RADIAL BASIS NEURAL NETWORK AND DISCRETE WAVELET TRANSFORM BASED RMS ESTIMATION FOR FAULT ASSESSMENT IN THREE PHASE TRANSMISSION LINE

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Abstract:

Quick identification, accurate classification, and proper estimation of the location of faults in transmission lines are utmost required for smooth and reliable operation of the electrical system. This work deals with the line-to-ground (LG) fault assessment in transmission line. At one end three phase current signals have been analyzed by discrete Wavelet transform (DWT) based root-mean-square (rms) analysis for fast detection of faults. Then computed rms values have been used in Radial Basis Neural Network (RBNN) for classification of faulty phase and estimation of fault locations. Using the proposed technique, very quickly, the fault has been detected and with high accuracy, almost 100 of % fault has been classified, and the distance of the fault has been properly estimated. In different cases algorithm have been tested successfully and the results are very much optimistic.

1 Introduction

Transmission lines are an essential part of power systems that transmit electrical energy from power plants to distribution centres or consumers. They play an important role in delivering power efficiently over long distances with minimal loss. Transmission lines are important for efficient power delivery, but their exposure to environmental elements and external interferences can lead to faults. Mitigation measures and technological advancements are important in maintaining the reliability and resilience of transmission lines in power systems. Mathematical morphology (MM) and decision tree (DT) based technique used in [1], to identify faults in a transmission line. From the transmitting end of the transmission line, a sampled three-phase current signal along with its zero sequence components has been captured and then processed by a morphological median filter to extract the feature by which the fault has been detected. Further, based on classification. This feature has classified fault by a DT-based approach. Another technique proposed in [2], where current signals are pre-processed by Adeline and least square algorithm to measure and extract DC offset and fundamental component information. In this approach, the DC offset and the fundamental current component are used as inputs to a Bagging Tree (BT)-based fault detector/classifier to evaluate faults and power swing conditions in transmission lines. In [3], the suggested technique is verified on a 400 kV, 50 Hz two-bus system and an IEEE-39 bus 345 kV system, applying EMTDC/PSCAD and MATLAB, effectively demonstrating its ability to discriminate faults under diverse conditions. Practical feasibility is validated through a hardware experiment using the NI LabVIEW platform. Several methodologies have been developed for improved power system protection algorithms to eliminate faults immediately upon occurrence [4].

This article provides a brief, comprehensive review of various fault diagnosis schemes, highlighting their strengths and shortcomings, serving as a useful guide for researchers in selecting appropriate techniques for

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transmission line fault analysis. Alienation coefficient and Wigner distribution have been used in [5] to calculate the fault index for the assessment of transmission line faults in different conditions. Using this proposed technique, high accuracy has been obtained to assess different faults, though the total assessment time has not been mentioned clearly. The Daubechies Wavelet (db4) was used to extract characteristics like energy and standard deviation from the three-phase fault current waveforms. [6]. These characteristics were used to train classifiers, such as Bayes, Naive Bayes, and Multi-Layer Perceptrons (MLP). Based on accuracy, misclassification rate, kappa statistics, Mean Absolute Error (MAE), Root Mean Square Error (RMSE), Percentage Relative Absolute Error (%RAE), and percentage root relative square error (%RRSE), the results showed that the NB classifier performed better than MLP and Bayes. B. Rathore et al. [7] proposed Wavelet alienation coefficients and an Artificial Neural Network (ANN) based technique to assess faults in STATCOM compensated transmission line. In this analysis, the fault index has been calculated from the approximation wavelet transform coefficients, which were again used for classification and the distance location of faults. To identify line-to-line and line-to-ground problems in the IEEE standard 9 bus system, S. Datta et al. suggested a statistical analysis based on the discrete Wavelet transform (DWT) [8]. Stockwell transform (s-transform) is also used as a technique for electrical fault assessment, where detailed frequency information is extracted in fault conditions using the S-transform, but the time requirement for fault assessment is a little bit higher than the Wavelet transform (WT) [9][10]. Nor Adni Mat Leh et al. [11] proposed a method leveraging Artificial Neural Networks to identify and categorize transmission line issues for electricity. The approach was tested on a 14-bus system using MATLAB simulations, with performance evaluated through metrics like Mean Square Error, linear regression, and the confusion matrix. This approach aims to improve the overall quality and reliability of power systems by enhancing the ability to identify and address faults in transmission lines. Majid Jamil et al. demonstrated a technique for detecting and classifying power transmission line problems using artificial neural networks [12].

