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DETECTION OF HIGH IMPEDANCE FAULT USING A PROBABILISTIC NEURAL-NETWORK CLASSFIER

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ABSTRACT

In this paper, a simple and efficient method for detection high impedance fault (HIF) on power distribution systems using an intelligent approach the probabilistic neural network (PNN) combined with wavelet transform technique is proposed. A high impedance fault has impedance enough high so that conventional overcurrent devices, like overcurrent relays and fuses, cannot detect it. While low impedance faults, which include comparatively large fault currents are easily detected by conventional overcurrent devices. Both frequency and time data are needed to get the exact information to classify and detect no fault from HIF. In the proposed method, DWT is used to extract feature of the no fault and HIF signals. The features extracted which comprise the energy of detail and approximate coefficients of the voltage, current and power signals calculated at a chosen level frequency are utilized to train and test the probabilistic neural network (PNN) for a precise classification of no fault from HIFs.

Keywords: *Discrete Wavelet Transform, Fuzzy systems, Power distribution faults, probabilistic neural network (PNN).*

1 INTRODUCTION

Detection of high impedance fault on distribution systems is very hard. It often occurs in power distribution systems and, in general, cannot operate common protection devices because of high impedance, which prevents the fault to draw high current value, at the fault point. These types of faults usually occur when a loose contact between an overhead conductor and high impedance surfaces or the conductors touch a high impedance object like a tree[1]. The main objective in HIF detection, in incompatible with low impedance faults, is not to protect the devices, but to provide the public safety and prevent fire risks because of the electric arcing [2]. HIFs can be classified into two types: the passive faults and the active ones. Passive HIFs do not make an electric arc. They are very dangerous to human and animal life since there is no any statement of the energisation case of the conductor. Active high impedance faults are usually pursued by arc and drawn currents less than the protection devices set[3]. Generally, fault currents reduce over time until the arc is complete extinction[3]. Most of the methods have utilized for detection HIFs take advantage of fault signals produced by the arc (harmonic and non-harmonic components). While, sometime the detection system cannot gather enough data to make sure the fault due the electric arc may vanish before that.

Few other electrical events also behave like the HIF (capacitor bank operation, air switching operation, nonlinear load and starting induction motor)[4], therefore, the algorithm proposed to detect HIF should have ability to discriminate HIF from other normal events 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. A lot of detection algorithms have been proposed to detect HIF, some of these have used frequency-

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based to extract relevant features of the harmonic components[5][2][6][7][8] other have utilized time–frequency-based features to examine the transient phenomena of HIFs signals in both the time and frequency domains [3][9–16], 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) , discrete time–time transform (DTT) [3] and the wavelet packet transform (WPT) [16].

This paper represents a HIFs detection method that includes capturing the voltage and current signals produced in a distribution conductor under HIF and non-fault cases. Discrete wavelet transform is employed to extract the vector, which comprises the energy of detail and approximate coefficients of the voltage, current and power signals. The findings presented in this research relate to a typical 13.8-kV, the faulted signals of which are attained using the known Power Systems CAD PSCAD software. An embodiment of HIF model is involved in this simulation. The system generalization is then tested for HIF signals within a range of different non-fault and fault cases faced in practice.

2 SYSTEM STUDIED

2.1 Model of Distribution Feeder

A 13.8 kV distribution feeder was performed in PSCAD/ EMTDC. This comprises a substation and three distribution feeders with radial network. The Figure 1 illustrates the schematic diagrams. The generator is of 30 kV and 10 MV connected to the transformer with 30/13.8 kV and 10 MV.

The distribution network functions at 13.8 kV voltages. The linear and nonlinear loads with various loading conditions are stimulated. The nonlinear load is represented by 6-pulse rectifier. The selected sampling rate is 12.8 kHz.

The figure 2 illustrates the waveform of HIF current signal under linear and nonlinear loads. The fault has occurred at 0.2 sec. Under linear loading condition, the signal of HIF comprises higher harmonic components compared with the signal before the fault (figure 2a). Thus, the distinguish HIF from other normal operations, in this cases, is easy. However, in case of HIF under nonlinear loading condition, the signal before and during the HIF has comprised higher harmonic components (figure 2b). Consequently, it becomes hard to differentiate HIF from other normal condition under nonlinear loading condition and this is a crucial problem in power distribution network. Additionally, it is mandatory to examine the reliability of any HIF method due to the transient event generated by capacitor bank switching, which is like for those that HIF in frequency domain. Many of capacitor energisation events have been considered while studying the distribution system.

