Automated Classification of Power Quality Disturbances using Hilbert Huang Transform and RBF Networks

T. Jayasree, D. Sam Harrison, T. Sree Rangaraja

Abstract: This paper presents Radial Basis Function Neural Network based approach for automatic Power Quality (PQ) disturbance classification. The input features of the Neural Network are extracted using Hilbert Huang Transform (HHT) and they are given as input to the Radial Basis Function Neural network. The data required to develop the network are generated by creating various faults in a test system. The proposed method requires less number of features and less memory space without losing its original property.

Keywords: PQ, HHT

I. INTODUCTION

The increased use of non-linear loads and the occurrence of fault on the power system have resulted in deterioration in the quality of power supplied to the customers. In order to improve the quality of electric power supplied, it is essential to detect and identify the power quality problem distinctive features of the disturbance waveforms.

Many signal processing techniques have been proposed in the literature for this purpose. The most commonly used signal processing techniques are Fourier Transform (FT), Wavelet Transform (WT) and S-Transform [1]. The Fourier Transform based signal processing techniques are Fast Fourier Transform (FFT) and Short Time Fourier Transform (STFT)[2]. But the Fourier Transform (FT) based techniques are suitable only for analyzing stationary signals and extracting spectrum components of the signals at specific frequencies [3].

The Wavelet Transform (WT) traces the signal changes in time domain and simultaneously decomposes the signal in frequency domain. In the Wavelet Transform based approach, a mother wavelet is employed for finding the wavelet coefficients of the signal which affects the effectiveness in identifying the disturbance present in the signal. The advantage of using WT is that it does not need to assume the stationarity and periodicity of signals.

Anton V. Shupletsov et al [2] applied the Wavelet Transform for extracting the features. Feature extraction technique using the standard deviation of the wavelet coefficients is discussed in [5].

Gouda et al [6] employed seven levels of decomposition for finding the wavelet coefficients. The Wavelet Transform based approach has the following limitations: Wavelet Transform is sensitive to noise. Also proper selection of mother wavelet and the level of decomposition are necessary for effective recognition of disturbance signals.

S-Transform produces a time-frequency representation of a signal. It uniquely combines a frequency dependent resolution that simultaneously localizes the real and imaginary spectra. Ming He Zhang et al [11] employed S-Transform for the analysis and detection of power quality disturbances. Ameen M. Gargoom et al [1] proposed the analysis of power quality events using amplitude and phase spectrum derived from the S-Transform of the signal. Dhas et al [6] employed the S-Transform based feature extraction technique for disturbance detection. Here the change in energy and standard deviation calculated from the S-Transform contour are considered as input features of the network. The S-Transform based approach requires the selection of a suitable window to match with the specific frequency content of the signal which is generally not known a priori.

In this paper, Hilbert-Huang Transform (HHT) is proposed for extracting the features from the disturbance signal. The Hilbert-Huang Transform (HHT) is an adaptive data analysis method designed for analyzing non-stationary signals.

Classification is another important task in automatic power quality disturbance recognition. Artificial Neural Network (ANN) models have been proposed for disturbance classification. Lee et al [18] developed an automatic disturbance recognition system using Multi Layer Perceptron (MLP) with the back propagation weight updating algorithm having unipolar activation function. Most of the authors have used feed forward neural networks with sigmoidal nonlinearities for model development. The shortcoming of this network is that, it takes long time for training. In this work, Radial Basis Function (RBF) neural networks are proposed for classification. This type of neural network has a number of advantages over conventional multilayered neural network; such as higher accuracy, less training time, simple topology and no local minima problem [25]. Simulation results demonstrate the effectiveness of HHT based RBF network for power quality disturbance recognition.

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II. PROPOSED METHODOLOGY

The proposed methodology for disturbance waveform classification is based on Artificial Neural Network. Artificial Neural Network approach for any application involves two stages: network development and actual usage of the network. The various stages involved in the network development are

- Data generation
- Feature extraction and
- Network training

Generation of the appropriate training data is an important step in the development of ANN models. A large number of training data is generated by creating various faults in the test system. The features of the input data are extracted by finding the Hilbert-Huang Transform of the signal. Standard statistical techniques are applied to the transformed signal.

The extracted features are presented to the RBF neural network for training. After training, the network is tested with the test data to assess the generalization ability of the network.

