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Distribution System Fault Detection and Classification using Wavelet Transform and Artificial Neural Networks

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Abstract

The detection and classification of fault and its location in electric power distribution systems is a complex task due to availability of large number of buses/nodes and laterals in the distribution system. This paper presents a methodology for automatic fault detection and classification in electrical power distribution systems using the concept of signal analysis, wavelet transform, pattern recognition and artificial neural networks.In order to extract the characteristic features of the faulty signals, discrete wavelet transform was used on the collected data of phase currents and neutral currents. From the high frequency component signals that occurs during the fault, signals information are extracted and used as an input data to train the artificial neural networks for fault detection and classification. After the fault classification is done, different Neural Networks can be trained for fault location in the network separately. Thus, the fault detection and classification algorithm becomes the base for the fault location technique. The training data are selected in such a way that the differences in data are achieved and the neural networks clearly identify the fault types and fault location in the distribution system. A standard IEEE 15 bus distribution system, with 11 KV, 50 Hz supply at the substation with total feeder load of 1126.5 KW and 1251.182 KVAR was used to test the proposed algorithms, providing the good performance result for all fault types at various location for low fault resistances.The fault detection and classification algorithms work effectively for the ground resistances of 20 ohms and less. The single point current measurement at the sub-station and then extracting the features of fault signals using Discrete wavelet transform to train the neural networks require less memory and reduces the computational time. Thus, this paper is able to detect the fault occured and classify the type of fault in any distribution network.

Keywords

Fault Classification, Fault Detection, Artificial Neural Networks, Pattern Recognition, Distribution Network, Wavelet Transforms, Multiresolution Analysis

1. Introduction

The electric power system consists of various elements from the generating stations to the consumer end for proper operation and smooth flow of electric power. But these elements are prone to the disturbances and the faults occurring in the network. So, the power system must have protection systems that should be able to detect and clear the fault in least possible time. The generating stations and transmission lines are mostly protected by the utility at installation time by predicting the faults and disturbances in those systems. While talking about the distribution network, distribution lines have to bear various climatic conditions, falling of trees, accidents due to public and private transports, human and animal contact, equipment failure and other factors[1]. These events can cause the faults to occur in the distribution lines.

The technological advancement and economical growth has increased the requirement of the efficient and reliable electrical power to the consumers, thus creating a new opportunities for research in that field so as to meet their requirements [2]. Since the consumer uses the electricity for their sensitive loads [3], so it is required to have no or minimal voltage drop and frequency deviations[4]. The purpose of electric distribution system is power supply continuously within the accepted range of voltage and frequency deviations, having sine waveform of the supply, reliably and with least outage time[5, 6]. Thus, fault classification and location program becomes crucial for the analyzing the causes of fault and restoring the power supply quickly and effectively. For this reason, the research work regarding the fault location is seeking attention now-a-days. But, most research work is being done in the fault cause and classification or location in the transmission networks. Hence, a good fault detection and classification system in distribution network is needed which helps the utility to provide reliable, quick, secure and efficient power supply through the distribution system network to its valued customers[7].

The fault classification and location methods can be divided into three categories- impedance and fundamental frequency based methods, high frequency and travelling wave based methods and Knowledge based methods like machine learning approaches [8]. The impedance based method is simple with low accuracy while high frequency and travelling wave based method are not used effectively now a days due to its complexity. The advancement of machine learning approaches are finding more attractions for the fault analysis since it is more accurate and requires least time for the classification and location by extracting the features of the faulty signals. Thus, the concept of Wavelet Transforms , Multiresolution Analysis, wavelet energy entropy and Artificial Neural Network are used for the fault classification and determination of fault location [9, 10, 11, 12].

The methods based on impedance calculations and fundamental frequency [12, 13, 14, 15, 16], high frequency and travelling wave method[17],wavelet and travelling wave theory[18], wavelet concept and machine learning approach[19, 20, 21], and hybrid methods[12] has been proposed for fault classification and location in distribution and transmission networks. The measurement of both current and voltage quantities at different buses or along the line using various meters needs more memory and large computational time to process the data and display the result.