2.2 HIF Simulation

In the past, several HIF models have been presented based on Emanuel arc model. These models have been analyzed by researchers to select the best model for HIF. A simplified Emanuel model proposed in 2003 comprises pair of DC voltage sources, Vn and Vp, which signify the beginning voltage of air in soil and between distribution line and trees. The two varying resistors, Rn and Rp, were employed to signify the fault resistance, irregular values enables to simulate an asymmetric fault currents. The fault current flows to the earth if positive DC voltage is less than the phase voltage, however, when the negative DC voltage Vn, is higher than the line voltage. No fault current flows when values of the phase voltage between Vp and Vn. The figure 3 illustrates a simplified model of HIF [17].

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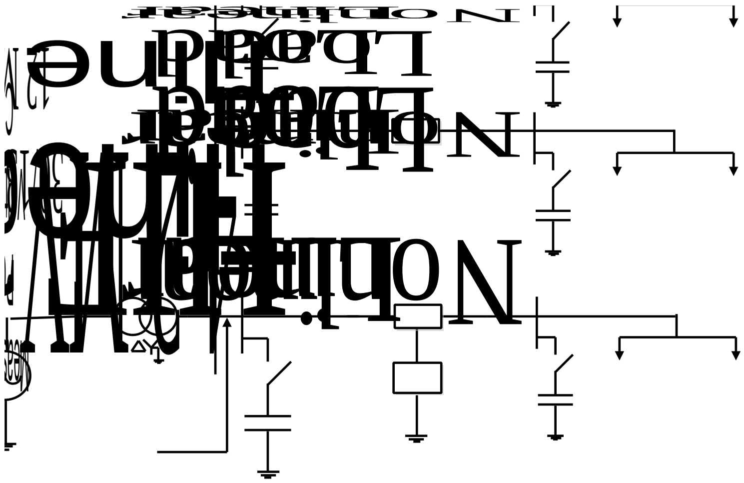

Figure 1: Graphic Diagram of the Simulated 13.8kV Radial Power System

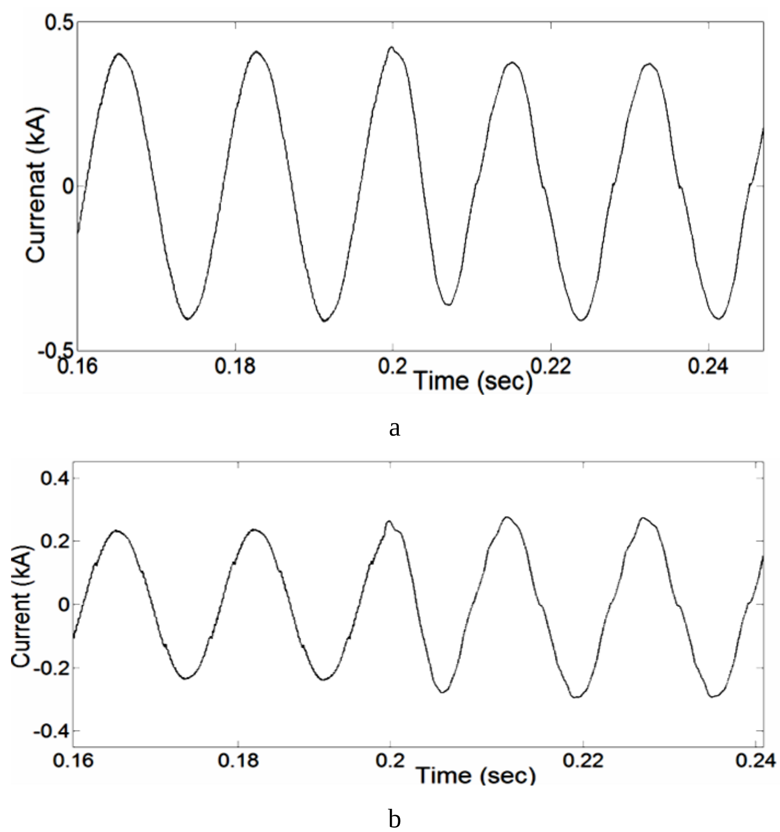

Figure 2: Typical HIF Fault Currents (A) HIF Current Signal (Linear Load) (B) HIF Current Signal (Nonlinear Load).

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Figure 3: Model of A High-Impedance Faults.

