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A novel transmission line relaying scheme for fault detection and classification using wavelet transform and linear discriminant analysis

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Shunt faults;
Multi-location faults

Abstract This paper proposes fault detection and classification scheme for transmission line protection using WT and linear discriminant analysis (LDA). Current signals of each phase are used for the detection and identification of faulty phases and zero sequence currents are used for the detection of ground. Current signals are processed using discrete wavelet transform with DB-4 wavelet up to level 3. Approximate coefficients are reconstructed using wavelet reconstruction. Performance of the proposed based scheme is tested by variations of parameters such as fault type, location, fault resistance, fault inception angle and power flow angle. The scheme is applicable for both single circuit and double circuit transmission line. All shunt faults and multi-location faults which occur in different locations at the same time are also detected and classified by the proposed scheme within one cycle time. The simulation results show that the proposed scheme is not affected by non-linear high impedance fault and CT saturation.
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1. Introduction

Fast and reliable fault detection and fault classification technique is an important requirement in power transmission systems to maintain continuous power flow. Many researchers proposed different techniques for fault detection and classification. Among the various techniques reported wavelet based techniques are used for detection and classification of faults by researchers [1,2]. Different artificial intelligence techniques such as ANN, fuzzy, ANFIS, and SVM also used for detection and classification of faults. Artificial-neural-network (ANN) based approach is used for fault detection, fault phase selection and fault classification in [3–5]. ANN in combination with wavelet transform is used for detection and classification of fault in [6,7]. Combination of particle swarm optimization (PSO) and ANN is also used for classification of fault in [8]. Fuzzy logic is used for fault phase identification and classification in [9,10]. Fuzzy logic in combination with neural network called as adaptive neuro fuzzy inference system (ANFIS) based distance relaying has been used for protection of power system [11]. Support vector machines (SVM) are used for classification

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of fault in [12]. In [13] phase space based fault detection scheme for distance relaying is proposed. Fault classification and faulted phase selection schemes are also proposed based on the symmetrical components of reactive power for single-circuit transmission lines [14]. Detection and classification of faults in power transmission lines using functional analysis and computational intelligence is proposed in [15].

Moreover the reach setting or the protection range reported in all above discussed papers is much lesser than 90% of the line length i.e. if the fault occurs in between 90% and 100% of the line, these scheme will not be able to detect the fault. However if any protection scheme can provide protection to larger portion of the line length then that scheme will be beneficial for protection of transmission line. Many researchers did not mention about the fault detection time which is the most important task in transmission line relaying. Fault detection time is important because from this it can be observed that how quickly the normal flow of power can regain. Thus in this paper a protection scheme is designed using wavelet transform and linear discriminant analysis to detect the fault, identify the faulty phases and classify the type of shunt faults that may occur in power transmission lines. Instead of designing 10 modules for 10 types of fault only 4 modules are designed to identify the faulty phases and classify the faults. Only three line currents and zero sequence current measurement are sufficient to implement this technique. The number of samples given in training is quarter cycle data (5 samples) after pre-processing through discrete wavelet transform. The time taken by this method is about within one cycle (20 ms).

2. Discrete wavelet transform

Wavelets have both scale and a time aspect that is why it is used for signal analysis in power system protection [16]. Wavelet analysis represents a windowing technique with variable-sized regions which allows the use of long time intervals where more precise low-frequency information is required and shorter regions where high-frequency information is required. Advantage of wavelets is the ability to perform local analysis which analyzes a localized area of a larger signal. Wavelet analysis is capable of revealing aspects of data that other signal analysis techniques may miss. Wavelet analysis is the breaking up of a signal into shifted and scaled versions of the original wavelet to obtain a better resolution.

For analysis of power system transients, DB wavelets have been used in majority of the power system transient detection algorithms and also DB wavelets are described as best mother wavelet of choice of the power system researchers in [17]. So in the proposed work DB wavelet is taken as mother wavelet. In wavelet analysis signals divided into two parts approximations and details. The approximations are the high-scale, low-frequency components of the signal. The details are the low-scale, high-frequency components. Decomposition of a signal S up to level three is shown in Fig. 1. The decomposed signal contains the approximate and detail coefficients up to certain level. Proposed method is first designed by using different levels of decomposition of wavelet up to level 5. But the accuracy of the method remains constant after level 3. So if level higher than level 3 will be considered it will take more time for decomposition due to which processing time will increase but the accuracy will be same as level 3. So it is better to take

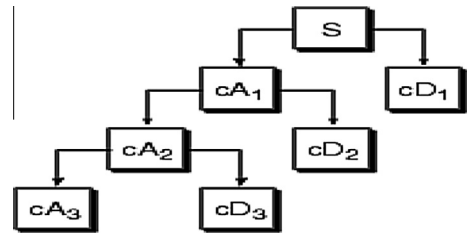

Figure 1 Wavelet analysis of signal S up to level 3.

decomposition level up to level 3 to detect fault quickly than other higher levels.

The decomposed components can be assembled back into the original signal without loss of information which is called wavelet reconstruction, or synthesis or inverse discrete wavelet transforms (IDWT). Wavelet Reconstruction is used here for the approximate coefficients. Signals use zero padding to construct the original signal. Reconstruction process of proposed method is shown in Fig. 2. After reconstruction required numbers of samples are taken from the signal for further use in the training of LDA network.