The approach is analyzed and validated through simulations in MATLAB, demonstrating its efficiency and potential for broader applications in power distribution networks. Chris Asbery et al. [13] addressed the challenges associated with electrical faults in transmission lines and proposed artificial neural networks to locate and classify faults. The analysis involves various fault cases and transmission line configurations, with the aim of providing practical insights into the effectiveness of different neural network structures and input measurements for improving system reliability. Anamika Yadav et al. [14] specifically focused on applying ANN in detection, classification, and localization of transmission line faults. In transmission lines, ANN is considered a dependable method for tasks including fault detection, classification, direction determination, and defective phase identification. ThisThis work compares several approaches for faulty phase selection, direction estimation, localization, classification, and fault detection. The study also highlighted the effectiveness, precision, and resilience of artificial neural networks in tackling a range of power system safety issues, especially when it comes to location, classification, and detection of transmission line faults, among other related activities. The comparative study and extensive survey contribute to further research and development in this area. Vincent Nsed Ogar et al. [15] underscored the significance of precise fault detection and localization in power systems, especially for transmission lines. The use of artificial neural networks is proposed as an effective solution that achieves great precision in locating and detecting faults. The comparison with other techniques and the practical application of the proposed model in fault protection and management systems highlight the potential significance of the research findings. 100% fault detection accuracy and 99.5% fault localization accuracy at various distances were reported in the article. The detection time is mentioned as 0.0017 μs with an average error falling from 0%-0.5%. Priyanka Khirwadkar Shukla et al. [16] addressed the persistent challenge of power system faults and emphasized the importance of efficient restoration through swift fault classification and clearance. The study included methods for fault classification, including long short-term memory (LSTM) and artificial neural networks (ANN), with or without window regression (WR). Deep learning methods make it easier to classify faults and enable automated feature extraction.

The study examines five kinds of transmission line short-circuit faults: three-phase, line-to-ground, double line-to-ground, line-to-line, and line-to-ground faults. The results demonstrate the effectiveness of these techniques, particularly LSTM and LSTM-WR, in achieving high accuracy in fault classification. Capsule networks and wavelet transform-based methods have been utilized to identify and categorize various transmission line issues [17]. Four different topologies of transmission line have been considered, but the limitation of the mentioned approach is that fault location has not been found. Another study [18] explores the potential to enhance advanced protection systems for power transmission lines, focusing on various faults such as short circuits, overvoltage, and overloads. Conventional protection, like the Mho distance (admittance) relay, will be examined alongside modern techniques like neural networks. The study highlights that neural networks can improve the accuracy and speed of detecting short-circuit faults. Simulation results confirm the effectiveness of these methods for automatic fault diagnosis. In [19], a unique model is presented that uses entire transient data from pre- and post-fault cycles as inputs for DRNN models, using current and voltage signals recorded by Phasor Measurement Units (PMUs). These models use Long Short-Term Memory (LSTM) networks in conjunction with Sequential Deep Learning (SDL) to properly categorize and anticipate problems. Tested on a Two-Area Four-Machine Power System, the algorithms demonstrated superior fault detection, classification, and localization performance, achieving high accuracy and robustness compared to existing methods. The paper's main contribution [20] is the useful information that can be obtained from oscillography for training neural networks. Tests on Brazilian transmission lines under genuine fault situations show that the technique is resilient, even with multi-terminal and series-compensated lines, and an effective representation of voltage and current is suggested. Using wide-area measurements, the study [21] presents a system integrity protection approach that separates the system into protective zones and uses current data to identify flaws.

