40	408	825	390	668	408	1 566	1 325	0.011
60	408	766	390	602	408	1 502	1 304	0.011

R_f (Ω)	F8 (A)				F10 (A)			
	P1	P2	P3	N	P1	P2	P3	N
1	408	1 728	1 425	754	1 761	1 823	1826	0.0001
10	408	1 693	1 401	751	1 724	1 788	1782	0.0001
20	408	1 612	1 388	722	1 656	1 732	1725	0.0001
40	408	1 566	1 325	668	1 603	1 693	1 684	0.0001
60	408	1 502	1 304	602	1 546	1 627	1 622	0.0001

As the fault resistance increases (1, 10, 20, 40, and 60 Ω), the standard deviation (SD) values of the faulty phases decrease, while the SD values of the healthy phases remain unchanged or show negligible changes. For the F2 fault, the SD value of the F2 phase decreased from 930 A to 766 A as the fault resistance increased. The SD value of N also decreased from 793 A to 602 A. Table 3 shows similar results for LL, LLG, and LLL faults.

With the change in FIA, the minimum change in SD values for F2 and F5 faults has been recorded in Table 4.

Table 4. Standard deviation values for F2 and F5 faults with varying fault inception angle

Fault in caption angle (in $^\circ$)	F2 (A)				F5 (A)			
	P1	P2	P3	N	P1	P2	P3	N
0 $^\circ$	415	942	395	791	411	1 789	1 478	0.011
30 $^\circ$	414	925	394	788	409	1 738	1 434	0.011
60 $^\circ$	412	930	392	793	408	1 724	1 422	0.011
90 $^\circ$	414	926	395	790	410	1 731	1 445	0.011

SD values of faulty and healthy phases are nearly constant. SD values of faulty phase P2 and ground current N are higher than those of healthy phases P1 and P3. Table 4 shows that SD values of P2 and N are 942 A and 791 A, respectively, for the F2 fault at 0 $^\circ$ FIA, and SD values of P1 and P3 are 415 A and 395 A, respectively. Similarly, for F5 faults with varying FIA, P2 and P3 phases show higher SD values.

SD values for B-G (F2) and B-C (F5) faults when acted simultaneously in both line circuits of the double-circuit transmission line have been shown in Table 5.

Table 5. Standard deviation values for simultaneous F2 and F5 faults in both line circuits

Fault types	Standard deviation (A)			
	P1	P2	P3	N
F2, F2	407	916	401	787
F5, F5	402	1 663	1 370	0.011
F2, F5	403	1 752	1 460	0.23
F5, F2	406	868	425	759

The variations of SD values have been examined with F2 and F5 fault sat 100 km in the top line (L_1) and 150 km in the bottom line (L_2). SD values have been measured for current signal at B_1 of L_1 . The SD values of P2 and N are 916 A and 787 A, respectively, for F2 faults in both lines. The SD values of P1 and P3 are 407 A and 401 A, respectively. For the F2 in L_1 and F5 in L_2 , the SD values of P2 and P3 are 1 752 A and 1 460 A, respectively. Results for other combinations of F2 and F5 faults in L_1 and L_2 have also been shown in Table 5. It is observed that, as current signals are measured at B_1 SD value for faulty phases of L_1 shown higher values compared to the other phases.

Discrete Meyer (Dmey) wavelet has been used here for feature extraction before calculating SD values. SD values using the Dmey wavelet for different fault types have been shown in Table 6. For the F2 fault, the SD values of P2 and N are 852 A and 790 A, respectively, while those of P1 and P3 are 380 A and 317 A, respectively. SD values of P1 and P3 are lower compared to P2 and N. For the F5 fault, SD values of P2 and P3 are 1 419 A and 1 350 A, respectively. The SD values of P1 and N are 369 A and 0.011 A, respectively. For the F10 fault, the SD values of P1, P2 and P3 are 1 665 A, 1 717 A, and 1 712 A, respectively.

