Detection of High Impedance Fault in Distribution Networks by Using Time-Frequency Transform S and Artificial Neural Network

Iman Safinejad
Hormozgan Electric Distribution Company
Iran, Hormozgan
Im.safinejad@gmail.com

Mehrdad Hajizadeh
Hormozgan Electric Distribution Company
Iran, Hormozgan
mehr.haji@yahoo.com

Mohammad Medi Khademi
Hormozgan Electric Distribution Company
Iran, Hormozgan
Khademi366@gmail.com

Abstract

High impedance faults due to the high magnitude of impedance in their paths have little fault current. Therefore, network security devices are generally unable to identify them. This paper presents a new method for identifying high impedance faults. First, the high impedance waveforms that have been extracted from actual experiments are de-noising by the wavelet transform. The waveform of other transient network conditions is also derived from the simulation of the standard 13-bay IEEE distribution system in PSCAD software. Then, by using time-frequency transformation S, extraction of the selected features of this waveform is performed by principle components analysis (PCA) of the monitoring sample points and entering the neural network. Finally, to distinction between transient states and high impedance faults and detection this fault, the multilayer perceptron neural network has been used. The results show clearly the effectiveness of this method

Keywords
High Impedance fault - Basic Components - S- Transform - Neural Network

1. Introduction

High impedance faults in distribution networks usually occur when part of the network conductors is interrupted and placed on the ground or branches of trees or other levels. 5 to 10 percent of distribution network fault is due to this type of fault [1]. The high impedance fault has a small, non-linear, random, unsteady, and highly variable current. This current is small in size and therefore not detectable by the current over current relays in the distribution network [2]. High impedance faults do not have a significant effect on the normal performance of the distribution network, but dropped conductors can have serious risks to human life. The resulting arc can cause fire. Also, due to the nonlinear nature of these faults, the harmonics created by them can have a negative effect on the quality of the delivered electricity to subscribers [3].

This paper presents a new method for detecting these types of faults. The proposed method is the simultaneous use of wavelet transform, S transformation, principle component analysis and neural network. Information on the high

impedance fault is obtained from a real test on the 20kv distribution network. Transient state information is also derived from the simulation of a 13-bus IEEE standard system in PSCAD software. The next section introduces the scientific principles of the proposed method. The third part describes how the proposed method is implemented, and the results are analyzed in the fourth and final part.

2. Scientific Foundations of the Proposed Method

In order to accurately detection of the fault, after the extraction of the initial data, accurate analyzes should be performed on them. In the proposed method, wavelet transform is used for de-noising of waveforms of fault currents. Then S transform is used to extract the features. Also, to monitor the information and prepare them for entering the neural network, principle component analysis was performed, and a multi-layer perceptron neural network was used to classify the data and to distinction between high impedance fault and other transient states. The following are scientific description of each these steps.

2-1- Wavelet transform

Wavelet transform is a finite waveform with average value of zero. information about both frequency and time is extracted from this transform. Also, information about the high or low frequencies can be obtained [4]. The continuously wavelet transform defined as a sum of the product of the time signal as bellow:

$$W(a,b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{+\infty} x(t).\, g(\frac{t-b}{a})dt \tag{1}$$

In (1), x (t) is the main signal: a and b are also time shift coefficients. Also, g (t) is the main function of the wavelet. The result of the transformation of a continuous wavelet is a large number of coefficients that are a function of the scale variable and the signal weights.

2.2 s-transform

In many applications of signal processing due to the unwanted noise, it is necessary in addition to knowing the frequency content. It was also known about the time distribution of frequency components. To determine the frequency components, a signal around the signal τ is multiplied by a function called the window. By obtaining the Fourier integral from this product, the frequency information of the signal is extracted in the neighboring τ. However, the invariance of the scale of the window causes the time-frequency separation of this conversion to be in the page. Time-frequency constant [5]. In 1996, Stakwell et al. Corrected the Fourier transform time conversion method by converting the result of their work by scaling the window into a short time Fourier transform. The transformation S for a function such as h (t) is obtained from the following equation:

$$S(\tau,f,\delta) = \int_{-\infty}^{+\infty} h(t)w(\tau-t)e^{-j2\pi ft}dt \tag{2}$$

