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Modelling and Simulation of Fault Distance Locator for Underground Cable Detection

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Abstract: Underground cables have been widely employed for power distribution networks for hundreds of years. Meanwhile, the preponderance of underground faults is detected by excavating and approach known the entire length of armoured cable. If a visual check is still not practicable, the entire cable length is replaced. To address the issue of faults in underground cables, this project will use wavelet analysis to detect fault locations and an artificial neural network (ANN) to evaluate fault performance. The objective of this method is utilized to detect the point and distance location of faults from the source end of an underground cable through transmission line. The underground cable system is to designed with MATLAB Simulink based on the IEEE bus system, which has 13 buses and 16 lines. There are three types of faults: single phase to earth fault (LG), double phase to earth fault (LLG), and three phase to earth fault (LLLG). The simulation results show that the voltage and current wavelet delaying in onset at 1.37ms and 1.66ms with distance (D) fault is 2.886 km from bus 4. The voltage and current wavelets of LLG is delayed in onset at 1.36ms with a distance (D) fault of 16.223 km from bus 9. Meanwhile, the voltage and current delaying in onset 1.35ms is observed for LLLG with a distance (D) of 2.499 km from bus 8.

Keywords: Underground Cable Detection, Fault Distance Locator, Artificial Neural Network

1. Introduction

Underground cables have been frequently employed for electrical distribution networks over the years. This is due to their appropriateness for underground connections, improved security against vandalism and theft, and resistance to dangerous weather conditions including thunderstorms and whirlwind [1]. Furthermore, underground cables remove the threat of storm damage caused by wind. Flooding does not affect the underground cable, thus it is not ruined and electric service is not disrupted [2]. It ensures that there are fewer temporary outages as a result of trees falling on wires or electric poles collapsing, hence boosting public safety. Contact injuries caused by life-wires are dramatically

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decreased [3]. It results in the removal of unsightly poles and cables from the roadways, consequently increasing the visible range of drivers and pedestrians [4].

A fault occurs when two or more conductors come into contact with each other or with ground. Earth faults are the most prevalent cause of power outages, accounting for more than 80% of all outages. This project aims to provide a system that can detect the defective areas in an underground cable in order to promote faster repairs, increase system reliability, and minimize outage time to the absolute minimum [5]. When faults occur, the power flow is redirected towards the fault and the supply to the consumer is impeded [6]. To do so, the time domain reflectometry (TDR) method is utilized to calculate the fault distance from the end point within the line length of the cable, which is estimated to be 100 km, using a simulation model of an IEEE bus system with 13 buses using continuous wavelet transform (CWT) and artificial neural network (ANN). From transient travelling waves, wavelets analysis can extract time and amplitude (represented as wavelet transform modulus) information. On transmission lines, the TDR method was among the most frequently applied traveling-wave based fault location methods [7]. If the velocities of the modal components remain constant, an earth fault can be identified through time delay of modal components regardless of moving wave reflection [8].

This project employs the travelling wave approach, with fault classification performed by comparing waveform signals at all phases in a power cable. LG, LLG, and LLLG are single phase to earth fault, double phase to earth fault, and three phase to earth fault, respectively. In the schematic tab of the software, the length of the cable, as well as other properties such as delay time and characteristic impedance, will be input. As a result, faults in underground cable systems can be easily identified using MATLAB Simulink software. It is also to run simulations on those fault distance locators to perform analysis and get different forms of faults [9]. The Simulink model will be used to evaluate the essential component blocks of voltage and current in the underground link system by shifting fault locations in MATLAB Simulink. First and foremost, having the appropriate framework for building the specific framework application is crucial, as is having the highest possible assurance against the ground fault.

2. The Proposed Method

The purpose of this methods has been used to determine the distance fault location in underground cable based on IEEE bus system using continuous wavelet transform (CWT) and artificial neural network (ANN). These projects are conducted on wavelet analyzer and neural network tool in MATLAB Simulink software used as a distance faults detection and analyze performance of faults point from the source end. The voltage and current dataset were prepared by creating LG, LLG, and LLLG faults at different distributed parameter line. In Figure 1 shows the block diagram of the proposed system for detecting and analyzing the distance fault location.

