# Development of a Wavelet – ANFIS Based Fault Location and Identification System for Underground Power Cables

**Rajveer Singh, Vinay Krishna Gharami**

***Abstract:*** ***Transmission lines are the backbone of electrical power systems and other power utilities as they are used for transmission and distribution of power. Power is distributed to the end-user through either overhead cables or underground cables. In the case of underground cables, their propensity to fail in service increases as they age with time. The increase in failure rates and system crashes on older underground power cables now negatively affect system reliability and involve numerous losses. It is therefore easy to realize that the consequences of this trend need to be managed [3]. Identification of the type of defects and their locations along the length of the cables is vital to minimize the operating costs by reducing lengthy and expensive patrols to locate the faults, and to speed up repairs and restoration of power in the lines. In this study, a method that combines wavelets and neuro-fuzzy techniques for fault location and identification are proposed. For this methodology a power transmission line model was developed and different fault locations were simulated in MATLAB/SIMULINK, and, as an input to the training and development of the Adaptive Network Fuzzy Inference System (ANFIS), certain selected features of the wavelet transformed signals were used. Fault index obtained from wavelet transformation are used as input variable for fuzzy input block function. Different membership functions were observed within input block function. As per formulation of rules, for membership function, the output value of the defuzzifier component was decoded to give a crisp value of ANFIS output. ANFIS results were compared with actual values. A comparison of the ANFIS output values and the actual values show that the percentage error was less than 1%. Thus, it can be concluded that the wavelet-ANFIS technique is accurate enough to be used in identifying and locating underground power line faults. Which will help in solving this time taking and tedious problem more efficiently and thereby reducing human effort in finding the type of fault and its location.***

***Keywords: ANFIS, Discrete wavelet transform (DWT), Fault location, Fault types, and Underground cables***

## I. INTRODUCTION

Electrical power can be distributed to the end-user through either overhead cables or underground cables. The main objective of transferring power to the end-user in a safe, reliable, and affordable way. This is achieved by maintaining a stable voltage level, correcting the power factor by using reactive compensation, and delivering as near a service as possible to fulfill demand.

The demand for electricity has grown rapidly in metropolitan areas in the last decade. Around the world, large scale underground cable systems replace overhead transmission lines in densely populated areas due to environmental concerns. Underground cables are primarily used in distribution systems because they are secured and are not damaged by lightning or storms other than overhead lines. Underground cable systems are produced with reliability for a long life [1] [2]. Underground cable defects may occur in the form of serial failures where the cable is cut without a breakdown of electrical insulation, or shunt defects where electrical insulation is breached without the conductor being cut itself. Studies have shown that a high impedance fault (HIF) is one of the most frequent failures leading to the failure of underground cables [4].

This study aimed at developing an underground cable fault identification and location system by the use of artificial intelligence and wavelet analysis.

## II. METHODOLOGY

The transmission system is developed and then used to identify the fault type. Fault signals were generated which were analyzed under wavelet analysis then later used in the development of an ANFIS for fault location.

### A. Development of the Transmission Line Model

The basic structure of the transmission line consists of the generator, the transmission system, and a constant load. From the model, actual system parameters were used to come up with a MATLAB model that was simulated to generate fault signals. The development of the transmission line was done under MATLAB/SIMULINK environment. The assumption was made that the underground cables were not affected by external interference of other cables on the underground and the system was designed solely to identify actual faults, not disturbances in the systems that could be corrected.

### B. Fault Introduction

Fault identification was done in post fault conditions. The fault was believed to have occurred already when the simulation was started for the system to locate the fault in post fault conditions. In the three-phase toolbox, the essence of the fault and the fault parameters were updated. This allows the system to have different types of fault and to cover a wide range of scenarios that could affect the transmission system at different locations. Since transmission lines can have single, double, or three-phase defects, faults with different behavior have also been implemented in these various locations.