Table 6. Standard deviation values for different fault types ($R_f = 1$, FIA = 60°, FL = 150 km)

Fault types	Standard deviation (A)				Logical display			
	P1	P2	P3	N	P1	P2	P3	N
F1	737	416	334	757	1	0	0	1
F2	380	852	317	790	0	1	0	1
F3	363	416	816	732	0	0	1	1
F4	1 505	1 477	328	0.053	1	1	0	0
F5	369	1 419	1 350	0.011	0	1	1	0
F6	1 287	405	1 338	0.053	1	0	1	0
F7	1 370	1 312	325	767	1	1	0	1

F8	373	1 547	1 421	754	0	1	1	1
F9	1 391	407	1 377	720	1	0	1	1
F10	1 665	1 717	1 712	0.0001	1	1	1	0

Fuzzy logic has also been used here for the classification of fault types. In Table 6, for the occurrence of the F2 fault, the display connected to P2 shows 1, the display connected to N shows 1, and the other displays show 0. Like the F2 fault, when the F1 fault occurs, the displays connected to P1 and N show 1, and this is maintained for LL, LLG, and LLL faults. This logical table also matches the corresponding SD values of Table 6. For the F2 fault, the SD values of faulty phases P2 and N are 930 A and 793 A, respectively, using the Db4 wavelet in Table 1. But the SD values of P2 and N are 852 A and 790 A, respectively, using the Dmey wavelet in Table 6. Using the Db4 wavelet, the SD values of P1 and P3 are 412 A and 392 A, respectively and with the Dmey wavelet, these values are 380 A and 317 A, respectively. Therefore, from the analysis, it can be concluded that SD values obtained using the Dmey wavelet are lower compared to the SD values obtained by using the Db4 wavelet. Moreover, the ratio of faulty phases to healthy phases is lower for the Dmey wavelet.

3.3. Results for DFT-Fuzzy based fault location identification

Results of fuzzy logic-based fault location identification for F2, F5, and F10 faults have been tabulated in Table 7. These faults have been created at 20 to 180 km of the transmission line at intervals of 20 km. The apparent impedances for fault location are calculated from the fundamental components of voltage and currents processed using the DFT. The per-unit fault distance (p) is calculated using (8). FIS has been used to calculate the actual fault location from the per-unit fault distance. For F2 and F5 faults at 120 km, distances measured using the DFT-fuzzy logic-based fault location model are 119.53 km and 119.7 km, respectively. Similarly, for F2 and F5 faults at 140 km, the measured fault locations are 139.4 km and 139.6 km, respectively.

Table 7. Fault location identification

Actual Location of Fault (km)	L-G (F2)			L-L (F5)			LLL(F10)		
	Measured distance (km)	Error	%Error	Measured distance (km)	Error	%Error	Measured distance (km)	Error	%Error
20	20.7	+0.7	0.35%	20.8	+0.8	0.4%	20.8	+0.8	0.4%
40	40.42	+0.42	0.21%	40.24	+0.24	0.12%	39.85	-0.15	0.075%
60	60.57	+0.57	0.285%	60.52	+0.52	0.26%	60.37	+0.37	0.185%
80	80.63	+0.63	0.315%	80.44	+0.44	0.22%	80.51	+0.51	0.255%
120	119.53	-0.47	0.235%	119.2	-0.8	0.4%	119.7	-0.3	0.15%

140	139.4	-0.6	0.3%	139.4	-0.6	0.3%	139.6	-0.4	0.2%
160	158.4	-1.6	0.8%	158.9	-1.1	0.55%	159.2	-0.8	0.4%
180	177.6	-2.4	1.2%	177.6	2.4	1.2%	177.4	2.6	1.3%

The percentage of error for fault location identification has been calculated by using (9). It has been observed that the percentage of error for fault location identification is generally less than 0.5% for F2 (B-G) and F5 (B-C) faults. However, for faults occurring at the far end of the transmission line, specifically F2, F5, and F10 cases, the percentage error exceeds 1%.

Comparison of the fault location identification performance for the proposed and simple reactance method for the F2 fault is shown in Fig. 7.

