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# Empirical Mode Decomposition with Wavelet Transform Based Analytic Signal for Power Quality Assessment

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***Abstract*—This paper proposes empirical mode decomposition (EMD) together with wavelet transform (WT) based analytic signal for power quality (PQ) events assessment. EMD decomposes the complex signals into several intrinsic mode functions (IMF). As the PQ events are non stationary, instantaneous parameters have been calculated from these IMFs using analytic signal obtained form WT. We obtained three parameters from IMFs and then used KNN classifier for classification of PQ disturbance. We compared the classification of proposed method for PQ events by obtaining the features using Hilbert transform (HT) method. The classification efficiency using WT based analytic method is $97.5\%$ and using HT based analytic signal is $95.5\%$.

***Keywords*—Empirical mode decomposition, Hilbert transform, wavelet transform.

## I. Introduction

MAGNITUDE and frequency variation of the voltage or current waveform causes PQ problems. PQ is an important issue for the producers, distributors and consumers. Voltage sag, swell, flicker, transients and harmonics are some examples of PQ events, which causes malfunctioning of electronic equipments and are threats for them. Duration of these PQ disturbances vary from nanoseconds to minutes. Different types of PQ events may cause under voltage, over voltage, light flickering, heating and saturation of devices. Thus, assessment of PQ disturbance is necessary for proper operation of electrical devices.

Semiconductor devices used in various applications also require to eliminate these PQ problems. Elimination of these unwanted PQ events use feature extractions and classification methods. Different signal processing methods have been presented in literature to process the PQ disturbances. In [1], Flores proposed an overview of different PQ events. The author discussed various methods used for signal components estimation such as discrete Fourier transform, fast Fourier transform and different types of wavelets. The paper also presented various methods used for detection, quantification and classification of variety of PQ disturbances such as automatic classification based on wavelet feature extraction and Bayesian classifier. In [2], Chilkuri generated optimal feature vectors using S transform and classified the PQ events using pattern recognition system that uses fuzzy logic. The features obtained using the S transform are useful for efficient and accurate classifier due to time frequency representation of S transform. The advantage of the method is that the S transform of time varying signal presents quantifiable parameters which are useful for localization, detection and quantification of the signal. In [3], Gargoom et al. presented automatic classification of PQ events using HT and Clarke transform together with K nearest neighbour (KNN) technique for classification. KNN provides effective classification of PQ events. Mishra et al. [4] proposed S transform for feature extraction of PQ events. They used neural network for PQ classification. They showed that S transform based probablistic neural network (PNN) classifier performs better classification as compared to other neural network based methods. In [5], Han et al. proposed a stochastic analysis for prediction of sag frequencies and then performed the probabilistic risk assessment for life cycle cost of the equipment. Manjula [6] proposed EMD and HT together with probabilistic neural network for PQ disturbance classification. In [7], Kumar et al. proposed variational mode decomposition (VMD) and empirical wavelet transform (EWT) using support vector machine for classification of PQ events. They showed that VMD provides better classififcation as compared to EWT for feature calculation and classification. In [8] et al. proposed Hilbert Haung transform (HHT) for analysis of PQ abnormalities. HHT is the combination of HT and EMD. The advantage of HHT is that it can be implemented for non-stationary signals and nonlinear signals. Also, it has low order complexity. Reddy [9] presented single and multiple PQ events classification with Stockwell transform (ST) and random forest classifier. ST provides time frequency localization using energy concentration maximization based optimization. They extracted twelve features from the PQ signal using modified ST. The modified ST uses a signal dependent window obtained using maximization of energy concentration. In [10], Shukla et al. used EMD for denoising of PQ events by thresholding them. Then, thresolded IMFs were combined to obtain the denoised signal and HT was used for feature extraction. Fuzzy product based classifier was used for classification of PQ events. They also compared the proposed method with S transform based denoising method and wavelet based denoising method. In [11], Shukla et al. used probablistic neural network based classifier to classify the PQ events by using EMD to obtain IMFs. Features were extracted by implementing HT. Haung et al. [12] proposed method using fuzzy logic for PQ index

