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Fault Detection and Location in Distribution Networks Using the Traveling Wave Theory Based on Hilbert-Huang Transform

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ABSTRACT

Identifying and locating various faults in distribution networks can significantly reduce maintenance costs in these systems. For this reason, intelligent methods for fault detection and location with high accuracy and speed have recently gained attention from system operators and planners in power systems. This paper proposes an intelligent fault detection and location model based on the concept of traveling waves (TW), where the input signal is generated using the Hilbert-Huang Transform (HHT). In the proposed method, the voltage at all network terminals is measured and converted into the phasor domain in the complex space. The obtained phasor components are processed using the Hilbert-Huang Transform (HHT), and the intrinsic mode functions (IMFs) are extracted. The instantaneous magnitude of the first IMF associated with each voltage signal determines the branch where the fault has occurred, and this component is also used for fault detection and determining the fault occurrence time. Subsequently, by identifying the branch and comparing the time-domain components of the traveling wave signals from both the initial and terminal terminals of the branch, the precise fault location on the branch is determined using the concept of traveling waves. Simulation results show that the fault location estimation accuracy under various scenarios is over 98%.

1. INTRODUCTION

Fault detection and accurate fault location are essential for improving the reliability and operational efficiency of distribution networks. Previous studies have shown that integrating intelligent algorithms with advanced signal processing methods can significantly enhance fault diagnosis capabilities. For instance, Rahmani et al. (2010) demonstrated the use of machine vision and thermo-vision imaging with multi-class SVM to identify major faults in overhead substations, while Haddadnia et al. (2014) applied artificial neural networks and vibration signal analysis for detecting induction motor bearing faults [1-2]. Building on such approaches, the traveling wave theory combined with the Hilbert-Huang Transform (HHT) offers a powerful framework for fault detection and localization in distribution networks. By decomposing transient fault signals into intrinsic mode functions and analyzing their

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instantaneous frequency and energy, HHT enables the precise identification of fault initiation times and locations. This integration ensures a faster, more accurate, and adaptive fault diagnosis process, thereby enhancing the resilience and performance of modern power distribution systems.

Distribution networks, due to their low and medium power levels and complex structure, are exposed to various faults that, if not accurately detected and located, can cause significant damage to the network [3-4]. From the data acquisition perspective, fault detection and location strategies in distribution networks can be categorized into three groups: parameter-based or model-based methods, frequency component-based methods, and awareness-based methods. Traditional fault detection methods, such as impedance-based methods in the time domain [5] and virtual impedance-based methods [6], fall into the parameter-based category. These methods suffer from high estimation errors, and their accuracy depends heavily on the network parameters. To address these challenges, frequency component-based strategies have been proposed, with the most common ones being gap frequency spectrum analysis [7], and widely used methods based on traveling waves (TW) [8-12]. TW-based protective schemes are faster and more accurate alternatives to traditional algorithms. Various methods for extracting TW from voltage and current signals are employed in TW-based algorithms. Fast Fourier Transform (FFT), used in [13], can only extract frequency information of TWs. Wavelet Transform (WT) has been widely used for this purpose [14-16], but it has disadvantages such as complex computations and low output resolution. The S-Transform (ST), used in [17, 18], has also been applied for extracting TWs. ST has previously been used in power quality [19] and differential transformer protection [20]. Due to its high computational load and low output resolution, ST is not ideal for TW-based algorithms. Time-Time Transform (TTT), used in [21], is even more complex than ST and WT and is not a good option for use. In some studies, exploratory methods like Principal Component Analysis (PCA) [22] have been used to extract TWs. Although PCA has the capability to accurately detect fault timing, it requires a covariance matrix that can be inverted, which limits its applicability [23].

The Hilbert-Huang Transform (HHT) is a relatively new method for signal analysis in the time-frequency domain, capable of calculating the instantaneous amplitude and frequency of nonlinear and non-stationary signals [24]. Unlike other mathematical transforms, HHT operates based on an adaptive algorithm, meaning no prior knowledge of the signal is required [25]. In this transform, the Hilbert Spectrum (HS) method is integrated with the Empirical Mode Decomposition (EMD) method, resulting in an experiential approach to generating time-frequency spectrums for various nonlinear and non-stationary signals [26, 27]. HHT has been successfully applied in fault detection of electrical machines using vibration data [28] and rotor bar fault detection in induction motors using stator current data [29].

