



Single-Phase Fault Location in Four-Circuit Transmission Lines Based on Wavelet Analysis Using ANFIS

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Abstract

This paper presents an efficient and effective method to determine the location of the single phase to ground fault in four-circuit transmission lines. In the proposed method, wavelet analysis based on advanced signal processing techniques are used to extract important features and record the dynamic characteristics of the fault signal using current sampled data of one side of the line. In this regard, the ANFIS network is used to find the relationship between the obtained characteristics from wavelet signal analysis of the fault signal and the changes in different fault conditions. In proposed method, there is no need to know the type of the fault or line information. Also, determination of faulty circuit and the use of intelligent methods to reduce computations are among the advantages of the proposed method. Studies and simulations have been implemented on a four-circuit transmission line of 500 kV and 200 km in PSCAD software. The results of wavelet analysis have been applied as an input of ANFIS network in MATLAB software. The results of the simulations are based on the implementation of different fault conditions, including the faulty circuit, fault location, fault inception, and fault resistance. These results indicate the high accuracy of the proposed method.

Keywords Fault location · Four-circuit transmission lines · Wavelet analysis · Adaptive network-based fuzzy inference system (ANFIS) · Single-phase to ground fault

1 Introduction

Nowadays, in power systems, increasing the reliability and capacity of transmission lines is of particular importance. In the past few years, energy companies use four-circuit transmission lines to increase their Power transferable capacity [1]. On the other hand, the mutual effect of phases and the number of involved phases in the fault have made it harder to increase the reliability of these lines and reducing the duration of interruptions and fixes. So it is not very effective to find the location of fault in four-circuit transmission lines through conventional methods in single-circuit and double-circuit transmission lines.

The methods for locating faults in power systems can be generally categorized into two categories of soft [3–6] and

hard [7–9] computational methods. In spite of the many studies that have been done to use hard computational methods to calculate the fault location, soft computational methods have recently attracted more attention from researchers due to significant advances, overcoming complexities, and considering all aspects of work. In soft computational methods, learning algorithms are commonly used to determine the fault location of transmission lines [3–5]. In training-based methods, it is suitable that the algorithm is trained according to existing patterns and changes in the system. In this way, the algorithm is required to find the complex relationships between the extracted features and the location of the fault [6]. It should be noted that in training-based methods, selecting the most suitable features is of particular importance to the algorithm. Finding the data related to the fault location can be of great help in increasing the accuracy of the used algorithm [6]. In the method presented in this paper, the features extracted from the current signal during the fault is a key feature. The behavior of the extracted properties is directly related to the parameters like fault location, fault inception and fault resistance. In this way, the changes

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that occur in different fault conditions affect the extracted properties [10].

The presentation of different fault location methods in single-circuit [11–15] and double-circuit transmission lines [16–20] has been widely carried out. While the proposed methods for determining the fault location in the four-circuit transmission lines are limited [21–24]. In [21], data taken from two sides of the transmission line are completely decomposed into 12 sequence components. Determining the fault location taking into account the principle that the calculated voltage from both sides of the transmission line is equal at the fault point. The method presented in this paper is suitable only for transposed lines, and the lumped line model for calculations is also used. In [22], the fault locating method for un-transposed four-circuit transmission lines is introduced, which only uses data from one side of the line. Contrary to article [21], in this paper, the distributed parameter line model and the mutual effect between all phases are considered. However, the proposed method cannot be implemented if the type of fault is not specified. In addition, the equivalent source impedance at one of the terminals is needed. Also, the determination of the fault location is sensitive to the source impedance variations and the accuracy of the line parameters.

In [23], a new method for un-transposed four-circuit transmission lines is provided using voltage and current meters from two end terminals. The proposed method is based on the assumption that the current of healthy phase are the same on both sides of the line. Failure to implement it on faults that are involved with all phases or the type of fault is unknown is one of the major problems in this method.

In [24], a fault location method is proposed for the four-circuit transmissions lines of two terminals. The data required to estimate the fault location are the current phasors on both sides, and the voltage phasor of the one terminal. Problems with the proposed method are including the heavy calculation and synchronization of the taken data.