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evaluation. They measured the severity level of PQ disturbance using frequency of identification, voltage imbalance duration, harmonic disturbance rates etc. Pavas et al. [13] analyzed the causes of PQ events and proposed improvement to the method of disturbance interaction. They also proposed an analysis tool that can be used for optimization of smart grids. In [14], Roy and Nath used discrete WT based multi resolution analysis to obtain energy distribution at different levels of resolution. This energy difference at different levels have been used to classify PQ disturbance using neural network. In [15], Chattopodhya et al. used Park transformation method for analysis of fundamental voltage waveform, harmonic voltage waveform and current waveform to asses the PQ events. Barros et al. in [16], proposed method for on line monitoring of voltage quality by controlling the voltage related parameters such as unbalance factor, deviation magnitude etc. for induction motor PQ events. Yong [17] et al. proposed PQ classification method by using optimal selection of features. To extract features, they used WT and rest support vector machine. Then, optimal features have been obtained using data mining process and used support vector machine for classification. In this paper, we used WT to obtain the analytic signal for instantaneous feature calculation of PQ disturbances and constructing the feature vector which are fed to KNN classifier. We also compared the classification accuracy by constructing the feature vector using analytic signal by HT.

The paper is organised as follows:- Section II presents brief description of empirical mode decomposition. Section III presents brief introduction of analytic signal. This section also describes the method to obtain analytic signal using Hilbert transform and the wavelet transform. Section IV presents brief introduction to KNN classifier. In Section V, simulations are performed to verify the effectiveness of the proposed method. Finally, Section VI concludes the paper.

## II. Empirical Mode Decomposition Algorithm

EMD is used for nonstationary and nonlinear signals to extract the mono components and symmetric components form the signal via sifting process. EMD is used to decompose the signal into IMFs. The IMFs are of the same length as the original signal.

These IMFs has to satisfy following two characteristics:

1. The extrema number and the zero crossings number should be either equal or vary at most by one for the entire signal.
2. The mean value of the envelope generated by the local maxima and the envelope generated by local minima must be zero at any point of the signal.

The sifting process steps are:

1. It identifies all the local maxima in the signal.
2. It forms upper envelope by connecting all the local maxima using cubic spline.
3. It identifies all the local minima of the signal.
4. Then it forms lower envelope by connecting all local minima using cubic spline.

These upper and lower envelope are such that they are able to cover all data points between them. The computed mean $m_1$ of upper and lower envelope is subtracted from the signal for the first component $h_1$ as

$$x(t) - m_1 = h_1 \tag{1}$$

If this $h_1$ satisfies the definition of IMF, then it is used as signal in the next step. This process is repeated until IMF is obtained. EMD consists of following steps:

1. Determination of local maxima and minima of generated signal, $s(t)$.
2. Implementation of cubic spline interpolation between the maxima and the minima to obtain the envelopes $e_{max}$ and $e_{min}$, respectively,
3. Estimation of the mean value of envelope
$$M(t) = \frac{e_{max} + e_{min}}{2}$$
4. Substraction of mean value from original signal $c_1 = s(t) - M(t)$
5. Steps 1 - 4 are repeated on $c_1(t)$ instead of $s(t)$, until $c_1(t)$ is an IMF,
6. Computation of the residue, $R_1(t) = S(t) - c_1(t)$
7. Steps 1 - 6 are repeated if $R_1(t)$ does not satisfy the threshold value of error tolerance.

To avoid loss of information from IMF computation, stopping criteria is used. The standard deviation between the two consecutive sifting process is used for stopping the process.

## III. Analytic Signal

### A. Analytic Signal Using Hilbert Transform

Hilbert transform is used to obtain an analytic signal. The imaginary part of analytic signal is the HT of the real part. This analytic signal is defined using amplitude and phase. The derivative of the phase gives instantaneous frequency. HT of a real-valued signal x (t) is defined as:

$$\tilde{x}(t) \triangleq H[x](t) = \frac{1}{\pi}\int \frac{x(\tau)}{t-\tau}d\tau \tag{2}$$

$$H(j\omega)=\begin{cases} -j, & 0<\omega<\pi; \\ +j, & -\pi<\omega<0. \end{cases} \tag{3}$$

or in discrete time domain, it is:

$$h[n] = \frac{1}{2\pi}\int_{-\pi}^{\pi} H(j\omega)e^{j\omega n}d\omega \tag{4}$$

$$=\begin{cases} \frac{1}{2\pi}\frac{sin^2(\pi n)}{n}, & n \neq 0; \\ 0, & n=0. \end{cases} \tag{5}$$

Support of $h[n]$ is infinite. The basis characteristic of HT is that it is a $\pm\pi/2$ phase shift operator. Discrete time HT is defined as an all pass having imaginary transfer function.

