High Impedance Fault Detection using Wavelet Transform and Artificial Neural Network

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ABSTRACT

The detection of High impedance faults (HIFs) on distribution system is most difficult problem faced by electric utility system. These faults remain undetectable. Therefore maintenance personnel will not identify fault until a hazard is reported. When one of the phases of the transmission line makes electrical contact with a semi-insulated object like a tree, pole, road surface, gravel, concrete, dry land, etc., the fault path hasa very high resistance, which is known as a fault with high impedance (HIF). The fault current values ranges from 0 to 75 amperes and cause arcing and flashing at the point of contact, poses the greatest risk of public electrical shock or fire for HIF. As a result, the public and reliable operation view the detectionas more significant. An empirical solution to fault detection using Discrete Wavelet Transform (DWT) and Neural Network ispresented here. This is achieved by training the Artificial Neural Network using the features (standard deviation values) extracted from the fault current signal by DWT technique for different conditions of fault with different fault resistance values in the system.

Keywords: High impedance fault, Artificial Neural Net- work, Wavelet transform

1 Introduction

An overhead distribution feeder suffers HIFs when an energized primary conductor comes in contact with high impedance surface or quasi -insulating object such as tree, structure falls to ground. The significance of these undetectable faults is that they create serious public hazard as well as arcing at point of contact.
HIFs have high impedance that are not detected by over current relay. It produce current level in 0-70 ampere range. As a result anyone comes in contact with the surface gets charged. This led to the development of effective methods for accurate fault detection.
At first researchers use PC based algorithms for fault recognition in over current relays and fault location using impedance based method [1], [2]. But remain ineffective. Then various reasoning domains such as time domain, frequency domain, time- frequency domains are used. Magnitude of current and voltage signals are taken in case of time domain [3]. Harmonics based fault signals are analyzed in case of frequency domain [4]. The main disadvantage of time domain was presence of noises reduces its accuracy. Frequency based domains are confusing.[5], [6] More algebraic calculations are needed for time - frequency based rules.
Once the fault discovered, next critical issue is identify location of fault. Power line communication device equipped at the beginning of line used, but it would not be economical [7]. Then least square guess approach along with HIF model were used. The design is verified in structure accompanying length of 1524m which is tinier than physical feeders. Therefore it can't be accepted [8]. Weight least square approach need practical adaptations of thresholds for correct values in threshold for correct values in fault location. But does not satisfy HIF characteristics [9], [10]. Harmonic patterns are used to capture HIF characteristics like the magnitudes and angles of the third and fifth harmonics, even order harmonic power, and inter harmonic currents [11], among other things. Kalman based approaches [12] also. This kind of techniques effectively

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infuseshigher than fundamental recurrence signals like positive/zero voltage signals. These methods try to detect HIFs using simple thresholds and logic, but they don't have a systematic wayto figure out the best features for different systems and situations during HIFs. Methods based on fuzzy interference and ANFIS [13] are available Fuzzy permits decision on definite choices in view of loose information. It consider some fault cases be normal cases. Feature selecting methods, models of HIF explained. For simplicity in classification, Reference [14] employs the nearest neighbor rule. A white box for interpretations is provided by the proposed decision tree learning method in [15]. The literature defines fuzzy inference to identify HIFs [16]. However, the labeled dataset, which may not bewidely available for the HIF database, is a crucial requirement for these supervised learning techniques. Additionally, the classifier is never aware of any fault or non-fault events. Lastly, utility companies have a slow and almost nonexistent process for recording and correctly labeling events [17], [18].

This paper suggests a method which can handle wavelet transform and neural network efficiently. WT disintegrate current signal into various frequency bands. It helps to classify various faults. By extricate these features neural network can be trained. Thus fault can be detect and classified. The proposed method is explained as block diagram in Figure 1.

Table 1: *Type of Terrain and Current Levels*

Terrain	Current(A)
Dry asphalt	0
Dry sand	0
Concrete(non-reinforced)	0
Wet sand	15
Dry sod	20
Dry grass	25
Wet sod	40
Wet grass	50
Concrete(reinforced)	75

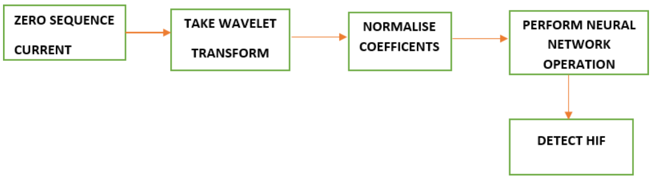

Figure 1: *Block diagram*

2 Typical Fault Current Levels

Over current protection devices that conventionally used cannot detect high impedance to ground. In case of phase conductors to earth surface is provenance of resistivity, soil will be the fault resistance. Presence of minerals, moisture and temperature decreases resistivity of soil. Table 1 reveals current range for different terrain.