The method works with both transposed and non-transposed lines and efficiently manages several concurrent errors with its performance validated through simulation-based studies. In this work, DWT based RMS have been calculated of phase current for quick detection of faults, after that using Radial Basis Neural Network (RBNN) faults have been classified and fault distances have been located with excellent accuracy. The rest of the document is structured as follows: Network simulation is covered in Section 2, while analytical techniques for fault evaluation are covered in Section 3, section 4 explains flow chart of the proposed method, section 5 explains the results, section 6 discusses advantages of proposed method with other existing method and section 7 is the conclusion of this work.

2 Network Simulation

In this work, 220 kV double end fed 110 km single circuit has been considered for line to ground fault analysis whose single line diagram is depicted in Figure 1. This circuit is simulated in MATLAB Simulink platform. Here double fed, 220 kV voltage source and 50 Hz system frequency have been considered. Within a 110 km transmission line, line-to-ground (L-G) faults are created at different distances. In normal and different fault (L-G) conditions, the three-phase outgoing currents of bus 1 are captured for analysis. Distributed parameters line has been considered for the analysis where Zero and positive sequences capacitance, resistance, and inductance values per km are considered as 0.01273 Ω, 0.3864 Ω, 0.9337e-3 H, 4.1264e-3 H, 12.74e-9 F and 7.751e-9 F. Total simulation time is regarded as 0.5 second (sec).

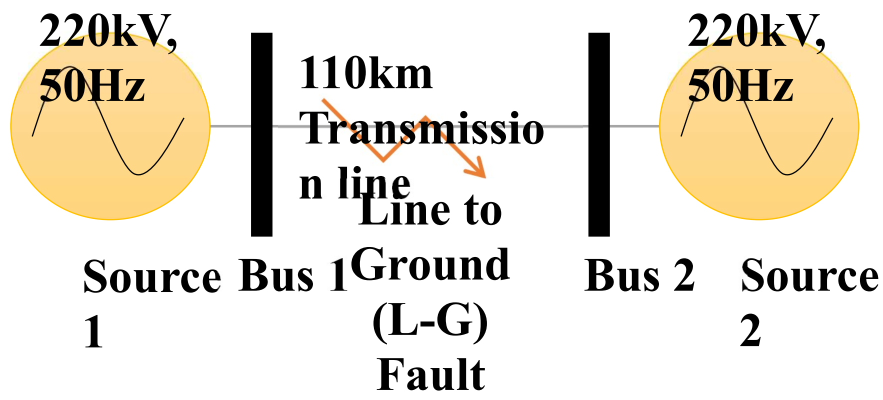


Figure 1. 220 kV Double End Fed Transmission Line.

3 Analytical Tools

Discrete Wavelet Transform (DWT) and Radial Basis Neural Network (RBNN) have been used as tool to detect and distance location of fault in transmission line. The Analytical tools have been discussed below.

3.1 Discrete Wavelet Transform (DWT) Based RMS Analysis

To extract time-frequency information from a non-stationary signal, the Wavelet Transform (WT) is used. WT can be classified as Continuous Wavelet Transform (CWT) and Discrete Wavelet Transform (DWT). CWT generates lots of data for analysis. So, to reduce the time and computation complexity DWT is used. IN WT, mother wavelet plays a vital role because each time convolution is considered in between analyzed signal and mother wavelet. Here, 'dB4' is considered as the mother wavelet for analysis as it is appropriate to detect unexpected changes in any non-stationary and stationary waveform. DWT is used to represent discrete signals in a more redundant manner.

The signal goes via a filter bank in DWT. Two filters make up the filter bank. Low pass filter and high pass filter are two filter banks in DWT. Detail level coefficients, which contain higher order harmonics, are the high pass filter's output in DWT. Approximation or approximate coefficients, which comprise lower order harmonics, are the low pass filter's output. The approximation coefficients from each DWT decomposition level can be further decomposed to extract detail and other approximation coefficients in the following level. In this work, approximation coefficients at DWT decomposition level one (1) have been considered for detection of fault. After DWT of analyzed signal x (n), the output of low pass and high pass filter has been given below.

$$z_{low}(n) = \sum_{k=-\infty}^{\infty} x[k]q[2n-k] \tag{1}$$

$$z_{high}(n) = \sum_{k=-\infty}^{\infty} x[k]r[2n-k] \tag{2}$$

Where, q and r is the corresponding low-pass and high-pass filters.
After DWT decomposition of three phase outgoing current of BUS 1, root mean square (rms) value of approximation coefficients at DWT level one (1) has been calculated in various instances to detect the L-G fault. Further, RMS values and maximum RMS value between the three-phase currents have been used as input in RBNN to locate the distance of fault occurrence.