III. HILBERT HUANG TRANSFORM

The Hilbert-Huang Transform (HHT) is an adaptive data analysis method designed for analyzing non-stationary signals. In HHT, the signal is decomposed into a finite small number of components, called Intrinsic Mode Functions (IMF). This process of decomposition is called Empirical Mode Decomposition (EMD).

A. Empirical Mode Decomposition (EMD)

The EMD decomposes the signal in terms of IMFs, each of which is a mono-component function [13]. The procedure for extracting the IMFs from a signal $x(t)$ is given below:

1. Identify the local extrema of the signal. A signal has at least two extrema (maximum and minimum).
2. Two smooth splines are constructed which connects all the maxima and minima of $x(t)$ to obtain its upper and lower envelope.

Let m_1 be the mean of the two envelopes. The difference between the input signal $x(t)$ and m_1 is the first component, h_1

$$x(t) - m_1 = h_1 \quad (1)$$

This is the first round of shifting. In this round, h_1 is treated as proto-IMF. In the next round, it is treated as the signal, then

$$h_1 - m_{11} = h_{11} \quad (2)$$

After repeated shifting, upto k times, h_{1k} is obtained as

$$h_{1(k-1)} - m_{11} = h_{1k} \quad (3)$$

The function h_{1k} is defined as the first IMF component and expressed as

$$c_1 = h_{1k} \quad (4)$$

The stopping criteria of the decomposition process is determined by the Cauchy type of convergence test, given by the equation

$$SD_k = \sum_{t=0}^{T} \left| h_{k-1}(t) - h_k(t) \right|^2 / \sum_{t=0}^{T} h^2{}_{k-1}(t) \quad (5)$$

The shifting process is stopped, when SD_k becomes smaller than a pre determined value. Once the shifting process is stopped, the first IMF c_1 can be obtained, which contains the finest scale or the shortest period component of the signal.

After separating c_1 from the original signal $x(t)$, the residue of the signal is obtained

$$x(t) - c_1 = r_1 \quad (6)$$

This process can be repeated for all r_j and the result is

$$r_1 - c_2 = r_2 \quad (7)$$

$$r_{n-1} - c_n = r_n \quad (8)$$

The shifting process stops finally when the residue r_n becomes a monotonic function, from which no more IMFs can be extracted. By summing up the equations it follows that

$$x(t) = \sum_{j=1}^{n} c_j + r_n \quad (9)$$

Thus the decomposition of a signal in n-empirical modes is achieved. The components of the EMD are physically meaningful, as the characteristic scales are defined by the physical data. The instantaneous frequency can be computed by finding the Hilbert Transform of the IMF components.

B. Feature Extraction using Hilbert-Huang Transform

The features of the disturbance signals are extracted by finding the energy of the IMFs which are derived from each of the disturbance waveforms. Let c_1, c_2, c_3 be the first three IMF components and E_1, E_2 and E_3 be their corresponding energies. Energy of the IMF is calculated using the following equations.

$$E_1 = \|c_1\|^2 \qquad (12)$$

$$E_2 = \|c_2\|^2 \qquad (13)$$

$$E_2 = \|c_3\|^2 \qquad (14)$$

where $\|.\|$ represents norm.

IV. DEVELOPMENT OF RBF NETWORK

The schematic diagram of RBF neural network is shown in figure 1. The RBF network [18] has an input layer, a hidden layer consisting of Gaussian node function, a set of weights W, to connect the hidden layer and output layer. The transfer functions in the nodes are similar to the multivariate Gaussian density function:

$$\Phi_j(x) = exp\,(-\|x-\mu_j\|^2/2\sigma_j^2) \qquad (15)$$

Where x is the input vector, μ_j and σ_j are the center and spread of the corresponding Gaussian function. Each RBF unit has a significant activation over a specific region determined by μ_j and σ_j. Thus each RBF represents a unique local neighborhood in the input space. The connections in the second layer are weighted and the output nodes are linear summation units. The value of k^{th} output node y_k is given by :

$$y_k(x) = \sum_{j=1}^{h} w_{kj}\,\Phi_{j(x)} + w_{k0} \qquad (16)$$

where w_{kj} is the connection weight between the k^{th} output and the j^{th} hidden node and w_{k0} is the basis term.