3. Linear discriminant analysis

Linear discriminant analysis is used to study the difference between two or more groups of objects with respect to several variables simultaneously, determining whether meaningful differences exist between the groups and identifying the discriminating power of each variable [18]. Any data set contains observations with measurements on different variables called predictors and their known class labels. For new observations with predictor values, classes can be determined based on the old data set in case of classification of data [19]. The observations with known class labels are usually called the training data. Training data are used to train the LDA network. After training re-substitution error is computed to know the proportion of misclassified observations on the training set. Then the confusion matrix on the training set is computed to obtain the different sets of misclassification data. A confusion matrix contains information about known class labels and predicted class labels [20]. The element (i, j) in the confusion matrix is the number of samples whose known class label is class i and whose predicted class is j. The diagonal elements represent correctly classified observations.

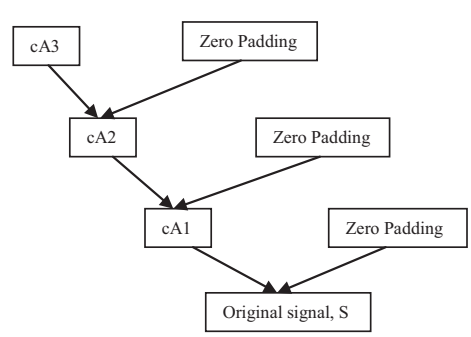

Figure 2 Wavelet coefficient reconstruction up to level 3 to get signal S.

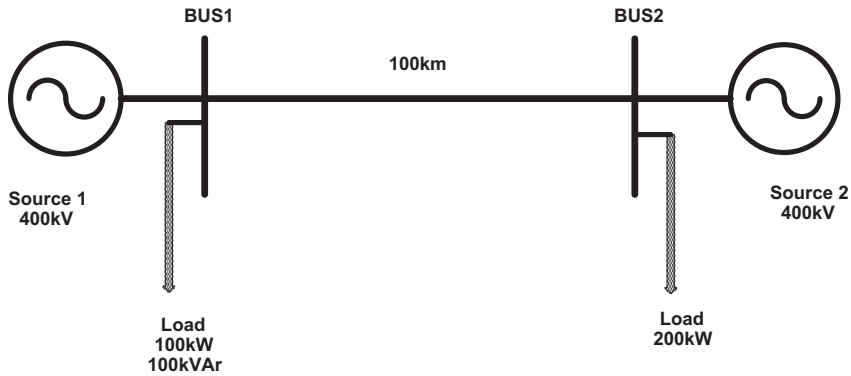

Figure 3 Single line diagram of proposed power system network.

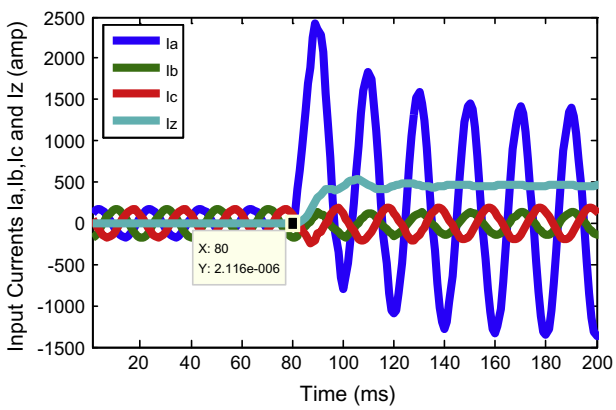

Figure 4 Three phase current signals Ia, Ib, Ic and zero sequence current signal Iz during AG fault at 80 ms.

When another labeled data set is not present, it can be simulated by doing cross-validation. N-fold cross-validation is used for estimating the test error on classification algorithms. It randomly divides the training set into N disjoint subsets. Each subset has roughly equal size and roughly the same class proportions as in the training set. Because cross-validation randomly divides data, its outcome depends on the initial random seed.

Table 1 Confusion matrix of fault detection training module.

Predicted value	Actual value	
	No fault	Fault
No fault	100	0
Fault	0	1900

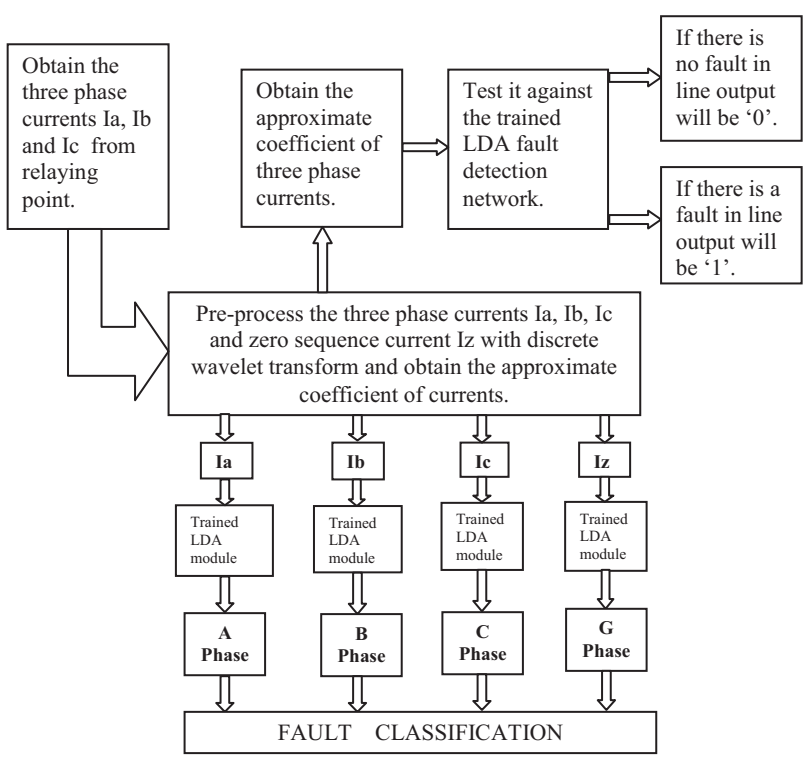

Figure 5 Proposed method for fault detection and classification.