3.2 Radial Basis Neural Network (RBNN)

Radial basis neural networks can be used to obtain function equality. Neurons are progressively added to the hidden layer of a radial basis network until the mean squared error objective is attained. The larger the dispersion, the smoother the function approximation. A high spread means many neurons are needed to fulfill a rapidly changing function. If the spread is too tiny, numerous neurons will be required to suit a smooth function, which could hinder the network's generalization ability. RBNN with various spreads to determine the best value for a specific issue. Here 25 neurons are considered for analysis. Here, radial basis transfer function is used in neural network. Four (4) inputs which are rms value of approximation coefficients of three phase current and maximum rms value among them at DWT decomposition level one (1) and four (4) output values which are R phase to ground, Y phase to ground, B phase to ground and distance have been considered to detect the faulty phase and distance of fault. For a fault condition of one phase, the output value is considered one (1), and for a no fault condition, it is considered as zero (0). In this RBNN, spread has been considered as five (5), because at this value of spread, best result has been observed. The neural network shown in the figure below, with 10 layers, 4 inputs, and 4 outputs, has been considered for L-G fault analysis. Performance of this RBNN is depicted in Figure 3.

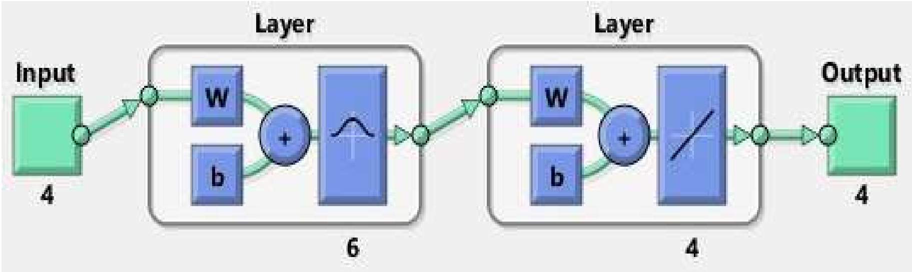


Figure 2. Structure of Radial Basis Neural Network (RBNN).

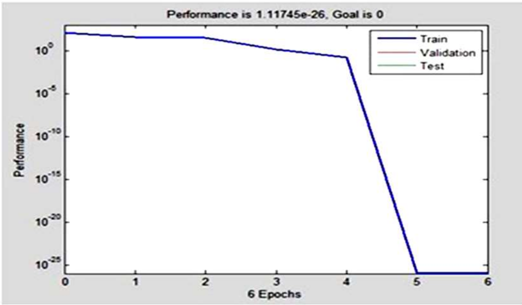


Figure 3. Performance of neural network.

4 Flow Chart of Fault Detection, Classification and Distance Location

The flowchart for fault classification, distance estimation, and fault detection in transmission lines used in this work is shown in Figure 4.