2. Methodology

The fault detection and classification in distribution network is done by the analysis of wave-forms as seen from the display installed at the substation. The three phase currents and neutral currents data are collected from the smart meters connected at the substation for the normal conditions and the faulty state in the distribution network. The proposed methodology uses the modern concept of using the wavelet transform to determine the detail coefficients of the transient signals after the disturbance occurred in the network due to the fault. Figure-1 shows the proposed methodology of fault detection and classification in a distribution system network.

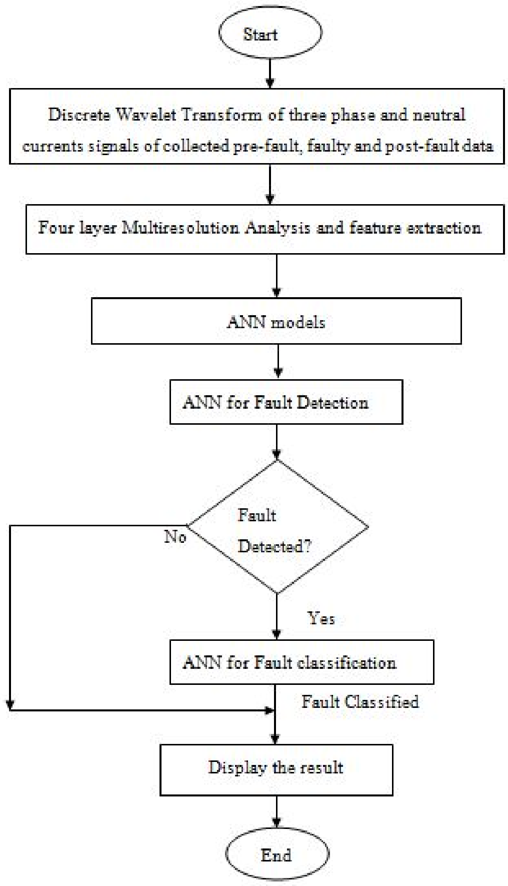

Figure 1: A proposed Algorithm of Fault Detection and Classification in a Distribution Network

The purpose of the proposed methodology is to first detect the fault occurred in the network and then classify the fault type.The discrete wavelet transform and multiresolution analysis is used to extract the features of the faulty signals and then using the absolute sum of the decomposed signals as an input of neural network helps to detect and classify the fault.

2.1 Data Collection Algorithm

It is crucial to attain the real fault data of any network. So, in order to generate the normal and faulty data in the distribution network, the data collection algorithm is used for this purpose. For collecting the normal and faulty data of the distribution system, the Simulink model is developed in the MATLAB/SIMULINK environment of a standard IEEE 15 bus distribution network. The pre-fault data was collected by running the simulation in normal condition. Then 10 types of fault i.e. AG, BG, CG, AB, BC, AC, ABG, BCG, ACG and three phase fault is introduced one by one in each section for different distance and the simulation was done to generate the fault data and stored them in an excel sheet.For data generation, 3 phase balanced and unbalanced load was considered and low impedance fault was taken into consideration. The bus and line data was taken as per the given standard values of IEEE 15 bus. Figure-2 shows the flowchart of data collection procedure in a distribution network.