Table 2 Fault detection time in case of near boundary faults (near end and far end) with $R_f = 0.001\ \Omega$ and $\Phi_i = 0°$.

Fault location (km)	Fault detection time (ms)	Fault phase identification time (ms)				Fault classification
		A	B	C	G	
0.1	12	7	–	–	8	AG
0.3	12	–	6	–	9	BG
0.5	12	–	–	8	10	CG
0.7	12	9	6	–	8	ABG
0.9	12	–	8	7	12	BCG
1.1	12	11	–	9	10	CAG
1.3	12	9	7	–	–	AB
1.5	12	–	12	7	–	BC
85	15	10	–	11	–	CA
87	15	7	11	9	–	ABC
89	15	5	–	–	7	AG
91	15	–	9	–	11	BG
93	15	–	–	8	12	CG
95	15	9	6	–	10	ABG
97	16	–	8	9	9	BCG
99	16	7	–	6	8	CAG

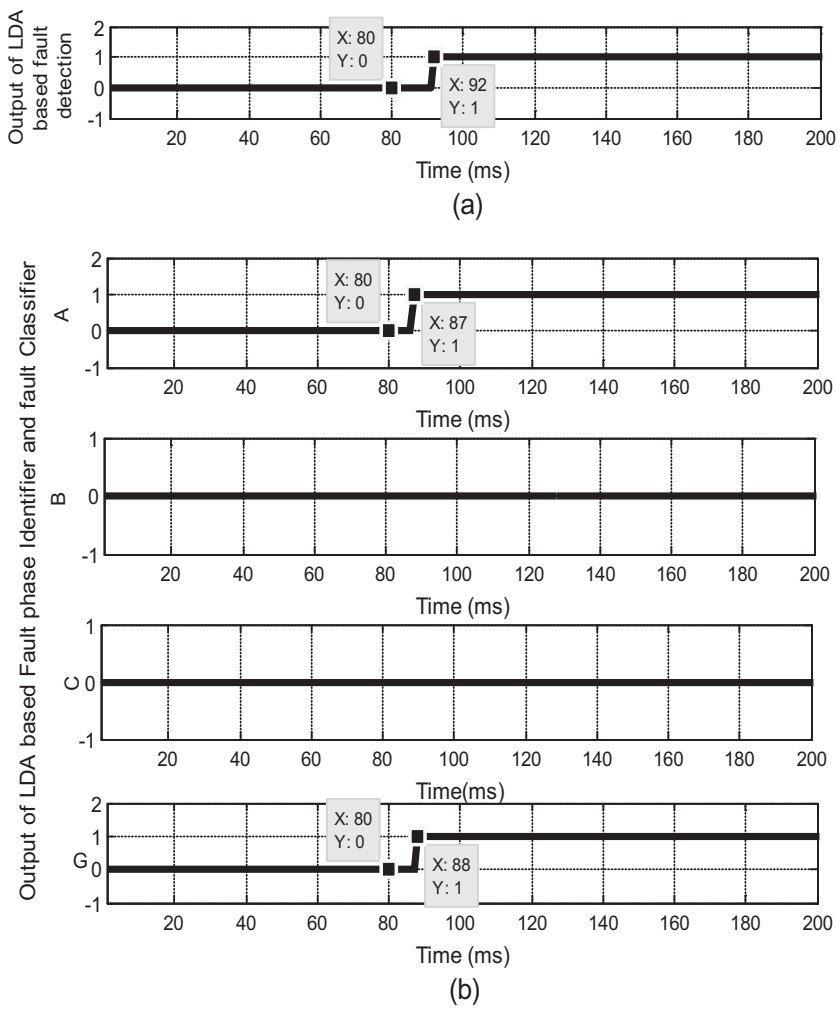

Figure 6 (a) Output of fault detection. (b) Output of fault classification during AG fault for $R_f = 0.001\ \Omega$ and $\Phi_i = 0°$ at 0.1 km.

4. Proposed method using linear discriminant analysis

The proposed method consists of three stages: developing the model of the power system network for fault simulation studies, pre-processing of the signals to obtain the input–output patterns/data set and designing of LDA network for fault detection and fault classification. MATLAB/SIMULINK platform has been used for the implementation of the three stages involved in the proposed method such as fault simulation, signal pre-processing and algorithm implementation. The single line diagram of the power system network under consideration is shown in Fig. 3. It consists of 400 kV, 50 Hz single circuit transmission line of length 100 km. Three phase source of 400 kV, 50 Hz is connected to bus-1 with 100 kW and 100 kVar load, the short circuit capacity of source is 1250 MVA and X/R ratio is 10. At bus-2 a load of 200 kW is connected and another 3 phase source of 400 kV, 50 Hz, SCC 1250 MVA, X/R ratio is 10 is connected.

4.1. Inputs to the network

Three phase current signals are obtained from the relaying point for different fault case studies. To analyze the current signals during faulty condition, consider a single line to ground fault has occurred at 80 ms. The waveform of the three phase currents and zero sequence current during AG fault is shown in Fig. 4. Before the inception of fault, the three phase currents in all the phases are same and zero sequence current has zero magnitude. At 80 ms, AG fault has occurred, so phase "A" current increases and zero sequence current also starts increasing while other phase currents remain same as shown in Fig. 4.