The w (τ-t) function of the Gaussian window is scalable and is expressed as follows:

$$w(t,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-t^2}{2\sigma^2}} \tag{3}$$

(4)

$$(f)=\frac{\delta}{|f|}\sigma$$

σ Here is the standard deviation. As a result, the relation of the transformation S is expressed as follows:

$$S(\tau,f,\delta) = \int_{-\infty}^{+\infty} h(t)\left(\frac{|f|}{\sqrt{2\pi}\delta} e^{\frac{-(\tau-t)^2 f^2}{2\delta^2}} e^{-j2\pi ft}\right)dt \tag{5}$$

The setting parameter δ is used to adjust the Gaussian window width, and its value is usually between 0.2 and 3 [6]. If δ is very small, the width of the Gaussian window decreases as a result of the frequency accuracy at high frequencies. If δ is large, the width of the Gaussian window decreases and the accuracy of the time decreases in low frequencies [7].

2.3 principle component analysis

To reduce the dimensions of the feature vector, principle component analysis can be used. This method is applicable to many practical tasks. The PCA method, by providing a linear transformation, transforms the covariance matrix of the feature vectors, which is correlated between its properties, to a matrix that does not correlate its properties. In other words, the covariance matrix turns into a diameter matrix. In this method, it is assumed that the distribution of data is normal distribution. In this case, the covariance matrix C will be equal to:

$$C = \frac{1}{N}\sum_{j}^{N} X_j X_j^T - mm^T \tag{6}$$

Where n is the number of feature vectors, X is the characteristic vector and m is the mean of the characteristic vectors. Since C is symmetric and positive, it can be represented by using the transformation matrix A in the form of a diagonal with the following relation:

$$C^* = CAC^T = diag(\lambda_1, \lambda_2, \dots, \lambda_k) \tag{7}$$

Where k is the number of attributes in the characteristic vector, λ_i is equal to the i-th value of the property of the matrix C and A of the transformation matrix, whose rows contain special vectors corresponding to the special values on the diameter of C. Matrix A transforms the space of special vectors that are correlated together into a new environment in which specific vectors are not solid. It has been proved [8] that in the PCA method, which, with the choice of m of a row (of the k row) of the matrix A, corresponds to the special values of the larger matrix as the transformation matrix, can maintain the most information while reducing the dimensions of the feature vectors. The following equation shows the percentage of mean square error (MSE) calculated from the removal of the i-th special vector [1].

$$MSE = \frac{\lambda_i}{\sum_{j=1}^{k} \lambda_j} \tag{8}$$

Regarding the recent relationship, the size of the feature vectors can be reduced to suit the acceptable error.

2.4 Multi-layer perceptron neural network

Neural networks can calculate any logical function. The smallest data processing unit is called neuron. The community of several neurons in parallel is called a layer, and the multi-layer community is called a series of multi-layer neural networks. Multi-layer Perceptron Neural Networks (MLPs) with post-error-tracing algorithms continue to be the most used in solving technical and economic problems [9]. Figure 1 shows the type of network.

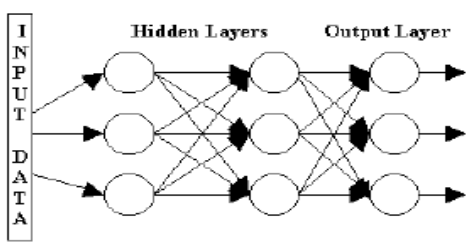

Figure 1: Multi-layer perceptron neural network

This network consists of three inbound and outbound input and output layers, the number of cells in each layer of trial and error. Input signals are normalized by means of the normalizing coefficients, and after the calculations, the output is returned to the real value. Also, the initial values of weights are taken randomly.

3. Case Study

Due to the fact that the exact model of high impedance fault does not exist, the results of a real test that was carried out in Qeshm Island power distribution system is used to extract the waveform of this fault. Other transient states are obtained from the simulation of a standard distribution system of 13 IEEEs in PSCAD software.

