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Comparison of Empirical Mode Decomposition and Wavelet Based Classification of Power Quality Events

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Abstract

This paper presents a novel method of power quality events classification like sag, swell, harmonics, flicker, notch etc based on Empirical Mode Decomposition (EMD) with Hilbert Transform (HT). EMD decomposes the disturbance signal into different mono component and symmetric component signals by sifting process. These mono component signals are called Intrinsic Mode Functions (IMFs) i.e. they are composed of single frequency or narrow band of frequencies. The magnitude plot of the Hilbert transform of the first IMF can correctly detect the disturbance. The characteristic features of the first three IMFs of each disturbance are used as inputs to Probabilistic Neural Network (PNN) for identification of the disturbances. A comparison is made with wavelet transform. Simulation results show that EMD method effectively classifies the power quality disturbances.

Keywords-Empirical mode decomposition, intrinsic mode functions, hilbert transform, power quality events, probabilistic neural network, wavelet transform.

1. Introduction

Power supply quality problem has become a major concern both for industries and utility owing to increased use of sensitive electronic equipment [1]. Any variation in magnitude and/or frequency of the voltage or current waveform is defined as power quality problem. Some of the power quality problems are the voltage sag, swell, interruption, flicker, and transients etc. which cause mal operation or failure of power equipment. Power quality events vary in wide range of time and frequency domains which make automatic detection a difficult task. This involves having a powerful tool or method which can detect, localize and classify the power quality events. This paper aims at classification of various power quality disturbances. A number of signal processing techniques are reported in literature [2]-[9]. A simple method to analyze any signal is by Fourier Transform [2] (FT). However it provides only frequency

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content, therefore this method is applicable for stationary signals. To over come this drawback, Short Time Fourier Transform (STFT) is proposed [3-4] which maps a signal into a two dimensional function of time and frequency. The STFT extracts time and frequency information, but the disadvantage is that the size of the window is fixed for all frequencies. The wavelet analysis [5-8] represents a windowing technique with variable regions to overcome the above deficiency. It provides a unified methodology to characterize power quality events by decomposing the signal into time and frequency resolution. A wavelet transform expands a signal in terms of trigonometric polynomial by using wavelets generated using transition (shift in time) and dilation (compression in time) of a fixed wavelet function. So, wavelet function is localized both in time and frequency, yielding wavelet coefficients at different scales. The drawback of wavelet transform is its inaccuracy in detecting the event under noisy conditions. The S-transform [9] on the other hand is an extension to wavelet transform and is based on moving and scalable localizing Gaussian window.

This paper presents Empirical Mode Decomposition [10] together with Hilbert transform for extracting mono component and symmetric components from non stationary signals. These mono component signals are called the Intrinsic Mode Functions. The advantage of this method is that it does not require predetermined set of mathematical functions and it allows projection of a non stationary signal onto a time frequency plane using a mono component signals, thus making it adaptive in nature.

The rest of the paper is organized as follows: Section 2 gives introduction to EMD and Hilbert transform. Section 3 presents the detection capability of the proposed method for power quality events. In section 4 gives the introduction of PNN. Section 5 the simulation results based on the EMD method are discussed. Finally section 6 gives the conclusions.

2. Empirical mode decomposition

When a signal is not stationary amplitude and frequency change with time as in the case of most power quality disturbances. Representing such a non-stationary signal as a combination of different sinusoidal signals will not be accurate and single frequency can not be defined. This accounts for a parameter which varies with time. So it is necessary to have a more flexible and extended notion of frequency. This gives rise to an idea of Instantaneous frequency (IF) which means for a signal having a single frequency or narrow band of frequencies. Many of the power quality disturbances are non stationary and the concept of IF would be of great help. Therefore it becomes important for such an algorithm which separates different components of single frequency such that IF can be defined for each signal. Empirical mode decomposition is a method which extracts mono component and symmetric components from the non linear and non stationary signals by sifting process. Sifting indicates the process of removing the lowest frequency information until only the highest frequency remains. The key feature of EMD is to decompose a signal into so called Intrinsic Mode Functions. These IMFs extracted from the original signal are mono component composing of single frequency or narrow band of frequencies. Huang et al., defined an oscillating wave as an IMF if it satisfies the following two conditions:

1. For a data set, the number of extreme and the number of zero crossings must either be equal or differ at most by one.
2. At any point, the mean value of the envelope defined by the local maxima and the local minima is zero.

The algorithm for extracting an IMF is by sifting process as given below:

Step1: The upper and the lower envelopes are constructed by connecting all the maxima and all the minima with cubic splines, respectively.