Various fault parameter variations such as fault type, fault location, fault inception angle, and fault resistance are studied. The total number of fault cases simulated for training including variations in fault type: LG, LLG, LL, LLL faults, fault locations, fault inception angles, and fault resistances are 380. Three phase current and zero sequence current signals are processed with DB-4 wavelet up to level 3. In the proposed technique approximate DWT coefficients of three phase currents obtained after wavelet reconstruction process are used as inputs to LDA based fault detector. On the other hand in addition to approximate DWT coefficients of three phase currents and zero sequence currents are also used as input to LDA based fault classifier. Fault detection and classification are carried out in separate modules which will be described below.

4.2. Proposed fault detection method

Proposed LDA based fault detection scheme is shown in Fig. 5. LDA based fault detection module consists of training and testing phase. Training data set for the detection of fault consists of samples of fault and no fault cases. The number of fault samples for one fault case is 5. So total number of fault samples for training is 1900. Total number of no fault samples given in training is 100. So total of 2000 samples are given as input to training module. The LDA based fault detection module detects the fault against the trained LDA network. Input samples of three phase currents are given to the network and trained using LDA. The output of the detector will be low (0) when there is no fault in the system. The output of the detector will be high (1) when there is fault in the system.

Training accuracy is estimated by calculating the re-substitution error and cross-validation error which is 0% in LDA based method. Confusion matrix of the training is given in Table 1. Diagonal values of the confusion matrix show the accurate number of classified data for a particular class. After training network is tested for different fault cases and output of fault detection is obtained which will be discussed in next section.

4.3. Fault classification

After fault is detected the phases of fault are identified using LDA. Proposed fault phase identification and fault classification scheme is shown in Fig. 5. For fault classification separate modules are designed for each phase A, B, C and ground G. Input given to each classifier A, B, C is the phase currents and zero sequence current for ground G. Training accuracy is 100% in case of fault classification. After training the network, test data are generated and tested for checking the performance of the relay for the classification of fault. First fault phases are identified individually and from phase identification output faults are classified.

5. Results and discussion

The proposed relay has been tested for around 5000 test fault cases involving different faults (LG, LL, LLL, and LLG) at 50

Table 3 Fault detection time in case of varying fault resistance with $\Phi_i = 180°$.

Fault type	Fault location (km)	Fault detection (Ω)	Fault resistance time (ms)
AB	12	0	6
BC	22	5	11
CA	32	10	10
ABC	42	10	7
AG	52	0	15
BG	62	20	18
CG	72	40	20
ABG	82	60	12
BCG	92	80	14
CAG	99	100	17

Table 4 Fault detection time in case of different power flow angles with $R_f = 0.001\ \Omega$ and $\Phi_i = 0°$.

Fault type	Fault location (km)	Power flow angle (°)	Fault detection time (ms)
AG	0.1	5	18
BG	1	15	13
CG	11	25	8
ABG	21	35	6
BCG	51	45	4
CAG	61	5	18
AB	71	15	16
BC	81	25	9
CA	91	35	7
ABC	99.9	45	3

different locations with varying fault resistance (0 Ω, 50 Ω and 100 Ω) and fault inception angle (0°, 45°, 90°, 135°, 180°, 225°, 270°). Some of the test results are discussed below.

5.1. Fault near boundaries

In order to check the performance and to evaluate the reach setting of the proposed technique different types of faults at different locations between 85 and 99 km from the relaying point bus-1 with increment of 2 km have been studied. To study performance of relay in case of close in faults various near end faults having fault location ranging from 0.1 km to 1.5 km with step of 0.2 km are reported in Table 2. After

Table 5 Fault detection time in case of different power flow angles and faults with R_f = 0.001 Ω.

Fault type	Fault location (km)	Fault inception angle (°)	Fault detection time (ms)
AG	3	0	18
ABG	13	45	20
AB	23	90	14
ABC	33	135	19
BG	43	180	17
BCG	53	225	13
BC	63	270	20
CG	73	315	18

