DETECTION OF HIGH IMPEDANCE FAUL ON POWER DISTRIBUTION SYSTEM USING PROBABILISTIC NEURAL NETWORK

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Abstract-**High impedance fault (HIF) is abnormal event currents on electric power distribution feeder which does not draw sufficient fault current to be detected by conventional protective devices. The waveforms of normal and HIF current signals on electric power distribution feeders are investigated and analysis the characteristic of HIF. The purpose of this study is to use a new feature which indicates HIF faults. Fast Fourier Transformation (FFT) is used to extract the feature of the fault signal and other power system events, odd harmonics frequency components of the phase currents are analyzed. The effect of capacitor banks and other events on distribution feeder harmonics is discussed. The features extracted are using to train and test the probabilistic neural network (PNN) which is used as the classifier to detect HIF from other normal event in power distribution system.**

Keywords—**High Impedance Faults; FFT; Power System; Probabilistic Neural Network**

I. INTRODUCTION

A High Impedance Fault (HIF) is a weird event and difficult to detect on electric power distribution feeder [1]. A high impedance ground fault results when a primary conductor makes poor electrical contact with a road surface, sod, tree limb, sidewalk, or with some other surface, or object which restricts the flow of fault current to a level below that reliably detectable by conventional overcurrent devices. The resulting level of fault current is usually less than the normal current (about 10 to 50 A) of the electric power distribution feeder[1], The failure of HIF detection leads to serious threat in electric shock to human beings and potential fire hazards. HIF does not usually pose any risk to the electric power distribution feeder; however, the protection against them desirable. The nature of HIFs has been studied since the early 1970's with the hope of finding some characteristic in the current or voltage waveform that would make detection possible and practical[1].

HIF has many characteristics, the most two characteristics are the low current and arcing. Arcing is the due of air gaps because of the loose contact made with the ground or a grounded object. Also, there may be air gaps in the ground (soil) or in the grounded object (concrete, tree etc.). When the air gap breaks down, a high potential is produced over a short distance and the sustainable current level in the arc is not sufficient to be reliably detected by conventional means.

There are some other electrical events that behave like the HIF (capacitor bank operation, air switching operation, nonlinear load and starting induction motor), the algorithm which proposed to detect HIF should have ability to discriminate between HIF from other normal event in power distribution system. Most of the detection methods require extensive computation in the reprocessing stage for feature extraction of the input signals. Then a strategy is applied to obtain detection parameters

During the past decades, protection engineers and researchers have tried to find a complete solution to this type of fault. The fault has many characteristics like presence of harmonics and high frequency components, detection techniques aim to identify useful features of HIF from the pattern of the voltage or current signals associated. Many detection algorithms have been proposed to detect HIF, some of these have used frequency-based to extract relevant features of the harmonic components [2–6] other have utilized time–frequency-based features to examine the transient phenomena of HIFs signals in both the time and frequency domains [7–14], the extracted features usually can be obtained after process the signals with one of methods of signal processing like discrete Fourier transform (DFT), discrete wavelet transform (DWT) and some other time–frequency analysis methods such as discrete S-transform (DST) and discrete time–time transform (DTT) [14]. In this paper A Fast Fourier Transform (FFT) method is used for feature extraction, a normal current waveform and an arcing fault waveform are studied in the frequency domains. The features extracted are using to train and test the probabilistic neural network (PNN) which is used as the classifier to detect HIF from other normal event in power distribution system.

II. PROPOSED DETECTION ALGORITHM

The proposed algorithm to detect HIFs, as well as to discriminate them from other normal transient switching operations, included two stages.
In a first stage, the current signals of the feeders, using FFT, are analyzed to obtain the relevant data signals. Afterwards, in a second stage, the trained PNN are used as a classifier processing, in order to classify the state of each feeder. The structure of the application of FFT and PNN in the proposed method is shown in Fig. 1, which describes the different stages of the methodology.