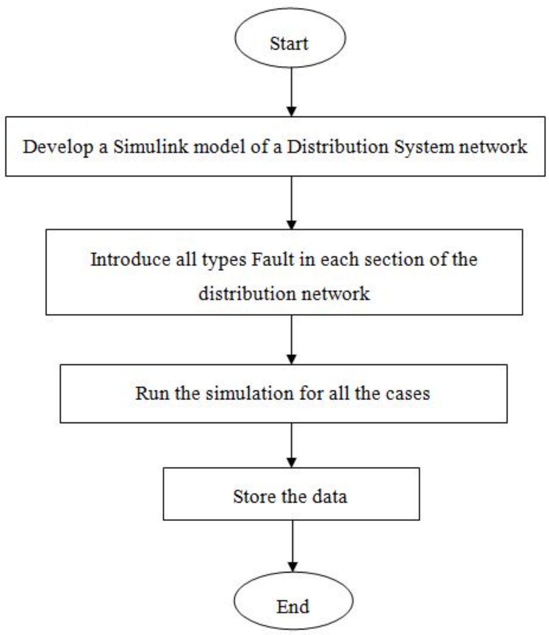

Figure 2: A Fault data Collection Algorithm in a Distribution Network

2.2 Wavelet Transform

The wavelet transform is very useful tool for the analysis of signals that contains transients, noises, aperiodicity, intermittency, disturbances, sag or swell conditions and other abnormal behavior of the signals. The wavelet transforms, being able to examine and analyze the signal in both time and frequency domain, makes it very effective and appropriate in the power system network analysis [22]. The discrete wavelet transform of the signals can be found by using equation (1) and (2) listed below [23].

$$DWT(m,n) = \sum_{-\infty}^{\infty} x(t) * \Psi^{*}_{m,n}(t)dt \qquad (1)$$

$$\Psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}} * \Psi(\frac{t - na_0^m b_0}{a_0^m}) \qquad (2)$$

where $\Psi_{m,n}(t)$ is the mother wavelet, ‘m’ denotes the discrete steps of scaling parameter or level , which determines the wavelet frequency and ‘n’ denotes the discrete steps of translation parameter or the position, * stands for complex conjugate. The scale parameter $a = a_0^m$ and translation parameter $b = na_0^m b_0$ where $a_0 > 1$ and $b_0 > 0$ in finding the DWT of the signal x(t).

The DWT, on the basis of the sub-samples of the CWT, makes the analysis of the signals much more efficient, reducing computational time and memory, easy implementation and even complete recovery of the original signal with no loss of data. A continuous time signal can be discretized by choosing appropriate sampling frequency based on Nyquist Theorem stating that the sampling frequency should me minimum of twice the available highest frequency present in the signal. Mallat(1989) developed an approach called Mallat Algorithm to implement DWT, in which the signal is passed through high pass filters (HPFs) and low pass filters (LPFs) to obtain the detail and approximate frequency components respectively.

2.3 Multiresolution Analysis

The structure of MRA wavelet decomposition in four level is shown in Figure-3. The original signals having n samples passes through the two filters HPF and LPF represented by g(n) and h(n) respectively,as shown in Figure-3, which separates the frequency content of the input signal in frequency band of equal width.

The discrete wavelet transform uses multi-resolution analysis of the signals by the implementation of the HPF and LPF banks to detect the features of the sampled signals. The signals are decomposed into more than one resolution and scales to extract the approximate and detailed information contained in the signals [24]. Thus the features that may go undetected at one resolution can be easily detected in the further resolutions. Thus, the wavelet transform and multi-resolution analysis of the signal is very useful and appropriate method for feature extraction of the signals or data. The advantage of using Wavelet Transform over Fourier Transform in power system signal analysis is that WT provides both time and frequency information of the voltage or current signals or data.

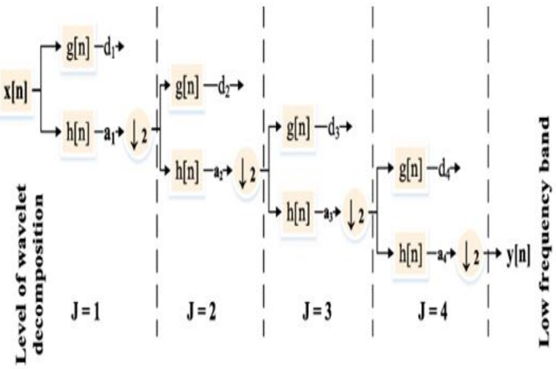

Figure 3: MRA wavelet decomposition in four levels

2.4 Artificial Neural Networks

Artificial Neural Networks (ANNs) are the effective and efficient data-driven modeling tool used for the pattern recognition and classification of the data due to their capabilities to capture the features available in them. The architecture of the ANN is based on the structure, features and the functions of the biological neural networks [25]. The ANN also contains the neurons arranged in various layers, similar to the neurons of the brain. The ANN basically contains of three layers as input, hidden and output layer. Each adjacent layer from input to the output is connected to each other through a cyclic arcs.The input layer collects the data from the network or the source. The raw data and information from input layer is fed to the hidden layer for processing and extracting the information available in the data. The processed data from hidden layer is sent to output layer, which further processes the information and gives the suitable output on the basis of the training algorithm. Generally, the back propagation algorithm is used to learn the data-set and the neurons weights are modified with reference to the error value obtained between actual output and the target.Thus,It is able to train the input data and can also classify the testing data based on the trained data.