Single phase to ground fault is one of the most probable type of fault that can occur in transmission lines. The probability of a single phase to ground fault is approximately 14 times that of a double-phase to ground fault [2].

In this paper, a method based on wavelet analysis is proposed using the ANFIS (Adaptive Network-Based Fuzzy Inference System) Intelligent Network [25] to determine the location of the single phase to ground fault. Significant features of the one-side current signal of the line are extracted by wavelet analysis and used as input data of the ANFIS network. The main advantage of this method is the use of facilities in the system monitoring without the need for additional tools and network analysis. Since a significant part of data show the normal conditions of the transmission line current performance, only a subset of data is considered to observe the behavior of the current signal under fault conditions.

In this paper, simulations have been carried out taking into account the distributed-line parameter model of un-transposed transmission line in PSCAD software [26]. Fault in different conditions such as faulty circuits, fault resistance, fault inception, and different fault locations are investigated. The proposed method is a simple and independent method of data synchronization. Compared to previous methods [21–24], the advantages of the proposed method are the high-speed fault location, the reduction of computational complexity, the non-dependence of the proposed method on knowing the parameters of the lines, the ability to execute for each type of fault, the use of information of one-side current signal of the line and its high precision. The maximum error rate in the proposed method is less than 2%.

2 Wavelet Multi-Resolution Analysis (MRA) in Transmission Line Fault Analysis

Wavelet Multi-resolution analysis (MRA) is a technique for signal decomposition into low and high frequency bands for estimating approximate and detail signals [27, 28]. A large number of researchers have used MRA to analyze fault in transmission lines [29–32]. Most of the work has been based on the relationship between the magnitude and the phasor of voltage and current.

In this paper, the focus is on the extraction of characteristics from a three-phase sending end current signal during a fault in the 2000–1000 Hz frequency range includes fault transient features to estimate the signal's detail and determine the fault location. The MRA multi-resolution decomposition process of an input signal is shown schematically in Fig. 1.

To clarify the subject, a summary of the wavelet transform is given below:

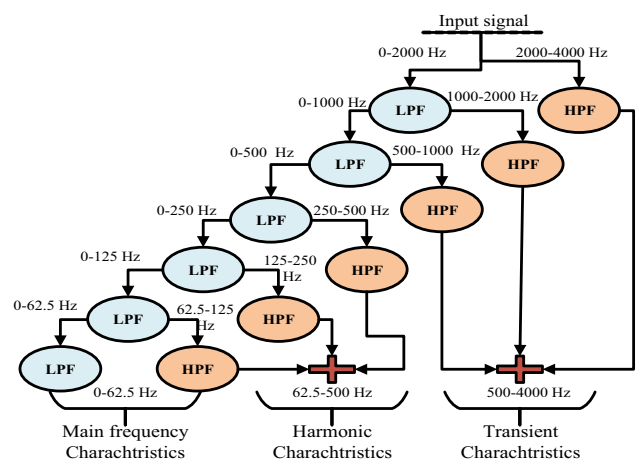


Fig. 1 Frequency division multi-resolution levels up to 6

The Continuous Wavelet Transform (CWT) of the signal $x(t)$ is expressed as follows [31]:

$$CWT(x \cdot a \cdot b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \varphi_{a,b}^* \left(\frac{t-b}{a} \right) dt \quad (1)$$

where $\varphi(t)$ is the mother wavelet, and other wavelets $\varphi_{a,b}(t) = \frac{1}{\sqrt{|a|}} \varphi\left(\frac{t-b}{a}\right)$ are its dilated and translated version. The constants a and b are respectively the dilated and translated version.