Step 2: Take the mean of the two envelopes and let it be defined as m(t). Subtract the mean m(t) from the original signal x(t) to get a component $h_1(t)$, *Where* $$h_1(t) = x(t) - m(t) \quad (1)$$

Step 3: If $h_1(t)$ satisfies the two conditions of IMFs , then $h_1(t)$ is the first intrinsic mode function else it is treated as the original function and steps (1) - (3) are repeated to get component $h_{11}(t)$ such that

$$h_{11}(t) = h_1(t) - m_1(t) \quad (2)$$

Step 4: The above sifting process is repeated k times, $h_{1k}(t)$ becomes an first IMF and be known as IMF1.
Separate IMF1 from x(t) and let it be $r_1(t)$, such that

$$r_1(t) = x(t) - h_{1k}(t) \quad (3)$$

Step 5: Now taking the signal $r_1(t)$ as the original signal and repeating the steps (1)-(4) second IMF is obtained.

The above procedure is repeated n times and such n IMFs are obtained. The stopping criterion for the decomposition process is when $r_n(t)$ becomes a monotonic function from which no more IMF can be extracted.

2.1. Hilbert transform

The Instantaneous frequency of each IMF is calculated by using the Hilbert Transform. The Hilbert Transform of a real valued time domain signal x(t) is another real valued time domain signal, denoted by $\hat{x}$ (t), such that z(t) = x(t) + j $\hat{x}$ (t) is an analytic signal. From z(t), one can define a magnitude function A(t) and a phase function *θ(t)*, where the first describes the envelope of the original function x(t) versus time and *θ(t)* describes the instantaneous phase of x(t) versus time.
The above algorithm is implemented on a voltage sag waveform. Fig. 1(a) –(b) shows the waveforms of sag and magnitude plot of hilbert transform of IMF1 and (c)- (g) corresponding intrinsic mode functions of sag in voltage.

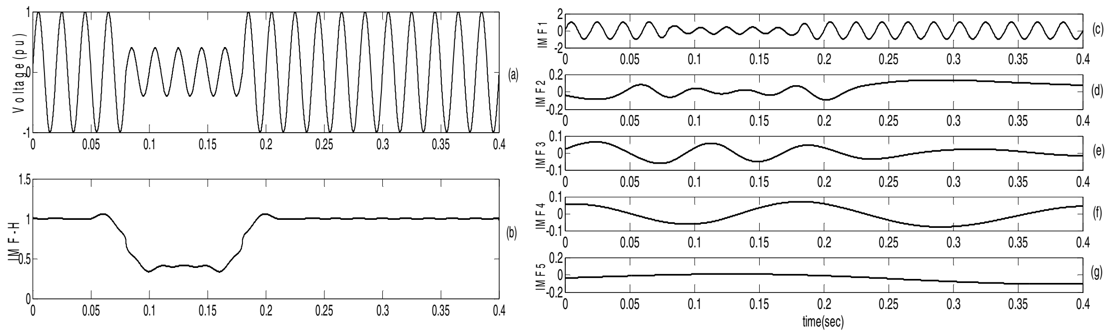

Fig. 1(a). Waveform of voltage sag ,(b) magnitude plot of hilbert transform of IMF1, (c) – (g) IMF1 to IMF5.

3. Detection and Feature Extraction by EMD method

This section presents the application of EMD for detection of power quality events. The magnitude plot of the Hilbert transform of the first IMF obtained by sifting process gives the information of the magnitude and frequency content of the signal. The change in the magnitude of signal is identified which detects the disturbance. For the same disturbance signals Wavelet analysis is also performed to detect the PQ events.

3.1. Voltage swell

Fig. 2(a) shows the case of voltage swell signal. . The event occurs from 0.14 to 0.3sec for about 8 cycles with 1.5pu magnitude. 2(b) shows the magnitude plot of Hilbert transform of the IMF1 which correctly detects the swell event. Fig. 2(c) shows level 1 detailed coefficient obtained by performing wavelet transform using db4 mother wavelet.

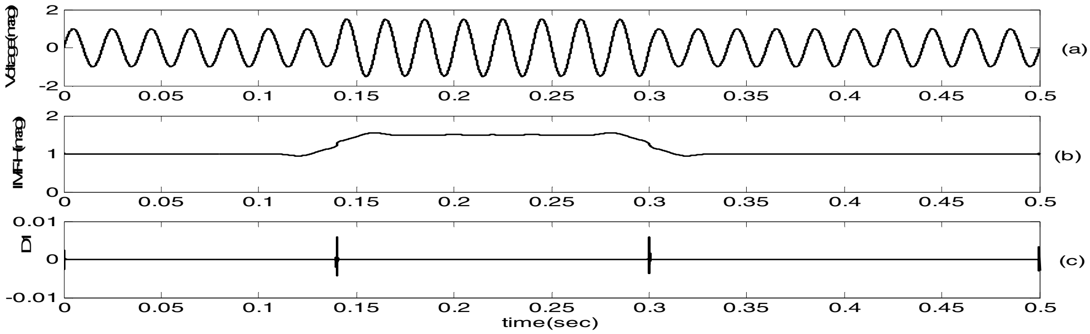

Fig. 2(a). Waveform of voltage swell , (b) magnitude plot of hilbert transform of IMF1, (c) D1 coefficients by WT.