The ANN for the Fault detection have an input vector containing absolute values of wavelet decomposed data obtained from the three phase and neutral current signals measured at the substation for normal and different types of fault cases in distribution network. The output will be either 0, for no fault or 1, for faulty cases in the display.

The ANN for the Fault Classification have an input vector containing absolute values of wavelet decomposed data obtained from the current signals and the output of fault detection. The output of this ANN will be the fault types as 1phg (AG, BG, CG), 2ph (AB, BC, AC), 2phg (ABG, BCG, ACG) or three phase type of fault occurring in the network.

3. Result and Discussion

3.1 Modelling and simulation of Test feeder

A standard IEEE 15 bus distribution system, with 11 KV, 50 Hz supply at the substation with total feeder load of 1126.5 KW and 1251.182 KVAR is used to test the proposed algorithms. All the loads on the buses are considered as 3 phase loads and IEEE 15 bus standard data of line resistances and impedances are taken. Furthermore, the fault and ground resistances are taken to be 0.001 ohm and 20 ohms respectively, thus the model is developed and implemented for low impedance fault cases. A single line diagram of Standard IEEE 15 bus distribution is shown in Figure-4.

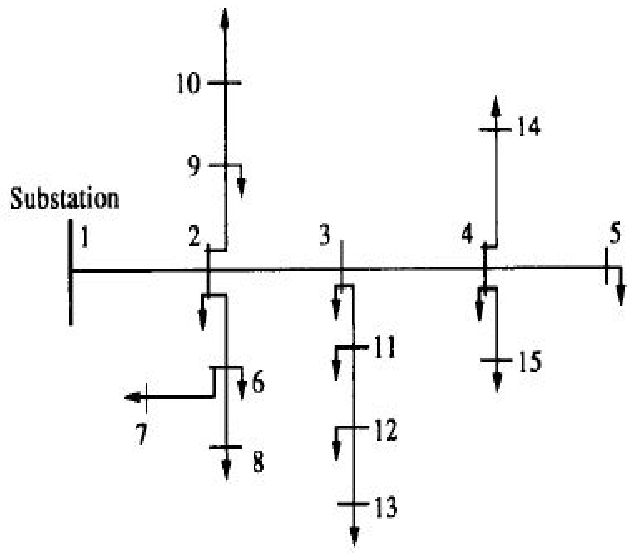

Figure 4: A single-line diagram of standard IEEE 15 bus distribution network

The proposed method of fault detection and classification in distribution network is divided into three steps. At first, the faulty data of three phase and neutral currents are collected. Then, the features of faulty signals are extracted using DWT based multiresolution analysis. Lastly, the processed data are used as an input to ANNs to train them for detection of fault and its classification independently. The proposed algorithm is executed in MATLAB/SIMULINK environment, and the results are verified with the original data. Table-1 show the various parameters used in simulation and generation of data for the proposed work.

Table 1: Table for Simulation Data

Parameters	Values
Fault Resistance	0.001 Ω
Ground Resistance	20 Ω
Fault Type	10 types
Fault Section	15 sections
Fault Location	10 locations (0.1km to 1km)
Total no.of Simulations	$10 * 15 * 10 = 1500$

3.2 Fault Detection and Classification ANNs Design

The fault in the network is detected and classified using the neural networks trained in MATLAB/SIMULINK environment using nnstart command and the pattern recognition app inbuilt in the software. The summary of the correctly classified data are summarised in Table-2. The input vector for fault detection was taken as three phase and ground currents wavelet decomposed data and the input vector for fault classification was taken as phase current data and output of fault detection.