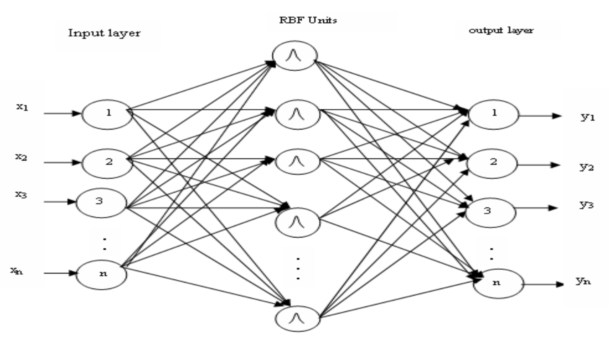

Figure 1 Architecture of RBF neural network

The Fuzzy C-Means algorithm consists of two processes: the calculation of cluster centers and the assignment of points to these centers using a form of Euclidian distance. This process is repeated until the cluster centers stabilize. The details of FCM algorithm is given in the appendix.

Next, the unit widths σ_j are determined using a heuristic approach that ensures the smoothness and the continuity of the fitted function. The width of any hidden node is taken as the maximum Euclidean distance between the identified centers. Finally, the weights of the second layer connections are determined by linear regression using a least squares objective function.

V. EXPERIMENTAL SETUP FOR DATA GENERATION

An induction motor-based experimental setup was fabricated in the laboratory to collect the real time power quality disturbance data. The experimental setup consists of induction motor, DAQ hardware and Personal Computer (PC). The photograph of the real-time set up is given as figure 2. The system first samples and collects the voltage data from a measurement point by means of transducers and DAQ hardware. After DAQ hardware gathers the raw data, the data is sent to the PC through the RS 232 communication protocol.

Figure 2: Experimental setup for real-time PQ data generation

The voltage distortions are created by introducing a chopper circuit. The different types of disturbance waveforms are generated by varying voltages, frequency and adding harmonic distortion. Voltage sag is measured during the starting of induction motor. Transient signal is generated by connecting a switching capacitor between the induction motor and the load and measuring the voltage across the capacitor. Harmonic signal is obtained by connecting non-linear devices across the load and measuring the voltage across it. When the load is switched off suddenly, voltage swell is produced. Flicker is produced by connecting a choke across the load and measuring the voltage across it. Figure 3 shows the DAQ hardware used in the system.

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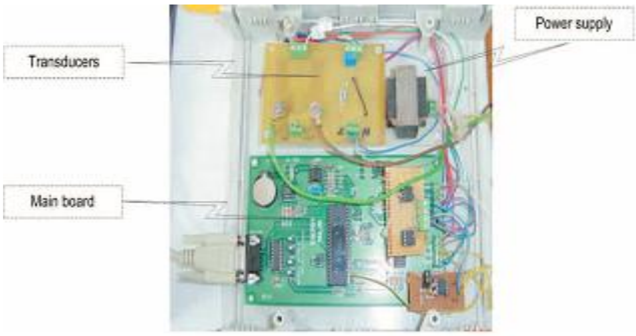

Figure 3 The DAQ hardware

The DAQ hardware captures and samples the disturbance signals. Then these signals are transferred to the MATLAB workspace for further analysis. Some of the real time power quality disturbance data collected from the experimental set-up is shown in figure 4.