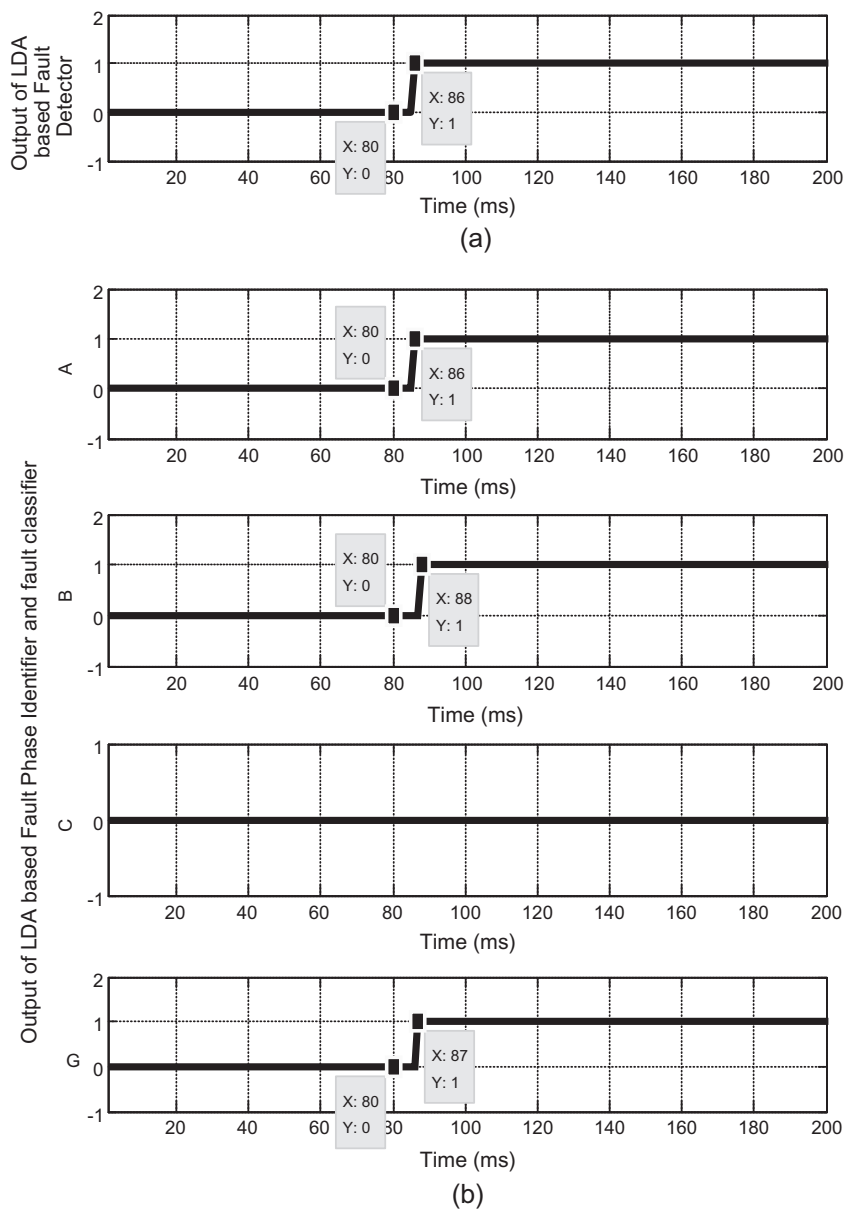

Figure 7 (a) Output of fault detection. (b) Output of fault classification during ABG fault for R_f = 0.001 Ω and Φ_i = 0° at 0.1 km at 80 ms for 25° power flow angle.

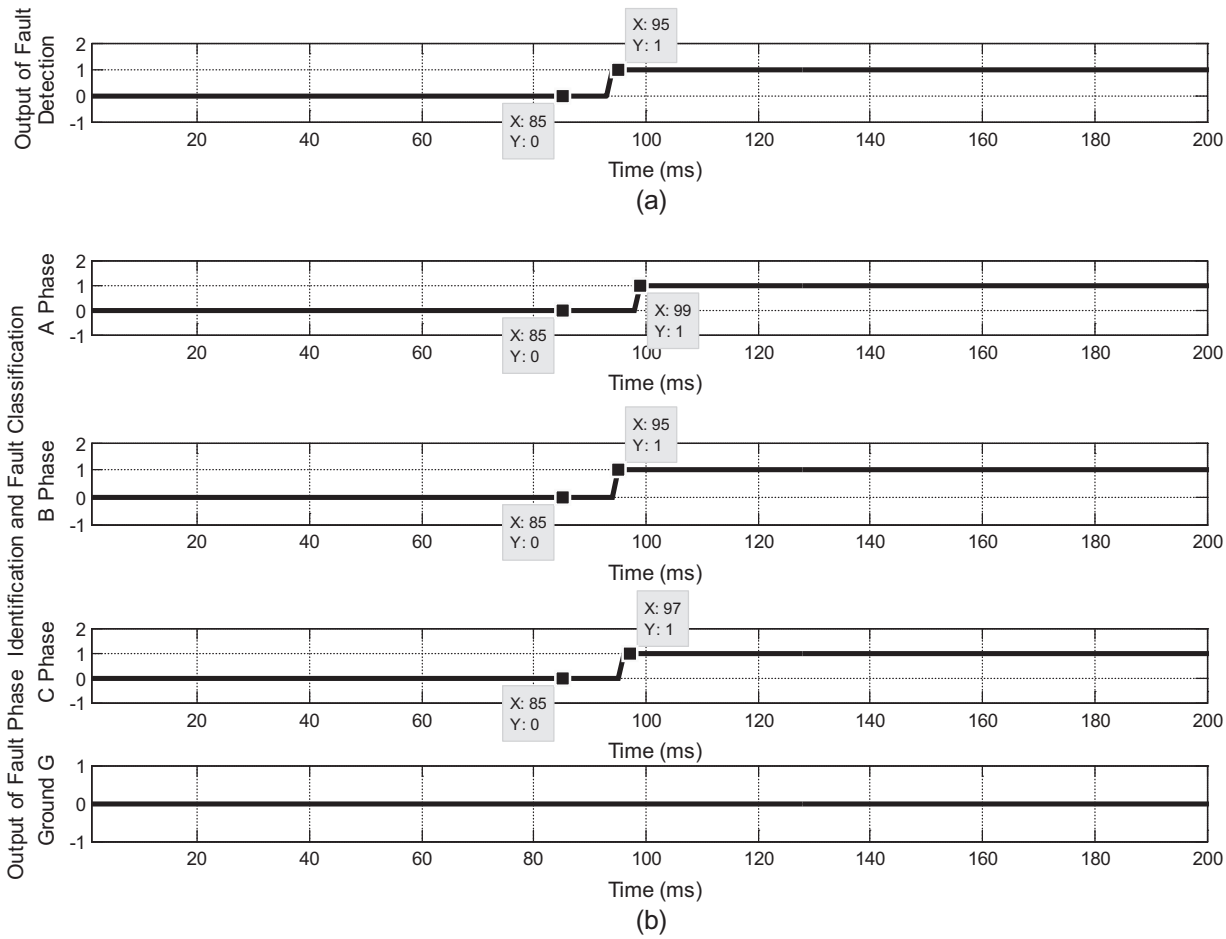

Figure 8 (a) Output of fault detection. (b) Output of fault classification during ABC fault at 65 km with fault resistance of 0.001 Ω and fault inception angle of 90° at 87.5 ms.