Table 2: Summary of Training Data-set

Parameters	Training Data	Validation Data	Test data	Total Data
Fault Detection	18601	3982	3988	26571
Phase A Fault	18568	3982	3980	26530
Phase B Fault	18609	3989	3990	26588
Phase C Fault	18623	3990	3990	26603
Phase G Fault	17857	3834	3828	25519

Table-3 shows the neural network parameters used for fault detection and classification. The algorithm used for training the neural network was Scaled Conjugate Gradient (trainscg) available in the software. This algorithm uses a step size scaling method that reduces the training error and increases accuracy of the neural networks and trains faster than other training algorithms. For this work, tansig(n) transfer function is taken for hidden layer that takes an input of N matrix and normalize the data between -1 and +1 to feed the hidden layer neurons in the neural network. Logsig(n) activation function is taken for the output layer that takes an input of N matrix and returns the values between 0 and 1 in the output terminal.

Table 3: ANN parameters for fault Detection and Classification

Parameters	Fault Detection	Fault Classification
No. of Input	4	2
No. of Output	1	1
Hidden Layer Neuron	10	10
Training Algorithm	trainscg	trainscg
Hidden Layer Activation Function	Tansig(n)	Tansig(n)
Output Layer Activation Function	logsig(n)	logsig(n)
Weight Update Method	Batch-mode	Batch-mode

The confusion matrix of fault detection and fault classification in phase A of the trained artificial neural networks are shown in Figure-5 and Figure-6 respectively. It shows the accuracy of the trained neural network and the error percentage based on the classified data. The green box indicates the correctly classified data and the pink box indicates the number of mis-classified data. The last diagonal element shows the overall accuracy of the trained neural network.