3 PROBABILISTIC NEURAL NETWORK

Neural networks have been utilized for application in power system fault detection, especially in HIF models since early 1990s. Among the networks used were FNN 1992 [18], ANN 2006-8 and 2011[19], PNN 2008 [3] and (MLPNNs) 2011[20]. A typical neural network is the multilayer feed-forward network, often called the Back propagation network (BPN). The problems with using this network are: (i) the training time becomes too long if the searching space is large (ii) It is need extensive training if added or removed training data and (iii) it is difficult to decide how many layers and nodes are required for a practical application. A more suitable candidate for classification of power transients is the probabilistic neural network (PNN).

The probabilistic neural network (PNN) was proposed by Donald Specht. Bayesian classifier technique represents the main part of probabilistic neural network. The probability density functions are determined, using Parzen windows, for every classification class. This is employed to calculate the given input vector probability affiliating to a given class. The maximum probability class for the given input vector is chosen by the PNN through summing with the relative frequency of every class [21].

An input is set to the class for which it possesses higher value of probability. The training of PNN is easy and instantaneous [22]. Weights are not “trained” but assigned. Also when add or remove training data, existing weights don't need to retrain but only new vectors are inputted into existing weight matrices when training. So it can be used in real time. The speed of PNN is very fast because of the training and running procedure can be made by matrix manipulation. Figure 4 shows the PNN structure used to perform the decision rule for classifying the input events into two classes. This network has four layers:

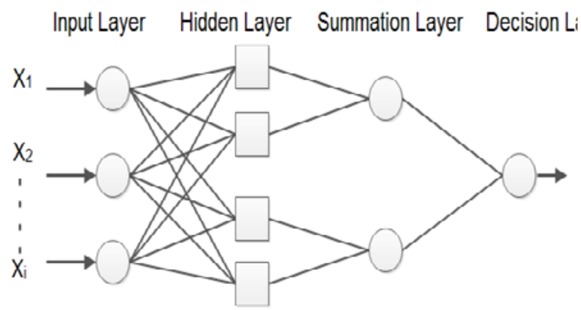

Figure 4: PNN Structure

3.1 (1) Input layer

In the input layer, there is just one neuron for each feature of input vector. The feature vector values (the output of The input layer) are fed to every neurons in the second layer (hidden layer).

3.2 (2) Hidden layer

The second layer is called a hidden or pattern layer. It has one neuron which represents typical samples set for each case in the training input vector. The main function of hidden layer is to compute the Euclidean distance of the input test case from the center of neuron, and send the resulting value to the neurons in the following layer.

3.3 (3) Summation layer

Summation layer has one pattern node for every particular class classification problem. It computes the outputs of pattern nodes associated with a given class. A summation layer neuron simply sums up the outputs of pattern layer nodes that correspond to the class it receives.

3.4 (4) Decision layer

The final layer is a decision layer which selects the class that has the Maximum probability obtained from the last layer. Meaning that, a comparison of the weighted votes for each target category accumulated in the summation layer and uses the largest vote to predict.

4 INTRODUCTION TO DISCRETE WAVELET TRANSFORM (DWT)

Discrete Wavelet Transform (DWT) was developed by Mallat [23]. It is a computationally effective way and a common tool to execute time localization of the various frequency components of a given signal. Using DWT, time and frequency

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resolution of a signal are achieved through the use some important analyzing functions, named mother wavelets. The most important characteristic of the mother wavelets is that the time intervals are short for high-frequency components, whereas the time intervals are long for low frequency components. The DWT is defined as:

$$DWR(m,k) = \frac{1}{\sqrt{a_0^m}} \sum_n x(n) g\left(\frac{k - nb_0 a_0^m}{a_0^m}\right) \quad (1)$$

where x(n) is the input signal, g(n) is the mother wavelet, and the translation and scaling parameters “b” and “a” are functions of integer parameter m. The result is geometric scaling (i.e. 1, 1/a, 1/a2,….) and translation by 0, n, 2n,….

Figure 5 depicts implementation of the tree structure of filter-banks for one dimensional DWT, h[n] stands for the low pass filters, where g[n] for the high pass filters, and the arrows for the down sampling process.

Figure 5: Implementation of The Tree Structure of Filter-Banks for One Dimensional DWT

The DWT generates as many wavelet coefficients as, there are samples in the original signal using a filter system. The decomposition procedure begins when a signal passes into these filters. The output of low pass filter is the approximation signal whereas the output of the high pass filter is the detail signal.