2.1 Safety From HIF Hazards

2.1.1 Features

Using the features personnel can identify high impedance fault

1) Very small current with fire risk: Compared with the normal load current HIF have low magnitude of fault current and arcing at point of contact.
2) Distorted fault current: Arching led to the irregular fault current results distorted waveform.

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3) Skewness in current waveform:

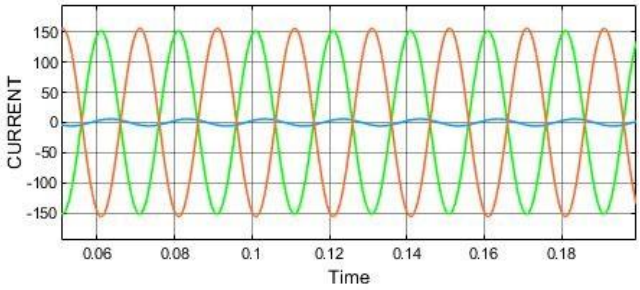

Figure 2: *HIF fault current in phase B*

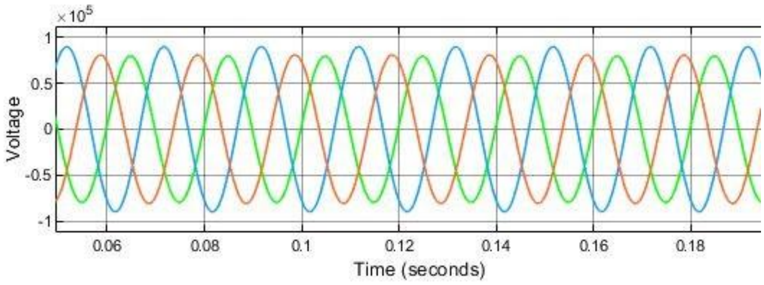

Figure 3: *HIF voltage in phase B*

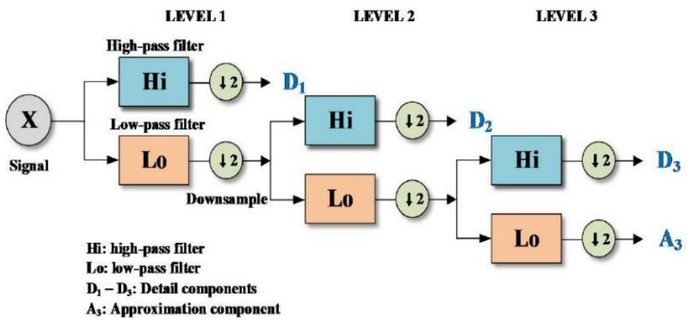

Figure 4: *Wavelet decomposition*

3 Suggested Method

1) First Step: Pre-processing, The fault current is gotten by simulating the MV appropriation network with various faults in the power framework. The fault current waveform obtained in Phase B is shown in Figure 2 and Voltage variance is shown in Figure 3.
2) Step 2 of the process: Using wavelet transform at variouslevels, the original fault current signal is extracted from the noise.
3) Step 3: Extracting Features: Using 4-level Discrete Wavelet Transform, the location of the fault's standard deviation (SD) is determined.
4) Stage 4-Traning: The ANN system was trained with the extracted SD values for various cases.
5) Stage 5-Characterization: The kind of fault that occurs inthe system is identified by a trained classifier algorithm based on ANN.

An empirical solution to fault detection using wavelet transform and neural network is presented here. Thus develop a high performance Digital signal processing (DSP) based fault detector. The detection of High impedance faults (HIFs) on distribution system or transmission system is most difficult problem faced by electric utility system. These faults remain undetectable. Therefore maintenance personnel will not identify fault until a hazard is reported.

3.1 Discrete Wavelet Transform

Wavelet is a small wave which has its energy concentrated in time. It gives a tool for comparing fleeting on stationary signals. Fourier transform cannot identify exactly where an event occurs. It cannot deal with dis continuous signal. Wavelet transform is a tool comparing transient signals. In power system transients are due to power quality disturbances or faults in system. Wavelet approach can be used to identify faults and transients in system. Wavelet is a short duration oscillatory waveform with average value zero that putrefy very fast to zero amplitude. In wavelet, signal decomposition is done by low pass filter and high pass filter. Approximation coefficient of original signal is given by low pass filter. High pass filer gives detailed coefficient. Crumpling of signal is done by multistage filter bank. Detailed coefficient helps to identify faults in power system.

