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Identification and Classification of Power System Faults using Ratio Analysis of Principal Component Distances

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Abstract
Power system reliability operation has been one of the most vital topics under research. The power system network, mostly the long transmission lines is often subjected to different types of faults leading to maloperation of power flow. The idea of a reliable protection system is to most accurately and efficiently identifying the fault, classifying and the locating of fault. This paper represents the application of dynamic phasors in the form of Principal Component Analysis (PCA) to identify fault in a three phase one end fed 150 km long radial power system transmission line. In the proposed work, (1/4) cycle pre-fault and (1/2) cycle post fault line voltages have been extracted from Electromagnetic Transient Programming (EMTP) simulation. The proposed algorithm is trained using only one set of receiving end data carrying out fault only at the midpoint of the line to generate fault signatures using PCA. The eigenvectors and the score matrix thus obtained corresponding to the three phases using the above analysis have been utilized to construct the component distances, which have been analyzed using ratio analysis to extract the similar features of any particular fault individually.

***Keywords**: power system faults, PCA, EMTP, MATLAB, ratio analysis*

1. Introduction

Fault identification and classification of faults is one of the most vital approaches of power system stability and quality management these days. Long transmission lines along with the large scale power systems are the most spatially extended technical systems and fairly often are most vulnerable to minor as well as severe faults since they are mostly exposed to the different atmospheric hazards [1]. The objective of power system fault analysis is to provide enough fault information to the detection mechanism to understand the reasons that caused the system to deviate from normal operation and to restore the normal operation as quickly as possible. Circuit breakers and other protective relaying mechanisms are to be given proper signals to activate the tripping circuit at the correct instants. Hence, prompt and accurate detection of fault along with precise fault distance measurement have been practiced by scientists in order to ensure system as well as protective equipment safety and in present era it has become one of the most promising challenges of the power system study [2- 5].

Power system fault analysis algorithm should be designed in such a way so that it should be highly efficient and accurate as well as it should have general applicability and it should be suitable for real time usage. Researchers have developed so many mathematical and computational tools for the detection, classification and localization of electrical power system faults in conjunction with relaying and protective devices in order to restore system stability at the earliest [2]. Artificial Neural Network (ANN) along with Neuro Fuzzy System and Wavelet based fault pattern recognition techniques have been extensively used these days [3]. But the ANN implementation requires a large number of training data as well as training cycles, thus requiring heavier amount of data and computational burden [6, 7]. Other techniques include wavelet transform with other methods such as Probabilistic Neural Network (PNN), adaptive resonance theory, adaptive neural fuzzy inference system, and support vector machines [8]-[10]. Fuzzy logic has also been combined with discrete Fourier transform, adaptive resonance

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theory, principles of estimation and independent component analysis to enhance performance [11].

Principal Component Analysis (PCA) a useful statistical technique that has found application in various fields of engineering study [12, 13]. It is, now-a-days, quite a common method using multivariate statistical procedure control technique and presently used extensively in power system operation, analysis and control. Dynamic phasor analysis like PCA offer several advantages over conventional methods in several areas of fault analysis like faster numerical simulations, as they produce slower variation even on very fast changes of instantaneous inputs allowing for larger step sizes in numerical experiments and faster simulations [1]. PCA transforms a set of multivariate data to a lower dimension orthogonal space, retaining the most variability of the original information, thus providing with the most significant direction of variation of the given multidirectional data set highlighting broadly the similarities and differences between the various types of faults. Because of the simplification of the analysis and reduced and orthogonal dimensionality of the data obtained, PCA has been used extensively in power system analysis, especially in fault detection, classification and distance prediction where multiple dimensional data are obtained regarding voltage, current and to some extent, power and frequency of the three phase or single phase system. The dimension of the fault data doubles when the test is performed on double circuit lines. In this regard, Component analysis helps quite accurately to reduce data dimension drastically and enables easier, faster and to a great extent, fairly accurate computation [2], [13-17]. Thus PCA has been chosen as the primary computation tool in the proposed work.