3.2. Notch and Spike

Fig. 3(a) shows the case of signal having 2 notches/ cycle. The magnitude plot of the IMF1 clearly detects the notches as shown in the Fig. 3(b). The level -1 coefficient from WT are shown in Fig. 3(c). Fig. 4(a) shows the signal having spike for 0.25msec with magnitude of 1.3pu. The magnitude plot of the IMF1 correctly detects the spike as in the Fig. 4(b). The level – 1 coefficient from WT is shown in Fig. 4(c).

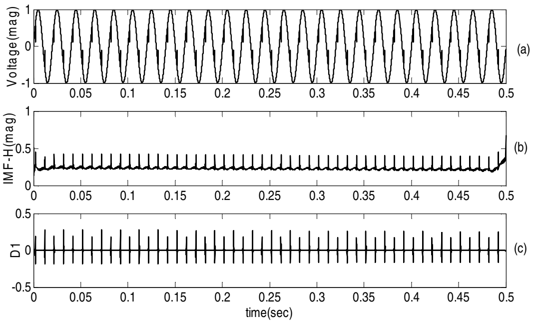

Fig. 3(a). Waveform of voltage notch , (b) magnitude plot of hilbert transform of IMF1, (c) D1 coefficients by WT.

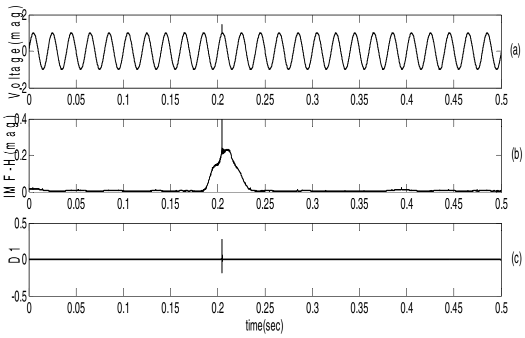

Fig. 4(a). Waveform of voltage spike , (b) magnitude plot of hilbert transform of IMF1, (c) D1 coefficients by WT.

3.3. Harmonic

Fig.5 (a) shows the waveform of harmonic signal. The signal y(t) = sin(wt) + 0.14sin(3wt) + 0.12sin(5wt) + 0.1sin(7wt) is considered. Fig. 5(b) – (d) are the IMF1 – IMF 2 waveforms which represents the frequencies of harmonic content. Fig 6 (a)- (e) are the detailed coefficients obtained from wavelet analysis.

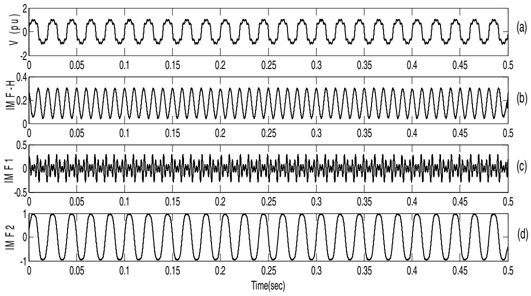

Fig. 5(a). Waveform of voltage notch , (b) magnitude plot plot of hilbert transform of IMF1, (c) –(d) IMF1 – IMF2

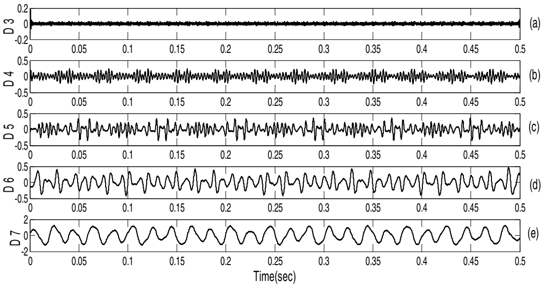

Fig. 6(a)-(e) Level 3-7 detailed coefficients by WT.

The following three features (1) Energy distribution, (2) Standard deviation of the amplitude and (3) Standard deviation of the phase angle are extracted from first three IMFs. Thus, we have nine features from the three IMFs of each disturbance.

4. Probabilistic Neural Network

The Probabilistic Neural Network (PNN) [11] is a supervised neural network that is widely used in the area of pattern recognition. The fact that PNNs offer a way to interpret the network's structure in terms of probability density functions (PDF) is an important merit of this type of networks. The following features are distinct from those of other networks in the learning processes.

- It is implemented using the probabilistic model, such as Bayesian classifiers.
- A PNN is guaranteed to converge to a Bayesian classifier provided with enough training data.
- The differences between the inference vector and the target vector are not used to modify the weights .