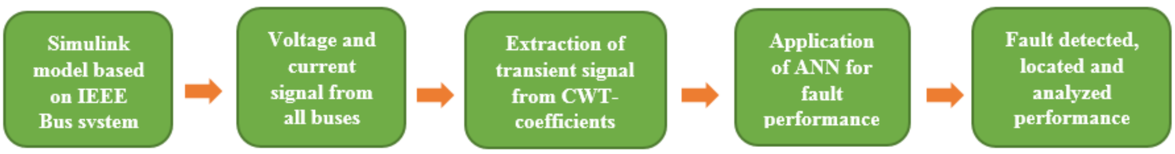


Figure 1: Block diagram of the proposed system

3. The Research Method

3.1 Simulink Model based on IEEE bus system

This project has been carried out according the block diagram of design simulation model as in Figure 2. The work is starting with study several references related to the fault distance underground cable detection for designing a simulation model of IEEE bus system with 13 buses for an underground cable of transmission line system using MATLAB Simulink. Simulink model is the first process for designing based on IEEE bus system with 13 buses and 16 lines for a transmission line underground cable system as illustration in Figure 3. The system was composed by 5 synchronous machines, 3 of which are 69KV generators, and 10 loads, with a net real and reactive power demand of 259MW and 1.3MVAR, respectively. The underground system in 100km length has been used block components and scope at sending end. Responses to various configurations and faults have been assessed. The fault points have been analyzed and compared for all faults, including single phase to earth faults (LG), double phase to earth faults (LLG), and three phase to earth faults (LLLG).

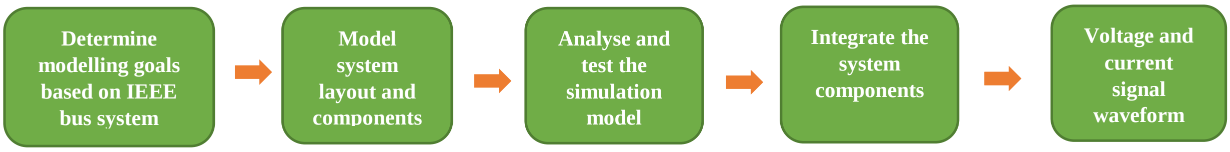


Figure 2: Block diagram of design simulation model based on IEEE bus system with 13 buses

