Power System Faults Analysis, Detection, and Localization in Underground Distribution and Transmission Networks by Deploying AI-Based Matlab Model/Simulink

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***Abstract*—Employing MATLAB/Simulink, this study designs and builds a fault detecting and locating approaches for underground distribution and transmission networks. The suggested approach detects and locates faults through an AI-based waveform shift, which has become an established technique in electric power system investigations. MATLAB/Simulink 2019a was implemented to build and test the suggested method on underground distribution and transmission line models. The simulation results revealed that the developed fault detection and localization technique is capable of accurately detecting and locating faults on distribution and transmission lines. The method proposed can assist power system operators in swiftly locating the fault and taking the necessary procedures to restore power supply. Overall, this article is a valuable resource for increasing the reliability and efficiency of electricity transmission and distribution networks.**

Keywords*—Power System Faults, Fault Detection, Electrical Underground Transmission Lines, MATLAB/Simulink 2019a, Electrical Distribution Lines.

I. INTRODUCTION

Electrical power networks are crucial system infrastructures that are essential to our everyday existence [1]. A consistent and stable supply of power is required for modern society to function [2]. Faults in electrical systems, on the other hand, can cause power outages and disrupt daily life [3]. Fault recognition and localisation are critical for power system reliability and efficiency[4]. Due to their complicated structure and difficulty of access, detecting and identifying faults in underground transmission and distribution lines is a difficult undertaking [5]- [6]. The conventional approach of detecting and locating faults is the use of circuit breakers, which disconnect the faulty segment from the power grid [7]. This strategy, however, can result in power interruptions and enormous economic losses [8]. To address these issues, many defect detection and locating approaches like as wavelet transform, artificial neural networks, and fuzzy logic have been developed [9]. These techniques detect and locate defects in power systems using mathematical models and simulations, primarily using MATLAB/Simulink, a widely used power system analysis and simulation software tool [10]. As a result, the study's goal is to create a fault detection and locating strategy for underground transmission and distribution lines using MATLAB/Simulink and AI-wavelet transform [11]. The developed system can assist power system operators in swiftly detecting and locating faults in underground transmission and distribution lines and taking the appropriate procedures to restore power supply, which is crucial for power system reliability and efficiency.

II. RELATED WORKS

A frequency-domain algorithm employing wavelet multi-resolution assessment has been offered for real-time fault analysis of transmission lines [12]. To enhance real-time reliability, this investigation presents an experimental prototype design for a 20V, 200 km transmission line, simulating a 400 kV extra-high voltage transmission line. To gather representative data with accurate characterization and transmission fidelity, the model employs an efficient National Instruments-based data acquisition equipment and LabVIEW. The model's distinguishing features include accurate fault identification and classification via a frequency-domain technique that is unaffected by faulty susceptibility or fault inception inclination [13].

C. Apisit et al. proposed and investigated the Discrete Wavelet Transform for Fault Types in Underground Distribution Systems [14]. Daubechies4 was used as the primary wavelets for splitting components with high frequencies from faulty data. Positive sequential current signal values are determined and applied in the fault detection judgment process [15].

In, a defect classification technique based on discrete wavelet transform (DVT) and back-propagation neural networks (BPNN) was created [16]. The technique presents a method for identifying fault types on single circuit transmission lines that employs DWT and BPNN, as well as ATP/EMTP for fault signal

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simulation and fluctuations of the first-scale high-frequency factor as data to develop processes.