To address the limitations of traditional transform-based methods, this paper proposes a fault detection and location model based on the concept of traveling waves and the Hilbert-Huang Transform. In the proposed HH method, first, the IMF components related to the measured signal are extracted by applying the EMD method. Then, the first IMF component is applied to the traveling wave algorithm to determine the fault location. The initial signals, the three-phase voltages of the distribution network terminals, are transformed into a single signal corresponding to each terminal using a phasor transform in the complex space. The first peak in the IMF(1) component corresponding to each signal is used for fault detection, determining the fault occurrence time, and identifying the branch where the fault occurred. Finally, by comparing the times of the first peak in the first IMF component corresponding to the voltages at both ends of the branch, the precise fault location will be determined.

The remainder of the paper is organized as follows: Section 2 describes the Hilbert-Huang Transform method and the concept of traveling waves. Section 3 presents the simulation results, and the paper concludes with Section 4, which provides a summary and conclusions.

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = \sqrt{\frac{2}{3}} \begin{bmatrix} 1 & \frac{-1}{2} & \frac{-1}{2} \\ 0 & \sqrt{\frac{3}{2}} & -\sqrt{\frac{3}{2}} \end{bmatrix} \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} \tag{1}$$

Then, the final phasor signal is obtained as a complex component from the relation $v_f = v_\alpha + jv_\beta$. It is important to note that the IMF components are derived by applying Empirical Mode Decomposition (EMD) on v_f. For this purpose, the Empirical Mode Decomposition (EMD) method is used.

2. EMPIRICAL MODE DECOMPOSITION (EMD)

In this method, the time-domain signal *S(t)*, as described by equation (2), is decomposed into a series of intrinsic mode functions (IMFs) plus a residual value. The key point is that the first IMF contains the most information about the original signal *S(t)*, and therefore, it is used for processing with the Hilbert-Huang Transform.

$$S(t)=\sum_{i=1}^{n}c_i(t)+r(t) \tag{2}$$

In this relation, ci(t) represents the intrinsic mode functions, and r(t) denotes the residual. n indicates the number of IMFs. The extraction of IMFs from the original signal continues until the residual r(t) becomes a non-oscillatory signal.

3. HILBERT-HUANG TRANSFORM (HHT)

This section explains the HH transform. This method is based on the concept of Empirical Mode Decomposition (EMD), which decomposes the error signal to extract the intrinsic mode functions (IMFs) from the signal. Then, by applying the Hilbert transform to each IMF, the instantaneous amplitude of the first extracted IMF is determined and used for fault detection and location. It is important to note that the first IMF component contains the most information about the error signal, and therefore, this component is used. If the signal X(t) is a time-domain signal, its Hilbert transform is defined by equation (3) [30].

$$Y(t)=H[X(t)]=\int_{-\infty}^{\infty}\frac{X(\tau)}{t-\tau}d\tau \tag{3}$$

In this case, the components X(t) and Y(t) form an analytical signal, which is defined by equation (4). This signal has instantaneous amplitude, phase, and frequency, which are obtained based on equations (5) to (7), respectively.

$$Z(t)=X(t)+Y(t) \tag{4}$$

$$A(t)=\sqrt{X^2(t)+Y^2(t)} \tag{5}$$

$$\theta(t)=tan^{-1}\left(\frac{Y(t)}{X(t)}\right) \tag{6}$$

$$f(t)=\frac{1}{2\pi}\frac{d}{dt}\theta(t) \tag{7}$$

Since the occurrence of faults in the distribution network directly impacts the instantaneous amplitude component (equation (5)) of the signal, causing severe peaks, the instantaneous amplitude corresponding to the first IMF for each terminal of the network will be used for fault detection and location using the traveling wave technique. This technique is explained in the next subsection.