**Revised Manuscript Received on September 05, 2020.**

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### C. Fault Identification

After designing a transmission line, the system was simulated to identify the type and phase of a fault affecting the system. The figure highlights the basic flow process which was followed to identify the type of fault affecting the system. To achieve the target, the initial stage was to analyze the wave signals of the transmission line to determine the phase(s) affected. In the MATLAB / SIMULINK environment simulation of cable data from a fault, this stage is transferred for data processing and analysis to Discrete Wavelet Analysis.

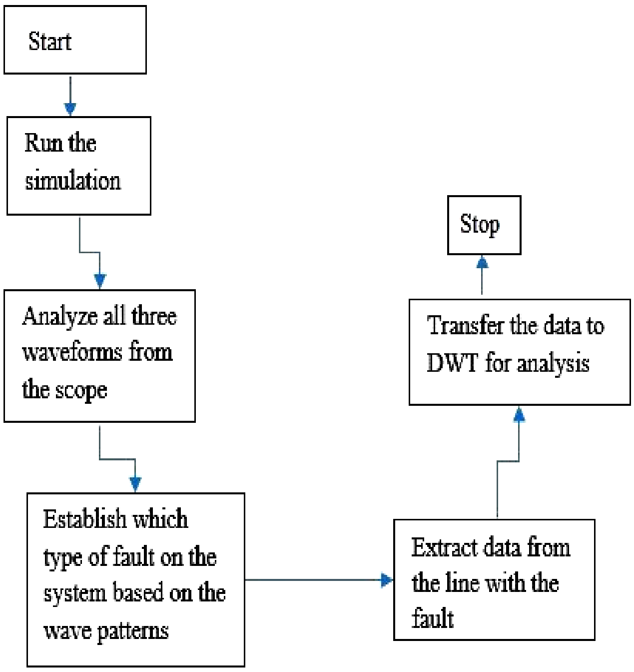


**Fig 1. Fault identification flow chart**

To identify the defect type of the affected phase, the model transmission line system was simulated. The system was intended on a single platform to monitor all phases of the transmission line. The fault data from the toolbox on the line was used to locate the fault. Various waveforms have been observed to distinguish the faults. Only one phase had a lower voltage than the other two for one single line fault. Two fault signals indicated certain deviations from the expected waveform in a double-phase fault. When the fault type was determined, fault data, which could be described as the line signal s, was analyzed for useful information about the fault.

### D. Fault Location Using Discrete Wavelet Transformation

To enable fault location along the transmission line, the initial stage is to analyze the fault signals to identify the affected phase(s). Simulated line data from the affected phase is transferred to the Discrete Wavelet Transformation environment for data processing and analysis [6]. To accomplish this task, line voltage signal features are extracted with daubechies4 (db4) as the mother wavelet, based on a discrete wavelet transform. Daubechies is an orthogonal wavelet family, which for some support defines a discrete wavelet transformation characterized by a maximum number of moments of disappearance. There is an orthogonal multi-resolution analytic scaling function for each type of wavelet of this class. The mother wavelet db4 was chosen because it works best for fast transients. The feature extracted from the line is an index representing the location of the fault, represented by spikes on the DWT. The analysis of signal s in the context of a discrete wavelet analysis involves many filters passing the signal. First, the sample signal s is transmitted by a low pass filter with an impulse reaction g, which results in the convolution of the two. Passing the signal under a low pass filter enables the extraction of approximation coefficients of the signal to identify changes in signal properties. This can be illustrated by Equation.1

$$s(n) = (x * g)[n] = \sum_{k=-\infty}^{\infty} x[K]g[n-k] \qquad (1)$$

The signal was decomposed by a high-pass filter h simultaneously. Passing the signal under a high pass filter enables the extraction of detailed coefficients of the signal to identify changes in signal properties. Both outputs from the high pass filter and low pass filter produce detail coefficients and approximation coefficients respectively. The extraction of the features will help in giving a clear view of the signal and helps to magnify the changes so that it can be easily identified. The two filters are related and referred to as the figure 2 quadrature mirror filters.