In, a novel traveling-wave detection method for fault location was devised and developed, based on two successive window sliding processes and curve matching [17]. This method presented a new way for deriving traveling wave arrival timings by using aerial modes of three-phase voltage signals and two successive sliding windows of unequal length. High precision in determining traveling wave arrival timings is accomplished by fitting a line to samples inside each window and measuring the angle between them. This approach removes the need to switch between time and frequency domains, which reduces the impacts of noise and sampling frequency. EMTP-ATP was used for transient simulations, and MATLAB/Simulink was used for sensitivity analysis [18]. Based on time linear dependence, a novel traveling wave fault location method for transmission networks was demonstrated in [19], To calculate the shortest transmission path of a fault moving wave, the proximal point optimization algorithm (PPOA) was utilized. On the Cartesian coordinate plane, a linear fit was formed between the arrival time of the traveling wave head and the transmission distance. To fix erroneous data, linear regression analysis was employed. The intersection of the fitted line and the coordinate axis yielded the precise fault location. The traveling wave location method was tested in Hunan Power Grid, and it proved to reduce arrival time recording error and enhance fault location reliability and accuracy.

Transfer Learning: A Framework for Artificial Intelligence (AI) Fatemeh Mohammadi Shakiba et al. invented Power Line Diagnosis [20]. This AI-based technique employs neural networks for real-time sensing, detection, and location of transmission line defects [21]. A unique transfer learning framework based on a pre-trained LeNet-5 convolutional neural network was proposed in this method. By transferring knowledge from a source convolutional neural network to anticipate a dissimilar target dataset, the approach was able to diagnose problems for diverse transmission line lengths and impedances.

The identification and evaluation of power transmission line problems using an artificial intelligence strategy were explored and implemented in [22]. This method presents a systematic, comprehensive, and up-to-date examination of several AI techniques for detecting and classifying defects on power transmission lines using unmanned aerial vehicles (UAV). The purpose of this study is to detect, assess, and pinpoint power system defects, mostly in subterranean distribution and transmission networks. The study also closes technical gaps discovered in prior studies, such as poor real-time fault monitoring and detection, high cost, unfriendly user interface, poor data integration of any sort of fault, and incorrect sensor location. In a study case network, the constructed model also showed an improved model for power system fault analysis, fault detection, and fault location.

III. MATERIALS AND METHODS

Matlab/Simulink 2019a was used to implement the developed fault location algorithm. The SimPowerSystems package for Matlab/Simulink was used to generate the models. The algorithm was designed with a single phase-to-ground failure in mind, as this sort of problem accounts for approximately 90% of all underground distribution and transmission line faults. The voltage and current phasors were used as fundamental frequencies for computing the phasors and network model algorithms. The transmission line was represented as a three-phase -section line. It was expected that a problem would occur at random per unit length (n) from the measuring equipment. Every time the model ran, the fault location was created at random and displayed via the "numeric display block" referred to as "exact fault location." A three-phase voltage source block was considered to provide the simulated line, while three-phase current and voltage sensors were considered to monitor the three-phase line current and voltage values, respectively. To calculate the zero-sequence line current and the first order components of the load voltage and fault current, sequence and Fourier analyzers were used and $I.Z_l$ determined by $\mathrm{I.Z_L} = (\mathrm{I_A} - \mathrm{I_0}).\mathrm{Z_{L1}} + \mathrm{k_0}.\mathrm{I_0}.\mathrm{Z_{L0}}$ (1) respectively. Where $\mathrm{Z_{L1}}$ is the positive sequence impedance of the line, $\mathrm{Z_{L0}}$ is the zero-sequence impedance of the line.
$\mathrm{k_0}$ is the ratio of the zero-sequence impedance to the positive sequence impedance of the line as shown in equation (2).

$$\mathrm{k_0} = \frac{\mathrm{Z_{L0}}}{\mathrm{Z_{L1}}} \quad (2)$$

For the case of the single-phase-to-ground (LG) fault at phases B and C. equation (3) shows appropriate phase quantities have to be used. For the case of line-to-line (LL) fault between phase A and B

$$\mathrm{V} = \mathrm{V_A} - \mathrm{V_B} \quad (3)$$

$$\mathrm{I.Z_L} = (\mathrm{I_A} - \mathrm{I_B}).\mathrm{Z_{L1}} \quad (4)$$

The necessary phase amounts were also employed for line-to-line (LL) faults between phases B and C and phases A and C. The transport delay was linked with multiple mathematical blocks to calculate the fault location per unit length as a difference between the line current and the load current. The fault detection technique is depicted in Figure 1 by measuring currents at nodes in order to create fault detector current settings to calculate signals between phase currents of each segment. If the maximum of the section's selected mean square difference signal between phase currents is more than the current values, the section is regarded faulty; otherwise, the section is in normal case condition.