Many Wavelet Transform applications for analysis transient signals of power system have been lately published in the literature. Applications of Wavelet transform for distribution network fault analysis are enriched by some interesting studies and researches. In this paper, different operation conditions have been simulated by using PSCAD/ EMTDC. The current and voltage signal generated in time domain for each case which is analyzed using a wavelet transform. A sampling rate of 12.8 kHz is chosen. Daubechies wavelet Db6 is selected as the mother wavelet, where it has presented best classification results for fault analysis in power system. Based on this sampling time, the signal is decomposed into 7 levels. Table 1 shows the frequency bands range for coefficients up to 7th levels.

Table 1: Wavelet Detail Coefficients for 1–7 Levels and Approximation Level 7

coefficients	Frequency band (Hz)
d1	3200-6400
d2	1600-3200
d3	800-1600
d4	400-800
d5	200-400
d6	100-200
d7	50-100
a7	0-50

5 FEATURE SELECTION

The main part to the success of any classification system relies heavily on the input features extracted. The system receives voltage and current signals (CT output) as the inputs then by multiplying voltage times current to get the power signals. These signals are preprocessed using DWT to extract different features in the incoming voltage, current and power signals.

Different operation conditions (HIF and non-fault cases) have simulated by using PSCAD/ EMTDC On the modeled distribution system. In this paper, feature extracted vectors were produced by utilized the Daubechies 6 (db6) mother wavelet. Utilized the chosen mother wavelet; the voltage, current and power signals are decomposed into number of components in various frequency levels, which are called also reconstruction wavelet coefficients of different levels (scales). The original signals can get again by overlay of these reconstruction wavelet coefficients. The lowest frequency components (output of low pass filter) are known the approximation wavelet coefficient whereas the other components (output of high pass filter) are known detail wavelet coefficients of different levels. In this study, After many investigations and comparisons between the performance of PNN with different types of features like standard deviation (STD) and RMS of each frequency bands (coefficients and signals), the energy of the four levels (4th, 5th, 6th and 7th) of detail coefficients and 7th level of approximation coefficients of the (current, voltage and power) signal is selected to be extracted and used as the input data vector to PNN. For signals sampled at a rate of 12.8 kHz, the proper feature extracted vector, the energies of the detail wavelet

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coefficients (ED4-ED7) and energy of the approximation wavelet coefficients (EA7), is established as follows:

$$EA7 = \sum_{j=1}^{N} \left| CA7_j \right|^2 \tag{2}$$

$$ED_i = \sum_{j=1}^{N} \left| CDi_j \right|^2, \qquad i = 4,5,6,7. \tag{3}$$

where N is the number of sample, EA7 is the approximation coefficient of level 7 of the (current, voltage and power) signal. EDi (i=4, 5, 6, 7) is detail wavelet coefficients (CD4, CD5, CD6 and CD7) of levels 4th, 5th, 6th and 7th.

The relationship among the features is illustrated in Figure 6a,b and c, each plot represents relation between two features, of which most of the features are distinctive, while some are overlapped. The plots provide information related to the capability of the extracted features for classification in raw feature form, for using those features as inputs to the designed PNN.

6 SIMULATION

6.1 Data Preparation

It is essential to divide training data into two data sets as follows,

a) An input data set which has values for the 15 inputs represent the energy of the7th level of approximation coefficients and four levels (4th, 5th, 6th and 7th) of detail coefficients of the (current, voltage and power) signal. 1440 input data points were selected from time–frequency plane of current, voltage and power signals. These points were placed into a single input data set.

b) An output data set which has values for the one output (1 or 10). The output of PNN either 1 for high impedance fault occurs or 10 for other normal event in power system. 1440 output data points, related to the chosen input points. These points were placed into a single output data set.

The remaining 160 input and output data points, which are dissimilar from the training data, will be employed for the purpose of testing. A special Matlab function, which is associated with the neural network Toolbox, was employed to produce the PNN based system,