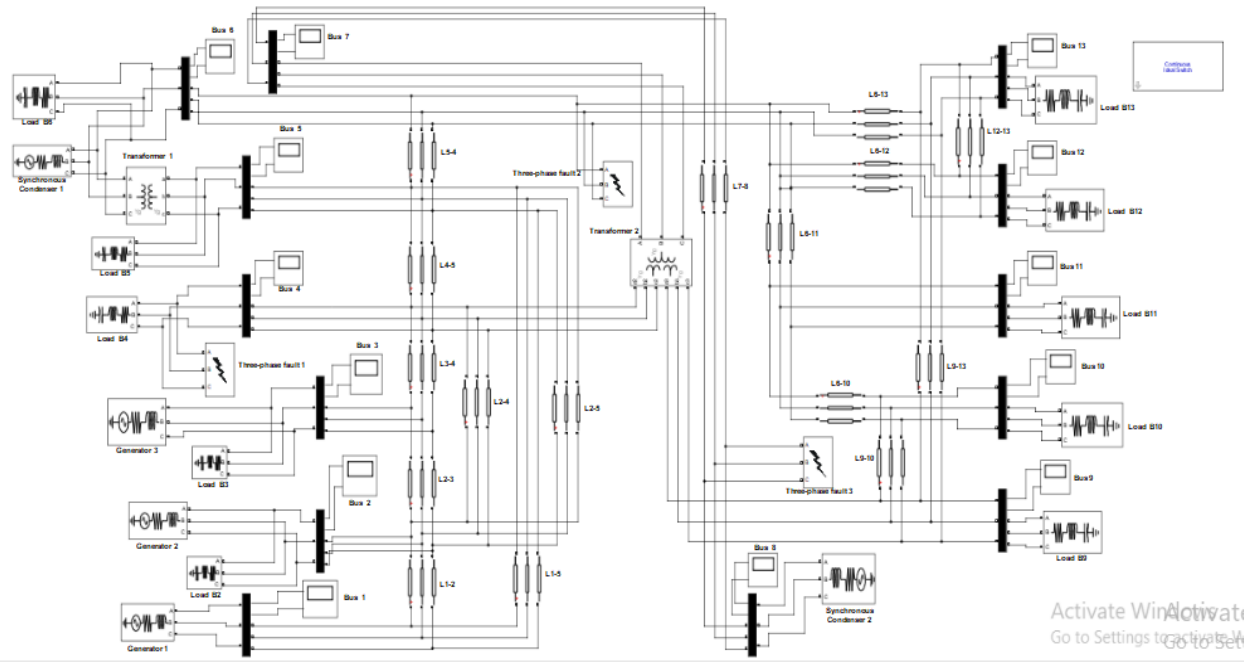


Figure 3: Simulink Model with 13 buses based on IEEE bus system

3.2 Continuous Wavelet Transform (CWT)

The Wavelet transform was similar to the Fourier transform, except it allows for the time localization of different frequency components in a signal. The wavelet transform modifies the time widths of the analytic functions, known as wavelets, based on their frequency with higher frequency wavelets being narrower and lower frequency wavelets being wider. The continuous wavelet transform (CWT) of a function is calculated by using the following:

$$WT(f, a, b) = \frac{1}{\sqrt{a}} \int f(t)\, \psi * \frac{(t-b)}{a}\, dt \qquad \textit{Eq. 1}$$

In the following stage of the research, the continuous wavelet transform (CWT) of the wavelet transforms technique [10] is a highly effective tool for high-frequency nonstationary signals as well as fault signals. The CWT methods have been chosen as the high-frequency fault, and a signal discontinuity should be analyzed for high-frequency signal extraction [11]. The proposed research utilized CWT for fault detection and location since the dB4, level 4 transform produces superior results.

The block diagram for the suggested approach as second objective is shown in Figure 4. The flowchart depicts the technique for defect identification and localization in great detail.

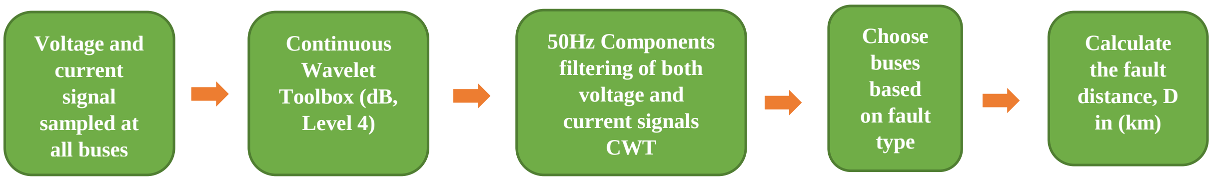


Figure 4: Block diagram of fault point and distance location using CWT coefficients

3.3 Artificial Neural Network (ANN)

The complete data set were segmented into three sets in the artificial neural network (ANN) based technique, namely the training, validation, and testing data sets. The aim of this method is to present an integrated strategy that uses ANN to complete each of these objectives. Back-propagation based on the neural network has been utilized for training and testing fault performance. The network design, learning rules selection, training method, and testing the fault locator based on ANN are the most significant parts of fault location systems. The sampling rate of each cycle for the ANN training data is 1 kHz. The technique consists of two steps: training and testing the fault's performance. For fault training data, the ANN system has one input, 18 hidden layers, and three outputs, which are compared to the pre-fault value to form the data set as shown in Figure 5.