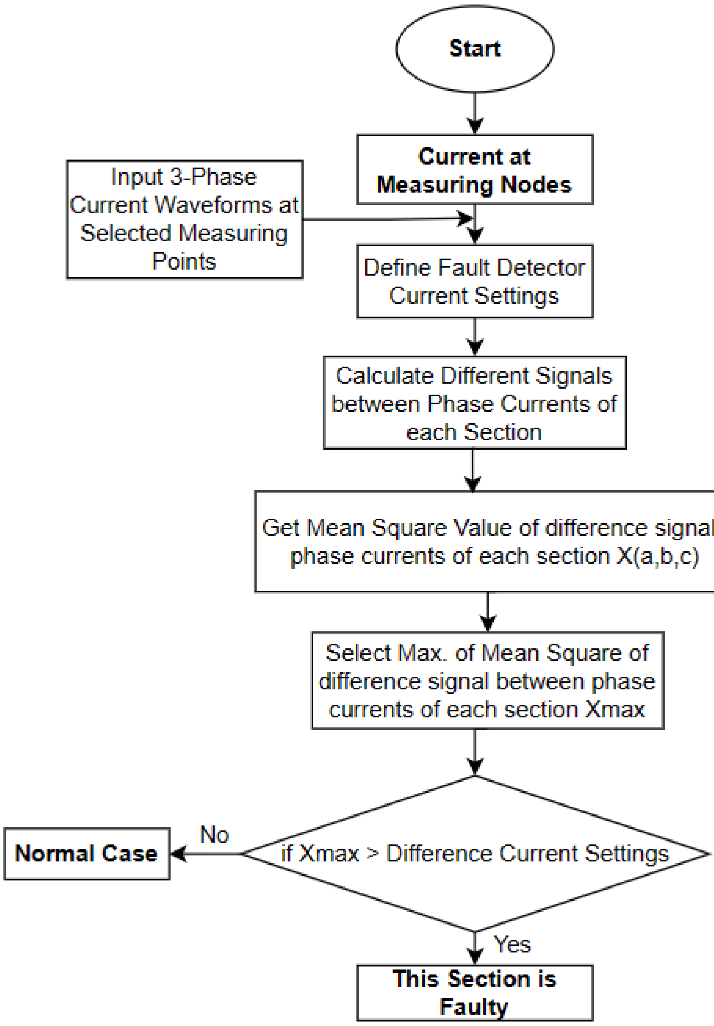

Fig. 1. Flowchart of Fault Detection Process.

The computed model used to simulate the algorithm is shown in the Fig. 2.