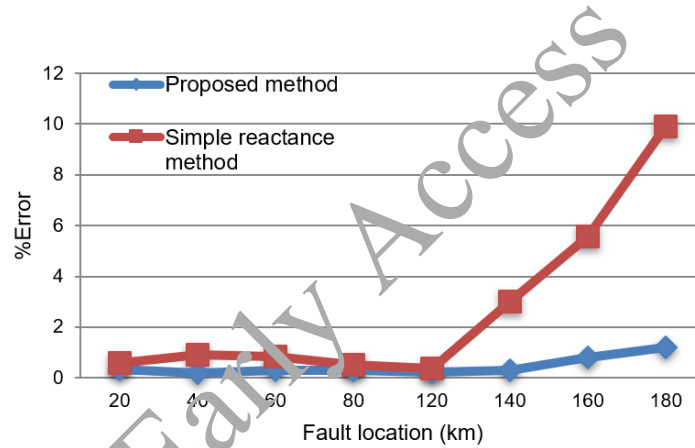


Fig. 7. Comparison of fault location identification performance

The percentage (%) error for the simple reactance method is higher compared to the proposed method for all fault locations. Notably, higher percentage errors are observed, particularly for far-end faults in the simple reactance method. The percentage of errors for the proposed and simple reactance methods are 1.2% and 9.9%, respectively, for the fault at 180 km.

4. Conclusions

In this paper, the algorithms using wavelet-fuzzy-based techniques for fault classification and DFT-fuzzy-based techniques for fault location identification have been developed for faulty-section identification in a double-circuit transmission line. A fault detection approach for transmission lines has been developed using the standard deviation (SD) value of third-level detailed coefficients, which are decomposed using the Db4 wavelet. This method, combined with fuzzy logic classification, has proven to be highly efficient and effective under various

fault conditions. The DFT-fuzzy-based technique for identifying fault locations employs apparent impedance calculations along with digital distance relay logic to accurately determine fault locations. Both the fault classification calculations and the methods for location identification are simple and effective. The proposed combined DWT-fuzzy-based fault classifier successfully classified all ten types of faults. Additionally, when accounting for fault resistance variations under different fault conditions, the standard deviation values for the faulty phases were higher than those for the other phases. A fuzzy logic-based fault classifier can effectively identify fault types based on variations in fault location and fault inception angles using standard deviation values. The results of the DWT-fuzzy-based fault classification method, which utilizes Db4 and Dmey wavelets, have been compared. Notably, the Db4 wavelet produced superior fault classification results when compared to the Dmey wavelet. Additionally, the DFT-fuzzy-based method achieved an error rate of approximately 0.5% in identifying fault locations across most test cases, thereby enhancing the functionality of the distance protection scheme. This proposed scheme may be implemented in real-time with digital distance relays in the future.

References

- [1] Anwar T., Mu C., Yousaf M.Z., Khan W., Khalid S., Hourani A.O., Zaitsev I., *Robust fault detection and classification in power transmission lines via ensemble machine learning models*, Scientific Reports, vol. 15, 2549 (2025), DOI: [10.1038/s41598-025-86554-2](https://doi.org/10.1038/s41598-025-86554-2).
- [2] Giri N., Nayak P., Mallick R.K., Mishra S., Flah A., Kraiem H., Kanan M., *Wavelet-based ensemble intelligent technique for a better quality of fault detection and classification in AC microgrids*, Energy Conversion and Management, vol. X, no. 24, 100813 (2024), DOI: [10.1016/j.ecmx.2024.100813](https://doi.org/10.1016/j.ecmx.2024.100813).
- [3] Chavan J.N., Kale A.M., Deore S.R., *Transmission Line Fault Detection Using Wavelet Transform & ANN Approach*, IEEE Integrated STEM Education Conference (ISEC), pp. 426–432 (2022), DOI: [10.1109/ISEC54952.2022.10025222](https://doi.org/10.1109/ISEC54952.2022.10025222).
- [4] Cano A., Ar'evalo P., Benavides D., Jurado F., *Integrating discrete wavelet transform with neural networks and machine learning for fault detection in microgrids*, International Journal of Electrical Power and Energy Systems, vol. 155, 109616 (2024), DOI: [10.1016/j.ijepes.2023.109616](https://doi.org/10.1016/j.ijepes.2023.109616).
- [5] Usman M.U., Ospina J., Faruque M.O., *Fault classification and location identification in a smart DN using ANN and AMI with real-time data*, The Journal of Engineering, vol. 2020, no. 1, pp. 19–28 (2019), DOI: [10.1049/joe.2019.0896](https://doi.org/10.1049/joe.2019.0896).
- [6] Yadav A., Sweta Padma A., *A single ended directional fault section identifier and fault locator for double circuit transmission lines using combined wavelet and ANN approach*, International Journal of Electric Power and Energy Systems, vol. 69, pp. 27–33 (2015), DOI: [10.1016/j.ijepes.2014.12.079](https://doi.org/10.1016/j.ijepes.2014.12.079).
- [7] Yousaf M.Z. et al., *Bayesian-optimized LSTM-DWT approach for reliable fault detection in MMC-based HVDC systems*, Scientific Reports, vol. 14, no. 1, 17968 (2024), DOI: [10.1038/s41598-024-68985-5](https://doi.org/10.1038/s41598-024-68985-5).
- [8] Taheri B., Hosseini S.A., Sedighizadeh M., *Novel hybrid fuzzy-SVR model for fault detection in VSC-HVDC transmission lines*, International Journal of Electrical Power and Energy Systems, vol. 172, 111222 (2025), DOI: [10.1016/j.ijepes.2025.111222](https://doi.org/10.1016/j.ijepes.2025.111222).