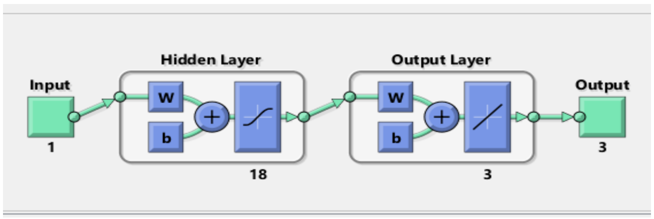


Figure 5: Artificial Neural Network in NN tool of MATLAB

3.4 Distance Fault Detection

When a fault point is discovered with CWT, the distances between the fault position and the source end is calculated using the time domain reflectometry principle. The transient signals at all phases in a power cable model in comparison using a travelling wave approach, and fault classification may be done by comparing the transient signals at all phases. When a network fault develops, the resulting transient signals are not stationary and have a broad frequency range. When a network fault occurs, the resulting transient signals travel throughout the network. When the transient wave reaches a discontinuity position, it partially reflected and the balance have been incident to the line impedance. These transient signals were captured by using wavelet analysis. Compare the wavelet coefficient to discover the time instant when the signals energy reaches its peak value to pinpoint the problem [12]. The following calculation has been used to compute the distance between the fault location and the bus of the defective branch:

$$D = \frac{v \times t}{2} \qquad Eq.2$$

While D is the distances to the fault, t denotes the time differences between the two subsequent peaks of the collected currents wavelet transform coefficients, and v denotes the wave propagation velocity given by equation:

$$v = \frac{1}{\sqrt{LC}} \qquad Eq.3$$

4. Results and Discussion

4.1 Simulation Results and Analysis

CWT was utilise as a signal processing technique in this project since it has a lot of potential for evaluating system transients. The Wavelet Analyzer was used to construct CWT coefficients for 'db4' at level 4 using the data of the transient voltage and current signals imported from the MATLAB workspace. Typical CWT coefficient plots of transient signals are shown in Table 1 till 3. The manual mode was used for all simulations, with the scale of the MATLAB vector set to 11.4285 (50 Hz supply) and the sampling period set to 0.00125.