4. TRAVELING WAVE (TW) TECHNIQUE

According to TW theory, any disturbance or sudden change in a distribution or transmission line generates traveling wave signals that move forward and backward, propagating from the disturbance point towards both terminals of the line. The initial values of these waves depend on several factors, such as the fault location, fault path resistance, fault initiation angle, and fault type. Furthermore, these signals experience reflection and refraction at points of discontinuity, such as the fault point, busbars, or locations where overhead cables are connected. The basic principle of this method can be explained using the schematic diagram in Figure (1). When a wave reaches a discontinuity, such as an open circuit point, short circuit, or a point on the line where the characteristic impedance changes, part of the wave's energy passes through, and part is reflected. In this case, by using the wave propagation speed and the return or reflection time, which is received at both terminals of the line, the fault location can be estimated. The wave propagation speed (v) in distribution and transmission lines is related to the inductance (L) and capacitance (C) of the line, as described by equation (8).

$$v = \frac{1}{\sqrt{LC}} \tag{8}$$

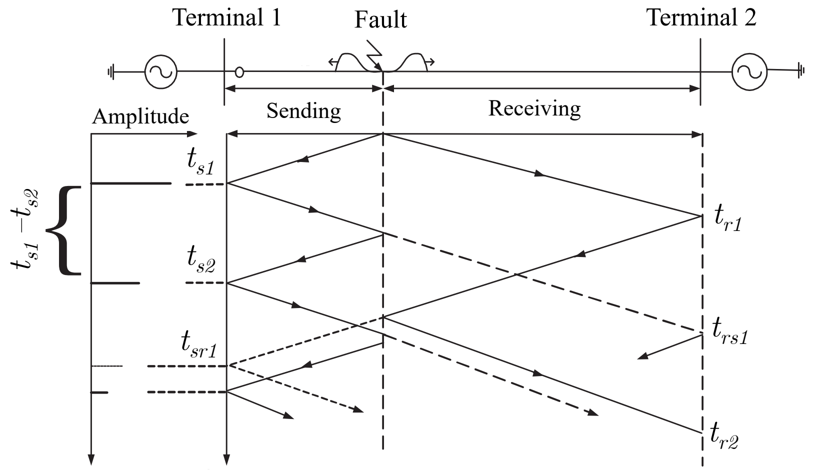

Fig. 1. Concept of traveling wave and calculation of the time difference of the first waves

According to traveling wave theory, if the arrival times of the TWs at terminals 1 and 2 are t_1 and t_2, respectively, and with the known wave propagation speed v, the fault distance d relative to terminal 1 in a line of length l can be calculated using equation (9) [30].

$$d = \frac{v(t_1 - t_2)}{2} + \frac{l}{2} \tag{9}$$

On the other hand, to detect the branch where the fault has occurred, the voltage signals measured at all terminals of the distribution network must be measured and processed using the method described. A notable point is that the two terminals that show the highest peak amplitude in the first IMF instantaneous magnitude, IMF(1), will be the transmitting and receiving terminals of the branch in question. Using this method, the faulty branch can first be identified from the network, and then, by applying the traveling wave theory, the fault location can be estimated.

5. SIMULATION RESULTS

In this study, a 20 kV distribution system consisting of 5 feeders, as shown in Figure (2), is selected as the case study. The distribution network is considered as compensated and ungrounded [31].

In this system, 9 terminals are connected to feeder 1 (terminal 10). The voltage at all terminals is measured for fault detection and location, and using equation (1), the v_f component is calculated for them. For example, the v_f component corresponding to terminal 1 is plotted in Figure (3). In this example, a single-phase fault to ground occurs at the midpoint (a distance of 2.5 kilometers) between terminals 4 and 5 at time t=0.6t = 0.6t=0.6 s.

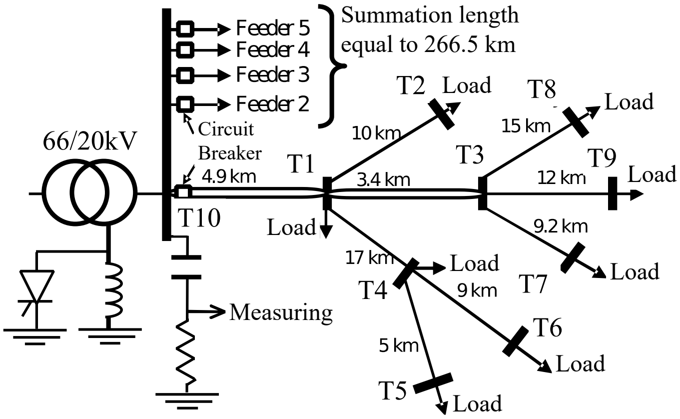

Fig. 2. Single-line diagram of the 20 kV distribution system consisting of 5 feeders