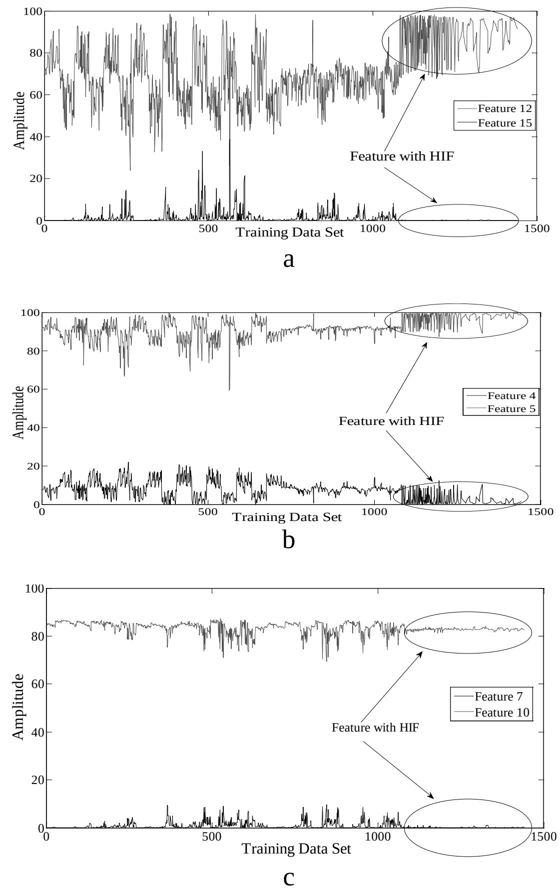

Figure 6: The Relationship Among The Features (a) Relation Between Features 12-15 (b)Relation Between Features 4-5 (c)Relation Between Features 7-10.

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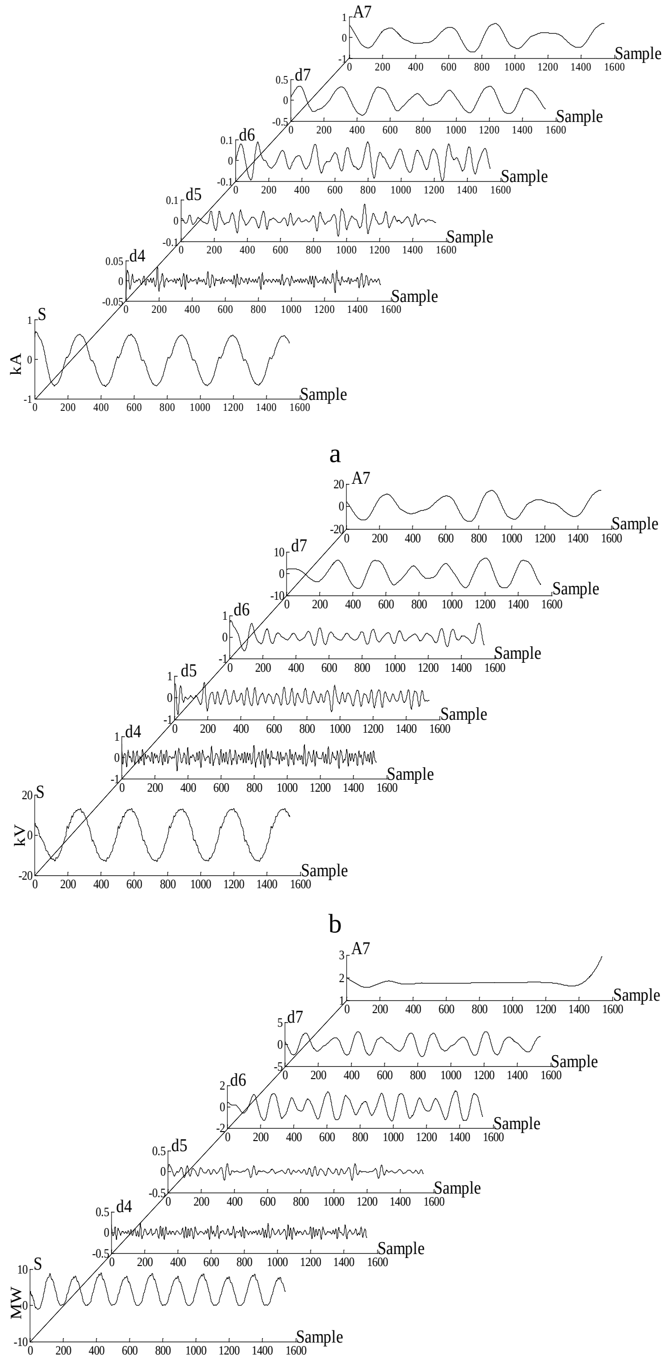

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Figure 7: Decomposing Signal Under A HIF Condition and Their Detail Coefficients at Levels 4, 5, 6 and 7 and Approximate Coefficient at Level 7 Using Db6. a) Current Signal b) Voltage Signal c) Power Signal.