3.1. Data collection

Information on the high impedance fault results from a real test on a 20 kV feeder called "Transmission" in Qeshm Island. The length of this feeder is 5/19 km and the fault is about 8.5 km away from the data recording site. In order to feed this feeder, at the beginning of the two transformers 100 kVA with a ratio of 20/4 kV and The Dy5 connection is used sequentially and fed from another feeder. The Y transformers connected to each other via a 250-amp switch. Connecting one of the transformers through the cathode fuses to another power supply and the D connection of the other transformer using the cable is connected to the feeder without a "transmit" power transmission after passing through an electrical switchboard where current transformers are located. Figure 2 shows schematic connections.

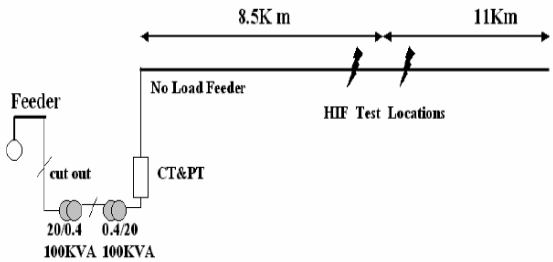

Figure 2. Schematic of feeder

Experiments on high impedance errors on 7 different surfaces, dry and wet asphalt, dry and wet sand, dry and wet cement, and dry tree in both locations and three times for each level.

Figure 3. Putting conductor on the ground and simulating fault

To obtain transient states such as load switching, capacitive switching, no loaded line switching, inrush current of transformator, short circuit fault, the simulation of a 13-bus IEEE standard distribution system has been used in PSCAD software.

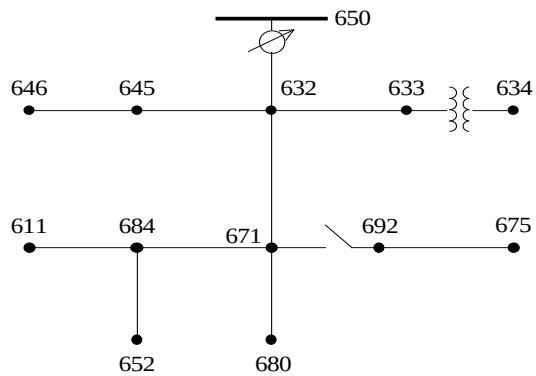

Figure 4:13-bus IEEE Standard Distribution System

3.2. Extract features

Due to the fact that the waveform is extracted from the actual experiments, this information must be denoized because of the insulator leakage current, practical test conditions, etc. A wavelet transform has been used for this purpose. Figure 5 illustrates one of the transient states of capacitive switching in the 675 bus, which is further transferred to MATLAB software for greater integration. Figure 6 shows the waveform of the fault current for the dry wood surface. Figure 7 corresponds to the same waveform after three stages of de-noising (three stages of the elimination of the detail coefficient in the wavelet transform).