The standard training procedure for PNNs requires a single pass over all to the patterns of the training set. This characteristic renders PNNs faster to train suitable for classification of power quality disturbances. Fig. 7 shows the flow chart used for classification of power quality events using probabilistic neural network.

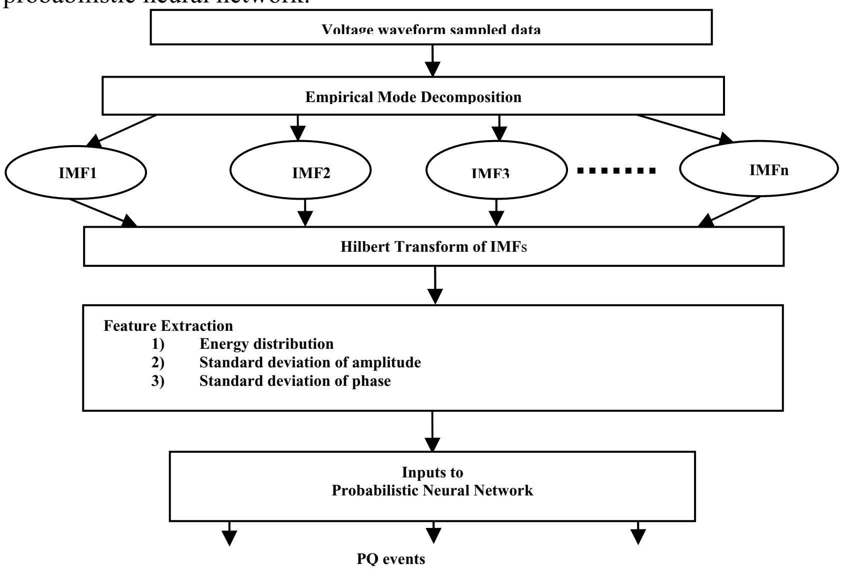

Fig 7. Flow chart for classification of PQ events using EMD.

5. Results and Discussion

Ten types of PQ disturbances are taken for case study. Disturbances as such Sag, Swell, Harmonic, Transient, Sag with Harmonic, and Swell with Harmonic, Outage, Flicker, Notch and Spike are generated using MATLAB/ Simulink software. Simulations are performed to generate 1200 signals, 500 data sets are used for training the PNN classifier and 700 are used for testing. PNN is trained with the spread factor of 0.1 tuned by trial and error method which has given better results. As shown in the Table 1 the overall efficiency of the EMD method is 97.57% and that of wavelet transform is 95.28% as given in Table 2.

Table 1: Percentage classification accuracy of PNN by EMD method.

Signal	Sag	Swell	Harmonics	Transient	Sag with Harmonics	Swell with Harmonics	Outage	Flicker	Notch	Spike
Sag	70									
Swell		70								
Harmonics			68	2						
Transient			5	65						
Sag with Harmonics	**3**				**67**					
Swell with Harmonics		5				65				
Outage							70			
Flicker			2					68		
Notch									70	
Spike										70
Classification Accuracy: 97.57%										

Table 2: Percentage classification accuracy of PNN by Wavelet Transform.

Signal	Sag	Swell	Harmonics	Transient	Sag with Harmonics	Swell with Harmonics	Outage	Flicker	Notch	Spike
Sag	70									
Swell		70								
Harmonics			68	2						
Transient			5	65						
Sag with Harmonics					**70**					
Swell with Harmonics						70				
Outage							70			
Flicker			5					65		
Notch									61	9
Spike									13	58
Classification Accuracy: 95.28%										

It is seen that wavelet transform performs unsatisfactorily for the two cases notch and spike, where 9 and 12 of them respectively are misclassified. The application of EMD decomposes the disturbance signal into number of IMFs. The number of IMFs for a given disturbance depends upon the severity of distortion and magnitude of harmonic content. In the case studied, for a disturbance like voltage sag and swell the

IMFs are five, in case of harmonics and flicker the IMFs obtained are two and one respectively , for sag and swell with harmonics it is decomposed into seven and six IMFs and for a disturbance like outage it has maximum number of eight IMFs. In the case of harmonics and flicker, as IMFs are mono component signals extracted from the disturbance, they directly give the information of the frequency content of the signal. As previously mentioned, EMD is a sieving process and the first IMF represents the finest scale of oscillation of the signal. Hence, an event like notch and spike which occurs for milliseconds of time can be classified very accurately by this methodology.

6. Conclusions

In this paper EMD with Hilbert transform is used to classify the power quality disturbances. EMD method decomposes the original signal into mono component signals to extract instantaneous frequency information of each mode of oscillation thus, making it a better method in assessing power quality disturbances. The results show the superiority of the method in correctly classifying the disturbances. Hence the proposed method is suitable for classification of non-stationary signals.

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