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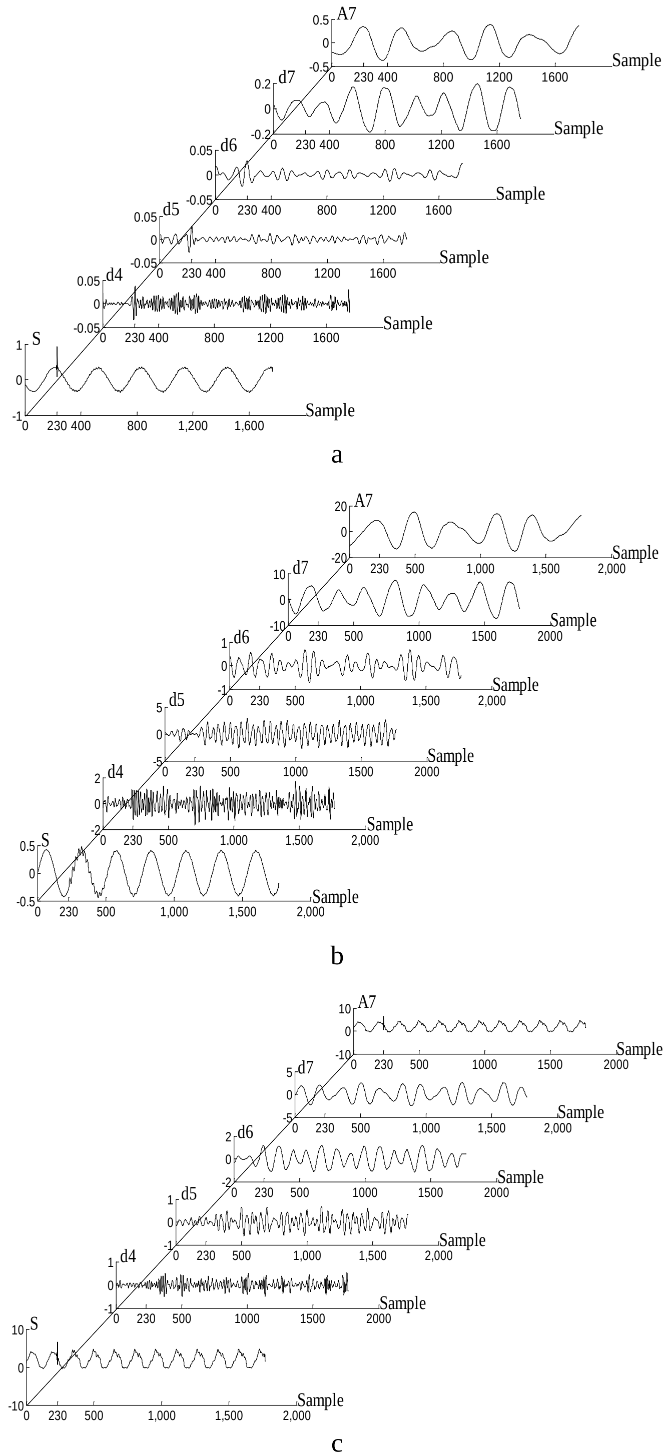

Figure 8: Decomposing Signal Under Capacitor Switching Condition and Their Detail Coefficients at Levels 4, 5, 6 and 7 and Approximate Coefficient at Level 7 Using Db6 a) Current Signal b)Voltage Signal c) Power Signal

7 RESULTS

After the decomposing process, Figure 7 depicts voltage, current and power decomposing signal under a HIF condition and their detail coefficients at levels 4, 5, 6 and 7 and approximate coefficient at level 7 using db6. The effect of the arc period clearly appears by high transient frequencies which are seen in the Wavelet levels D4 and D5. While Figure 8 appears the behavior of

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decomposition signal under capacitor operation switching conditions (no fault). Any increasing or decreasing in the values of current doesn't effect on the method developed results because of the high frequency part of the signal show only within a short period of time, at the instant of capacitor switching (at sample 230).

There have been 1440 training cases which were selected to train the network. Number of features in each input vector is 15 features which represent the energy of the four levels (4th, 5th, 6th and 7th) of detail coefficients and 7th level of approximation coefficients of the (current, voltage and power) signal. The training sets included 360 HIF cases and the rest are non-fault cases. The PNN has one output, the output is one when the system detect HIF case and is ten when other cases. Different combinations of inputs are used to train and test PNN, to assess the influence on classification rate. The rates of classification are computed on the training and testing data sets.