$CWT(x, a, b)$ shows the wavelet transform of signal x with the scale (dilation) a and the translation (time shift) b . The CWTs provide frequency and time information for the desired signal at different scales and locations. The CWT also has a known digital counterpart as the discrete wavelet transform (DWT), which is used in this paper. DWT of a signal is provided as follows [31]:

$$DWT(x, m, n) = \frac{1}{\sqrt{a_o^m}} \sum_t x(k) \varphi\left(\frac{n - la_o^m}{a_o^m}\right) \quad (2)$$

where a and b parameters in (1) replaced by a_o^m and la_o^m respectively. The DWT is implemented by the MRA, so that the DWT decomposes the signal to different levels of close approximation (a_1, a_2, \dots, a_n) and details (d_1, d_2, \dots, d_n). A signal is decomposed through the low and high pass filters of the main signal in the time domain. In the case of fault analysis in transmission lines, high-frequency information obtained from the wavelet transform provides useful data to determine the location of the fault. In this paper, the time domain current signal is received for different fault conditions from one side of the transmission line and analyzed using wavelet transform. Daubechies wavelet (DB4) has been used for fault analysis in power systems as the mother wavelet [29–32]. In this paper, the sampling rate is 8 kHz. Among the coefficients presented by different levels of decomposition, only a set of second-order details coefficients is considered for analysis. The reason for this is that (the detailed coefficients of the current signal for level 2) provides the details needed for the method presented in this paper that has transient properties.

3 Adaptive Neuro-Fuzzy Inference System (ANFIS)

As shown in Fig. 2, the structural basis of the fuzzy inference system (FIS) is such that it maps out the input characteristics into the inputs membership function, the input membership functions into rules, the rules into a set of output characteristics, the output characteristics into output

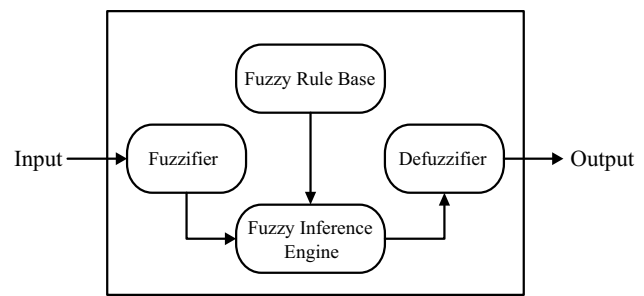


Fig. 2 Basic structure of the Fuzzy Inference System

membership functions, and output membership functions to a single output or an outbound decision maker [25].

Standard fuzzy functions are used to give undefined parameters. These membership functions derive from human intelligence and understanding, which includes both logical and semantic knowledge as well as true language values of a problem. Fuzzy logic resembles human thought in a way that defines this ability in place of a point in a range [25]. ANFIS can combine the learning and computing capabilities of neural networks with the explicit and explanatory abilities of the fuzzy system [25] and [33]. Finally, the function of neural networks becomes better when fuzzy systems are able to learn. A neural fuzzy system is a neural network that is functionally equivalent to a fuzzy inference model. The ANFIS network can be trained to expand fuzzy *if* and *then* rules, and to estimate the membership function variables in the underlying study. One can also use special knowledge in the structure of the neural fuzzy system and reduce the amount of computational load that has been created by the fuzzy inference structure with its connections.

ANFIS uses two modes for training. In the first mode, a forward path is constructed using the current default parameters to optimize the final parameters using the least squares estimation based on the output error. This is possible given that outputs are a linear function of the final parameters [25]. In the second mode, a backward path is made to change the assumed parameters using gradient-based learning. This learning process is called Hybrid. The backward path uses learning like back-propagation learning in neural networks [25]. In this paper, an ANFIS network is used to determine the circuit in which fault has been occurred and for each circuit an ANFIS network is considered to determine the location of the single phase to ground fault. The 2nd level detail coefficient set which are from the three-phase fault signal, called S_a , S_b , and S_c and these are used as the inputs of all ANFIS networks. The faulted circuit is considered as the output of the ANFIS1 network and the precise location of fault D as the output of the ANFIS networks that specify the fault location. Hybrid learning has been used to train all networks used.