In the proposed work, a simple technique for fault identification and classification in a radial system has been developed here. This PCA based fault detection scheme has been adopted here based on the pattern indices and fault signatures generated from phase voltages only. The proposed work investigates the application of dynamic phasors to balanced as well as unbalanced poly-phase power systems. EMTP-ATP simulation software has been used to develop and simulate the long transmission line model. 15 blocks of 10 km each has been interconnected in a radial network in a 400 kV-150 km long three phase single circuit transmission line. The simulation was followed by analysis of the three phase voltage waveform for classification of fault types using PCA algorithm in the MATLAB environment. Different types of faults along with the healthy condition of the network under varying fault locations have been tested for better robustness of the proposed power system protection algorithm which shows very much appreciable performance in prompt detection within half cycle after the occurrence of the fault. In the proposed work, EMTP simulation has been restricted to uncontaminated healthy signal only, i.e. only healthy voltage waveform i.e. pure sinusoidal signal of 50 Hz free from any harmonics has been considered here.

In the first phase of this paper orientation, simulation process in detail has been discussed here along with the methods of data collection. In the following stages, the proposed fault detection algorithm has been described elaborately with necessary figures and computations of the results obtained there from have been carried out. Finally, the utility and usefulness of the component analysis in power system fault diagnosis in relation to the results obtained has been discussed.

2. System Design

In the proposed work, a 400kV 150km long three phase transmission line model is experimented to obtain the necessary voltage and current waveform of the different fault condition of a radial power system network. In the proposed algorithm, only the receiving end three phase voltage waveform has been taken as the only experimental data. The single line schematic diagram of the EMTP simulated single source, one end fed radial power system network is shown in Figure 1. The voltage waveforms are monitored from the receiving end only for different types of faults occurring at different locations of the transmission line.

As shown in the Figure 1, the single side fed 400kV 50Hz power transmission system consists of an AC voltage source as the only power source. Fifteen three phase Line Cable Constants (LCC) blocks of 10 km each are connected in cascade for structuring the simulation model of a 150km long overhead transmission line [18, 19]. The frequency dependent ‘JMarti’ model has been adopted here as the basic LCC building block of the power system network [18-21]. The line resistance is taken to be 20 Ohm/km; the fault resistance is taken to be 10Ohm.

For 10 different types of faults occurred at different locations, the faulty voltage signals are collected and analyzed in ATP analyzer. The sampling frequency is kept fixed at 2000 samples/cycle, i.e. for the 50Hz sinusoidal signal, each cycle of 20ms is sampled into 2000 discrete values, yielding a sampling frequency of 100kHz.

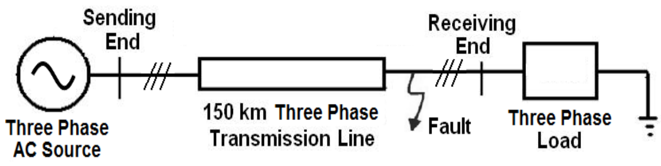

Figure 1. Schematic Diagram of the Simulated Single Fed Long Transmission Line

2.1. Building the System and Classifier Algorithm

The proposed power system long transmission line fault detection and classification algorithm is designed based on the Principal Component distances of each of the three phases obtained on processing the different fault voltage waveforms corresponding to different fault types. After the protection algorithm is designed, it is trained using training data set. In the proposed work, only one set of receiving end three phase voltage data corresponding to healthy condition and ten different types of fault (e.g. single-line-to-ground fault for phase A, phase B and phase C, double line fault for line AB, line BC and line CA, double-line-to-ground fault for line AB, line BC and line CA and finally three phase symmetrical fault) conducted at 70km from sending end, i.e. almost the midpoint of the transmission line is taken as the only training data. After training the PCA based protection algorithm intended for fault detection and classification, it is tested extensively using independent data sets consisting of different fault types and conditions carried out at different distances from the sending end. The fault locations are changed for ten different types of faults to investigate the effects of these factors on the performance of the proposed protection method. The EMTP simulation model of the radial system used in the proposed work is shown in Figure 2.