Classification results are described using confusion matrix, which is a standard tool for testing any type of classifier. Table 2 shows the confusion matrix along with the classification results achieved from this study. From the table, one can see that the confusion matrix has one row and one column for each class. The row represents the original class and the column means the predicted class by the PNN classification. The classification rate is found that the proposed algorithm is capable to categorize 91.67% in case of HIF testing and 95.64% for non HIF testing cases. The overall classification rate is 94.65%. The system is trained properly and has categorized different cases effectively.

To evaluate the suitability of proposed algorithm, test data cases were fed to the PNN and the obtained output is shown in Table 3. It shows that the proposed method could classify different input categories successfully and reliably. It is found that the proposed algorithm is capable to categorize 95% in case of HIF testing and 93.33% for non HIF testing cases. The overall classification rate cases are 93.33% Results of the testing phase, which demonstrates that the algorithm is reasonably reliable.

Table 2: The Classification Results of PNN With Training Data Set

Confusion Matrix		Target		Classification rate
		HIF	Non fault	
model	HIF	330	30	91.67
	Non fault	47	1033	95.64
overall Classification rate				**94.65**

Table 3: The Classification Results of PNN With Training Data Set

Confusion Matrix		Target		Classification rate
		HIF	Non fault	
model	HIF	38	2	95
	Non fault	8	112	93.33
overall Classification rate				**93.75**

Furthermore, three goals are selected to validate the method of HIF detection. The first objective is to selection of proper mother wavelet to be used in wavelet transform. The second objective is to examine the impact of input feature set on the classification rate performances of the PNN. And finally

7.1 Selection of proper mother wavelet

Proper selection of the mother wavelet represents a major part in detecting different types of signal variations. The selection relies on the application nature. For detection of low amplitude, short duration, fast decaying and oscillating types of signals, Daubechies and Reverse biorthogonal families mostly used for detection of low amplitude, fast decaying, short duration and oscillating types of signals, (e.g. db2, db3 etc. and rbio2.7, rbio3.7 etc.). Also, smoothness and wideness of mother wavelet relies on its number. So many investigations were done to select the proper wavelet family and its number.

After many examinations, the db6 mother wavelet was selected. The selection is based on the following reasons:

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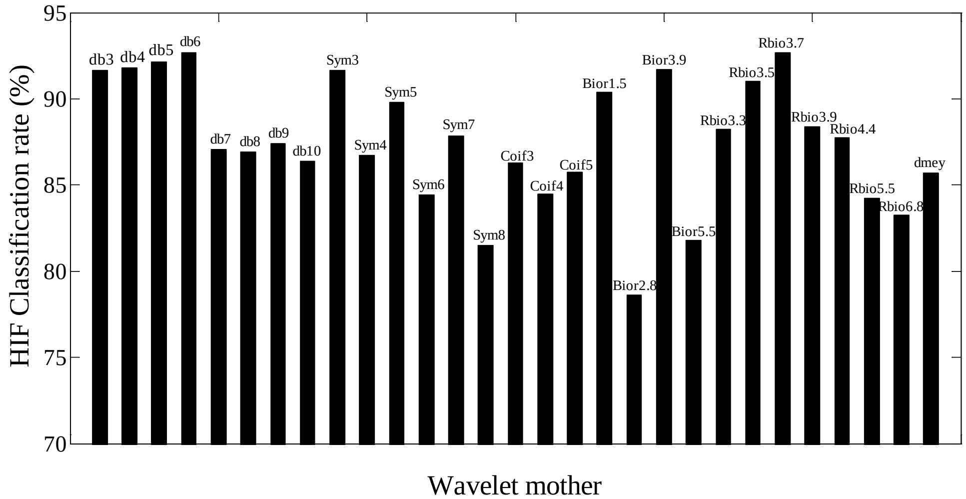

Figure 9: HIF Classification Rate of PNN Using Various Mother Wavelets

- As alternatives, 29 types of wavelets were used in training PNN, involving: Daubechie, Symlets, Coiflets, Biorthogonal and Discrete Meyer (dmey) Figure 9.
- The standard used to choose the better mother wavelet was the percentage of classification rate Figure 9.
- A total of 1440 tests were performed. Simulation results show a high average accuracy of 94.65% that justifies why db6 mother wavelet was selected.

7.2 The impact of input feature sets

Various feature sets are investigated to study the impact of input feature set on the classification rate of the PNN. Table 4 illustrates these sets, whereas the Table 5 tabulates the classification rate of the proposed method for each of the sets.