4 Four-Circuit Transmission Line Model

Figure 3 shows the schematic diagram of the study system. This system is simulated using the PSCAD software [26]. The transmission line is a un-transposed four-circuit transmission line, 500 kV with a length of 200 km at a frequency of 50 Hz. Due to the consideration of all the details and increasing the accuracy of the fault location, the distributed parameter model is used. Source impedance information is given in Table 1. The tower configuration is derived from the existing model in the PSCAD library [26]. Admittance and impedance matrixes derived from the DIGSILENT software are also included in the calculations [34].

5 Main Idea and Generalities

The algorithm of the proposed method consists of three steps, respectively, processing input data, determining the faulted circuit, and determining the exact location of the fault. Figure 4 shows the flowchart of the implementation process and the exact structure of the proposed algorithm. A sampling frequency of 8 kHz (160 samples per cycle) is used to record the transient details and extract the features by using the Daubechies4 wavelet. The sending end three-phase source current received and wavelet analysis applied. The second level details coefficients, called S_a , S_b , and S_c , from the three-phase fault signal are used as inputs of the ANFIS networks to determine the faulted circuit and fault locations.

5.1 Input Data Processing

Input data is processed as follows:

1. The three-phase currents from measurement transformer of one side of the transmission line are measured.
2. The analogue signal is converted to digital signals without noise.

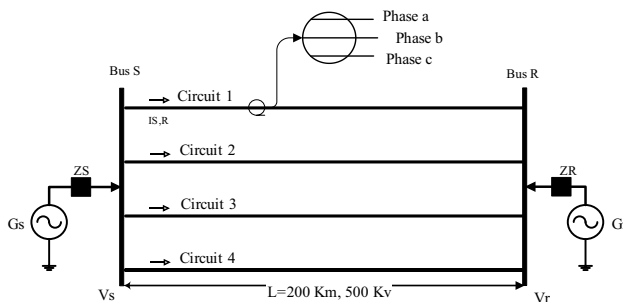


Fig. 3 Schematic of the Four-Circuit transmission line in the system under study

Table 1 The parameters of the two sources at both line terminals

Sequence	Bus S	Bus R
Zero	$2.8 + 32.4i$	$2.1 + 24.5i$
Positive	$1.6 + 18.5i$	$1.2 + 13.8i$
Negative	$1.6 + 18.5i$	$1.2 + 13.8i$

3. Wavelets are used to divide the frequency spectrum into six frequency bands. The wavelet signals are calculated for three-phase current signals on one side of the transmission line.
4. Finally, the second level details coefficients (S_a , S_b , and S_c) are calculated for the three-phase current signals a, b and c, respectively.

5.2 Fault Location and Identifying Faulty Circuit

This section consists of two steps: determining the circuit involved in the fault and determining the exact location of the fault. An ANFIS network has been considered to determine the faulty circuit and 4 ANFIS networks are used to determine the exact location of the fault. Extracted features from digital data by wavelet analysis are as inputs of ANFIS networks. The normalized values of the second level details coefficients set of the three-phase fault current are (named as S_a , S_b , and S_c) as inputs of the ANFIS networks. ANFIS1