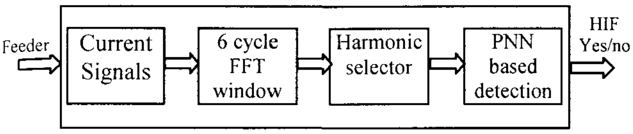


Figure 1 Block diagram of the proposed algorithm

III. PROBABILISTIC NEURAL NETWORK

The probabilistic neural network (PNN) was proposed by Donald Specht [17]. It is essentially based on Bayesian classifier technique often used in many classical pattern recognition systems. Parzen windows are used to find the probability density functions for each classification class [17]. This is used to determine the probability of given input vector belonging to a given class. The PNN chooses the maximum probability class for the given input vector by summing this with the relative frequency of each class. The Parzen estimate of the probability for input x belonging to class A is given by the probability density function.

$$F_A(x) = \frac{1}{N_k}\sum_{j=1}^{N_k}\exp\left(-\frac{\left\|x - x_{kj}\right\|}{2\sigma^2}\right) \qquad (1)$$

where x is the m dimensional input pattern vector, j is the pattern number, xj is the jth training pattern for class A, n is the number of training patterns, m is the input space dimension, and σ is an adjustable "smoothing parameter." The parameter σ must be determined experimentally [18]. An input is assigned to the class for which it has the highest probability value. With PNN, the training of PNN is easy and instantaneous [18]. Weights are not "trained" but assigned. Existing weights will never be changed but only new vectors are inputted into weight matrices when training. So it can be used in real-time. Since the training and running procedure can be performed by matrix manipulation. Fig. 2 shows the PNN structure used to perform the decision rule for classifying the input events into two classes. This network has four layers:

(1) Input layer

There is one neuron in the input layer for each feature of input vector. The input layer feeds the feature vector values to each of the neurons in the hidden layer.

(2) Hidden layer
It is also called pattern layer, because it is made up of some typical sample sets. It has one neuron for each case in the training input vector. The pattern layer is fully connected to the input layer, when presented with the x vector of input values from the input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the radial basis function using the sigma value(s). The resulting value is passed to the neurons in the next layer

(3) Summation layer
Summation layer has one pattern neuron for each particular class classification problem. It computes the outputs from the pattern-layer neurons. A summation layer neuron sums up the outputs of pattern layer neurons which belong to the class it represents.

(4) Decision layer
The decision layer picks the class for which the maximum probability was obtained in the summation layer. That means a comparison of the weighted votes for each target category accumulated in the summation layer and uses the largest vote to predict.

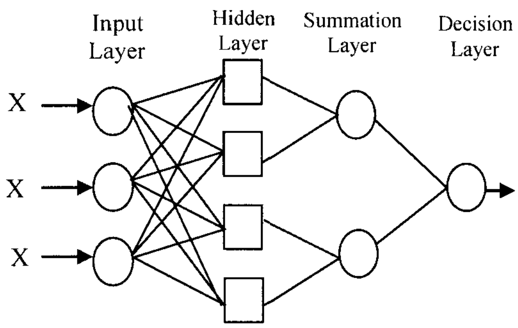


Figure 2 the proposed PNN architecture

IV. SYSTEM MODELLING

A. Distribution Feeder

A 13.8 kV distribution feeder was performed in PSCAD/ EMTDC. That consists of a substation and three distribution feeders with radial network. The schematic diagrams are given in Fig 3. The generator is of 30 kV and 10 MV connected to the transformer with 30/13.8 kV and 10 MV. The distribution network operates at 13.8 kV voltage. The networks are simulated under linear and nonlinear loads with different loading conditions. The 6-pulse rectifier is used to represent the nonlinear load.

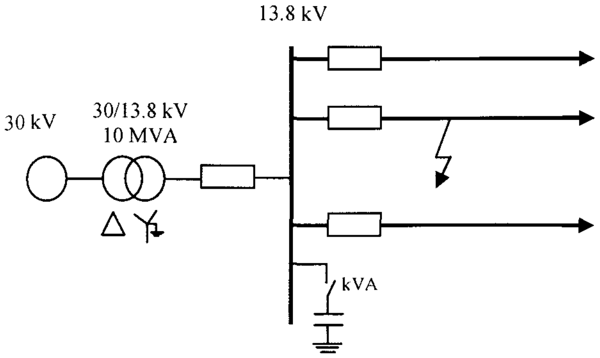


Figure 3 three phase distribution feeder

The simulation models are developed using PSCAD and the sampling rate chosen is 15.36 kHz.
The arcing and nonlinear characteristics of the current signals due to HIFs are similar to other events like add capacitor, load changes and switching operations. Therefore, the simulation of distribution system has been included both, linear and non-linear loads, the nonlinear loads are usually defined as loads in which the load current waveform does not change directly with the load voltage waveform. While the voltage and current waves in the linear loads increase or decrease proportionately. Additionally, the transient phenomena produced by capacitor switching similar to those of HIFs in frequency domain, so it is necessary to test the reliability of any HIF algorithm under this event. Many of capacitor energisation events have been taken into consideration in the studied distribution system.