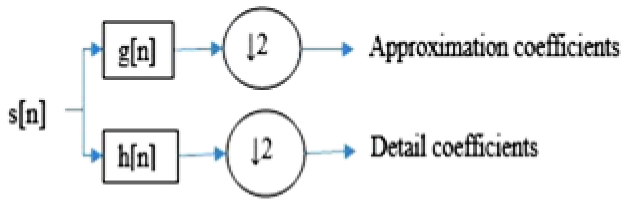


**Fig 2. Signal decomposition**

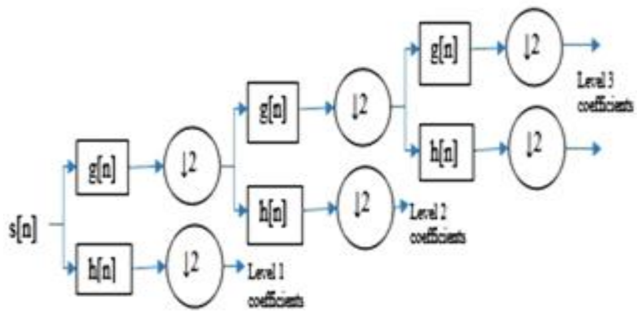


**Fig 3. Signal coefficients**

Half the frequencies of the signal have been removed at this stage, half the samples may be discarded according to Nyquist's rule. The equation is the two new coefficients of the initial signal.

$$y_{Low}[n] = \sum_{k=-\infty}^{\infty} x[K]h[2n-k] \qquad (2)$$

$$y_{high}[n] = \sum_{k=-\infty}^{\infty} x[K]g[2n-k] \qquad (3)$$

The signal halved time resolution after the first decomposition, as the signal characterizes only half of each filter output. Both outputs have half the input frequency range, thus doubling the frequency resolution. Depending on the level to which the signal has to be analyzed, the process of passing the new signal over the low pass and high pass filter will continue until the level of analysis has been achieved.

The levels depend on the user. At every level, the signal will be passed through high and low pass filter and the signal resolution will at each stage also double from the previous resolution. This will help the signal to be viewed and to remove any noise which might be in the signal or any disturbance which might occur. At every level, a certain amount of noise and small disturbances will be eliminated making the signal clearer to analyze and to expose the changes in the signal parameters. The summation of the two equations can be written more concisely as:

$$y_{Low} = (x * g) \tag{4}$$

$$Y_{high} = (x * h) \tag{5}$$

The decomposition process was repeated several times and then retrieved to further increase the signal frequency resolution and decomposed approximation coefficients with the high pass and low pass filter. This can be represented as a binary tree, called a filter bank, Figure 3, with nodes representing a subspace of different time-frequency localization. The signal is decomposed into high and low frequencies at each level (L) of Figure 3. Because of the decomposition process, the input signal was of a multiple of $2^n$ where n represents the number of levels (L). If a signal has to be analyzed to level three, it means the signal s when viewed from level 3, has been magnified to 8 times the resolution of the initial signal. This is shown by the table 1 below, where signal s is the initial signal.

**Table I. Resolution of signals**

| L | resolution | Name of signal | factor |
|---|---|---|---|
| 0 | initial resolution of signal s | S | s |
| 1 | 2 times resolution of signal s | d1 | 2*s |
| 2 | 2 times resolution of signal d1 | d2 | 4*s |
| 3 | 2 times resolution of signal d2 | d3 | 8*s |
| 4 | 2 times resolution of signal d3 | d4 | 16*s |
| 5 | 2 times resolution of signal d4 | d5 | 32*s |

Wavelet filter bank implementation can generally be viewed as computing the wavelet coefficients of the discrete child wavelet y(t). In this case, the mother wavelet is moved and scaled by the powers of two, as shown in equation 6.

$$\Psi_{J,k}(t) = \frac{1}{\sqrt{2^j}}\Psi\left(\frac{t-k*2^j}{2^j}\right) \tag{6}$$

Here, j scale parameter and k shift parameter. In the case of a child wavelet in the discrete mother wavelet, equation 7 shows below, the wavelet coefficient g of a signal x(t) is the projection of signal x(t) onto a wavelet analysis of length $2^N$.

$$y_{jk} = \int_{-\infty}^{\infty} x(t)\frac{1}{\sqrt{2^j}}\Psi\left(\frac{t-K*2^j}{2^j}\right) dt \tag{7}$$