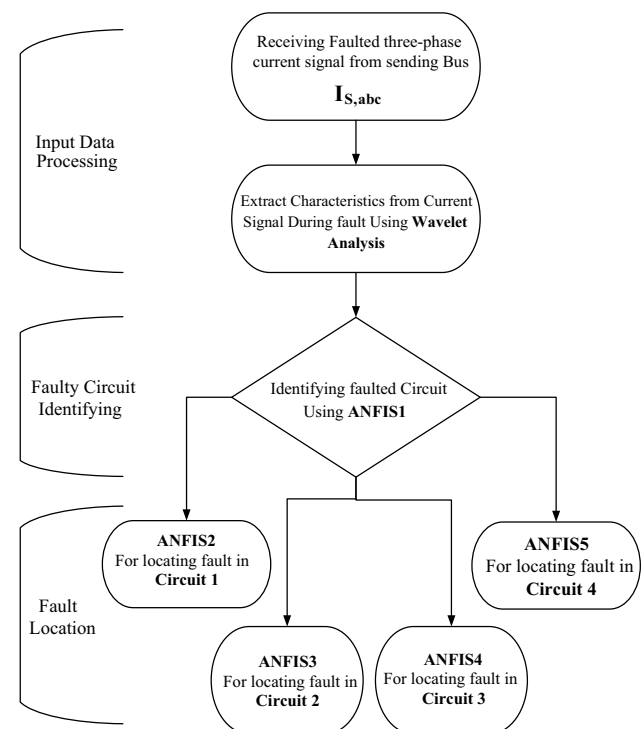


Fig. 4 Main Structure of the proposed algorithm

Table 2 Generation conditions of training patterns

Fault location	10–90% of the line length, with step 5%
Fault resistance (Ω)	0.01, 10, 30, 50, 100
Fault inception	4.5, 9, 18, 36, 72, 108, 144, 162, 171, 175.5
Faulty phase	Phase A, Phase B, Phase C
Faulty circuit	Circuit 1, Circuit 2, Circuit 3, Circuit 4

Table 3 Generation conditions of test patterns

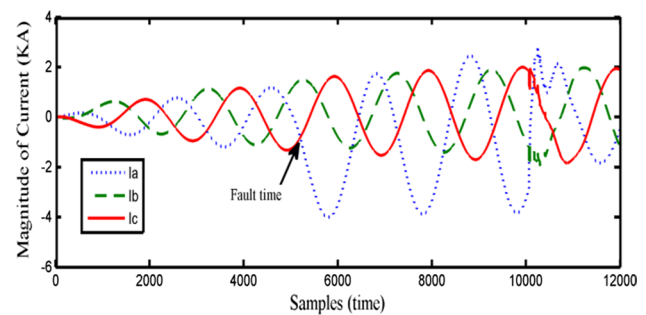
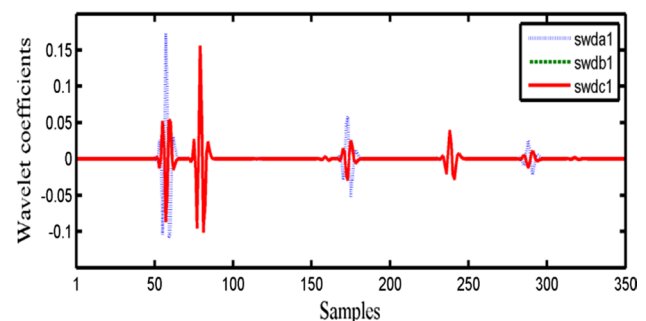
Fault location	10 Random places
Fault resistance (Ω)	2, 15, 20, 50, 80
Fault inception	13.5, 54, 90, 126, 157.5, 173.25
Faulty phase	Phase A, Phase B, Phase C
Faulty circuit	Circuit 1, Circuit 2, Circuit 3, Circuit 4

is trained to determine the faulty circuit. In the next step, 4 ANFIS networks (each for one circuit) are trained to determine the location of the single phase to ground fault. The inputs of these networks are S_a , S_b and S_c , and the output is the distance of the fault point (D) from the sending end of the transmission line.

To design the best ANFIS network, accurate training is required. The trained set should be carefully selected so that different conditions of fault inception, fault resistance and fault location are considered. ANFIS network performance is evaluated by patterns from outside of the training set. The methodology used here is in accordance with Hybrid learning [33]. To find the optimal values of the ANFIS parameters, the input pattern S_a , S_b and S_c , which corresponds to a specific fault condition, are entered into ANFIS and its output is matched to the optimal output pattern associated with this fault condition. ANFIS network parameters are updated after all patterns are presented in the ANFIS network. The system's elite database is obtained using simulation of the system under normal conditions and fault in the transmission line.

6 Numerical Study

Simulations are executed in accordance with Fig. 3 in the PSCAD software [26]. The MATLAB environment is used to apply wavelet analysis and ANFIS network. Training and testing patterns are generated through changes in fault location, fault resistance, fault inceptions, and faulty circuit. The conditions for producing patterns are based on different modes of single phase to ground fault. These conditions are presented in Tables 2 and 3 for training and testing patterns respectively.