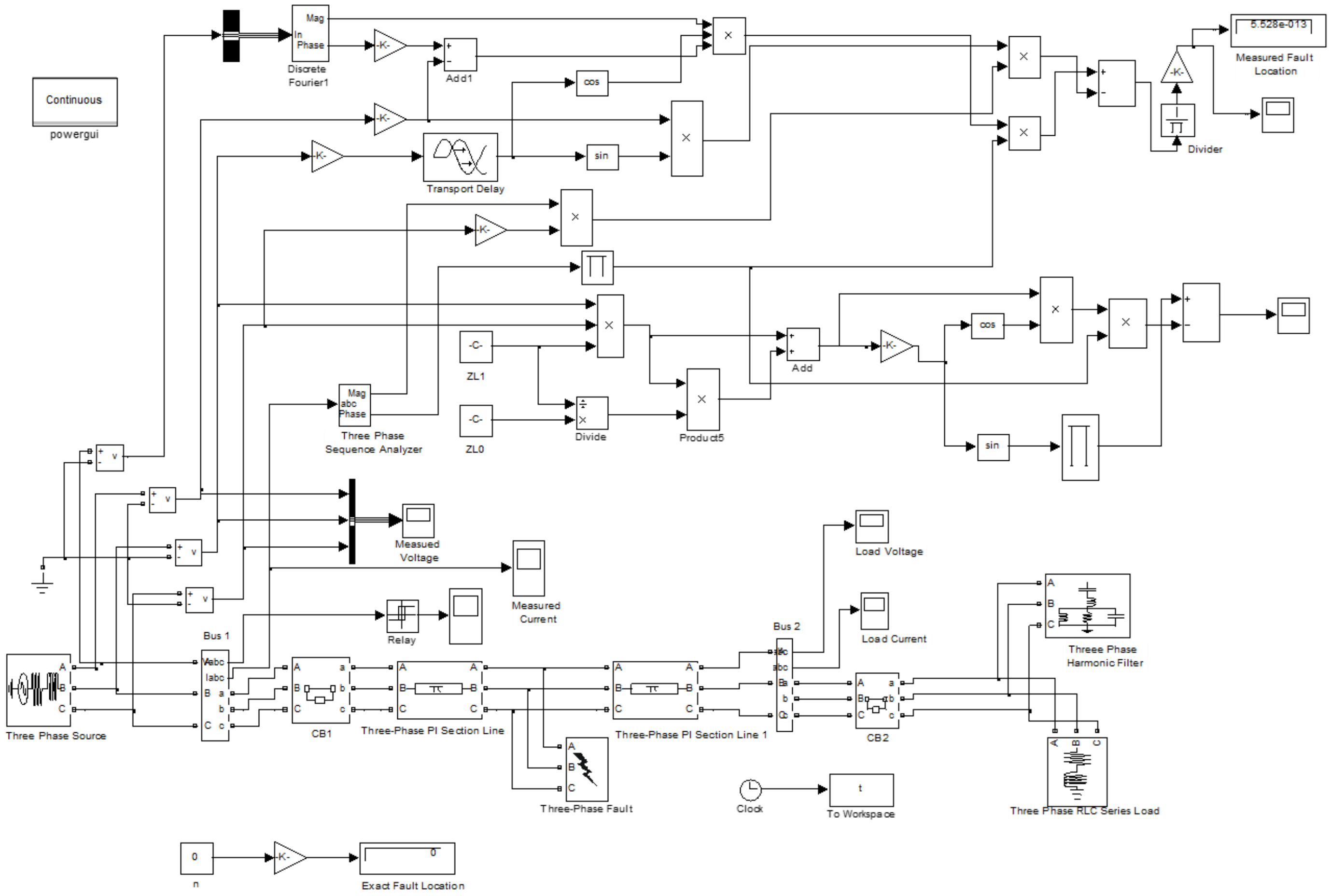

Fig. 2. Simulated Power Network.

The percentage error calculated as given in equation (5) was used to assess estimating accuracy.

$$\%Error = \frac{\text{Actual location} - \text{Estimated location}}{\text{Total length of the Line}} * 100\% \qquad (5)$$

IV. RESULTS AND DISCUSSION

4.1 Fault Location Simulations

The distance between the bus where the measurement equipment was installed and the fault point was used to determine the fault location. As demonstrated in Table 1, the fault location estimates were satisfactory.

Table 1. The Fault Locations on Simulated Line.