Table 6 Fault detection time in case of non-linear high fault impedance.

Fault type	Fault location (km)	Fault detection time (ms)
AG	7	10
BG	27	13
CG	47	14
AG	67	13
BG	87	14
CG	97	14

detecting the fault it identifies the fault phase and classifies the fault. Fault detection time and fault phase identification time are shown in Table 2. It shows that the fault detection time is within 20 ms of time for near boundary faults.

Fault detection and classification at 0.1 km are shown in Fig. 6. Fig. 6(a) shows the output of LDA based fault detection. Output is low (0) up to 80 ms of time shows that there is no fault. After 80 ms it started increasing and reach high (1) at 92 ms of time. So fault detection time in this case is 12 ms. Fig. 6(b) shows the output of fault phase identification and fault classification. Fault phases are A, B, C and G which are the four plots shown in Fig. 6(b). After 80 ms of time A and G phases started increasing to high shows that the fault is AG fault. Fault classification time is within half cycle time in this case. Proposed wavelet and LDA based relay accurately detect the fault for all fault cases.

5.2. Varying fault resistance

The proposed method is also tested for varying fault resistance including high resistance faults. High resistance fault which is not detected by many schemes proposed can be detected by the LDA method. Some of the results are shown in Table 3 for varying fault resistance. Fault detection time is within one cycle for varying fault resistance.

5.3. Varying power flow angle

Proposed LDA based relay is also tested for different power flow angles. Different power flow angles are 5, 15, 25, 35 and 45. Faults are detected and classified in this case. Fault detection time for different power flow angles is shown in Table 4. Fault detection time is within one cycle time for different power flow angles. Fig. 7(a and b) shows the outputs of fault detection and fault classification networks for power flow angle of 25° during ABG fault at 80 ms respectively. Fig. 7(a) shows output of fault detection which becomes high (1) level after 86 ms. Fault detection time is 6 ms in this case.

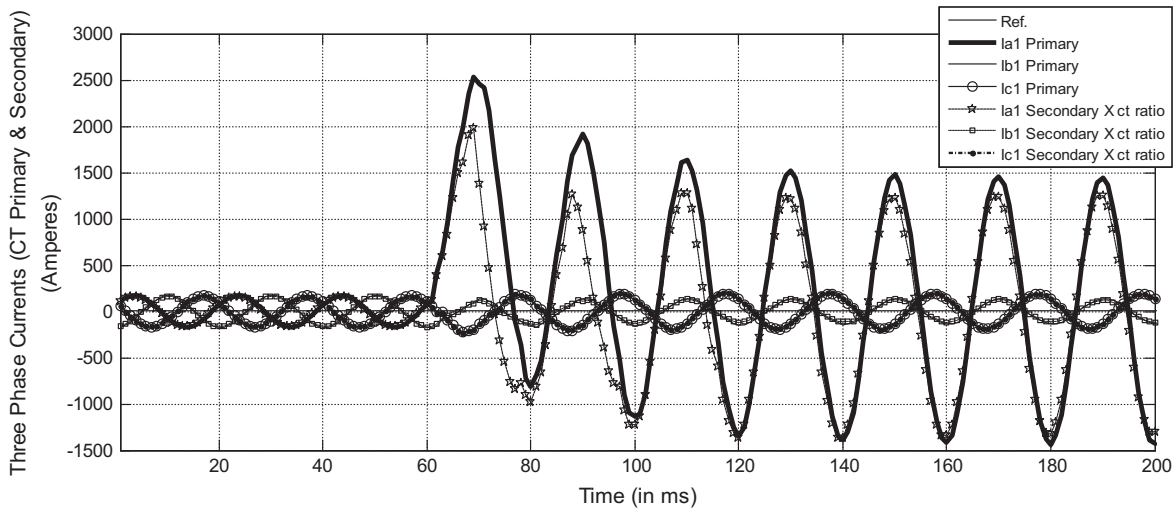

Figure 9 Three-phase current waveforms during an AG fault resistance of 0.001 Ω and inception angle of 0° at 90 km with and without CT saturation.

Table 7 Fault detection time in case of CT saturation.

Fault type	Fault location (km)	Fault detection time(ms)
AG	6	11
BG	16	13
CG	26	15
ABG	36	12
BCG	46	10
CAG	56	16
AB	66	9
BC	76	13
CA	86	11
ABC	96	14

Table 8 Fault detection time in case of double circuit lines.

Fault type	Fault location (km)	Fault detection time (ms)
A1G	9	16
B2G	19	15
C1G	29	11
A1B1G	39	17
B2C2G	49	12
C1A1G	59	15
A2B2	69	14
B1C1	79	11
C2A2	89	18
A1B1C1	99	12

Table 9 Fault detection time in case of multi-location faults.

Fault 1	Fault 2	Fault detection time (ms)
AG fault at 11 km	BG fault at 66 km	18
ABG fault at 34 km	CG fault at 79 km	15
BC fault at 56 km	AG fault at 87 km	17
AB fault at 43 km	CG fault at 91 km	11
BG fault at 81 km	CG fault at 96 km	14
CAG fault at 32 km	BG fault at 98 km	16

Table 10 Fault detection time in case different short circuit capacities of source.