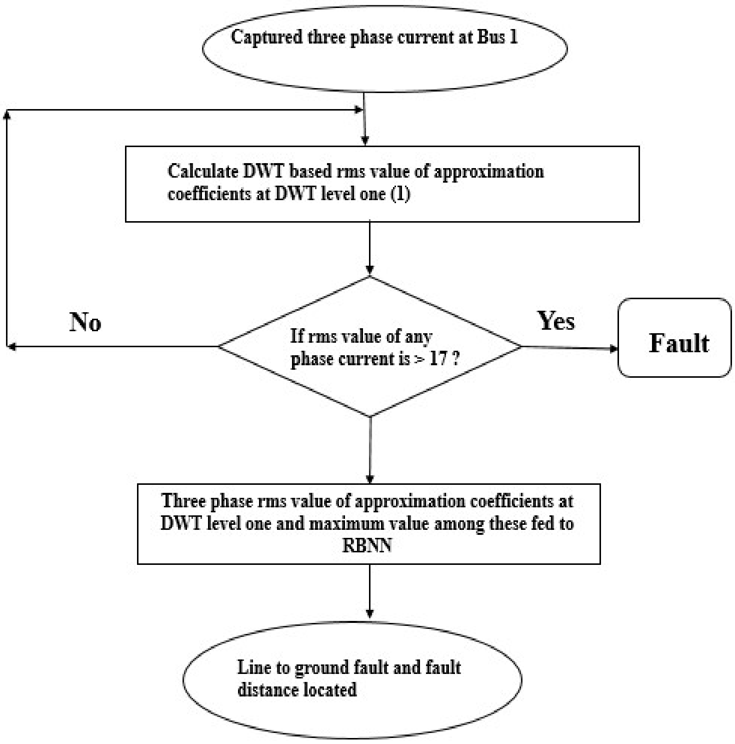


Figure 4. Flow chart of fault assessment.

5 Results and Discussions

Figure 5 depicts the three phase current at ideal condition. Figure 6 portrays line to ground fault for three phases. Five (5) cycle faults have been studied here where fault initiation and ending times are 0.3 sec and 0.5 sec respectively. Figure 4 shows the balanced three phase current in ideal situation with highest magnitude is less than 24 Amp. In Figure 7, highest magnitude of current at line to ground fault condition is almost 60 Amp. Figure 7 is DWT decomposition (Upto level three) of R phase current at ideal instance. No notches have been identified at detail level coefficients. Figure 8 is used to limn the DWT decomposition of R phase current at line to ground fault condition. In this figure starting notches and ending notches are precise at 0.3 sec (6000 samples value) and 0.4 sec (8000 samples value) respectively at detail levels which indicates line to ground fault.

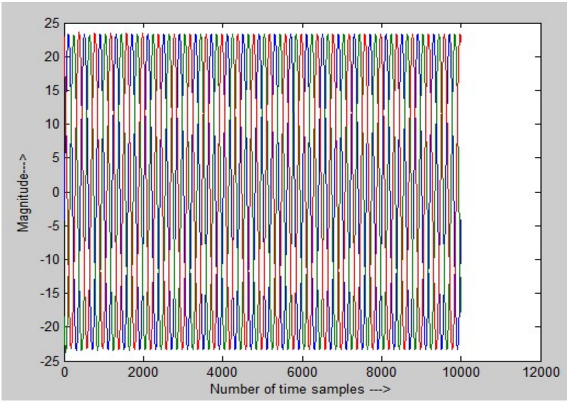
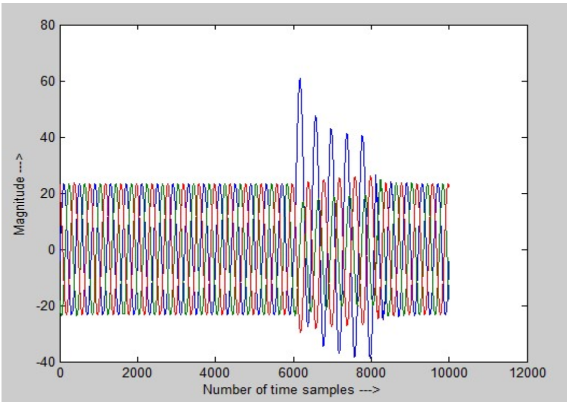
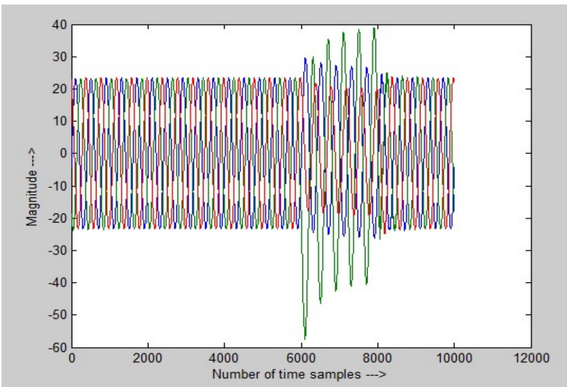