- [9] Dash P.K., Pradhan A.K., Panda G., *A novel fuzzy neural network based distance relaying scheme*, IEEE Transactions on Power Delivery, vol.15, no. 3, pp. 902–907 (2000), DOI: [10.1109/61.871350](https://doi.org/10.1109/61.871350).
- [10] Verma R., Ansari M.A., *Fault Detection and Classification Using Fuzzy Logic Controller and ANN*, Micro-Electronics and Telecommunication Eng. (ICMETE 2021), Lecture Notes in Network and Systems, Springer, Singapore, vol. 373, pp. 25–35 (2022), DOI: [10.1007/978-981-16-8721-1_3](https://doi.org/10.1007/978-981-16-8721-1_3).
- [11] Das B., Reddy J.V., *Fuzzy-logic-based fault classification scheme for digital distance protection*, IEEE Transactions on Power Delivery, vol. 20, no. 2, pp. 609–616 (2005), DOI: [10.1109/TPWRD.2004.834294](https://doi.org/10.1109/TPWRD.2004.834294).
- [12] Chatterjee B., Debnath S., *Fuzzy-Based Relaying Scheme for Transmission Line Based on Unsynchronized Voltage Measurement*, IETE Journal of Research, vol. 68, no. 5, pp. 3173–3186 (2020), DOI: [10.1080/03772063.2020.1754934](https://doi.org/10.1080/03772063.2020.1754934).
- [13] Almajali Z.S., Bashabsheh M.N., Alleimon S.A., Btoosh L.R., *Fault Classification in HVDC Systems: A Fuzzy Logic Classifier Approach*, IEEE International Conference on Advanced Systems and Emergent Technologies (IC_ASET), pp. 332–337 (2024), DOI: [10.1109/IC_ASET61847.2024.10596234](https://doi.org/10.1109/IC_ASET61847.2024.10596234).
- [14] Rana S.G., Talati S., Desai M.J., *Fuzzy Logic Technique based Fault Diagnosis for Electrical Distribution Network*, International Conference for Innovation in Technology (INOCON), pp. 1–6 (2024), DOI: [10.1109/INOCON60754.2024.10511821](https://doi.org/10.1109/INOCON60754.2024.10511821).
- [15] Das S., Adhikari S., *Fuzzy logic based fault detection and classification in Unified Power Quality Conditioner (UPQC)-compensated distribution line*, IEEE International Conference on Power Electronics, Drives and Energy Systems (PEDES), pp. 1–5 (2020), DOI: [10.1109/PEDES49360.2020.9379334](https://doi.org/10.1109/PEDES49360.2020.9379334).
- [16] Kumar N., Chakravarthy M., Kumar M.S., Nagaraju M., Ramesha M., Gururaj B., Kiran E.U., *Fuzzy Location Algorithm for Cross-Country and Evolving Faults in EHV Transmission Line*, International Journal of Fuzzy Logic and Intelligent Systems, vol. 23, no. 2, pp. 130–139 (2023), DOI: [10.5391/IJFIS.2023.23.2.130](https://doi.org/10.5391/IJFIS.2023.23.2.130).
- [17] Althi T.R., Koley E., Ghosh S., *Fuzzy Logic based Fault Detection and Classification scheme for Series Faults in Six Phase Transmission Line*, International Conference on Electrical Energy Systems (ICEES), pp. 479–483 (2021), DOI: [10.1109/ICEES51510.2021.9383768](https://doi.org/10.1109/ICEES51510.2021.9383768).
- [18] Osman A.H., Malik O.P., *Transmission Line Distance Protection Based on Wavelet Transform*, IEEE Transactions on Power Delivery, vol. 19, no. 2, pp. 515–523 (2004), DOI: [10.1109/TPWRD.2003.822531](https://doi.org/10.1109/TPWRD.2003.822531).
- [19] Sundararaman B., Jain P., *Fault Detection and Classification in Electrical Power Transmission System Using Wavelet Transform*, Engineering Proceedings, MDPI, vol. 59, no. 71 (2023), DOI: [10.3390/engproc2023059071](https://doi.org/10.3390/engproc2023059071).
- [20] Paul R., Sengupta A., *Wavelet based noise reduction of liquid level system using minimum description length criterion*, Int. Conf. on Communications, Devices and Intelligent Systems (CODIS), IEEE, pp. 592–595 (2012), DOI: [10.1109/CODIS.2012.6422272](https://doi.org/10.1109/CODIS.2012.6422272).
- [21] Shalby E.M., Abdelaziz A.Y., Ahmed E.S., Rashad B.A.E., *A comprehensive guide to selecting suitable wavelet decomposition level and functions in discrete wavelet transform for fault detection in distribution networks*, Scientific Reports, vol. 15, 1160 (2025), DOI: [10.1038/s41598-024-82025-2](https://doi.org/10.1038/s41598-024-82025-2).
- [22] Sadhu R., Paul R., *Classification of Faults in UPFC Compensated Transmission Line using MDL selected Wavelet based DWT Technique*, International Interdisciplinary Conference on Mathematics, Engineering and Science (MESHCN), IEEE, pp. 1–5 (2022), DOI: [10.1109/MESHCN55227.2022.10093645](https://doi.org/10.1109/MESHCN55227.2022.10093645).
- [23] Sit K., De S., Deb S., Maity A., Dalai S., Mondal S., *Implementation of Machine Learning Aided Discrete Meyer Wavelet Decomposition to Identify Overhead Line Insulator Surface Contaminations Based on Leakage Current Signatures*, IEEE Silchar Subsection Conf. (SILCON 2024), pp. 1–6 (2024), DOI: [10.1109/SILCON63976.2024.10910348](https://doi.org/10.1109/SILCON63976.2024.10910348).