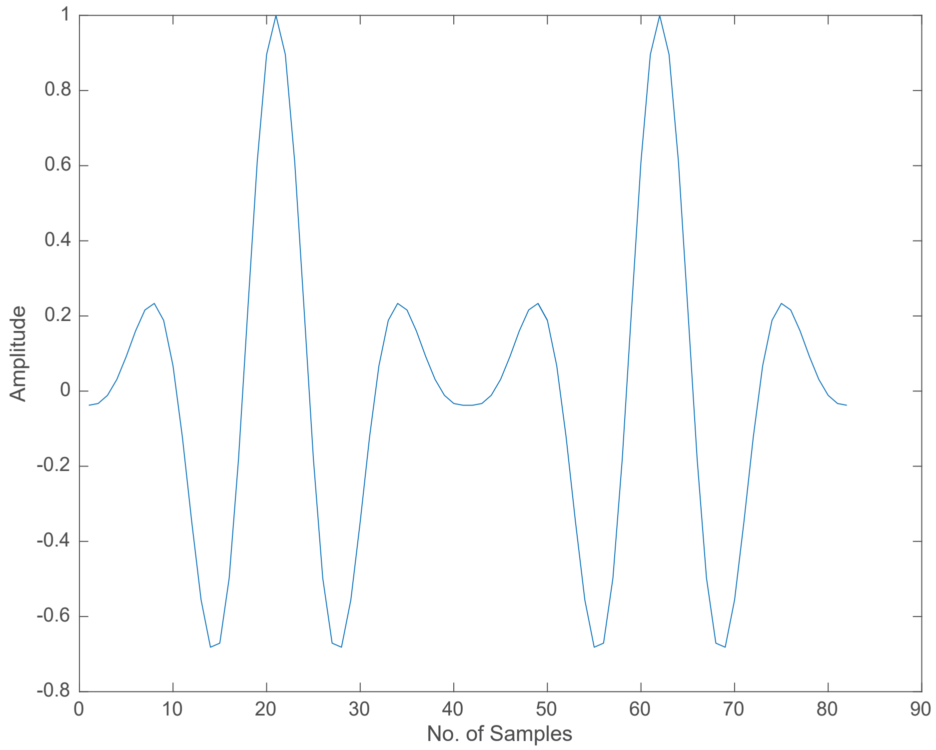


Fig. 1 Morlet wavelet

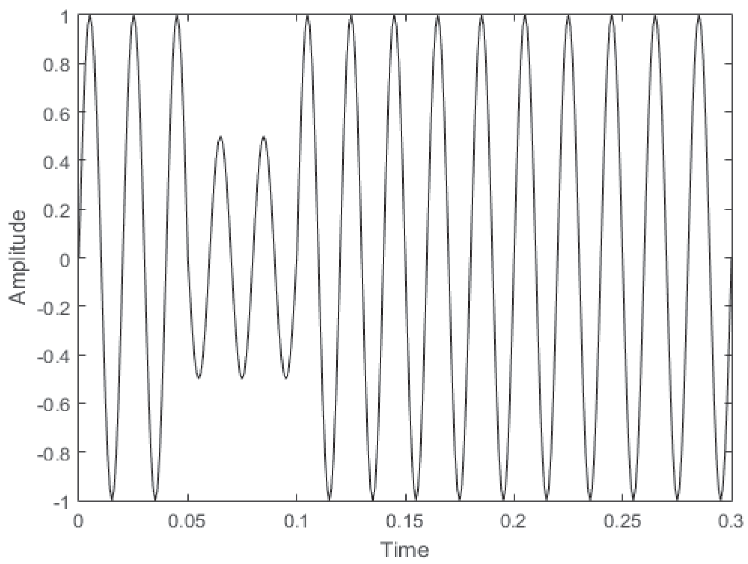


Fig. 2 Sag signal

### B. Wavelet Transform

Wavelet analysis is a mathematical method which provides localized bases in functional spaces and with the general type of operators such as differential, integral in such bases. Wavelet transform can be used for transient and non-stationary signals. The wavelets are generated by translated and scaled version of single function called mother wavelet. The localization of information in time frequency plane is the main characteristic of wavelets. Wavelets are able to trade one type of resolution for another, which provides the analysis of non stationary signals. The main difference between the wavelets is due to different filter lengths, which define the wavelet and scaling functions. Wavelet has to satisfy following characteristics also:- wavelets must be oscillatory in nature, it must decay quickly to zero and integration must be zero. The scaling operation allows the operation of stretching and compression of the mother wavelet. The stretching and compression of mother wavelet helps to obtain different frequency information of the signal to be analyzed. The compressed version of the mother wavelet obeys the high