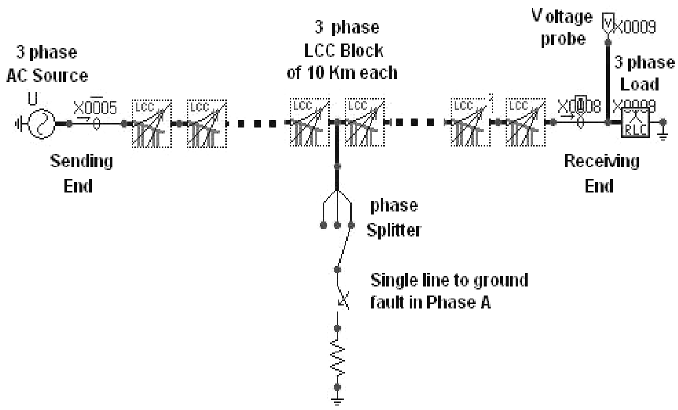

Figure 2. EMTP Simulation Model of the Radial, Single End Fed, Long Transmission Line for a Single Line to Ground Fault in Phase A

2.2. Training of Classifier Algorithm

The component analysis technique has been adopted here to identify and classify different types of faults. The receiving end three phase sampled voltage data corresponding to one healthy condition and ten different types of faults carried out almost at the midpoint of the 150 km long transmission line has been taken as the only set of training data. For each of the waveforms, quarter cycle pre fault and half cycle post fault voltage data has been taken for each waveform. Since sampling frequency has been taken as 2000 samples/cycle, the total sample data for each set of fault and each phase comes out to be 1500 samples. Thus the training data is a set of 11 × 3 vectors (10 types of faults and 1 healthy condition of the three phase voltage waveform) each consisting of 1500 data. The data thus taken has been used for training purpose only. Since Principal Component Analysis has been adopted here to analyze the voltage data, the principal components i.e. the most useful directions of variation of the scarred data and the score values are obtained as the defining parameters. In the proposed work, only the two major principal components have been taken to build the proposed algorithm i.e. only the two most primary correlated directions and the two corresponding directional score data. Thus the calculation has been restricted to two dimensional analysis only which has yielded satisfactory results. Using the two directional score values, the distance vectors have been calculated.

This distance vector is actually a measure of the difference or distance of the waveforms of each type of fault from the healthy signal. This distance computation has been carried out for each of the three phases and a total of 3 sets of 11 data i.e. 33 training data have been computed, each corresponding to different type of faults of the three phases. Another important point to be noted here in this context is that all the data have been scaled with respect to the peak value of the voltage signal at healthy condition so that even if the voltage level changes or in any other situation causing a change in the voltage or current level, a scaled or proportional value of the corresponding fault voltage is always used, thus generalizing the algorithm to suit any of voltage or current level.

2.3. Testing of Classifier Algorithm

Next, the test data have been taken as the three phase voltage waveform of the unknown fault or the healthy condition. Thus the test data is a 3×1500 matrix. This unknown data is compared with the same healthy waveform used for training and the score matrix is thus obtained for the unknown type. The score values are obtained from component analysis and the corresponding distances from the healthy phases are plotted for the three phases. The distances of each of the phases are compared with the ten different training fault data and the nearest distance mapping is obtained for each. Thus proximity analysis has been applied here to compare the experimental data with the fault signatures to find out the nearest distance or the maximum similarity with any of the ten different types of fault and the pure (healthy) signal.

3. Simulation Results

After simulating the power system transmission line model and acquiring the requisite data from EMTP-ATP simulation software followed by ATP draw data processing, the proposed protection algorithm is implemented in MATLAB environment. The fault data thus obtained have been processed by the proposed algorithm and detailed analysis has been carried out depending on which the test data have been categorized into different types of faults or no fault type.

Figure 3 shows the score plot of PCA which have been used as the fault signatures in the proposed work. Only the two primary directions or vectors i.e. the two most vital principal components of the score matrix are taken here to execute 2D computation of the three phase system. These figures show the cluster of different training fault data at different coordinates in the principal component axes plane. Thus combining all the three phase PC scores corresponding to each type, a 3D plot have been obtained and shown in Figure 4. Using these three different phase score values and taking the healthy phase as the reference, PC distance of each type of faults have been computed for the three phases and have been tabulated in Table 1 and graphically represented in Figure 5.