Table 4: Input Feature Set Types

Feature type		No. of feature
FS1	the energy of the four levels of (current, voltage and power) signal	15
FS2	the energy of the four levels of (current and voltage) signal	10
FS3	the energy of the four levels of (current and power) signal	10

It is evident that generally the FS1feature sets contain more selective information as against other feature sets, as exposed in average classification rate. Also, it can be concluded that the features of the FS1 has shown good results. Figure 10 shows the classification rate for the different feature set.

Table 5: The Classification Rate Of Input Feature Set Types

Feature set	Classification rate for	
	Training set (%)	Testing set (%)
FS1	94.65	93.75
FS2	91.8	90.62
FS3	91.87	91.25

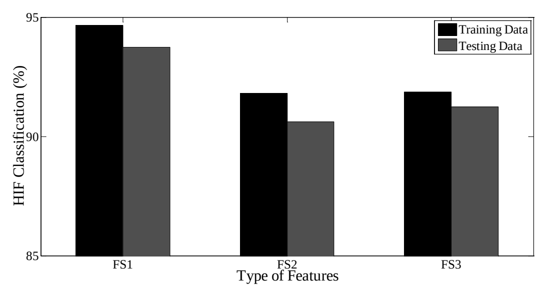

Figure 10: Classification Rate for The Different Feature Set.

7.3 The effect of number training data

The proposed PNN is trained and tested with 1600 stimulated cases. Various combinations of inputs are used to test the PNN, to assess the influence on classification rate. The rates of classification are computed on the training and testing data sets. In this stage, the PNN is trained with different numbers of training data set to get the best classification rate of the PNN. Figure 11 shows the HIF classification rate of PNN with input training

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data set (FS1) that has different number of training data. The maximum classification rate is 94.65% and 93.12% for training and testing data, respectively with 90% of training data and classification rate is reduced with others percentage training data.

Figure 12 show the effect the percentage of training data on the classification rate with input training data set (FS2, FS2).

8 DISCUSSION

A qualitative comparison was made among three types of number of features (FS1, FS2 and FS3) for HIF detection in power distribution feeder, in the proposed algorithm. Based on the outcomes, it was found that the feature of type FS1 provides better results compared with other features. The classification rate for radial distribution network is 94.65% for feature of FS1compared with 91.8% and 91.87% for both features of FS2 and FS3, respectively. Also with using 90% training and 10% testing data sets to train and test the PNN has given a good classification rate result.

9 CONCLUSIONS

This study has presented the PNN for HIF detection and classification. An effort has been made to classify the HIF from other event in distribution system under linear and nonlinear loads. In this paper, the energy of the four levels (4th, 5th, 6th and 7th) of detail coefficients and 7th level of approximation coefficients of the (current, voltage and power) signal is selected to be extracted features using wavelet transform and different features like (FS1, FS2 and FS3) were computed and used to train and test the PNN for HIF classification. HIF classification rate is more than 95%, obtained from PNN with using energy of details coefficients of current, voltage and power feature. Ultimately, the proposed approach is quick and precise in identifying HIF and can be extended to guard huge power distribution networks.

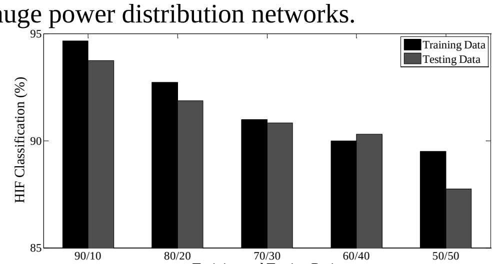
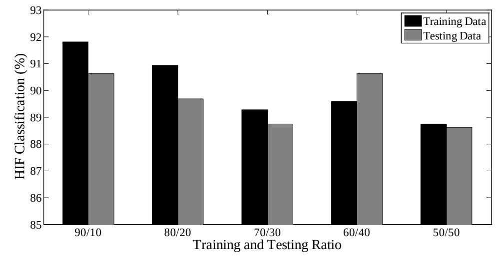


Figure 11: The HIF Classification Rate With Input Training Data Set (FS1).



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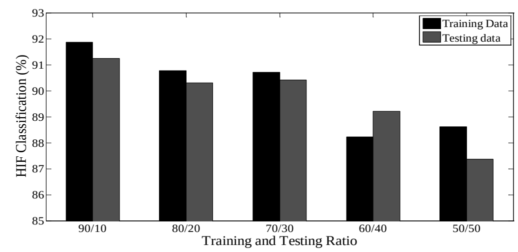

b

Figure 12: The Classification Rate With Input Training Data Set a) FS2 Data Set b) FS3 Data Set.

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