- [24] Sriwichai K., Sam-ang P., Kaennakham S.A., *Numerical Investigation of Various Forms of Wavelet in Financial Time Series Analysis*, 2021 International Conference on Electrical, Computer and Energy Technologies (ICECET), pp. 1–6 (2021), DOI: [10.1109/ICECET52533.2021.9698629](https://doi.org/10.1109/ICECET52533.2021.9698629).
- [25] Sherwali H.H., Abdrahem A.A., *Simulation of Numerical Distance Relays, Matlab - Modelling, Programming and Simulations*, InTech, pp. 971–991 (2010), available online at: www.intechopen.com/chapters/11615.
- [26] The MathWorks Inc., MATLAB version: 9.13.0 (R2022b) (2022).
- [27] Suliman M.Y., Alkhayyat M.T., *High impedance fault detection in radial distribution network using discrete wavelet transform technique*, Archives of Electrical Engineering, vol. 70, no. 4, pp. 873–886 (2021), DOI: [10.24425/aee.2021.138267](https://doi.org/10.24425/aee.2021.138267).
- [28] Sadhu R., Bhowmik P.S., *Different Setting of Unified Power Flow Controller (UPFC) and Its Effects on Performance on Distance Relay*, Modelling and Simulation in Science, Technology and Engineering Mathematics, Advances in Intelligent Systems and Computing, Springer Nature Switzerland AG 749, pp. 179–190 (2019), DOI: [10.1007/978-3-319-74808-5_16](https://doi.org/10.1007/978-3-319-74808-5_16).
- [29] Samonto S., Kar S., Pal S., Sekh A.A., Castillo O., Park G.K., *Best-fit membership function for designing fuzzy logic controller aided intelligent over current fault protection scheme*, International Transactions on Electrical Energy Systems, vol. 31, no. 5, 12075 (2021), DOI: [10.1002/2050-7038.12875](https://doi.org/10.1002/2050-7038.12875).