Measured fault location (km)	Simulated fault location (km)	Error (%)
10.05	9.970	0.03400
20.05	19.990	0.0200
30.05	30.001	0.0000
40.05	40.020	0.0300
50.05	50.030	0.0300
60.05	60.050	0.0400
70.05	70.040	0.0400
80.05	80.030	0.0300
90.05	90.020	0.0200

4.2 Fault Analysis and Simulations

At both ends, the double terminated line recording of fault signals approach was applied. The captured waveforms were converted into modal signals, which were then evaluated utilizing intelligent AI-Matlab code creation. The Matlab program that follows manipulates the fault signal to obtain the first two level coefficients of the first two peaks of the faulted wave signal of the three phase faults.

```
% faulted signal generation
signal= [0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0.08 0 .01 0 0 0 0 0 0 0 0 0];
s=signal.*signal;
[ca1,cd1]=dwt(s,'db4');
subplot(3,1,1);plot(s),title('faulted signal WCT^2');
plot(signal),title('fault signal')
% perform decomposition at level 2 of signal using db4
[c,l]=wavedec(s,2,'db4');
% reconstructs detail coeffs at levels 1,2, from the wavelet decomposition structure [c, l]
d2=wrcoef ('d', c, l,'db4',2);
d1=wrcoef('d',c,l,'db4',1);
Subplot(3,1,2);plot(d2),title('Bus A, Scale 1');
Subplot (3, 1, 3); plot (d1), title ('Bus B, Scale 1');
```

Fig. 3 shows the demonstrated fault signal analysis depending on signal travel time

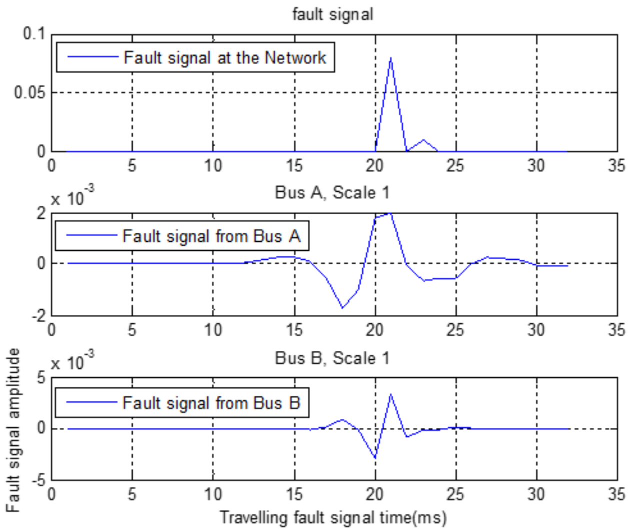

Fig. 3. Simulated Fault Signals.

Figure 4 depicts the phase voltage A for a double-phase failure that occurred at a distance of 23 kilometers in the cable section.

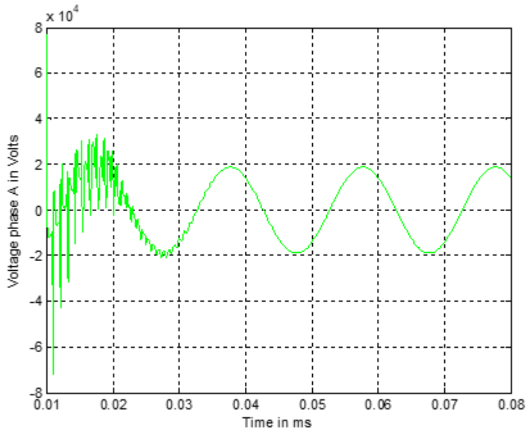

Fig. 4. Phase voltage A for double-phase fault.

As shown in Fig. 5, the phase voltage B for a double-phase fault that occurred at a distance of 23 km in the cable segment was simulated and computed.

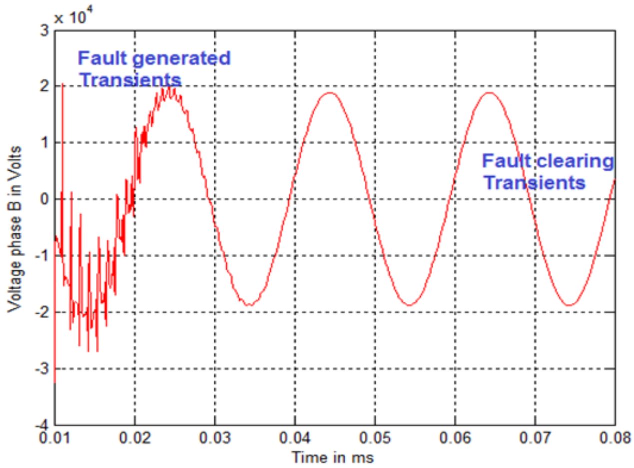

Fig. 5. Phase Voltage double phase fault analysis at bus B.