Signal S was analyzed up to level 5 and useful fault information from the wavelet analysis was used to develop an ANFIS. Appendix A shows the database which was used as inputs to the development of the ANFIS. In MATLAB/SIMULINK, wavelet analysis was simplified to click and execute the function using the graphic user interface (GUI) provided, the above- mentioned process is what happens inside the toolbox. In analyzing any signal, the signal is imported from a file and then identifies the wavelet type to use and analyze the signal to what level and the system produces the results. Further ANFIS model for fault location explains how fault index as input and one output for identifying fault location in ANFIS structure.

### E. ANFIS Model for Fault Location

The basic structure of the proposed design of ANFIS consists of the fault index from the wavelet transformation, the hidden layer, and the fault distance. The system has one input, the fault index, and one output which are for identifying the fault distance. Figure 4 is the basic structure of the ANFIS which was considered for fault location [5].

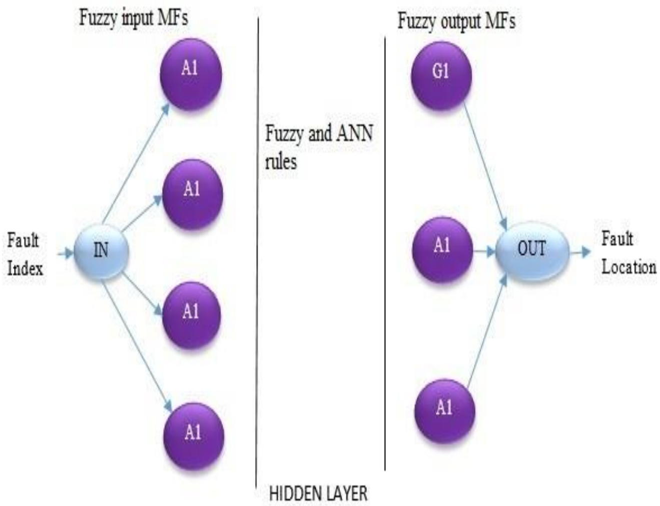


**Fig 4. ANFIS Structure**

The database created after wavelet analysis (Appendix A) for various faults and locations was used as input for the development of an ANFIS. Depending on the knowledge of the system, three types of estimation models can be used to solve such a problem. One of them, the black box, is very useful when the primary concentration is used to fit the data, irrespective of the mathematical structure of the model. The database created in the wavelet analysis (Appendix A) used to train, design, and test ANFIS as modeling of the Black-box is usually a trial-and-error process. Figure 5, displays the initial stage of loading data into the black box for the development of the ANFIS, and Figure 6 represents the training process of the system [7]. The result was to develop a model that can accurately estimate the fault location given the fault signals from the transmission line.