D_1, D_2, D_3 are detailed coefficients. A_1, A2, A3 are approximation coefficients. Daubechis wavelet is more suitable for decomposition of current signals. For comparing transient signals fault current passed through four decomposition levels. Original signal divided into high frequency and low frequency signals. They are down sampled by two. From detailed coefficient fault can be identified. Thus features can be taken by wavelet transform for training neural network. Wavelet decomposition is shown in fig 4. Here the signal is represented as

$$X(t) = A_4(t) + D_4(t) + D_3(t) + D_2(t) + D_1(t) \qquad (1)$$

3.2 Feature Abstraction

Feature Extraction SD calculation is used in this study to extract features and determine the type of fault. The SD of current sign (is determined for each stage under various fault conditions and it is gotten utilizing the condition as given beneath, where n is number of elements in data. The standard deviation values calculated from coefficients of wavelet was taken for training artificial neural network.

$$SD = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \qquad (2)$$

3.3 Neural Network

Neural network: Artificial Neural Network (ANN) have structure of human brain. It has neurons interrelated with one another in various networks. These neurons are termed as nodes. Artificial intelligence made neurons to work as human like manner so that computer can understand things and make decisions. It consist of input layer, hidden layer and output layer as in figure 5. Input layer consists of four inputs like $d_2[n]$, $d_3[n]d_4[n]c_4[n]$. Hidden layer made calculations. From various of transformations output is conveyed. ANN can deal with more than one task at same time. Disappearance of some data doesn't prevent network working. After training in spite of insufficient data output can be produced with information. Extraction of cells of ANN doesn't prevent it from producing output. Fault tolerance is other benefit. These are the advantages of ANN.0 and 1 are the output.0 means no fault occurs. 1 means HIF occurs.

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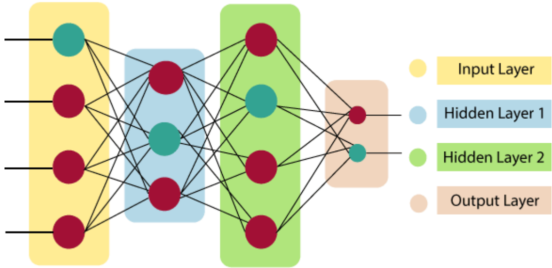

Figure 5: *Neural Network*

4 High Impedance Fault Model

There are many methods to model HIF. But for the easiness of simulation, modelling of fault with two diodes connected with anti parallel diodes with variable resistors. It denote asymmetric nature. There are methods using transient analysisof control systems (TACS) using switch. Then Kizilcay model based on control theory with respect of energy balance inarc. First method is easier than others in representing in Matlab Simulink. This model is represented in Figure 6.

During positive half cycle current flows through V*p*. Negative cycle current reverses. Arc period represents when $V_n \leq V_{ph} < V_p$.

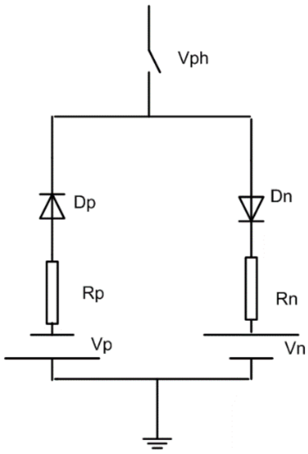

Figure 6: *HIF model*

5 Results

33 KV feeder is modelled in MATLAB. The HIF model created using MATLAB as described in figure 7 exists of saw tooth current regulator, irregular variable resistor, constant resistor and diodes. The created model has better arc current characteristics that denotes irregular ground resistance. The proposed HIF model is applied to feeder network. Current waveform extracted and decomposed using discrete wavelet transform. Then normalize coefficients using standard deviation values and applied neural network operation to classify type of fault.