As shown in Fig. 6, the phase voltage C for a double-phase fault that occurred at a distance of 23 km in the cable section was also simulated using the modeled power network.

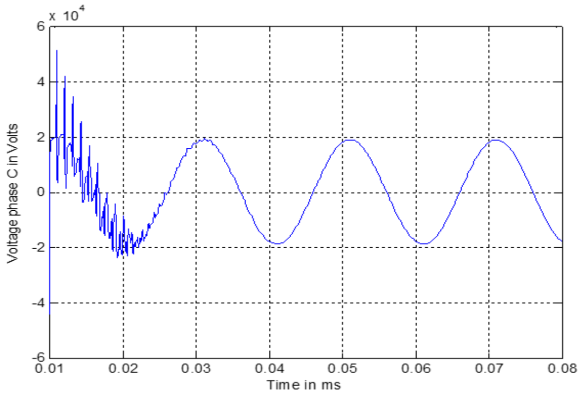

Fig. 6. Phase voltage C for double-phase fault analysis.

Otherwise, the subterranean line is classified as a fault section if the first incepted wave to the fault locator has the same polarity as the wave that struck it and the second one has a polarity that is reversed, as illustrated in Figure 7.

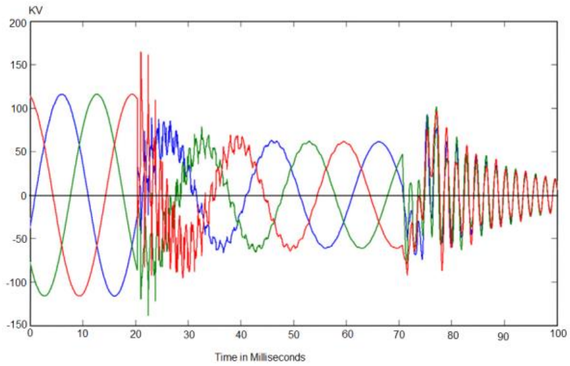

Fig. 7. Three voltage levels for a single phase to ground fault occurred in the underground wire at a distance of 74 kilometers.

The fault signal was reproduced in an underground transmission cable with an inception angle that varied. Furthermore, as shown in Fig. 8, the energy of the fault-induced signal varies with the fault inception angle according to a squared sinusoidal function.

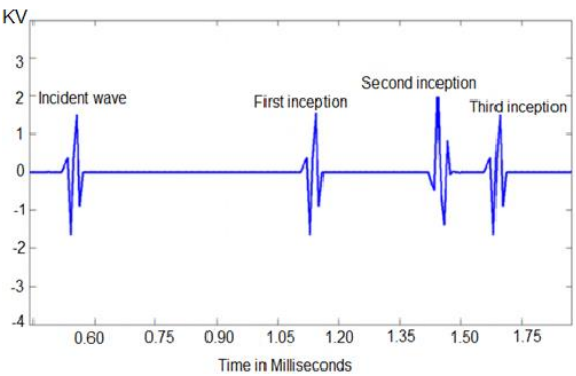

Fig. 8. Fault signal occurred in underground feeder in varying with inception angle.

4.3 Effects of Fault Resistance

Approximately 90% of underground distribution and transmission line faults are single phase to ground faults, which occur when one conductor is short-circuited to the ground without or through fault resistance. Most fault locating methods are influenced by fault resistance, making it critical to investigate its impact on the proposed algorithm's accuracy. Table 2 displays simulation findings for single and double-phase to ground faults in underground lines with varying fault resistances.

Table 2. Single and double-phase to ground faults at 75 km on the underground line with different fault resistances.