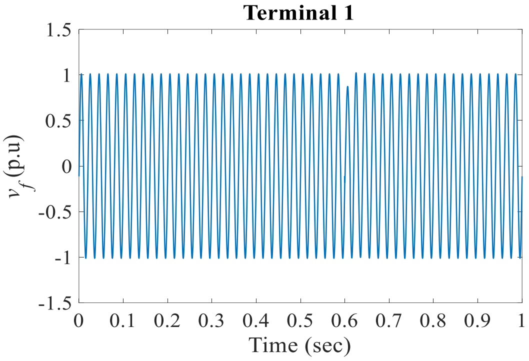

Fig. 3. v_f component corresponding to terminal 1

By applying the EMD method, 9 intrinsic mode functions (IMFs) for v_f at terminal 1 are obtained, as shown in Figure (4). It can also be observed that the residual r(t) will be a non-oscillatory signal. The first IMF is selected for processing with the HH transform.

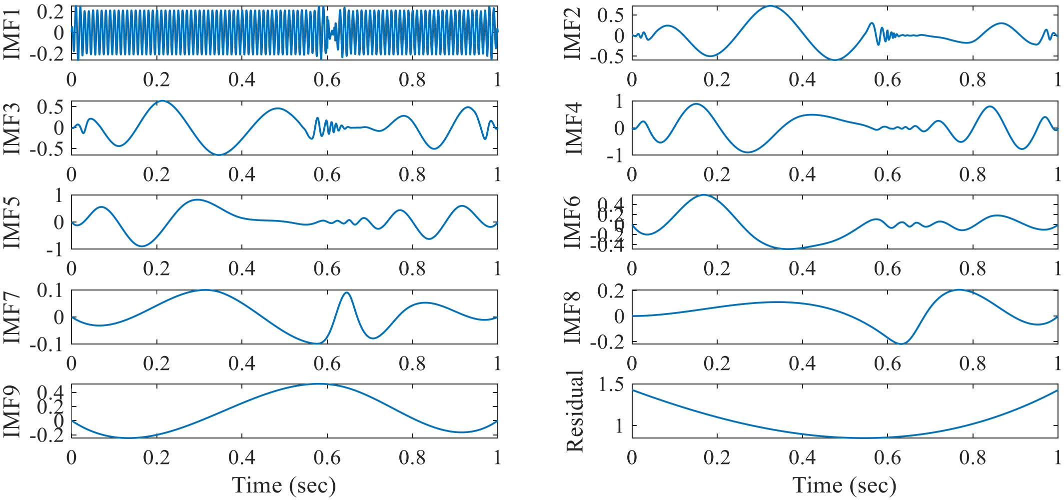

Fig. 4. IMFs corresponding to the $\mathbf{v_f}$ component at terminal 1

In this step, the Hilbert-Huang transform is applied to the first intrinsic mode function (IMF1), and its instantaneous amplitude is obtained. Figures (5) and (6) show the zoomed-in images of the $\mathbf{v_f}$ signals for the 10 terminals of the network and their corresponding instantaneous amplitudes, respectively. As observed, when a fault occurs on one of the branches of the network, all instantaneous amplitudes show a distinct peak value at the moment of the fault. Since the amplitude of this peak is directly related to the intensity of the fault's effect on the terminal voltages, the two terminals with the highest peak amplitude are identified as the two ends of the branch where the fault occurred. In the next step, by identifying the faulty branch, the peak times in the instantaneous amplitude graph are extracted and used with the traveling wave theory to calculate the fault location, according to equation (9). As seen in Figure (6), the peak amplitude in the instantaneous amplitude graph corresponding to terminals 4 and 5 is the highest. Therefore, it can be concluded that the fault occurred on the branch between these two terminals. Figure (7) shows the instantaneous amplitude corresponding to these two terminals. The peak time corresponding to terminal 4 is 0.611739 seconds, and the peak time corresponding to terminal 5 is 0.611439 seconds. The difference between these two-time values, Δt, determines the fault location. It is noteworthy that the inductance and capacitance values for all branches of the network are selected as L=0.9337 mH and C=12.74 nF, respectively. The length of the branch between terminals 4 and 5 is l=5 km, and thus the fault location, according to equation (9), is estimated to be 2.5435 kilometers, which, compared to the actual fault location (i.e., 2.5 kilometers), shows a discrepancy of only 43.5 meters, or 1.74%. This result indicates that the fault location estimation accuracy is 98.26%.