Short circuit capacity of source	Fault type	Fault location (km)	Fault detection time (ms)
1250 MVA	AG	12	14
	ABG	32	17
	AB	52	18
	ABC	72	15
2000 MVA	AG	12	8
	ABG	32	5
	AB	52	5
	ABC	72	5

Fig. 7(b) shows the outputs of fault classification network wherein the faulty phases A, B and ground G start increasing after 80 ms and reach to high level after 88 ms showing that the fault type is LLG and faulty phases are A and B. As depicted in Table 4, the fault classification time for different power flow angles is within one cycle time. Relay operation time is within 1 cycle time for the LDA based relay for different power flow angles with 100% accuracy in all fault cases.

5.4. Varying fault inception angle

Proposed LDA based method is tested for varying fault inception angle and the results are given in Table 5. For all the cases tested for varying fault inception angle, fault detection time is within 1 cycle time. Fault detection and classification outputs during three phase ABC fault at 65 ms at 90° inception angle are shown in Fig. 8(a and b) respectively. Fig. 8(a) shows the output of LDA based fault detection module which becomes high at 95 ms. Fig. 8(b) shows that the outputs of fault classification network wherein all the three faulty phases A, B and C become high after 99 ms, and ground output "G" is low all the time.

5.5. Performance of the proposed method during nonlinear high-impedance faults

The faults with nonlinear high-impedance are simulated using MATLAB and the proposed method is tested for non-linear high impedance fault with arc resistance of 100 Ω where arc resistance is function of arc current. Current threshold for arc extinction is 50 A. Some of the results during nonlinear high-impedance faults are given in Table 6 which shows that the proposed scheme is not affected by nonlinear high-impedance faults.

5.6. Effect in CT saturation

Proposed method is studied to observe effect of CT saturation. Three CTs are used to measure current using the saturated transformer block each rated 2000 A/5 A and 25 VA. To study the effect of CT saturation, CTs are assumed to saturate at 8 pu. Three-phase current waveforms during an AG fault at 99 km with $R_f = 0.001\ \Omega$, $\Phi_i = 0°$ with and without CT saturation are shown in Fig. 9. The test result of LDA based network for fault detection and fault classification with CT saturation is shown in Table 7.

5.7. Performance in case of double circuit line

Proposed LDA based method is also tested for double circuit lines considering the zero sequence mutual coupling effect. Current signals of both the circuits are taken as input to LDA based method for detection and classification of faults. The performance of the relay is tested by some fault cases in both the circuits and few test results for double circuit lines are shown in Table 8. From this Table 8, it can be concluded then the proposed scheme works correctly for double circuit line also.

5.8. Performance in case of multiple location faults

Proposed LDA based method is checked for faults occurring in multiple locations. Multiple location faults are the faults occur at different locations in same time; the conventional digital distance relay is unable to detect multi-location fault occurring at the same time. The performance of the proposed scheme during multi-location faults has been investigated and some of the test results of multiple location faults are shown in Table 9. From Table 9 it can be observed that proposed LDA based method can detect multiple location faults correctly within one cycle time.