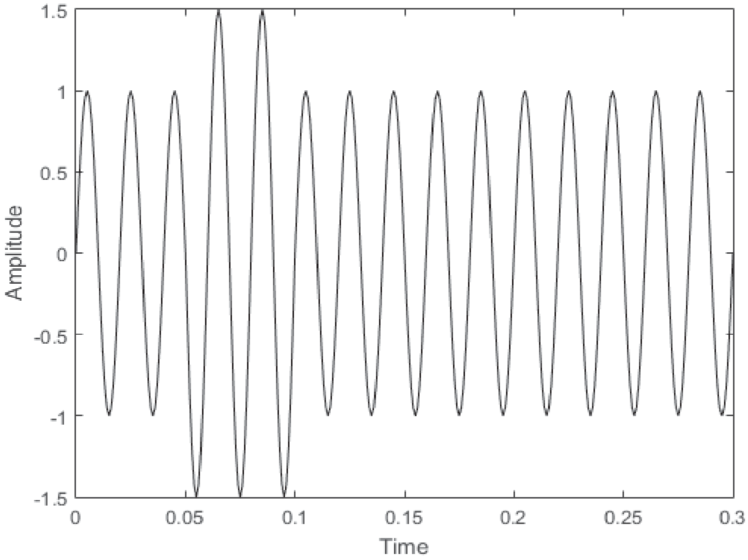


Fig. 3 Swell signal

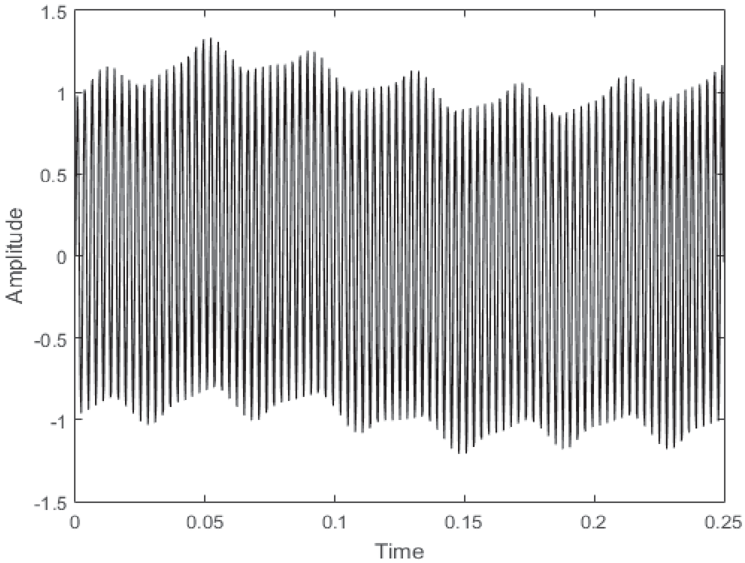


Fig. 4 Transient signal

frequency condition and the dilated version of the wavelet obeys the low frequency condition. The translated version of wavelet provides different time information. In this way, the set of scaled and translated wavelets are formed and provides a basis to represent the analyzed function or signal. Wavelets has good compression capability due to sparse representation of the signal. There are two types of wavelet transform:
(i) Continuous wavelet transform
(ii) Discrete wavelet transform

For a square integrable function $f(t)$, the continuous wavelet transform with respect to a wavelet $\Psi(t)$ is defined as

$$W(a,b) = \int_{-\infty}^{\infty} f(t) \frac{1}{\sqrt{|a|}} \Psi^* \left( \frac{t-b}{a} \right) dt$$

$a$ is called the scale or dilation variable. It is inversely proportional to frequency. $b$ is the translation parameter. The normalization factor $\frac{1}{\sqrt{|a|}}$ is used so that the energy is same for all $a$ and $b$.