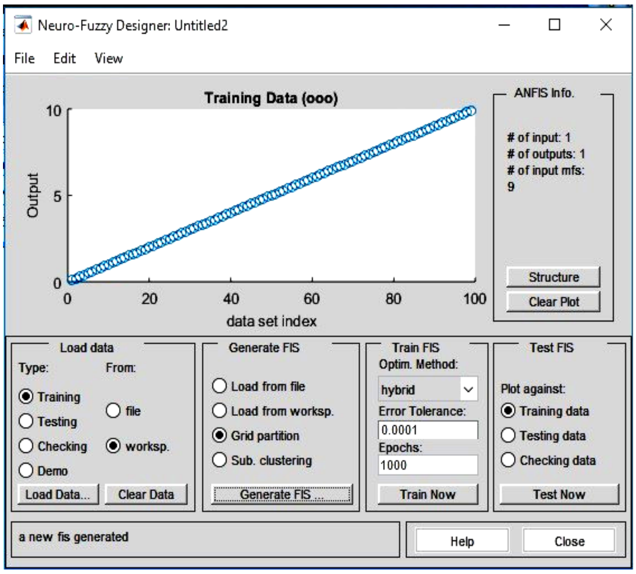


Fig 5. Loading Data for ANFIS

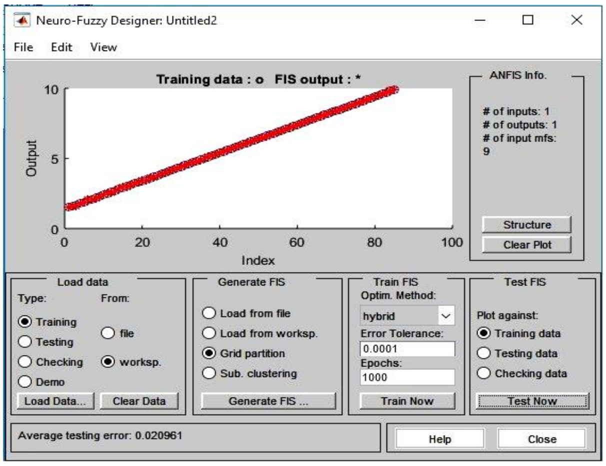


Fig 6. Training the ANFIS

The ANFIS was trained from the fault data which was developed under wavelet analysis after 99 simulations had been done. Testing of the system was done with the training data to see if the system has been properly trained. Figure 7 shows the verification process for testing the system and to identify any outliers to see the effectiveness of the training.

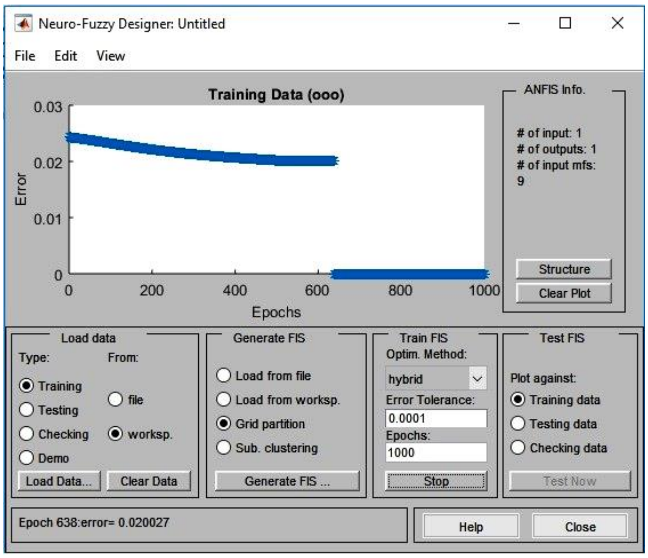


Fig 7. Testing the ANFIS structure

## F. Fuzzification

The fault index was the input variable used in the fuzzy input block function. Within the input block functions, after testing different membership functions it was observed that triangular membership functions were giving satisfactory results.

## G. Fault Index Input Variable:

The fault index is the variable which indicates when the fault is occurring. The index is a function of time considering the speed of the signal and when it is indicating the fault. The membership function was divided into nine levels, Upper High (UH), Medium-High (MH), Lower High (LH), High (H), Medium (M), Low (L), Lower Low (LL), Medium Low (ML), and Upper Low (UL). The membership functions for the index are represented in Figure 8.

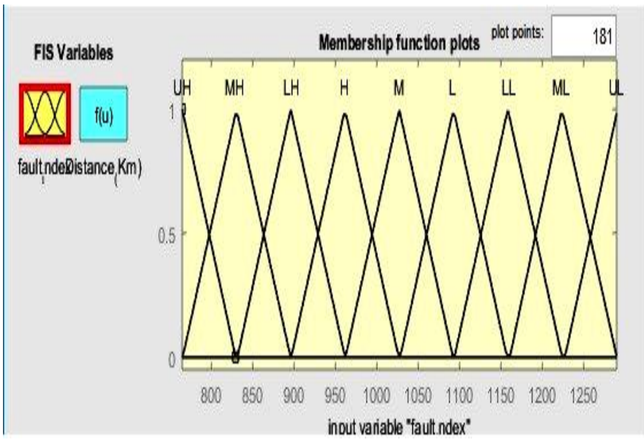


Fig 8. Membership Functions for Fault Index

## H. Formulation of the Rules

Lists of intuitive rules that govern the operation of the ANFIS were made. The system was using a hybrid training mechanism under the black box to generate the rules. The system managed to generate the rules on its own to solve the problem and locate the fault. Contrasting to the conventional control method which uses a mathematical model, the rules are developed in the linguistic form of IF-THEN statements. The ANFIS has a single input and single output. The input for the ANFIS is the fault index. The universe of discourse for the fault index covers a range of [760, 1300]. A choice of nine membership functions for the input fuzzy variables was chosen. Because it has one input, it means 9 rules in the rule base. These rules were generated automatically by the ANFIS since they used the black box to train the system.