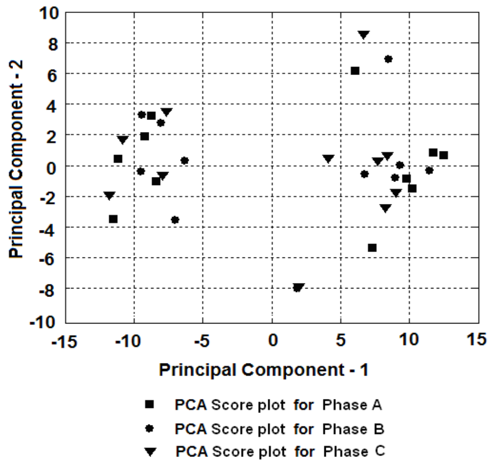

Figure 3. Principal Component Analysis Score Data of Three Phase Receiving End Voltage for 10 Types of Faults and Healthy Condition

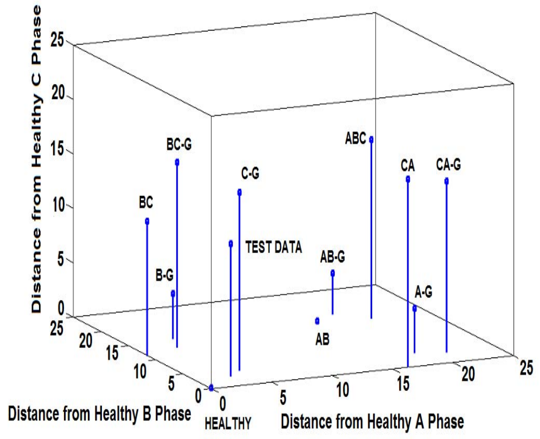

Figure 4. 3D Plot of Score Data Obtained after Carrying PCA for 10 Types of Faults, Healthy Condition and Test Data for the Three Phases

Table 1. Distance Matrix Formed by Analysis of the PCA Scores: Distance Matrix of the Three Phase Voltage Data Processed by PCA Based Proposed Algorithm of Healthy Condition and Different Types of Faults and Test Fault Data

Fault Type	Phase A	Phase B	Phase C
Healthy	0	0	0
A-G	18.59729408	3.897986946	4.079740659
B-G	3.942976457	15.59829201	4.132440837
C-G	4.306247249	4.30678011	16.32217946
AB	16.16352877	16.1619939	1.24E-14
BC	2.09E-15	11.60136715	12.27056062
CA	16.28723458	5.58E-15	17.24842321
AB-G	18.1715204	17.79263515	3.740532332
BC-G	3.134059665	13.07128151	16.97439821
CA-G	20.93901863	3.227872333	15.64272568
ABC	20.21006866	15.29592405	16.37250854
Test Data	3.017460919	3.02520429	12.10775897

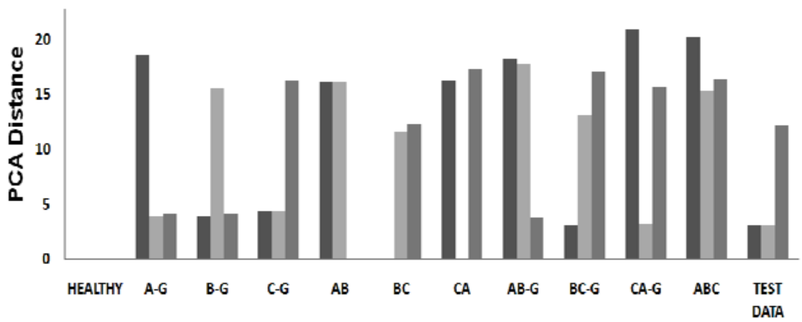

Figure 5. PCA Distance Plot for the 11 Training Data Set and the Test Data

Thus, observation of Figure 4 shows that the unknown test data plot is closest to the C-G fault than any other type, i.e. the vector distance of the unknown test data is least with C-phase-to-ground fault than compared to any other type. When vector analysis or similarity analysis is carried out with the score plot, the above conclusion is reached mathematically. When data corresponding to different locations but of the same fault were taken and compared, the distance computed was coming out to be minimum with the particular type of fault under test, i.e. in each case showing the true result, although the PC distances counted to be somewhat different for different fault locations.