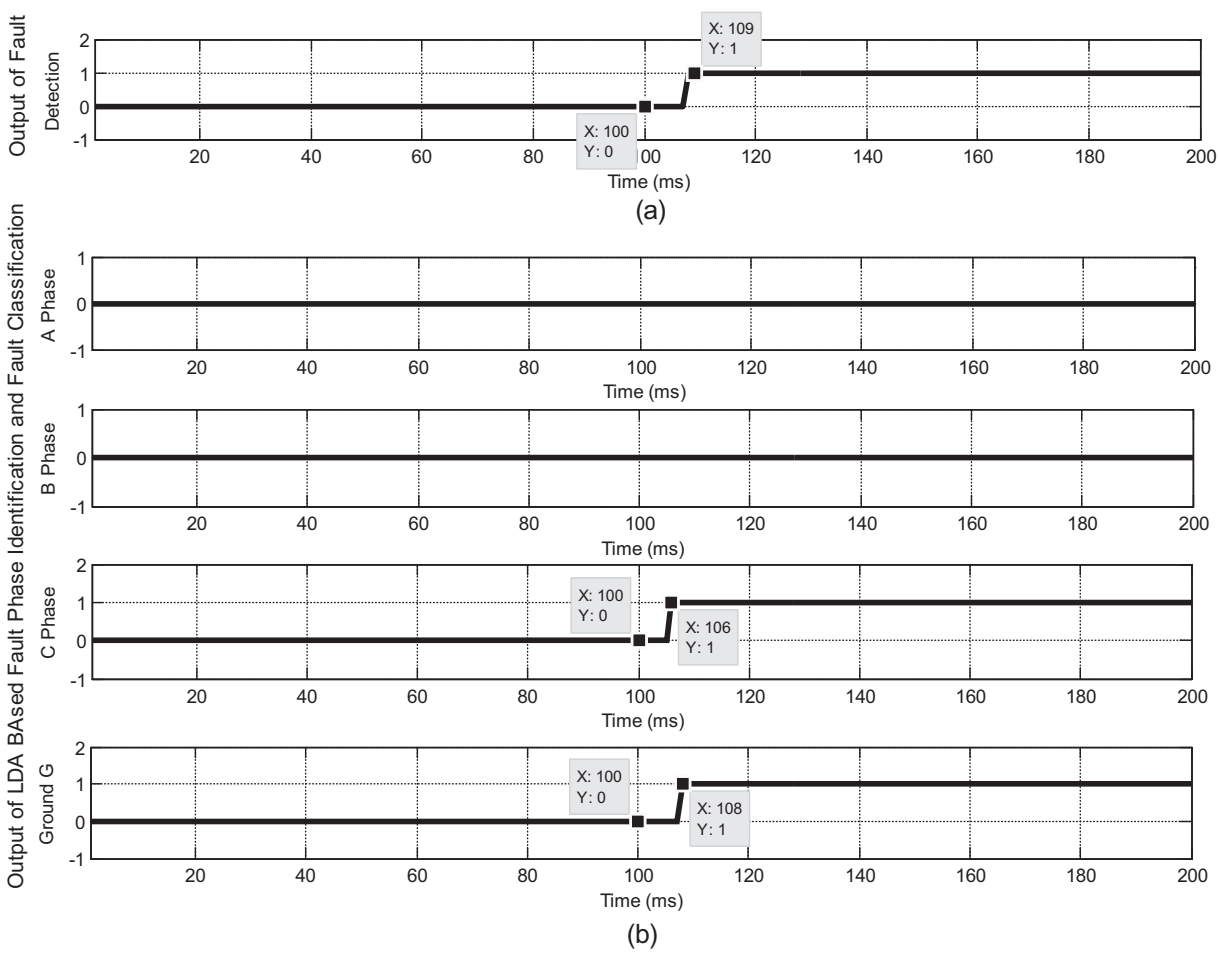

Figure 10 (a) Output of fault detection. (b) Output of fault classification for un-transposed line during CG fault at 70 km with R_f 0.001 Ω and $\Phi_i = 0°$ at 100 ms.

Table 11 Comparison with other schemes.

Methods	Inputs	Algorithm used	Reach setting	Accuracy
Youssef [1]	Three-phase voltage samples of quarter and half cycle	Wavelet transform	90% of line length	Percentage accuracy not mentioned
Upender et al. [8]	Detailed coefficients of phase current signals, measured at the sending end	Use particle swarm optimization (PSO) for training of ANN and wavelet transforms	100%	99.91%
Samantaray [10]	Current signals	Systematic fuzzy rule based approach	90% of line length	98%
Dash et al. [11]	Normalized peaks of fundamental component of current and voltage waveforms of the 3 phases	Fuzzy neural network (FNN)	80% of line length	Not mentioned
Parikh et al. [12]	Samples of one cycle duration of line currents and zero sequence current	Support Vector Machine	80% of line length	98.703%
Gomes et al. [15]	Voltage and current signals of 1.4 cycles	Elliptical 2-D structure	Not mentioned	Highest accuracy up to 98.44%
Proposed method	Three phase currents of quarter (1/4) cycle	Wavelet transform and linear discriminant analysis	99% of line length	100%

5.9. Performance in case of different sources

The power system network under study consists of 400 kV transmission line fed from sources at both the ends and the short circuit capacity of the two sources is considered equal to 1250 MVA and X/R ratio = 10. If the SCC of one source is changed, in that case the current flowing in the line will change, this requires adding the samples of no-fault condition in the training data set. The test result of proposed fault detection and classification scheme for power system network with different source capacities is shown in Table 10. It is clear that the proposed scheme is not affected by variation in source capacities.

5.10. Performance in case of un-transposed lines

The performance of the proposed LDA based fault detection and classification scheme is also evaluated for un-transposed line in this subsection. For this a single line to ground fault in "C" phase of the 400 kV, 50 Hz un-transposed is simulated using ATP-EMTP software and current signals obtained are then pre-processed in MATLAB software and then the proposed algorithm is tested for this fault case and results are shown in Fig. 10. Fig. 10 shows output of fault detection and classification during CG fault at 70 km with fault resistance of 0.001 Ω and fault inception angle of 0° at 100 ms. It can be seen that the proposed algorithm can correctly detect and classify the fault in un-transposed line within one cycle time. This is owing to the fact that the performance of LDA network depends upon the approximate DWT coefficients and not the magnitude of the instantaneous phase current.

6. Comparison with other schemes

Proposed method is compared with other fault detection and classification schemes as shown in Table 11. Most of the techniques given in Table 11 have reach setting within 90% [1,10–12,15] of line length while proposed method has reach up to 99% of line length. Proposed method requires only quarter cycle samples (5 samples) for detection and classification which is advantage. Accuracy of the proposed method is 100% comparison to all the other methods shown in table.

7. Conclusions

This paper presents the wavelet and LDA based fault Detector and Classifier for protection of both single as well as double circuit transmission line against various types of shunt fault e.g. LG, LL, LLG, and LLL. The performance of the proposed scheme is validated considering the effect of CT saturation, variation in power flow angle and different fault parameters such as fault type, fault location, fault resistance and fault inception angle. Inputs given to the LDA based fault detector and classifier are approximate coefficients of three phase currents and zero sequence current. Wavelet re-construction has been applied on the third level approximate coefficients to reconstruct the original signals in time domain. Five postfault samples of these signals are then used to train the network which is an offline process. Once the LDA network has been trained, it is tested for different fault

situations considering variation in different fault parameters. The performance of the proposed scheme has also been tested for multi-location faults which occur at different locations in same time and nonlinear high-impedance faults. The proposed scheme shows excellent results in all these fault cases and the accuracy of the proposed method is 100% for both fault detection and fault classification. Further it is to mention here that the simulation results show that the proposed scheme can detect and classify faults up to 99% of line within one cycle time which is advantage of proposed scheme over other schemes.

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