The rules can be read as shown below:

1. If (fault index is UH) then (Distance (Km) is MF1)
2. If (fault index is MH) then (Distance (Km) is MF2)
3. If (fault index is LH) then (Distance (Km) is MF3)
4. If (fault index is H) then (Distance (Km) is MF4)
5. If (fault index is M) then (Distance (Km) is MF5)
6. If (fault index is L) then (Distance (Km) is MF6)
7. If (fault index is LL) then (Distance (Km) is MF7)
8. If (fault index is ML) then (Distance (Km) is MF8)

9. If (fault index is UL) then (Distance (Km) is MF9)

10. If (fault index is ML) then (Distance (Km) is MF8)

11. If (fault index is UL) then (Distance (Km) is MF9)

The Sugeno-type inference engine was used for defuzzification. Figure 9 is showing the rule viewer which was used to identify the fault given the line fault details.


Fig 9. Fuzzy Model Rules

## I. Defuzzification

In this study, a Sugeno-type fuzzy inference system (FIS) was used. The output of the zero-order models is the smooth function of the input variables, and the total output of the first order fuzzy model is computed on the weighted average because the neighboring MFs have sufficient overlap in the antecedent. The fuzzy input sets and rules are converted into a fuzzy output set to identify the fault location at a tight output. By firing the ANFIS rules, the output value of the defuzzifier component was decoded to give a crisp value.

## J. Fault Distance Output Variable:

The output of the system included 9 membership functions that were generated by the ANFIS when it was trained for fault identification and location. The figure shows the structure of the output as seen in MATLAB.

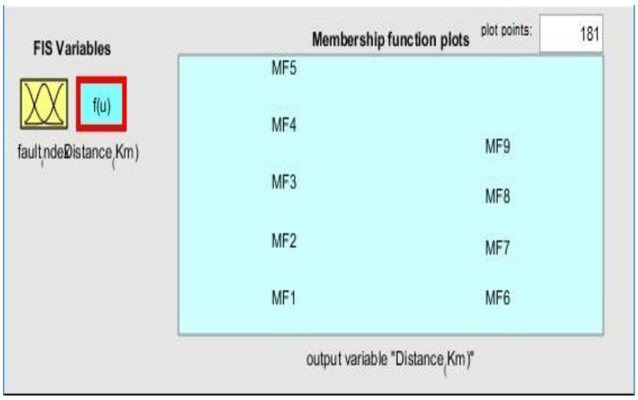


Fig 10. Membership function plots

# III. RESULT

This paper describes the results obtained through transmission line simulation, wavelet transform, and ANFIS for fault location. Analysis and evaluation of the results to obtain the accuracy of the system are also presented. The results of this paper identified the type of defect based on the signal from the transmission line: single-phase faults, double-phase faults, or three-phase faults.