4. Analysis of the PCA Output and Protection Algorithm Design

The topology used here is the ratio analysis of the obtained distances. On close observation of the PC distance matrix of the training data and the unknown or test data, as given in Table 1, it can be observed that for each of the three phases, the ratio of the PC distances i.e. the divergences of the voltage waveforms from the pure signal of the corresponding phase for the training data to the unknown fault at different distances vary in a definite pattern for each particular type of fault, e.g. say, for single line to ground fault for phase A, the ratio of the three phase distance vector of the training distance data (here being 70 km from the sending end) to the three phase distance vector for all the different distances are extremely analogous to each other and also vary in a certain pattern as the distance is increased or decreased away from the training point. On observation of Table 1, it can be observed that the no-fault or healthy condition is taken as the reference where each PCA distance value is taken as zero or reference and with respect to this reference value, all the other distance values have been derived. Figure 4 shows the PCA distance plot of the different training data along with the test data, all with respect to the healthy condition which is coming out to be zero for all the three phases. So, in order to establish the above observation in algorithm form, three different ratios has been taken for all the twelve conditions, i.e. eleven training data as well as the test data as follows:

a) Ratio 1 is the ratio of the PC distance of phase A to the PC distance of phase B,
b) Ratio 2 is the ratio of the PC distance of phase B to the PC distance of phase C,
c) Ratio 3 is the ratio of the PC distance of phase C to the PC distance of phase A,

Thus, when the above three ratios are computed say for this particular test data, the results are computed and tabulated in Table 2. Plotting the values in graphical form, Figure 6 is obtained.

Table 2. Ratio Matrix Formed by the PC Distances of the Three Phase Voltage Data Processed by PCA Based Proposed Algorithm of Healthy Condition and Different Types of Faults and Test Fault Data

Fault Type	Ratio 1	Ratio 2	Ratio 2
Healthy	1	1	1
A-G	4.770999579	0.955449689	0.21937281
B-G	0.252782577	3.77459536	1.048051106
C-G	0.999876274	0.263860603	3.790348885
AB	1.000094968	1.30E+15	7.70E-16
BC	1.81E-16	0.945463497	5.86E+15
CA	2.92E+15	3.24E-16	1.059014845
AB-G	1.021294499	4.756712032	0.205845865
BC-G	0.239766825	0.770058611	5.416105633
CA-G	6.486941389	0.206349737	0.747061071
ABC	1.321271509	0.934244378	0.810116423
Test Data	0.997440381	0.249856666	4.012565297

On close observation of the ratio matrix thus formed, the key features which have exploited in the design of the proposed algorithm can be observed. For instance, here single line to ground fault for phase C (SLG-C) at 30km distance from the sending end has been taken as the test data and the corresponding PCA distance data comes out to be 3.0175: 3.0252: 12.1078 as shown in the final row of Table 1. This signifies that A and B phases have been disturbed by the fault to some extent, but the major undulation has occurred in the third line, i.e. in C phase which has been directly faulted to ground. This is what can be expected theoretically.

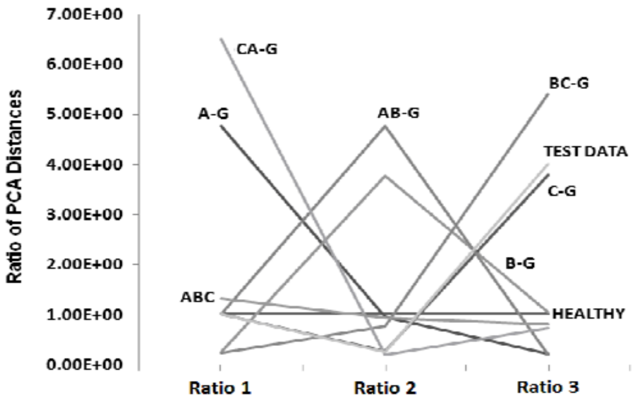

Figure 6. Ratio of PCA Distances of the Three Phases for Different Types of Faults used for Training, Test Data and the Healthy Condition