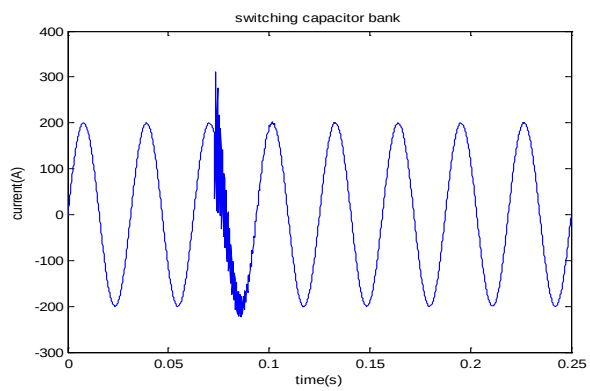

Figure 5: Switching in bus 675

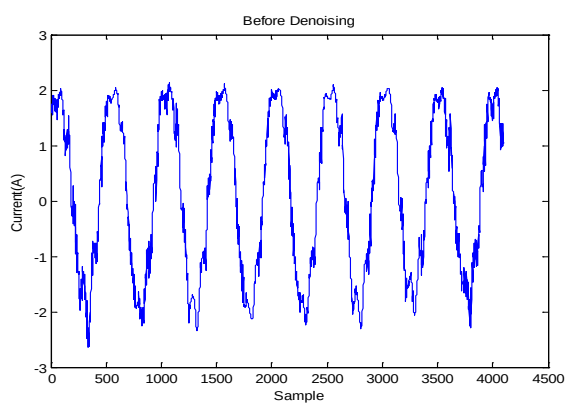

Figure 6: fault at the dry wood surface before denoising

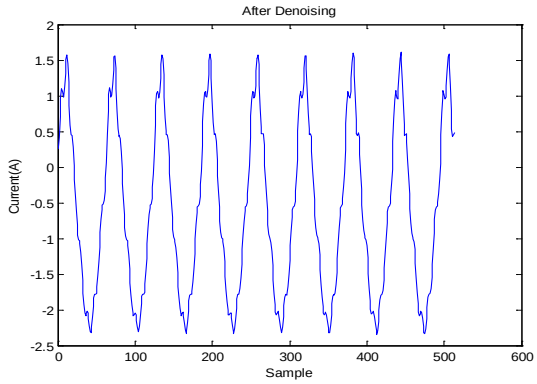

Figure 7: fault at the dry wood surface after 3-step denoising

After denoising, in the next step, the selected features are extracted by the s-transform from the waveforms. The output of the s-transform is a N × N matrix whose rows represent the frequency information and the columns represent the time information. [11]. Figure 8 illustrates the output of the MATLAB software after applying the -transform and the 14 relation for one waveform of the fault. Figure 9 shows the time information generated by the s-transform.

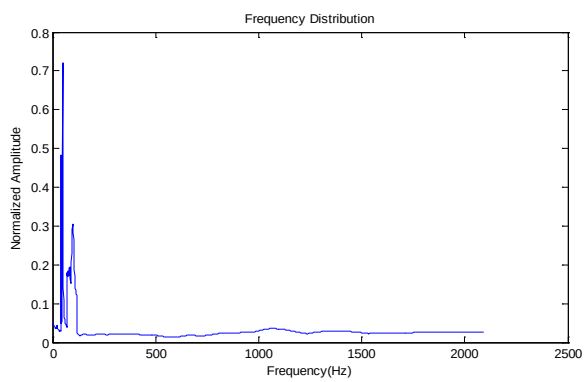

Figure 8: Frequency information after the s-transform

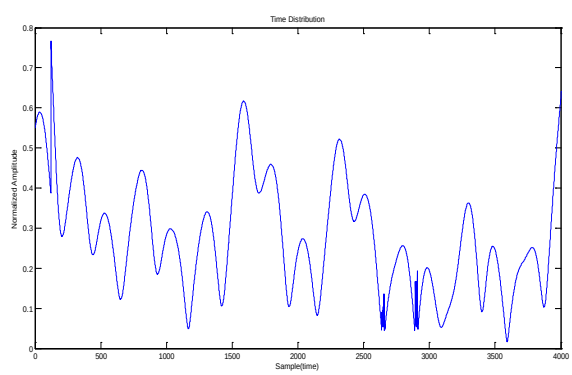

Figure 9: Time information extracted from the fault signal using the s-transform

Selected features for extracting the time and frequency information obtained from the s-transform are as follows:

$$F_1 = \sqrt{\frac{a_1^2 + a_2^2 + \cdots + a_n^2}{n}}$$

$$F_2 = \frac{|a_1| + |a_2| + \cdots + |a_n|}{n} \quad (9)$$

(10)

$$F_3 = \frac{a_1 + a_2 + \cdots + a_n}{n} \quad (11)$$

$$F_4 = \text{Standard deviation} = std(A) \quad (12)$$

$$F_5 = enrgy\ of\ signal = \sum_{i=1}^{n} a_i^2 \quad (13)$$

In the above relations, A = (a_1 + a_2 + ⋯ a_n). Selected properties are the root mean square sum, mean absolute value of data, mean of data, standard deviation, and signal energy. The number of 30 waveforms selected from the experiments. For each waveform, five characteristics of the frequency information before de-noise and after three de-noising steps, five other features of the frequency information and five features of the time information are extracted. So, a total of 15 attributes from each waveform are selected. The same number of features are also selected from the transitional state. So the dimension of the property matrix is 30 × 30. Figure 10 shows these feature points on a single screen.