**Fig. 5** Three-phase current signals measured at the measuring end under the SLG fault (A-G) at 140 km**Fig. 6** Wavelet MRA for AG fault with Db4 as mother wavelet created at a distance of 140 km from sending end having fault inception of 40 and fault resistance of 0.01 Ω

As shown in Figs. 5 and 6, a second level frequency is considered for generating input patterns. According to the wavelet analysis performed on the three-phase current signals of the sending end of four-circuit transmission line, each pattern has 160 characteristics. The sampling rate for the simulations is 8 kHz and Db4 is used as a mother wavelet. In connection with the necessary figures to explain the fault characteristic, it should be mentioned that the nature of the extracted features and their figures in the different types of fault are similar to Fig. 6. It is avoided repeating them. Of course, it's worth noting that the size and density of these features varies in any kind of fault, but it does not matter in nature.

Based on this sampling rate, the signal is decomposed into six levels. The 2nd level frequency band contains details of 1000–2000 frequencies and delivers transient characteristics such as fault disturbances from the current signal. Based on Table 2, the total number of training data is 9600, and according to Table 3, the total number of tested data is 3600.

Table 4 Results of fault locating for different fault distance

Fault location (Km)	Min error (%)	Max error (%)	Average error (%)
15	0.1440	1.8036	0.9796
38	0.1015	1.7356	0.4596
55	0.1170	1.7705	0.6676
76	0.1203	0.8000	0.3829
108	0.1002	0.9621	0.5666
116	0.1141	0.9146	0.2214
129	0.1118	1.8474	0.5788
146	0.1219	0.7355	0.7909
158	0.1005	1.8252	0.653
167	0.1311	1.8931	0.8109
All	0.2311	1.4287	0.6113

Table 5 Results of fault locating for different fault resistance

Fault resistance (Ω)	Min error (%)	Max error (%)	Average error (%)
2	0.06	0.9500	0.6245
15	0.07	1.1931	0.5917
20	0.04	1.2277	0.5690
50	0.01	1.2931	0.5571
80	0.02	1.8931	0.8615

7 Results and Discussions

In connection with the determination of the fault location, single phase to the ground fault have been simulated with different conditions of the fault inception, fault location, fault resistance, and faulty circuit. The 2nd level detail coefficient set, called S_a , S_b , and S_c are considered as network inputs and fault locations as outputs. The ANFIS-related neural network has trained membership functions to reduce fault location error. The network is set to 1000 steps to access error less than 1%. Hybrid learning has been used for network learning. To evaluate the accuracy of the proposed algorithm to calculate the fault location, the proposed method is tested under different fault conditions. From the obtained results, it can be proved that the proposed algorithm has an acceptable accuracy in the field of four circuit transmission lines. The exact fault location performance is tested using ANFIS2... ANFIS5 networks and its results are in Tables 4, 5, 6, 7. The error rate is defined as follows:

$$\%Error = \frac{|Estimated\ location - Actual\ fault\ location|}{Total\ length} \times 100$$

In order to investigate the effect of important parameters on the accuracy of the proposed method, the fault locating

Table 6 Results of fault locating for different fault inception inceptions

Fault inception (degree)	Min error (%)	Max error (%)	Average error (%)
13.5	0.013	1.2285	0.6827
54	0.028	1.3500	0.7684
90	0.001	1.1500	0.6732
126	0.023	1.0500	0.4681
157.5	0.015	1.0411	0.3663
173.25	0.062	1.2621	0.7035

Table 7 Results of fault locating for different faulty circuit

Faulty circuit	Tested data	Accurate estimated data	Error (%)
1	30	29	0.04
2	30	28	0.067
3	30	28	0.067
4	30	30	0

results related to the fault location, the fault inception, fault resistance and faulty circuit are presented in Tables 4, 5, 6, 7, respectively. Finding results for different fault distances are given in Table 4. There are 360 data for each fault point. By assessing the results obtained in Table 4, it can be concluded that the proposed method has a good accuracy, given that the test conditions differ from the training conditions. The average error for all network test inputs is 0.6% and the maximum error is 1.8%.