Table 1: Voltage and current transient signal for LG

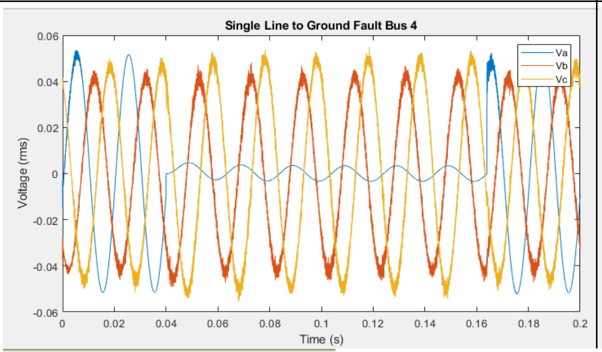
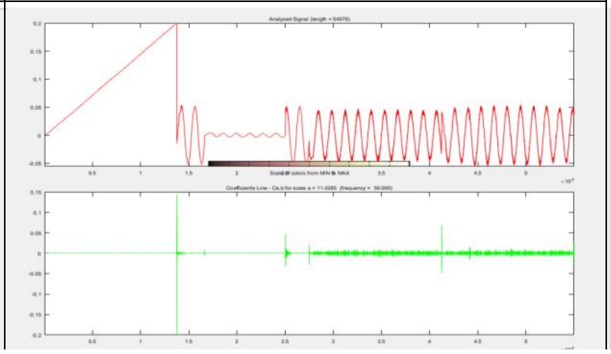
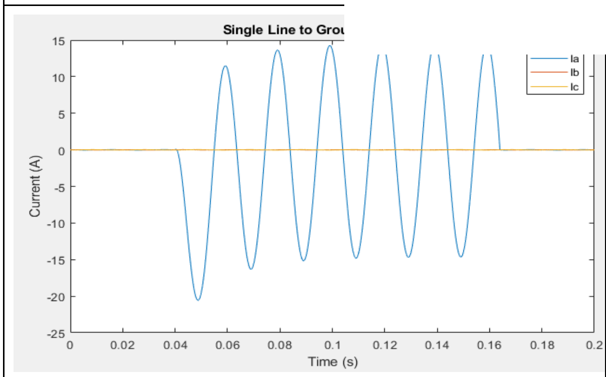
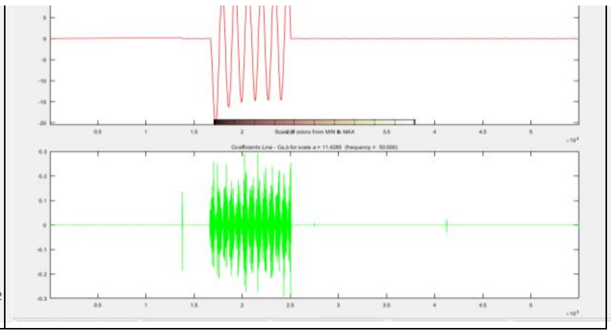
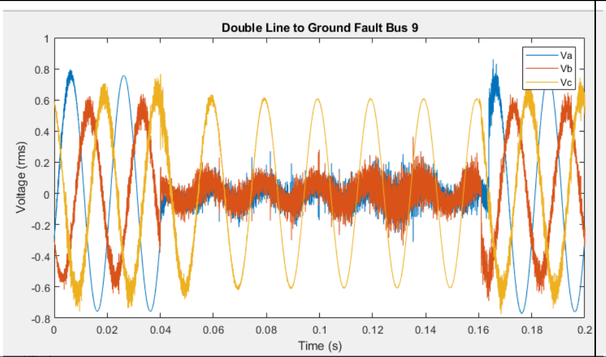
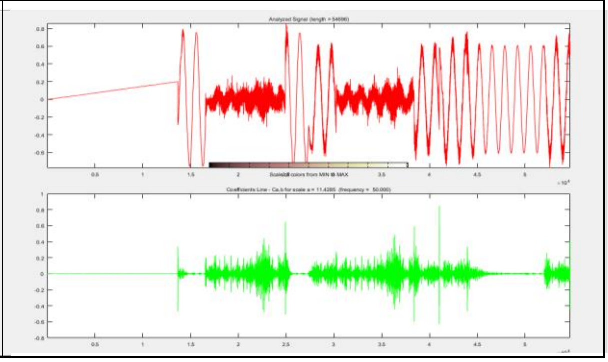
Signal Waveform at Bus 4	Wavelet dB4 Response at Bus 4
	
	