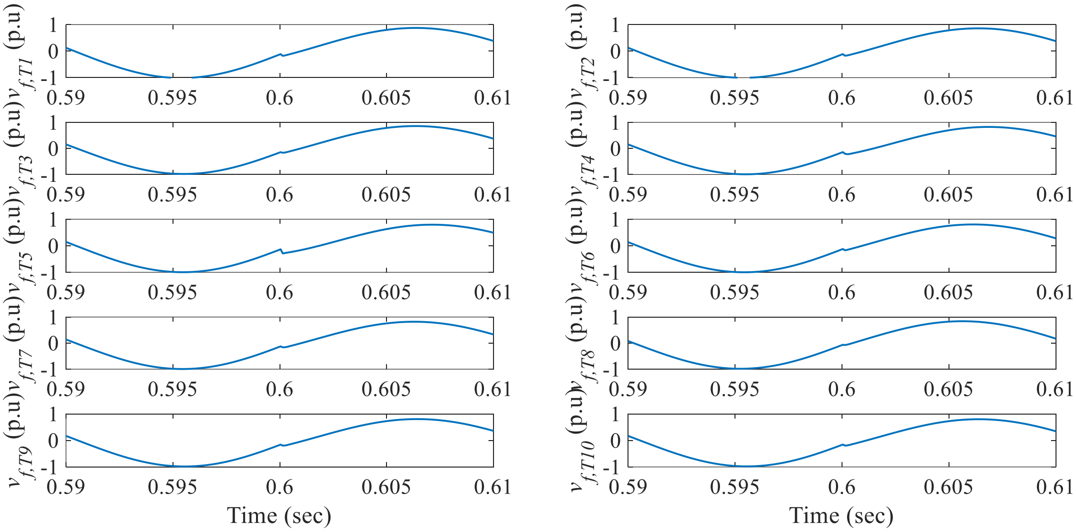

Fig. 5. $\mathbf{v}_f$ signals corresponding to the 10 terminals of the network (Feeder 1)

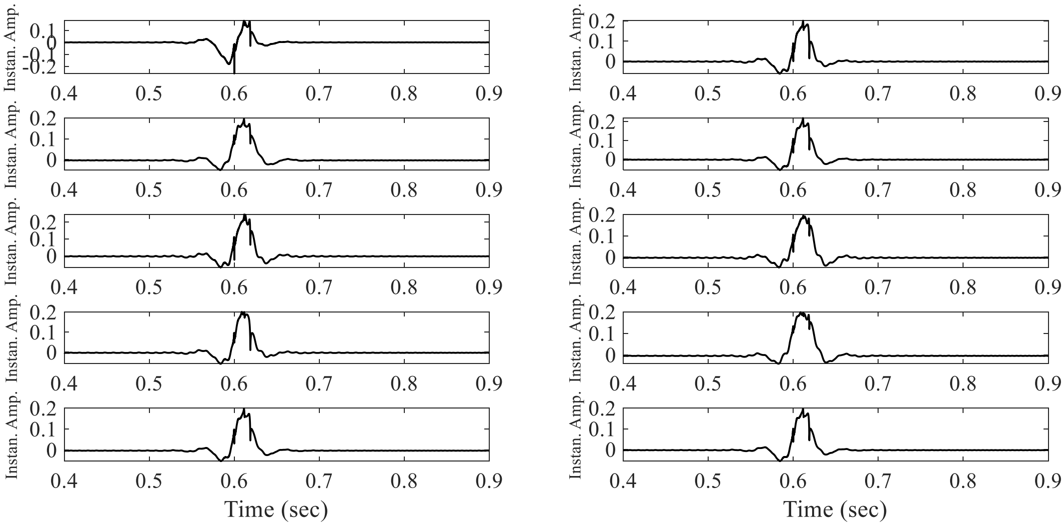

Fig. 6. Instantaneous amplitudes corresponding to the signals in Figure (5)