In the proposed method it is assumed that the impedance is absolute resistive. In order to investigate the effect of fault resistance on the proposed method, the fault for the different fault resistance is performed and the results of the error estimation are presented in Table 5. The maximum estimated error is 1.89 percent and the estimated average error is 0.64 percent for all cases. Obviously, the complex impedance has a negative effect on the accuracy of the proposed algorithm. However, the proposed method has achieved good results. By examining Table 5, it can be seen that the maximum error seen in the 80-ohm fault resistance occurred. So, in this amount of fault resistance, the average error seen is less than 1%.

In order to show the effect of fault inception, the fault in the fixed location with constant resistance at the various fault inceptions has been applied. The maximum and average estimated error for each fault in various angle are shown in Table 6. As it is shown, the accuracy of the fault location remains acceptable despite the change in the fault inception angle. The proposed fault locating method has been investigated for fault inceptions near the

Table 8 Results of comparison between different methods

Methods	Max error for single phase fault (%)	Average error for single phase fault (%)
Proposed method	1.893	0.6113
Method in [21]	0.776	0.0998
Method in [22]	2.620	1.256
Method in [23]	1.386	0.519
Method in [24]	2.630	0.673

zero-crossing point of current. A number of network testing patterns have been generated based on a fault inception angle of 2.25 and 177.75 degrees. The rest of the conditions for producing test data are presented in Table 3. The average and maximum error obtained for the angle of 2.25 degrees are 0.8018% and 1.6333%, and for the 177.75 degrees are 0.9911% and 3.5403%, respectively. This indicates that the fault inceptions which are near-zero points of the current affect the accuracy of the proposed method. If the fault inception angle from zero crossing point of current is less than 2.25, then the proposed method does not show the desired performance. In general, the proposed method has an acceptable performance of only 97.5% of the time.

In connection with the determination of the faulty circuit, in order to avoid overlapping of information in the trained ANFIS network associated with the determination of the fault location, initially, with respect to the extracted characteristics from the fault current signal in different circuits, The ANFIS1 network has been trained to determine the faulty circuit. According to the results presented in Table 7, it can be deduced that the proposed method for determining the faulty circuit has a high accuracy, so that in the tested data, the occurred error is less than 0.1%.

According to the results of the tables, it can be seen that the proposed algorithm for the single phase to ground fault in the un-transposed four-circuit transmission lines has an acceptable accuracy.

The fault locating algorithm accurately detects the exact fault location and faulty circuit in most cases and maintains the algorithm's error below 2%. Finally, to compare the proposed method with the previous methods proposed in the field of fault detection in the four-circuit transmission lines, Table 8 has been developed to determine the efficiency of the proposed method. It should be noted that in previous methods there are shortcomings such as the need for line information, type of fault, synchronization of information, complex and time-consuming computations that are not exist in the proposed method.

8 Conclusions

This paper has presented a method for locating single phase to ground fault in the un-transposed four circuit transmission lines. The proposed algorithm has consisted of three steps: extracting features, determining the faulty circuit and determining the fault location, respectively. Multi resolution analysis of the wavelet with ANFIS network have been used to overcome the complexities of the four circuit transmission lines, such as mutual coupling, un-transposed lines and different fault conditions. Compared to other classical methods, the proposed method has less complexity and less time-consuming. Wavelet transformation and smart computing such as ANFIS have been used to extract important features and get the exact location of the fault. In this paper, the sensitivity of the proposed method to parameters such as fault inception and fault resistance has been analyzed. The simulation results indicate that the proposed method is a fast, accurate, and reliable method to determine the fault location. The proposed method overcomes issues such as synchronizing received information from both sides of the line, knowing the line information, knowing the type of fault that was being addressed in the protection of four circuit transmission lines.

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