Table 2: Voltage and current transient signal for LLG

Signal Waveform at Bus 4	Wavelet dB4 Response at Bus 4
	

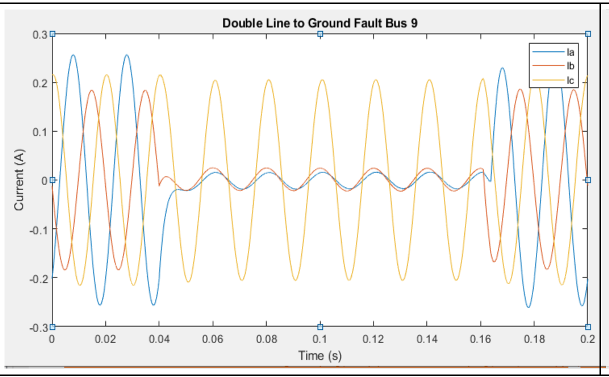
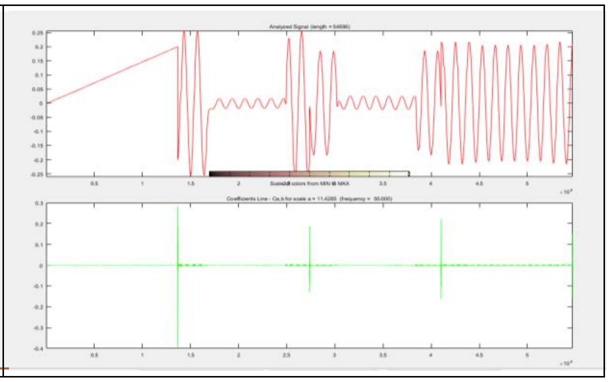
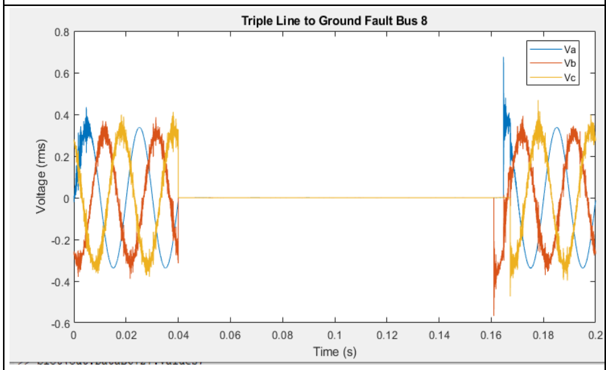
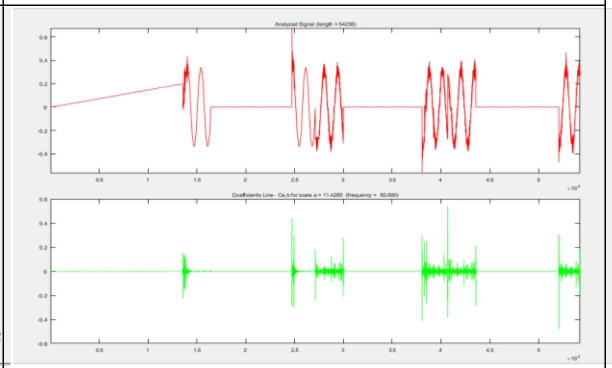
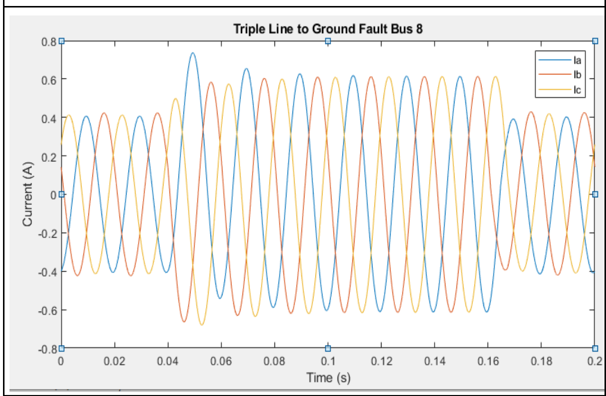
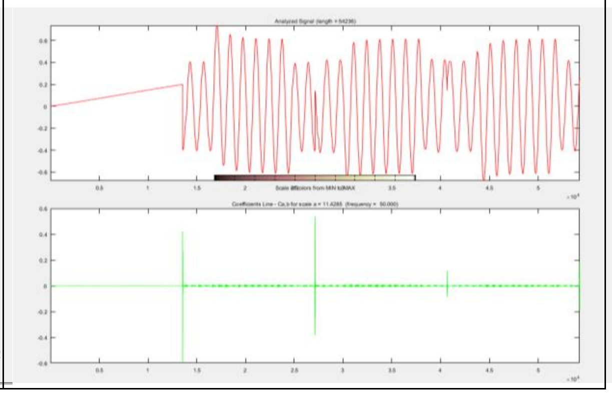
	

Table 3: Voltage and current transient signal for LLLG

Signal Waveform at Bus 4	Wavelet dB4 Response at Bus 4
	
	

4.2 Distance Fault Location

The distance to the fault has been equivalent to the unreal element of the measured impedance because the complete line length impedance is known. Calculating the transient signal between voltage or current at the source end with time, evaluating the timing of the return of the pulse, and multiplying it by the pulse velocity determines the distance of the fault site from the source end.