Again, it can be easily seen that the same fault i.e. SLG-C when taken during the training purpose at the midpoint of the transmission line, the PC distance values for the three voltage waveforms corresponding to the three phases were 4.3062: 4.3068: 16.3222 as shown in row 4. In this context, it may be noted that all the types of faults and the test fault under test are all compared with the same healthy signal to find out PCA distances of each type with respect to a fixed reference, for each of the three phases. In this particular case, for both the testing data and the corresponding true training data (here SLG-C), the three ratios are coming out to be around 1:0.25:4 as is observed from the 4th and 12th row of Table 2. This is also observed that both these ratios remain almost similar and more accurately, within a predefined tolerance level as the fault location is varied. Figure 6 is the graphical representation of Table 2. From this figure, it is also observed that test data line is matching almost identically with the SLG-C (C-G in fig. 6) line, i.e. both the lines have almost superimposed. On the contrary, the test data line is deviating far away from all the other types of fault as evident from Figure 6. On similarity analysis using the least square method between the test ratio data and all the twelve different types of training ratio data, the minimum deviation is found out. In this particular example, the test data deviated least from SLG-C line and much higher value of squared error was obtained for all other types.

The double line faults are not shown in the figure because it is observed from 7th, 8th and 9th row of Table 1 that for this type of fault, the two fault involving phases are deviated the most, i.e. their PC distances are much higher whereas the third healthy phase has almost zero deviation from healthy condition showing that this particular phase has been least disturbed by the particular type of fault, e.g. for line-to-line fault between lines A and B, the PC distances for A and B phases are 16.16352877 and 16.1619939 respectively and 1.24E-14 (which is almost equal to zero) for the healthy C phase. This feature has been exploited to easily and explicitly to find out line to line type of faults directly in the proposed algorithm. But for the line-line to ground faults (LLG), the third phase PCA distance is not exactly coming out to be zero, but something much higher than zero showing the involvement of ground in the fault, thus indirectly affecting the apparently the undisturbed third phase, thus making a differentiation between the two types very clear. Hence for the ground faults, the ratio analysis has been adopted. Here lies the novelty of the proposed scheme in applying the ratio analysis using the PC distances to good effect to find out especially ground faults and this direct double line fault classification. Hence, the proposed algorithm is most satisfactorily successful in determining and classifying the fault. It can also be observed from the same figure that different faults have different three phase PC distances. Although this ratio is differing from one type of fault to the other, but, for any particular type, this ratio of the three phase voltage PCA distances are remaining all within a certain limit on varying the physical distance of fault from sending end.

This design of the power system protection scheme has yielded a very good result of 100% overall accuracy as evident from Table 3 Thus the major point of interest is that by setting a properly judged limit of these three phase PCA distance ratios for the 10 different types of faults and the healthy signal the exact kind of fault can be easily defined. The entire PCA based algorithm for identification and classification of fault has been shown in Figure 7 in the form of a flowchart.

Table 3. Results Showing the Fault Classifier Performance with Only One Set of Training Data

Fault Type	Pure	AG	BG	CG	AB	BC	CA	ABG	BCG	CAG	ABC
Pure	**13**	0	0	0	0	0	0	0	0	0	0
AG	0	**13**	0	0	0	0	0	0	0	0	0
BG	0	0	**13**	0	0	0	0	0	0	0	0
CG	0	0	0	**13**	0	0	0	0	0	0	0
AB	0	0	0	0	**13**	0	0	0	0	0	0
BC	0	0	0	0	0	**13**	0	0	0	0	0
CA	0	0	0	0	0	0	**13**	0	0	0	0
ABG	0	0	0	0	0	0	0	**13**	0	0	0
BCG	0	0	0	0	0	0	0	0	**13**	0	0
CAG	0	0	0	0	0	0	0	0	0	**13**	0
ABC	0	0	0	0	0	0	0	0	0	0	**13**
					Overall Accuracy:		**100 %**				