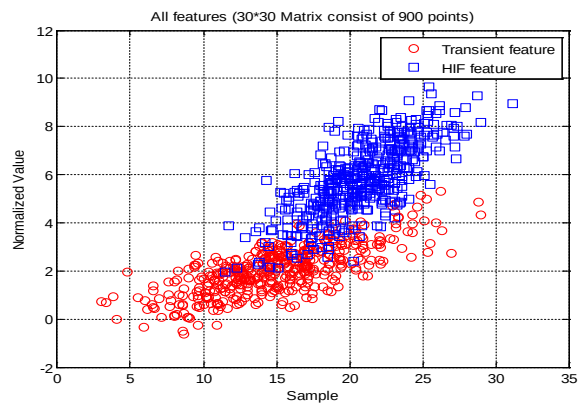

Figure 10: Total feature points

Due to the fact that the dimensions of the matrix are high and there is no proper resolution along the horizontal axis, by applying the PCA analysis, while reducing the dimensions of the feature from 30 columns to 16 columns, the horizontal axis is set to the maximum value of the variance in order to create a better resolution.

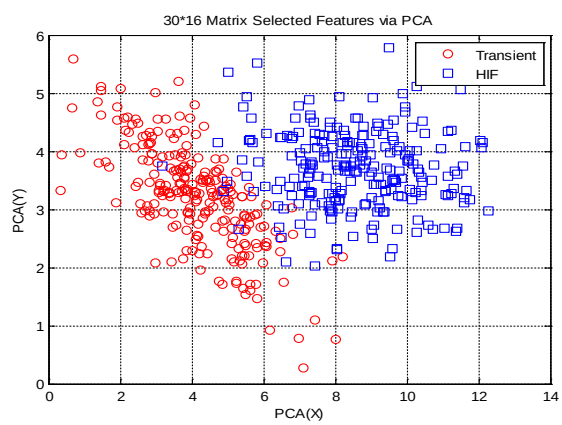

Figure 11: Feature points after pca analysis

4. Detection High Impedance Fault

Selected Neural Network to Detect High Impedance fault In this paper is a triangular perceptron neural network with midrange layers and linear actuator functions in the output layer whit post-error algorithm. To train the neural network, data is divided into two categories consist of learning and testing data. After examining different states, 20% of the data were selected as test data and 80% were selected as training data. Figure 12 shows the success rate of the neural network in training for test data. Circle points are the actual property points and the squared points of the neural network output. Obviously, as far as these points are near each other, it means better training of the neural network.

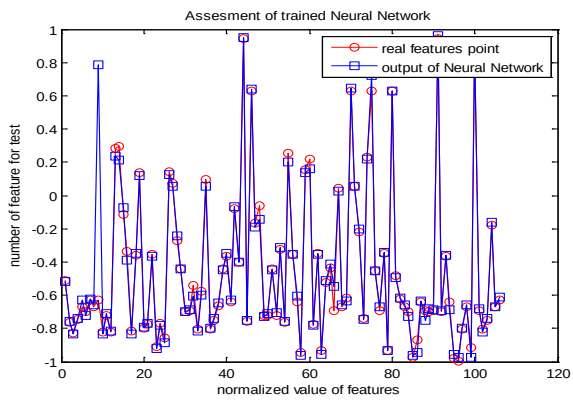

Figure 12: Success rate of neural network in training test data

After training the neural network, two classes of output were zero and one was related to high impedance fault and transient states. Table 1 shows part of the results of the neural network performance in classifying these two classes. The total network success rate by MATLAB software was 98.6%.