At buses 4, 9, and 8, Table 4 shows different cases where the distance fault site from the source end was estimated using equation (2). D is the calculated fault location distance, v is the propagation velocity, l is the cable line length, t is the time fault point from the bus, and d is a fault estimation point. The LG fault is used as a simulation case to compare the variance from the estimation point of fault values, and distance fault points are calculated along with percent inaccuracy.

Table 4: Percentage Error of Distance Fault Location in Different type of Fault

Cases	**Estimated point of Fault (km)**	**Calculated point of Fault (km)**	**Error% (D-*d*)/*l* *100%**	**Line Length of Cable (km)**	**Inductance, H**	**Capacitance, F**
LG	3 km	2.886 km	-2.28	5 km	0.17103	0.03460
LLG	15 km	16.223 km	6.115	20 km	4.1264×10^{-3}	7.751×10^{-9}
LLLG	2.5 km	2.499 km	-0.02	5 km	1×10^{-3}	1×10^{-6}

4.3 Training and Analyse Performance of Fault using ANN

A neural network was provided four inputs during the fault training procedure. The inputs are three voltages and three currents from each of the three phases. Normalized input voltages and currents are compared to their pre-fault values. The data collection was created with three different types of fault conditions in consideration. A total of 10,995 input and 2,062 output samples, as well as 687 samples for each fault, made up the training set. The chosen neural network 1-18-3, which has one neuron in the input layer, one hidden layer with 18 neurons, and three neurons in the output layer.

When the current fault data of single phase to earth fault (LG) at bus 4, double-phase to earth fault (LLG) at bus 9 and three-phase to earth fault (LLLG) at bus 8 is considered in the training performance plot, it is obvious that the neural networks training performance is satisfactory. Mean-square error is the average squared difference between output and targets. Lower values are better and zero mean no error in the data. Meanwhile, regression (R) values measure the correlation between outputs and targets. If regression value of 1 means a close relationship, while zero value is a random relationship.

The histogram of errors between the target and independent variable after training a feedforward neural network is known as the error histogram. These error numbers can be negative because they show how expected values depart from training set. In Table 5 shows the generated of training multiples with different results due to different initial conditions and sampling.

Table 5: Multiples Training with Different Type of Fault Data

Fault Data	Mean-square Error (MSE)	Error Histogram with 20 bin	FIT Regression
LG	0.0017913 at epoch 209	0.02551	0.99996
LLG	0.00018921 at epoch 745	0.001687	0.99357
LLLG	0.002448 at epoch 1000	-0.01297	0.99164

5. Conclusion

The purpose system able to demonstrated a precise technique for identification, trained and evaluated the performance, and generated a fault analysis. As the power systems basic protection, fault detection and location are important in the underground cable system of the transmission line. In the second stage, the fault distance is determined by extracting the feature from the sampled signals using the continuous wavelet transform (CWT). This feature vector was used to train and analyse fault data performance using an artificial neural network (ANN). By calculating the equation (2), the proposed scheme was obtained to detect the distance fault location. One of the most important decisions for fast digital relaying operation in an underground cable of transmission lines is fault detection and classification.

Furthermore, identifying the appropriate CWT is necessary for extracting the dynamic features of transient signals on a doubly-fed in underground cable during the period of fault onset. As a result, it is observed that the fault of voltage and current signals, as well as the accuracy and analysis of locating a fault in underground cables using CWT coefficients, is more. As a result, it can be concluded that the use of continuous wavelet transforms with artificial neural networks (CWT-ANN) based on travelling wave and analysis is a good choice in power systems.

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