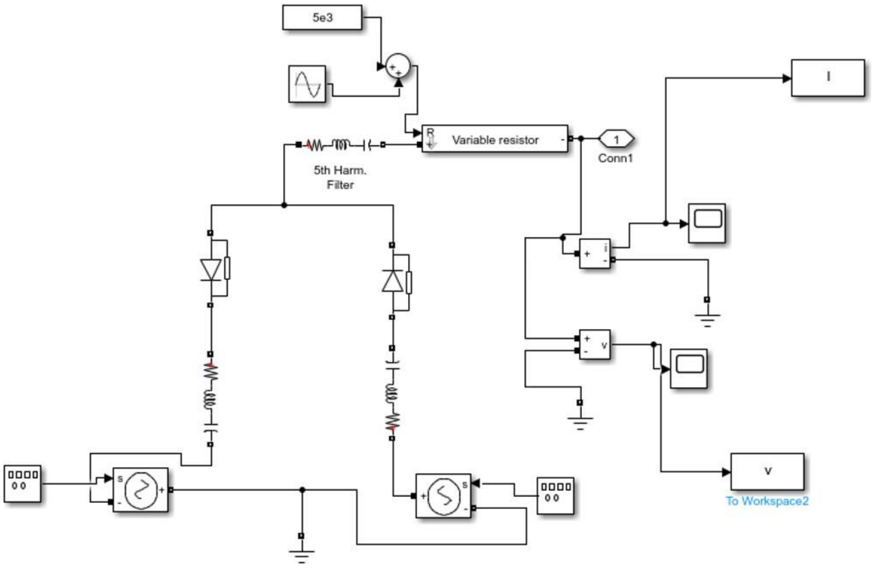

Figure 7: *HIF model in MATLAB Simulink*

Figure 8 shows Approximation coefficient signal obtained during DWT decomposition of current signal in phase B feeder. Figure 9 shows detailed coefficient signals in phase B feeder. The current signal is subjected to a DWT analysisin different faults. It is evident that for all faults, the transients are completely in levels d4, and the level d1 to d3 noise is of a high magnitude. Table 2 displays the feature extraction (SD values) calculated using equation (2). The SD values for this case can be obtained with Rf = 40, 50, 75 ohm, as shown in Table 2 and were used as training samples for the neural network. In order to train the ANN, the rules are formulated using the SD values of the current signal for various values of fault resistance. The neural network gives corresponding fault detection and classification based on faults. Fault detection andclassification obtained from ANN shown in fig 10.

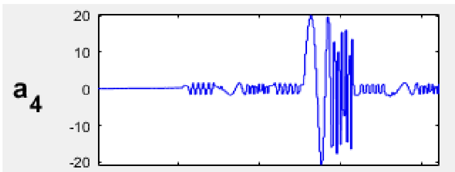

Figure 8: *Approximation coefficient signal of phase B*

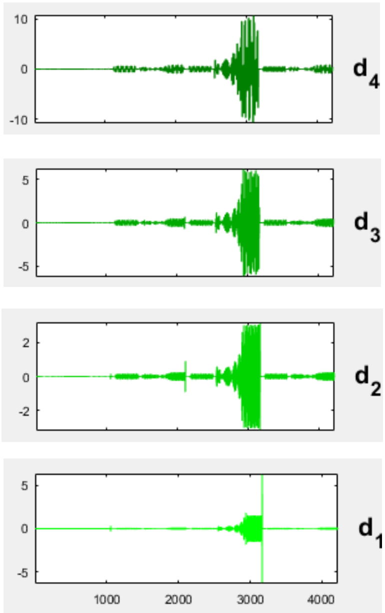

Figure 9: *Detailed coefficients signals of phase B feeder*

Table 2: *SD Values of Current Signal in Different Fault*

Fault with various Rf	S1	S2	S3
HIF A/75 Ohm	8	21	22.2
HIF A/50 Ohm	11	20.09	23.4
HIF A/40 Ohm	14.5	19	24
HIF B/75 Ohm	21	9	20.01
HIF B/50 Ohm	20.09	12.4	23.05
HIF B/40 Ohm	19	14	22
HIF C/75 Ohm	18.76	21	8.13
HIF C/50 Ohm	19.61	20.19	12.09
HIF C/40 Ohm	20.08	19.89	15.5

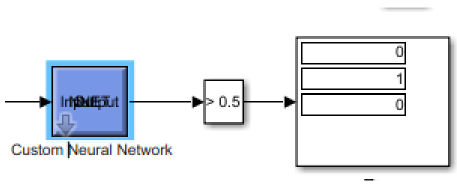

Figure 10: *HIF fault detection by ANN in phase B*

6 Conclusion

Using MATLAB and Simulink distribution network of 33 kV was simulated in this study by employing various fault types in the distribution network's feeder. Discrete Wavelet Transform (DWT) of the Db4 mother wavelet was used to analyze the current waveform that was obtained in each caseof High Impedance Fault (HIF) in order to identify the kindof fault in the distribution system. The signal was sampled with DWT using a variety of frequency bands, which arerepresented by the first, second, third, fourth levels of the detailed coefficient and approximation level of fourth level. The feeder network's type of fault has been classified usingthe SD values from each case's DWT analysis. By simulating the network with various values of fault resistance 40, 50,and 70 ohm—ANN trained with a large amount of data to classify the type of fault. The findings indicate that the ANN method of classification is better than any existing method. It has a success rate of 100%. The combination of these two methods are more suitable in DSP or microcontroller based fault detector.

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