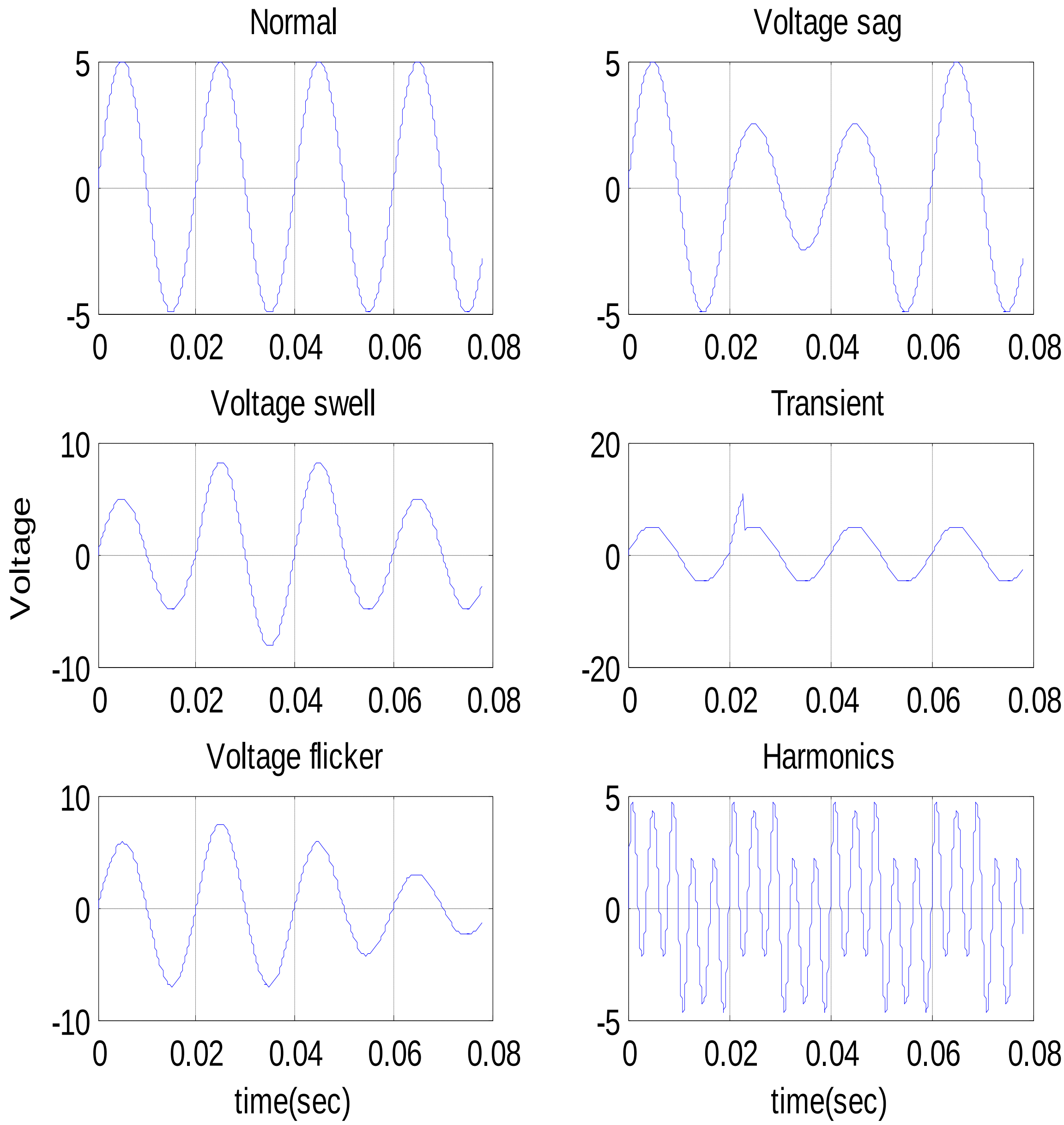

Figure 4 Real-time PQ disturbance generated from experimental setup

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VI. RESULTS AND DISCUSSION

The disturbance signals are generated using the method explained in section 5. Totally 500 samples are generated for each disturbance type. Out of this, 300 samples are used for training and 200 for testing. The IMF components of these disturbances are found out using EMD technique. The IMF components for voltage sag and voltage swell are shown in figure 5 and 6.

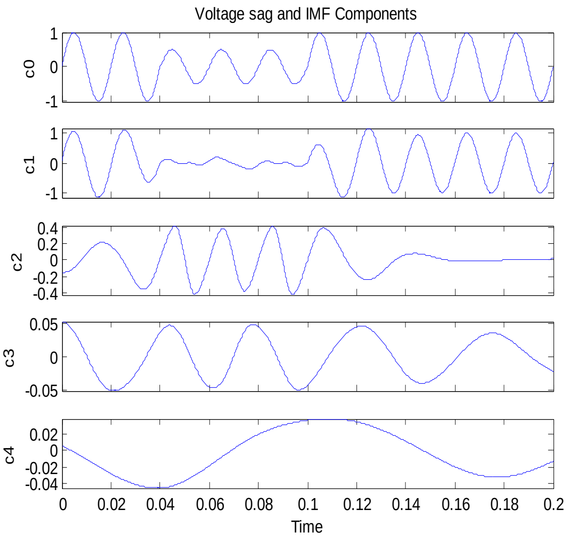

Figure 5 Voltage sag and its IMF components

As shown in figure 5, the voltage sag signal is decomposed into four IMF components c_1, c_2, c_3 and c_4. The maximum amplitude of the IMF decreases gradually from c_1 to c_4. Each IMF component shows variations in magnitude and its value depends on the amplitude of both top and bottom envelopes.