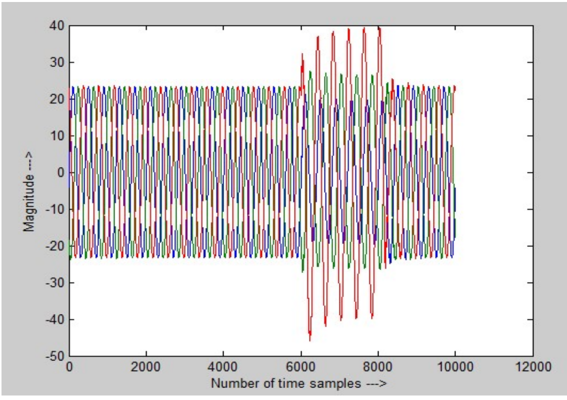
Figure 5. Three phase current at ideal condition.



(a)



(b)



(c)

Figure 6. (a) (b) (c). Three Phase current at different faults (a) R phase – Ground, (b) Y phase – Ground, (c) B phase – Ground.

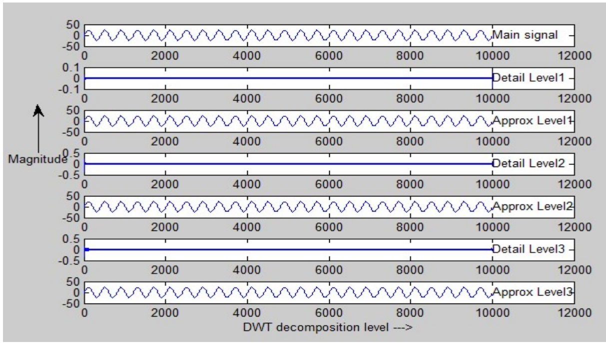


Figure 7. DWT decomposition of current at normal condition (Upto level three).

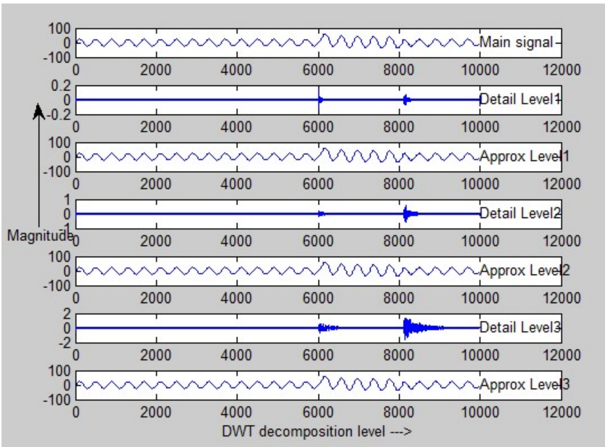


Figure 8. DWT decomposition of current at fault (R-G) condition (Upto level three).

Figure 9 illustrates the result of rms value of DWT level one coefficients with respect to distance (km) in various instances. In normal condition, value is 16.52 which is independent of distance and phase. The rms value is very high in line to ground fault condition. From these rms values of DWT level one (1) approximation coefficients, fault condition can easily be detected.

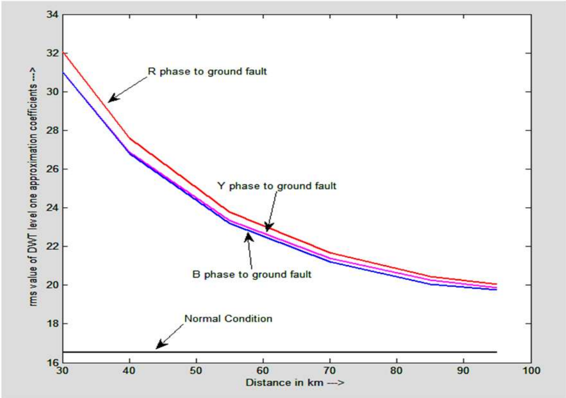


Figure 9. rms value of DWT level one approximation coefficients versus distance (in km).

Table 1 data is used to train the RBNN. The first four columns' data (from left side, excluding Sl. No. column) are used as the inputs of the neural network, and the next four columns are the output of the neural network. First four columns are approximation coefficients rms value for R, Y, B phase current and maximum rms value among these respectively. Last four columns indicate line to ground fault and distance of fault from bus 1, where 1 indicates the fault condition and 0 indicates no fault condition.