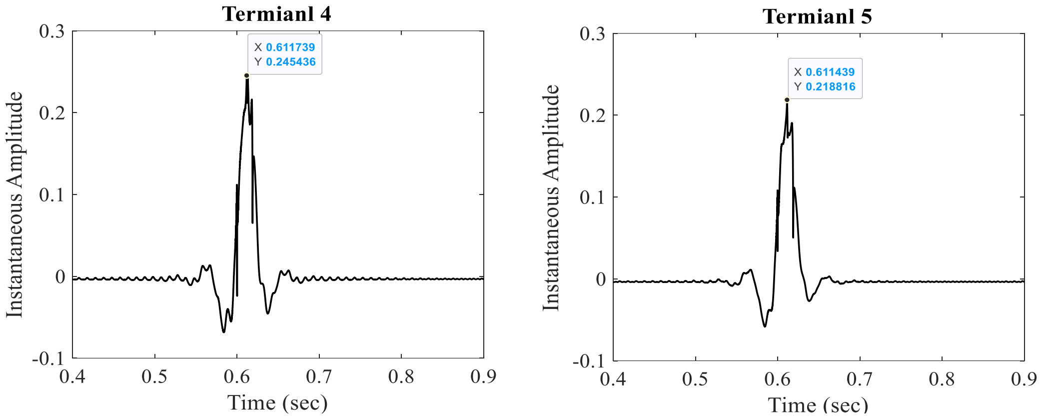

Fig. 7. Instantaneous amplitude corresponding to terminals 4 and 5

Various fault scenarios in the studied network have been implemented, and the performance of the proposed fault detection and location method has been evaluated under these scenarios. The results of this evaluation are presented in Table (1). As observed, the proposed method, based on the Hilbert-Huang transform and traveling wave theory, can accurately estimate the fault location in the studied distribution network with high accuracy (over 98%). Additionally, this method is applicable for various fault types, including single-phase-to-ground, multi-phase-to-ground, and phase-to-phase faults. It is important to note that the fault resistance in all scenarios is assumed to be Rf=0.1 Ω, and the ground resistance in phase-to-ground fault scenarios is assumed to be Rg=0.01 Ω. The low computational cost of the proposed method, compared to wavelet transform-based methods and Principal Component Analysis (PCA), alongside its high estimation accuracy, makes it advantageous. Furthermore, the proposed method in this paper can be implemented for any distribution network, regardless of its size and topology. This is because, in the first step, the branch where the fault occurred is identified simply by measuring and processing the terminal voltages, and in the next step, the fault location is determined by calculating the peak times of the components from the two terminals at the start and end of the branch in question.

Table 1. Fault location estimation results for different scenarios

Estimation Accuracy (%)	Estimation Error (%)	Estimated Fault Location (km)	Actual Fault Location (km)	Fault Scenario
98.26	1.74	2.5435	2.5	Single-phase-to-ground fault between T4 and T5
99.48	0.5153	12.3361	12.4	Single-phase-to-ground fault between T3 and T8
98.43	1.56	4.8752	4.8	Two-phase-to-ground fault between T4 and T6
98.39	1.60	3.6579	3.6	Two-phase fault between T1 and T2
99.38	0.62	6.3601	6.4	Three-phase-to-ground fault between T3 and T7
99.21	0.78	24.7044	24.9	Three-phase fault between T1 and T3

6. CONCLUSION

In this paper, a fault detection and location method for power distribution networks based on traveling wave (TW) theory, using the Hilbert-Huang transform (HHT), has been proposed. In the proposed method, the voltages at the network terminals are measured as the primary signals and, by applying the phasor transformation in the complex space, a corresponding complex signal for each terminal is obtained. Then, intrinsic mode functions (IMFs) are extracted for each signal, and by applying the Hilbert-Huang transform on the first IMF component, the instantaneous amplitude corresponding to each terminal is calculated. The peak value observed in the instantaneous amplitude indicates a fault occurrence in the network, and the amplitude of this peak is used to determine which branch the fault occurred on. Finally, by determining the terminals at the two ends of the faulty branch, the peak times are calculated, and based on traveling wave theory, the fault location is determined. Simulation results on a sample distribution network show a maximum estimation error of 1.74% under various fault scenarios. Additionally, the estimation accuracy under all fault scenarios exceeds 98%, which is considered satisfactory. Since the peak amplitude in the instantaneous component changes with the fault resistance, a decision tree can be defined to categorize faults for different fault resistance values using the proposed traveling wave method based on the HH transform. This capability of the proposed method will be explored in a future study.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

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Declaration of Interest

The authors declare that they have no competing interests.

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