Fault type	**Fault resistance (Ω)**	**Calculated distance (Km)**	**Error (%)**
Single-phase to ground Fault	0	74.941	-0.074
	40	75.161	0.201
	80	75.037	0.046
Double-phase to ground Fault	0	75.108	0.135
	40	74.899	-0.126
	80	75.173	0.216

4.4 Effect of fault inception angle

The paper examines the effect of fault inception angle on the accuracy of a proposed AI wave-based fault location method. In a cable section, simulations were run on double-phase and three-phase faults at a distance of 5 km from the fault locator. The results reveal that the inception angle of the defect has no effect on the algorithm's accuracy, and that variations in the angle have no effect on its accuracy. Table 3 depicts the faults that occurred in 5 km of cable section with varying fault inception angles.

Table 3. Fault occurrence within 5 km on the cable section with different fault inception angles.

Fault type	**Fault inception angle (°)**	**Calculated distance (Km)**	**Error (%)**
Double-phase fault	0.00	5.01400	0.04700
	30.00	5.05600	0.18600
	60.00	4.95900	-0.13700
	90.00	5.02800	0.09400
Three-phase fault	0.00	5.07300	0.24300
	30.00	5.06100	0.20300
	60.00	4.97300	-0.09000
	90.00	5.04500	0.15000

4.5 Effect of fault type

An method for finding faults in subterranean lines and cable sections is presented in this research. The accuracy of the technique is comparable for single, double, and three-phase faults with 34° fault inception angle and 63 fault resistances in the subterranean portion (Table 4) and zero fault inception angle and 1 fault resistance in the cable segment (Table 5). The results also show that the suggested algorithm's accuracy is constant across different types of transmission line problems.

Table 4. Results for fault occurred in different km on the cable section with different fault inception angles.

Fault type	Actual fault Distance (Km)	Calculated Distance (Km)	Error (%)
Single-phase to ground	2.3400	2.367	0.09000
	17.9500	17893	-0.19000
	29.0000	29.01200	0.04000
Double-phase to ground	2.3400	2.416000	0.250000
	17.9500	17.91200	-0.126000
	29.0000	29.02100	0.070000
Three-phase to ground	2.3400	2.393000	0.176000
	17.9500	17.978000	0.094000
	29.0000	29.0660000	0.220000

Table 5. Effect of fault type on the accuracy of the proposed method for faults on the cable section.

Fault type	Actual fault Distance (Km)	Calculated Distance (Km)	Error (%)
Single-phase Fault	3.0000	2.93300	-0.2230
	8.7500	8.76100	0.03700
	28.50000	28.53100	0.103300
Double-phase Fault	3.0000	2.97300	-0.09000
	8.7500	8.77300	0.077000
	28.5000	28.48800	-0.04000
Three-phase Fault	3.0000	3.011000	0.03600
	8.7500	8.769000	0.06300
	28.5000	28.47200	-0.09300

V. CONCLUSION AND FUTURE WORKS

An automatic fault location method for subterranean distribution and transmission networks is presented in this study. The system employs a new multi-end fault location algorithm written in AI-Matlab that was designed for composite distribution and transmission lines. The created algorithm identifies the faulted segment of the transmission line using the negative-sequence voltage profile, reduces the network, and predicts the fault site. A field case demonstrates the accuracy of the devised method for a phase-to-ground fault, which accounts for 90% of all faults encountered. Furthermore, when employing Ethernet-based communication without human interaction, the system reports defect location information in less than 1 minute after the user configures the system. This created approach has also been observed to increase multi terminal fault location accuracy with correct time stamps, particularly for problems with changing fault resistance. additional research on the influence of cable aging on fault location and detection in a combined overhead distribution and transmission line with underground power cable is required, and additional data for training and testing is advised when integrating AI algorithms with cybersecurity attack defense.

Data Availability

Upon request, the corresponding author will provide the data that support the conclusions of this paper.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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