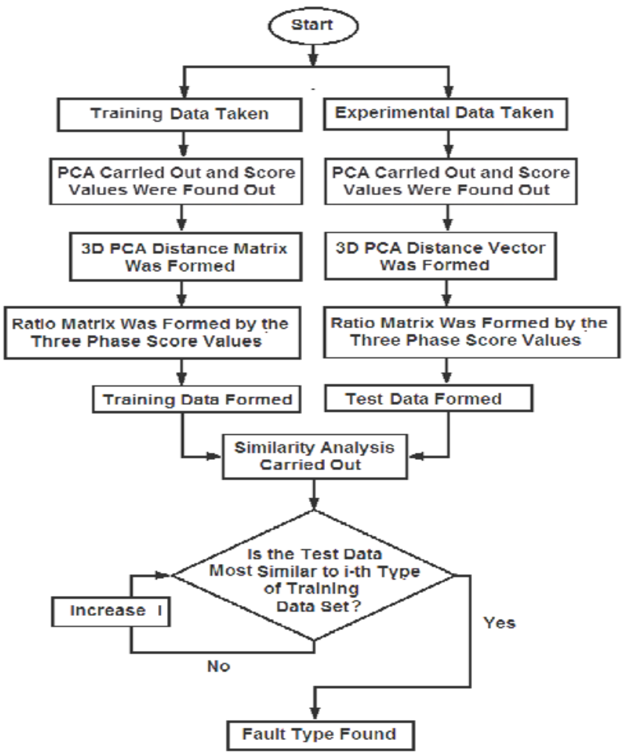

Figure 7. Flowchart of the Proposed PCA Based Protection Algorithm

Analysis of Table 4 shows that the proposed algorithm works very well to find out accurately each of the faults occurring at different locations from the sending end. The fault classifier accuracy becomes 100% with the proposed algorithm, i.e. the proposed classifier can successfully identify each fault and very successfully classify it according to the different training category. It is also observed that even when the protection scheme is tested with pure receiving end three phase voltage signals varying the magnitude of voltage, still the classifier is able to identify it to be a healthy system. Thus the system is well equipped with the capability of identifying fault from no-fault.

Table 4. Results Showing the Fault Classifier Performance with Varying Fault Locations

Location of the Fault (km)	Total Data Taken	Correct Results	Wrong Results	% Accuracy
10	13	13	0	100
20	13	13	0	100
30	13	13	0	100
40	13	13	0	100
50	13	13	0	100
60	13	13	0	100
80	13	13	0	100
90	13	13	0	100
100	13	13	0	100
110	13	13	0	100
120	13	13	0	100
130	13	13	0	100
140	13	13	0	100

5. Conclusion

A novel and effective power system protection scheme for the identification and classification of faults has been proposed here for a single side fed 400kV, 50 Hz, 150 km long radial transmission line. For this purpose, Principal component Analysis (PCA) tool has been used to idealize, design and implement the proposed protection algorithm. In order to perform the experiment, a power system transmission line model in EMTP simulation software has been designed and processed the data in ATP draw to obtain the receiving end fault voltage waveforms. MATLAB environment has been adopted for the design of the proposed algorithm. The design is made in such a way so as to identify any kind of fault

In order to design the protection scheme, PCA scores have been calculated for each phase using which, PC distance matrix has been constructed. These PC distances have been made to undergo a novel and simple ratio analysis algorithm so developed to identify faults directly. The results so obtained reveal that the classifier has successfully detected and identified each type of fault and justified the classification with 100% accuracy.

Based on the PC distances and the ratio analysis of these values, the proposed scheme is so robustly designed that, only one set of training data has been used which proved to be sufficient to produce 100% correct result for ten different faults carried out over the whole 150 km length, whereas most of the related woks have used more than one training data set, and some have used several.

Thus, the proposed algorithm requires much lesser execution time and lesser mathematical complexity due to the processing of only a single data set, thus allowing the circuit breaker to operate more quickly which is one of the most imperative part of any protection scheme. This faster operation, lesser memory requirement and finally and most importantly, the highly accurate ratio analysis process are the novel areas of this research work. Hence, it can be stated that the fault classifier has all the possibilities of developing an accurate fault classification scheme that may aid the development of reliable transient-based protection schemes. It is intended to carry out further investigations to further confirm the robustness and flexibility of the classifier performance under different varying conditions. The proposed scheme is also very simple and easy to implement in real time operation, thus having all the aspects of being implemented in practical power system network.

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