B. HIF Simulation

In the past, there are several models of HIF have proposed. All of these are based on Emanuel arc model and researchers have tried to complete it and come up to a better model for HIF. A simplified Emanuel model was introduced in 2003. The Two varying resistors were used to represent the fault resistance. A simplified two-diode model of HIF, shown in Fig. 4 [16].

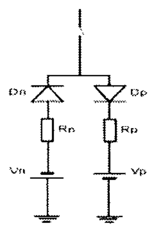


Figure 4. Simplified two-diode fault model of high-impedance faults.

V. DETECTION ALGORITHM

A. Feature Extraction

On the modeled distribution system, different operation conditions have been simulated by using PSCAD/ EMTDC. The simulated data then were transferred to MATLAB to complete the rest algorithm. The main goal of algorithm is to discriminate between HIFs and other similar waveforms.
In this algorithm, the current waveforms of distribution power are used only to extract the features of HIFs, but not on voltage waveforms. The discrimination is based on the amplitude of fundamental and other harmonics current waveforms in the frequency domain. A Fast Fourier Transform (FFT) method is used for feature extraction. The analysis is focused on current waveform which is obtained from the distribution power system feeder. In the frequency domain, odd harmonics, such as the 3rd, 5th, 7th and 9th, are predominant also some even harmonics, such as 2nd, have significant amplitudes. However, the fundamental harmonic is decreased when the fault is occurred.
A normal current waveform, when a capacitor bank is present, appears no significant varies in phase current in the amplitude, the odd harmonics are predominant also even harmonics can be seen to some extent. In this paper, various waveforms were obtained by changing different parameters. When all these waveforms were obtained, useful relevant data were used to find the features that were common to all and can discriminate HIF from other signals. These investigations led us to define the following features.

1- The ratio of harmonics amplitude (2nd, 3th, 5th, 7th, 9th and 11th) to the fundamental harmonic amplitude.

a) $$f1=\frac{I_2}{I_1} \quad (2)$$

b) $$f2=\frac{I_3}{I_1} \quad (3)$$

c) $$f3=\frac{I_5}{I_1} \quad (4)$$

d) $$f4=\frac{I_7}{I_1} \quad (5)$$

e) $$f5=\frac{I_9}{I_1} \quad (6)$$

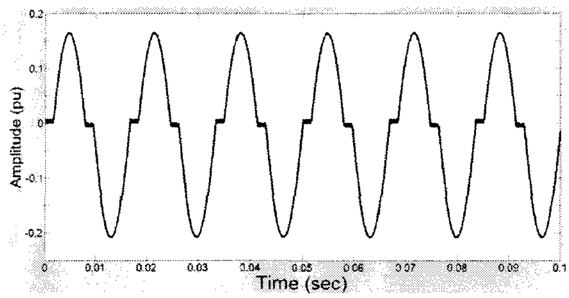
f) $$f6=\frac{I_{11}}{I_1} \quad (7)$$

Where $I_{2,\,3,\,5,\,7,\,9\ and\ 11}$ represent the 2nd, 3rd, 5th, 7th, 9th and 11th harmonics amplitude of the signal respectively, I_1 represent the fundamental harmonic amplitude, and f_i represent the extracted features.

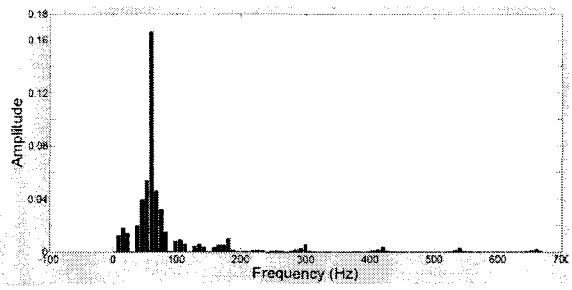
2- The ratio of sum of all harmonics above to the fundamental harmonic.

$$f_7 = f_1 + f_2 + f_3 + f_4 + f_5 + f_6 \qquad (8)$$

Gather all the extracted features to obtain one vector which represent the input data to training the PNN. The typical signals of HIF fault current under linear load and with capacitor bank also signal of nonlinear current and their spectrum is shown in Figs. 2 a, b, c, d, e and f respectively.