Table 1. Input and output for training of RBNN.

	Inputs to train the Neural Network				Output of the Neural Network			
Sl. No.	DWT level one approximation coefficients rms value (R phase)	DWT level one approximation coefficients rms value (Y phase)	DWT level one approximation coefficients rms value (B phase)	Maxi-mum rms value	R phase to ground	Y phase to ground	B phase to ground	Distance in km
1	32.05	16.75	16.30	32.05	1	0	0	30
2	27.59	16.65	16.40	27.59	1	0	0	40
3	23.80	16.53	16.51	23.80	1	0	0	55
4	21.69	16.41	16.63	21.69	1	0	0	70
5	20.46	16.24	16.80	20.46	1	0	0	85
6	20.03	16.05	17.01	20.03	1	0	0	95
7	16.30	31.01	16.74	31.01	0	1	0	30
8	16.40	26.86	16.64	26.86	0	1	0	40
9	16.51	23.35	16.53	23.35	0	1	0	55
10	16.63	21.39	16.41	21.39	0	1	0	70
11	16.67	20.93	16.36	20.93	0	1	0	75
12	16.88	20.01	16.15	20.01	0	1	0	90
13	16.75	16.29	31.01	31.01	0	0	1	30
14	16.52	16.52	23.22	23.22	0	0	1	55
15	16.40	16.64	21.22	21.22	0	0	1	70
16	16.35	16.68	20.75	20.75	0	0	1	75
17	16.22	16.80	20.03	20.03	0	0	1	85
18	16.13	16.89	19.77	19.77	0	0	1	90
19	16.13	16.89	19.77	19.77	0	0	1	95
20	16.65	16.40	26.80	26.80	0	0	1	40

To verify the proposed algorithm, different unknown cases have been considered, but among those cases, eight (8) cases are depicted in Table 2. At various distances, different line-to-ground faults have been considered, and in all those instances, the rms value of approximation coefficients in three-phase currents and the maximum value among these values have been used to detect the faults and to find out the fault distances. Table 2 values are used as inputs to the RBNN to assess the faults. Outputs of RBNN have been delineated in Table 3, where 1 indicates a line to ground fault and 0 indicates no fault condition. Table 4 is the actual value of different faults. Percentages of errors have been calculated in Table 5, where the maximum error is obtained as 0.8%, which is very much optimistic. Confusion matrix of the above cases is depicted in Figure 10. From this confusion matrix, it is very much clear that, RBNN has correctly identified and properly estimated faulty line and fault distances. Almost 100% accuracy has been achieved for all the cases.

Table 2. Three phase rms value of approximation coefficients at different conditions.

Sl. No.	R phase rms value of approximation coefficients at DWT level one (1)	Y phase rms value of approximation coefficients at DWT level one (1)	B phase rms value of approximation coefficients at DWT level one (1)	Maximum rms value of approximation coefficients at DWT level one (1)
1	22.97	16.49	16.55	22.97
2	26.05	16.60	16.44	26.05
3	21.20	16.36	16.68	21.20
4	20.20	16.16	16.89	20.20
5	20.03	16.05	17.01	20.03
6	16.79	20.25	16.24	20.25
7	17.00	19.85	16.05	19.85
8	16.13	16.89	19.77	19.77

Table 3. Radial Basis Neural Network Output.

Sl. No.	R phase to ground fault	Y phase to ground fault	B phase to ground fault	Fault Distance from BUS 1 in km
1	1	0	0	60.25
2	1	0	0	44.64
3	1	0	0	74.44
4	1	0	0	90.47
5	1	0	0	95.00
6	0	1	0	85.22
7	0	1	0	93.82
8	0	0	1	89.61

Table 4. Actual Value (in fault condition).

Sl. No.	R phase to ground fault	Y phase to ground fault	B phase to ground fault	Fault Distance from BUS 1 in km
1	1	0	0	60
2	1	0	0	45
3	1	0	0	75
4	1	0	0	90
5	1	0	0	95
6	0	1	0	85
7	0	1	0	94
8	0	0	1	90

Table 5. Error in Percentage (%).