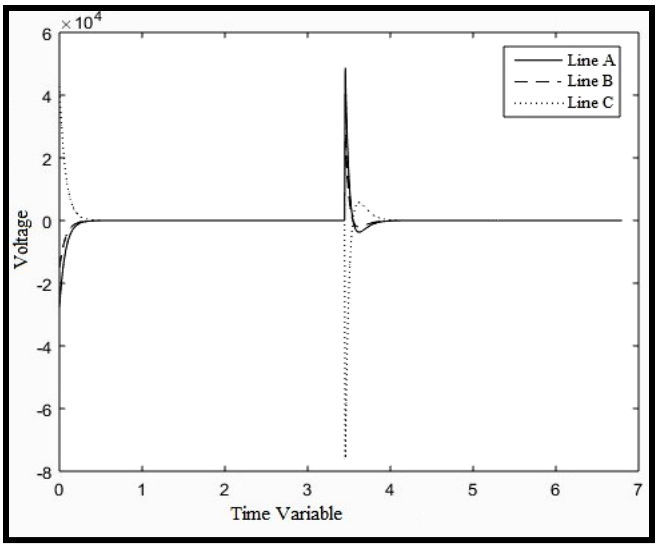


Fig 11. Three-phase Fault

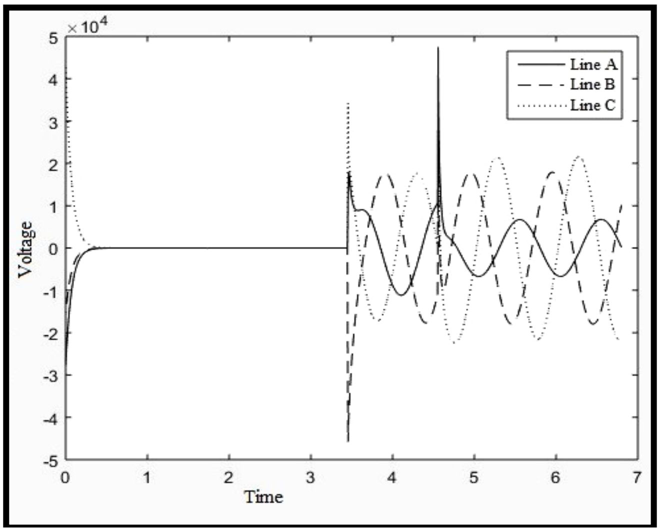


Fig 12. Single Phase Fault

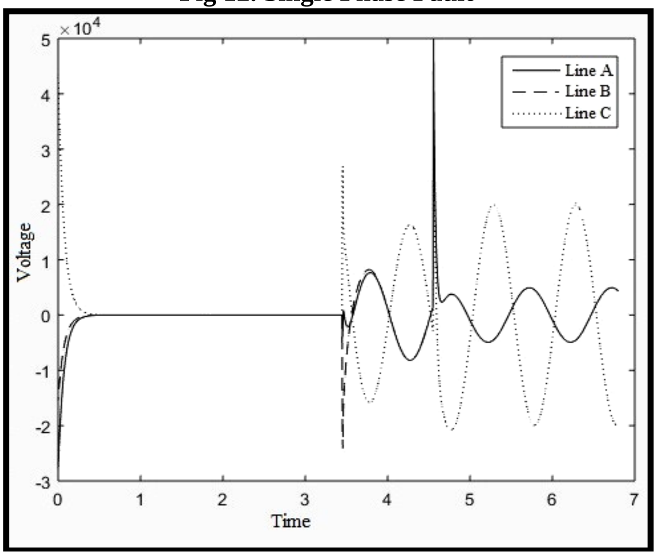


Fig 13. Double Phase Fault

After identifying fault type, actual fault distance and calculated fault distance are compared to find the average percentage error, which is less than 1%.

**Table II. Test values and error estimation**

| actual distance (km) | calculated distance (km) | difference (km) | % error |
|---|---|---|---|
| 1.45 | 1.53 | -0.08 | -5.52 |
| 1.96 | 1.99 | -0.03 | -1.53 |
| 2.03 | 2.09 | -0.06 | -2.96 |
| 2.65 | 2.55 | 0.10 | 3.77 |
| 3.14 | 3.14 | 0.00 | 0.00 |
| 3.90 | 3.90 | 0.00 | 0.00 |
| 4.21 | 4.26 | -0.05 | -1.19 |
| 4.73 | 4.73 | 0.00 | 0.00 |
| 5.30 | 5.29 | 0.01 | 0.19 |
| 5.91 | 5.91 | 0.00 | 0.00 |
| 6.43 | 6.44 | -0.01 | -0.16 |
| 6.68 | 6.69 | -0.01 | -0.15 |
| 7.32 | 7.33 | -0.01 | -0.14 |
| 7.56 | 7.56 | 0.00 | 0.00 |
| 8.45 | 8.43 | 0.02 | 0.24 |
| 8.84 | 8.83 | 0.01 | 0.11 |
| 9.30 | 9.29 | 0.01 | 0.11 |
| 9.68 | 9.68 | 0.00 | 0.00 |
| Average | | | **-0.40** |