Table 1: Part of Neural Network Performance Results

patern	description	neural network	
		real	ideal
HIF	wood	1.0003	1
HIF	wet wood	1.0004	1
HIF	cement	1.0025	1
HIF	wet cement	0.0001	1
HIF	wet cement	0.9988	1
HIF	wet soil	0.9997	1
cap.switching	3*250kva/bus15	0.0001	0
inrushcurrent	630kva/transbus1	0.0001	0
inrushcurrent	800kva/transbus2	0.0002	0
loadswitching	load in bus 3	0.0001	0
loadswitching	load in bus 6	0.0002	0
loadswitching	load in bus 13	0.9999	0

In Figure 13, the mean square error value (MSE) for the neural network in the classification of classes is based on the number of repetitions. As it is known, in the iteration of 306, the least error rate and the highest percentage of success have been achieved.

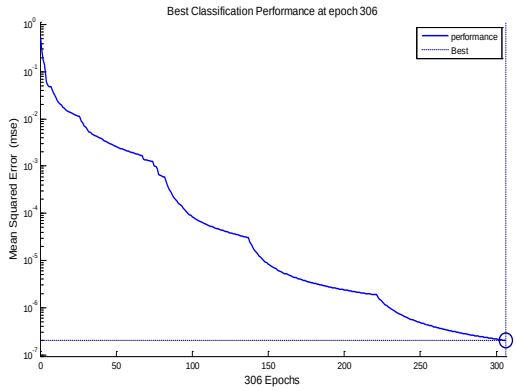

Figure 13: MSE error based on the number of iteration

Conclusion

In this paper, a new method for detecting high impedance fault using simultaneous application of wavelet transform, S-transform, fundamental component analysis and neural network was presented. Because of the high impedance fault data obtained from the actual tests and final results shows the acceptable percentage of success, then this method can be used as a safe method.

References

[1] A. Ghaderi, H. A. Mohammadpour, H. Ginn, Yong-June Shin "High Impedance Fault Detection in Distribution Network using Time-Frequency Based Algorithm."IEEE Transaction on Power Delivery 2014.

[2] S. Gautam, M. Brahma," Detection of High Impedance Fault in Power Distribution Systems Using Mathematical Morphology" IEEE Transaction On Power Systems, Vol. 28, No. 2, May 2013.

[3] J.C. Chen, B.T. Phung, H.W. Wu, D.M. Zhang and T. Blackburn. "Detection of High Impedance Faults Using Wavelet Transform" AUPEC 2014, Curtin University, Perth, Australia, 28 September – 1 October 2014

[4] S. El Safty, A. El-Zonkoly. "Applying wavelet entropy principle in fault classification",Electric Power Systems Research , pp. 604-608, 2009.

[5] R.G. Stockwell, L. Mansinha, and R. P. Lowe,"Localization of the complex spectrum: The S–transform," IEEE Trans. Signal Processing, vol. 44, pp.998–1001, Apr 1996.

[6] M.J. Dehghani, "Comparison of S-transform andWavelet Transform in Power QualityAnalysis,"PWASET, vol. 38, Feb 2009.

[7] S.S. Sahuw, G. Panda and N.V. George, "An Improved S-Transform for Time-Frequency Analysis,"IEEE International Advance Computing Conference (IACC 2009) 2009.

[8] J.T. Tou; R.C.Gonzalez;"PatternRecognition Principles " 4th Edition, Massachusetts, Addision-Wesley Publishing Company, 1981.

[9] Ibrahem Baqui, Inmaculada Zamora, "High impedance fault detection methodology using wavelet transform and artificial neural networks", Electric Power Systems Research, pp. 1325-1333, 2011.

[10] Siddiqui, Anaraki. (2009). "Identifying Impedance Errors in Distribution Networks" Ph.D. in Electrical Engineering, Tarbiat Modares University.

[11] S.R. Samantaray, B.K. Panigrahi and P.K. Dash,"High Impedance Fault Detection in Power Distribution Networks Using Time-Frequency Transform and Probabilistic Neural Network," IET General Transmission Distribution, vol. 2, no. 2, pp. 261-270, 2008.