Figure 6 shows the voltage swell and its IMF components.

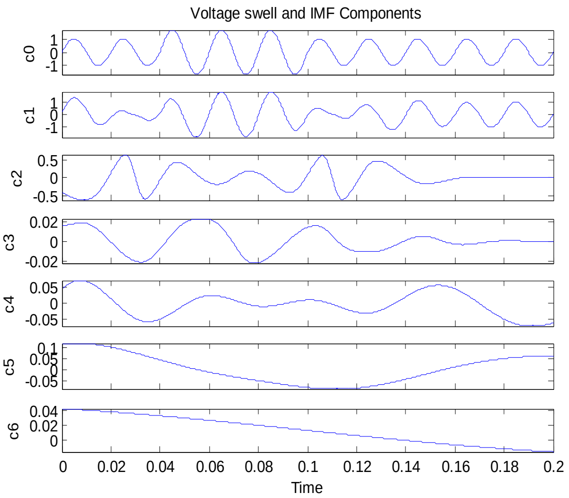

Figure 6 Voltage swell and its IMFs

As shown in figure 6, the voltage swell signal is decomposed into six IMF components. The total number of IMF varies depending on the maximum and minimum amplitude of the signal and the duration of the disturbance present in the signal.

The energy of the IMF for some of the power quality disturbances are given in Table 1

Table 1 Energy of IMF components for Power quality disturbances

Disturbance type	Energy of IMF		
	E_1	E_2	E_3
Voltage sag	0.424	0.698	0.828
Voltage swell	2.412	4.012	7.917
Transient	7.521	8.012	10.624
Harmonics	5.2219	7.364	7.825
Flicker	4.327	5.304	6.096

The energy E_1, E_2 and E_3 of the IMF component varies for different types of disturbances as shown in Table 1. These features are given as input to the RBF network for further classification.

VII. PERFORMANCE MEASURES

The performance of the classifier is tested by evaluating the following performance measures for the training set, test set and combined data set.

a) Mean Squared Error (MSE)

$$MSE = \frac{1}{n}\sum_{k=1}^{n}(E_k)^k \qquad (17)$$

Where DO_k - Desired output from the data generation

AO_k - Actual output obtained from the classifier algorithm

b) Classification Accuracy (CA)

$$CA(\%) = \frac{\text{No. of samples correctly classified x 100}}{\text{Total no. of samples in the data set}} \qquad (18)$$

c) Misclassification (MC) Rate

(i)Secure Misclassification (SMC) or False Dissimal

$SMC(\%) =$ No. of 0's classified as1 x 100 (19)

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Total no. of Insecure (0) states

ii) *Insecure misclassification (ISME) or False Alarm*

$$ISME(\%) = \frac{\text{No. of 1's classified as 0} \times 100}{\text{Total no. of Secure (1) states}} \qquad (20)$$

The performance measures of the disturbance recognition system developed based on signal processing technique and ANN are evaluated. For automatic disturbance recognition system, the classification accuracy should be high. The False alarm, false dissimal and Mean Square Error (MSE) should be low [14]. The ANN classifier must be designed to meet these requirements. The classification results are given in Table 2. Here, it is found that RBF based on FCM clustering algorithm produces high accuracy rate.

Next, the performance of the network is tested under the noisy environment. The disturbance signals are added with Gaussian noise of 30 dB. The relevant features are extracted from the noise corrupted signals based on the same method explained in section 7. These features are given as input to the RBFNN for training and it is further tested with the test data to asses the generalization ability of the network. The performance of the network during testing is given Table 2.

Table 2 Performance measures of HHT based RBFNN

Performance Measures	Without noise	With noise
Classification Accuracy (%)	98.6	95.3
Mean Square Error (MSE)	0.0083	0.0174
Secure Misclassification (SMC) (%)	3.184	3.602
Insecure Misclassification (IMSC) (%)	1.0124	3.815

From Table 2, it is found that, the HHT based RBFNN produces high classification rate and results in low MSE, SMC and IMSC

VIII. CONCLUSION

A new feature extraction method based on Hilbert-Huang Transform is presented in this paper for automatic classification of power quality disturbances. It is observed that, in HHT based feature extraction, the proper selection of mother wavelet or any window functions as in the case of Wavelet Transform and S-Transform are not necessary.

An RBF network developed using FCM is used for the classification of disturbance waveforms. The simulation results show that the classification accuracy of the network is very high even in the presence of noise.

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