The ANFIS was able to locate the fault with an accuracy of 99.6% as compared to other techniques ranging from 97.5% to 99%, to be used for fault location and identification.

$$\%\text{Error} = \frac{(\text{Actual distance} - \text{calculated distance})}{\text{Actual distance}} * 100$$

It is observed that the general difference between the simulated values and the actual fault locations are around 0.1 or -0.08. Based on the simulations done, the percentage error of the system is in the range of -5.52 to 3.77%, and the average error being = -0.4%

## IV. CONCLUSION

Simulations for the transmission line for underground power cable were performed using MATLAB/SIMULINK. In this work, the proposed method used wavelet decomposition which provided more features about the signal. The most suitable wavelet family was made to identify the fault type and estimate the fault location on the transmission line. It was found that better results were achieved using Daubechies 'db4' wavelet. The extracted information about the signal was used to develop an Adaptive Neuro-Fuzzy Inference System (ANFIS) which was later used to identify the fault location. Performance of Adaptive-Neuro Fuzzy Inference system in fault location was assessed and results were obtained. Finally, it was shown that the proposed method is accurate enough to be used in the detection of transmission line faults with a percentage error less than 1%. Therefore we can conclude that wavelet-ANFIS methodology for underground power cables fault detection and location is more effective and accurate.

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## APPENDIX A, ANFIS TRAINING DATA

| fault index | distance (Km) |
|---|---|
| 1290 | 0.1 |
| 1256 | 0.2 |
| 1256 | 0.3 |
| 1255 | 0.4 |
| 1238 | 0.5 |
| 1238 | 0.6 |
| 1238 | 0.7 |
| 1238 | 0.8 |
| 1238 | 0.9 |
| 1238 | 1 |
| 1219 | 1.1 |
| 1219 | 1.2 |
| 1203 | 1.3 |
| 1202 | 1.4 |
| 1192 | 1.5 |
| 1186 | 1.6 |
| 1186 | 1.7 |
| 1176 | 1.8 |
| 1172 | 1.9 |
| 1164 | 2 |
| 1163 | 2.1 |
| 1157 | 2.2 |
| 1151 | 2.3 |
| 1143 | 2.4 |

| | |
|---|---|
| 1134 | 2.5 |
| 1134 | 2.6 |
| 1126 | 2.7 |
| 1120 | 2.8 |
| 1114 | 2.9 |
| 1113 | 3 |
| 1107 | 3.1 |
| 1098 | 3.2 |
| 1094 | 3.3 |
| 1088 | 3.4 |
| 1086 | 3.5 |
| 1079 | 3.6 |
| 1078 | 3.7 |
| 1074 | 3.8 |
| 1067 | 3.9 |
| 1064 | 4 |
| 1059 | 4.1 |
| 1055 | 4.2 |
| 1047 | 4.3 |
| 1043 | 4.4 |
| 1037 | 4.5 |
| 1033 | 4.6 |
| 1030 | 4.7 |
| 1023 | 4.8 |
| 1016 | 4.9 |
| 1010 | 5 |
| 1003 | 5.1 |
| 997 | 5.2 |
| 993 | 5.3 |
| 987 | 5.4 |
| 984 | 5.5 |
| 978 | 5.6 |
| 973 | 5.7 |
| 968 | 5.8 |
| 964 | 5.9 |
| 959 | 6 |
| 954 | 6.1 |
| 959 | 6.2 |
| 954 | 6.3 |
| 949 | 6.4 |
| 934 | 6.5 |
| 930 | 6.6 |
| 924 | 6.7 |
| 920 | 6.8 |
| 914 | 6.9 |
| 910 | 7 |
| 905 | 7.1 |
| 901 | 7.2 |
| 896 | 7.3 |

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