Sl. No.	Fault Distance from BUS 1 in km (Actual Value)	Fault Distance from BUS 1 in km (Measured Value)	|Error| in Percentage(%)
1	60	60.25	0.41
2	45	44.64	0.8
3	75	74.44	0.74
4	90	90.47	0.53
5	95	95.00	0.00
6	85	85.22	0.26
7	94	93.82	0.19
8	90	89.61	0.43

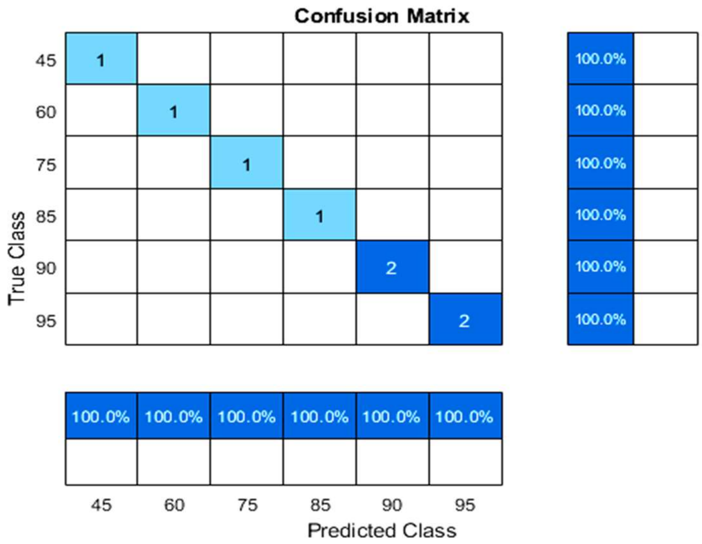


Figure 10. Confusion matrix of RBNN result.

6 Comparative Study of Results with Other Methods

A comparative study of results with others existing methods has been given below in tabulated form; where from precedence of this work is very much clear.

Table 6. Comparative Study with Other Methods.

Reference Number	Detection Time	Fault Classification	Distance Location (Fault)	Accuracy	Overall Contribution to Fault Assessment
[1]	2.0449 ms	Fault classified	Not mentioned	99.98 %	Feature selection is the main intricate thing of this work to detect and classify the faults. Fault distance has not been properly detected.
[2]	4.012 sec	Fault identified	Fault Distance located (99%)	>98%	Statistical analysis for random fault cases are carried out but detailed frequency information is missing.
[3]	Not mentioned	Fault classified	Not mentioned	>98%	New algorithm is proposed to discriminate the faults and faulty phase detection
[5]	1 sec	Fault almost classified	Fault Distance located (98%)	99%	Accuracy is high but assessment time is not mentioned clearly
[9]	0.22 sec	Fault classified	Not mentioned	100%	Quick fault detection and classification is achieved but distance location information is missing
[16]	Not mentioned	Fault identified	Fault Distance located (99%)	100%	Classification of faults explained clearly but fault detection time has not mentioned. Huge data is also required for analysis.
[21]	Not mentioned	Fault classified	Fault Distance located (99%)	>99%	Fault zone or fault location has been identified properly for single or multiple fault condition but no others information have portrayed.
Proposed Technique	0.015 second	In three phase, faults classified properly	Clearly identified (100%)	100%	In the proposed technique fault can be detected in 0.015 second which is very fast. High accuracy, almost 100% has been achieved for fault classification and fault distance location.

7 Specific Outcome of this work

Specific outcome of this work is given as follows

- Fault detection is very fast. Detection time is 0.015 sec
- Fault location is detected properly
- Faults classified with 100% accuracy.

8 Conclusion

Ground fault in the transmission line has been assessed in this article. Three phase current signals were captured with proper sampling frequency, then it has been decomposed by DWT analysis for calculating the rms value of approximation coefficients at level one. In fault conditions almost two times of rms value has been recorded with respect to normal condition which is used to detect the faults. These rms values were used further as inputs in RBNN to identify the faulty line and to locate the fault distance. Several unknown cases have been tested using this proposed algorithm where almost 100% accuracy has been achieved for all the cases. This algorithm can also be used to detect other faults in transmission lines at very early stages with the highest degree of accuracy.

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