a



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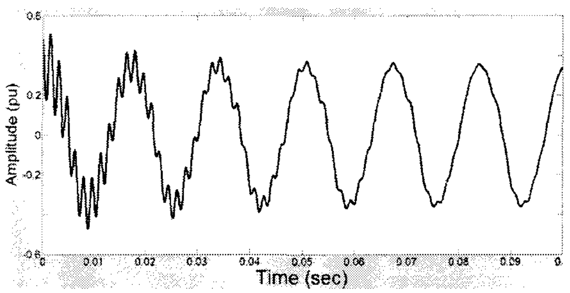

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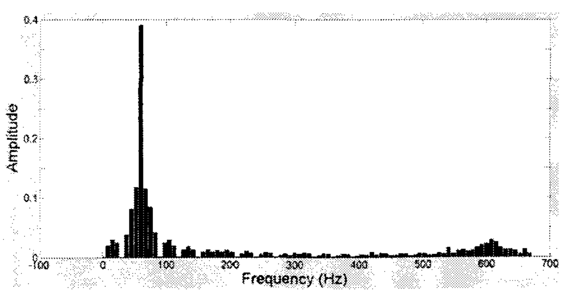

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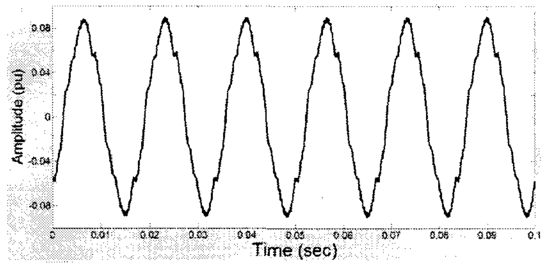
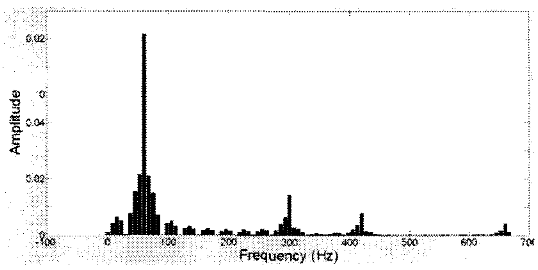


e



f

Figure 5. Signals of the Feeder
A,c: The typical signals of HIF fault current under linear load and with capacitor bank
b,d: FFT for signals in a and b
e,f : The typical signal of nonlinear load and its FFT

B. Classification

The PNN model is one among the supervised learning networks and has many features different from those of other networks in the learning processes.

There are 300 of HIF signals and 1050 of normal work cases represent data training set. Also, there are 150 and 400 cases for bath the HIF and the other normal event under deferent operation work respectively, represent data test set. The data training set used to train designed PNN. The PNN is tested with testing data set to show the impact on classification rate. The PNN was implemented by using MATLAB software package. The spread value (S.V.) of the radial basis function was used as a smoothing factor and classifier accuracy was examined when different values of S.V. were used. The primary work of training a PNN network is selecting the optimal spread values to control the spread of the RBF functions. If the spread value is too large, then the model will not be able to closely fit the function, if the spread value is too small, the model will overfit the data because each training point will have too much influence

The classification rates are calculated on the testing data sets. The maximum classification rate is 98.94% at the 0.01 of the spread value. Results are shown in Table 1. According to Table 1, the classifier presented an accuracy of around 86.3% when S.V. was 0.2 and it improved to 92.4% when S.V. was 0.1. Classifier performance reached to 98.9% when S.V. was 0.01.

Table 1. The Results of PNN

Spread Value	Accuracy (%)
0.2	**86.3**
0.1	**92.4**
0.01	**98.9**

VI. CONCLUSION

In this paper a normal current waveform and HIF waveform of distribution power system are simulated with PSCAD software program, the signals are studied in frequency domains after process the signal with FFT to extract the relevant feature which can discriminate when a HIF occurs, the ratio of amplitudes of the odd harmonics to amplitude of fundamental harmonic have used as a data input to PNN to detect HIF. PNN has the ability to discriminate clearly between fault and non fault events. The proposed algorithm discriminates between HIF currents and nonlinear load and capacitor bank switching which are some electrical waveforms, which could be considered similar to HIF. The algorithm can be expanded and improved considering other comparable waveforms.

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