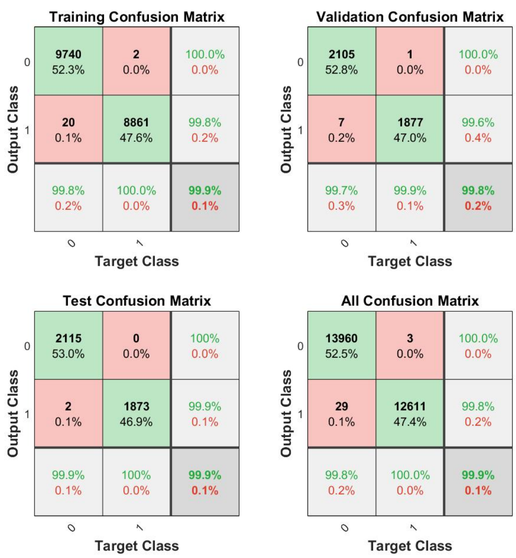

Figure 5: Confusion Matrix of Fault Detection

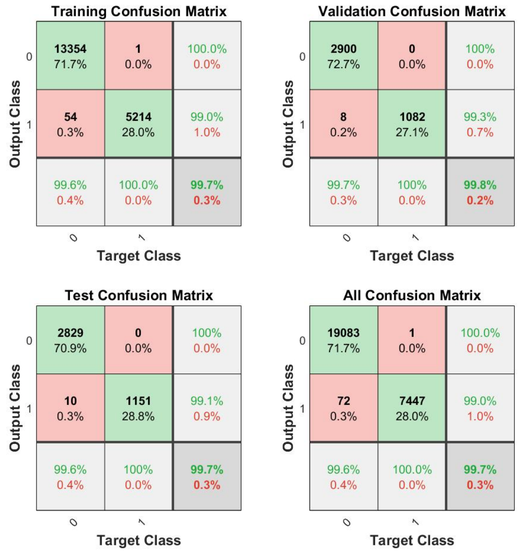

Figure 6: Confusion Matrix of Fault Classification in phase A

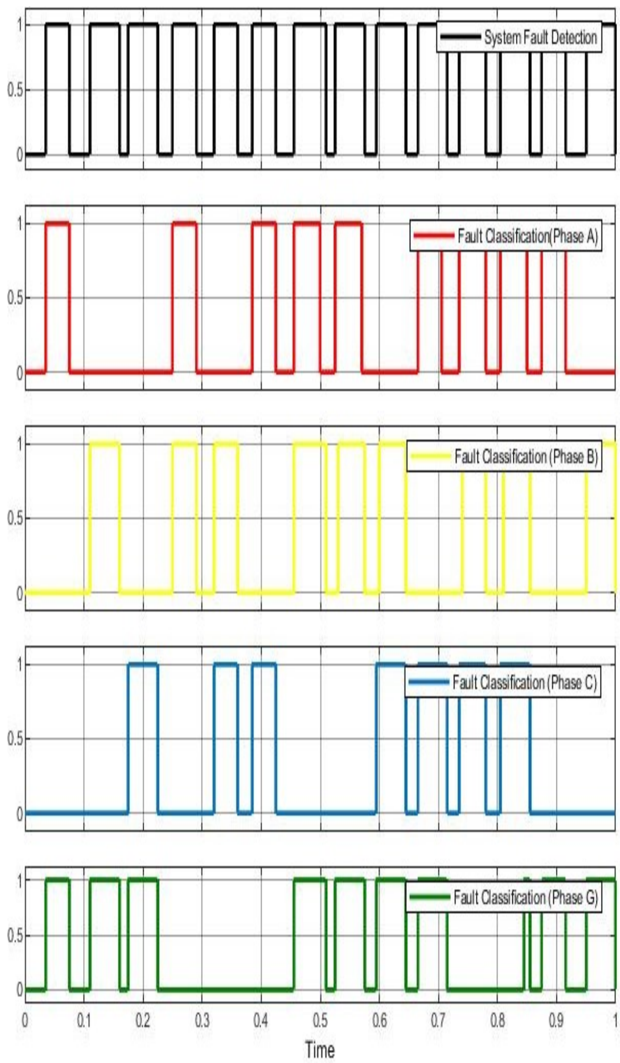

Figure 7: Fault detection and Classification Output

The various types of fault detected and classified in different time frame after training is shown in Figure-7. The red, yellow, blue and green color shows the A, B, C and G type of faults occurred in the network respectively. The high value (1) shows the fault detected and low value (0) show no-fault in the network. The black colour in the graph shows the system fault detection in the network.

Table-4 shows the test result of the proposed design.It shows that fault detection neural network has the error of 0.1 percentage and fault classification of A, B, C and G type of fault have the error of 0.3, 0.1, 0 and 4.1 percentage respectively.

Table 4: Test Results of Proposed Design

Parameters	Percentage Error
Fault Detection	0.1
Phase A Fault	0.3
Phase B Fault	0.1
Phase C Fault	0
Phase G fault	4.1

4. Conclusion

This paper has developed an algorithm which is furthermore implemented to develop a model based on discrete wavelet transform, multiresolution analysis and artificial neural networks in MATLAB/Simulink environment that provides an efficient, quick and reliable method of fault detection and classification in distribution networks.The healthy and faulty current data recorded at the substation are processed, analysed, and trained them separately for each specified task.The fault detection is done first and the classification work is done only for the fault detected cases.The features of current signals are extracted employing the discrete wavelet transform based multiresolution analysis using forth order Daubechies (Db4) mother wavelet. The proposed algorithm is tested and verified in a standard IEEE 15 bus system with three phase balanced and unbalanced loads and low impedance fault. Since, this work requires only the current signals recorded at the substation, so, reduces the cost, memory and computational time. The trained neural network for fault detection provided the percentage accuracy of 99.9 and the classification ANNs has the percentage accuracy of 99.7, 99.9, 100 and 95.9 for Phase A, Phase B, Phase C and Phase G respectively.

Thus, it can be concluded that the developed model can be easily implemented for fault detection and classification in any distribution network by using the faulty data recorded using the smart meters or fault recorders at the substation for training purpose due to its simplicity and accuracy. The noisy data can be easily filtered out by the use of Discrete wavelet transform and multiresolution analysis of the decomposed signals.

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