The mother wavelet satisfies regularity and admissibility conditions. Also, $\Psi(t)$ has compact support.

### C. Analytic Signal Using Wavelet Transform

The analytic signal formation using wavelet transform proposed by Gao [18] has been used in this work for instantaneous parameter computation. Defining wavelet transform of $s(t) \in L^2(R, dt)$ as

$$S(b,a) = \frac{1}{a} \int_{-\infty}^{\infty} s(t) \bar{g}(\frac{t-b}{a}) dt \tag{6}$$

where $g(t)$is analytic wavelet, $\bar{g(t)}$ is the complex conjugate of $g(t)$, $t, b \in R$, $R$ is the real number set and $a > 0$. Also, $g(t)$

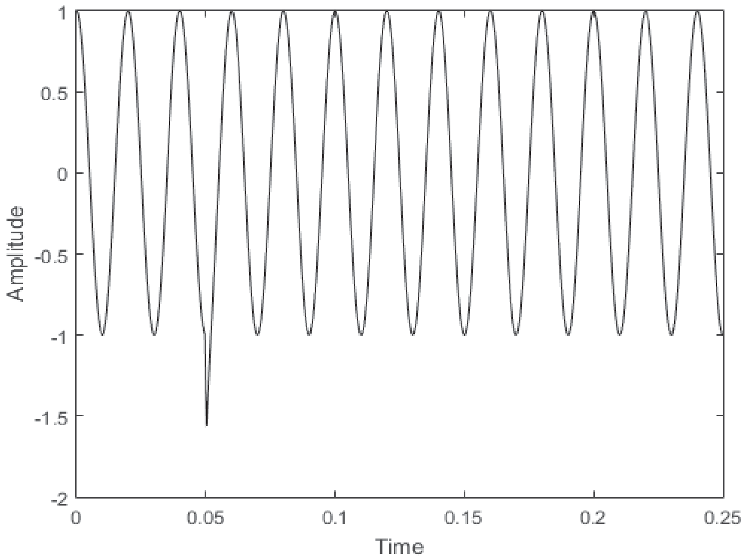


Fig. 5 Harmonic signal

and its Fourier transform $g(\omega)$ satisfy the conditions given in [18].

It is shown that $g(t)$ is analytic having real part $g_R(t)$, which is even. Defining

$$C_g = \int_0^\infty (\hat{g}_R(\omega)/\omega)d\omega \tag{7}$$

where $0 < C_g < \infty$. Then the HT of $s(t)\ (t) \in L^2(R, dt)$, is given as:

$$\frac{1}{C_g}\int_0^\infty S(t,a)\frac{da}{a} = s(t) + jH[s(t)] \tag{8}$$

## IV. KNN Classifier

A classifier takes a set of labelled data called classes and group another new data set based on some decision rule. The KNN classifier finds a cluster of K instances in the training vector closest to the query instance using distance measurement.

## V. Simulation Results

We generated four signals:- sag, swell, harmonic and transient in MATLAB with frequency 3.2 kHz. Then we implemented EMD to obtain IMFs of these signals. We used three IMFs for feature extraction. Then WT has been utilized to obtain the analytic signal. We used modified Morlet wavelet to obtain the analytic signal. The modified Morlet wavelet [18] is defined as

$$g_\tau(t) = e^{imt}e^{(-1/2)}[\sqrt{2}\sigma m/(2\pi\tau)t]^2 \tag{9}$$

where $\tau$ denotes number of cycles in the envelope of carrier wave, $m$ denotes angular frequency and $\sigma$ denotes precision and $C = \sqrt{2}\sigma m/2\pi\tau$. For numerical computation $m^2/(4C^2)$ is large. Morlet wavelet is shown in Fig. 1.

The parameters used are: $\sigma = 5$, $\tau = 4$, $m = 28.28$.

Using these analytic signal, instantaneous parameters have been calculated. They are: energy, standard deviation of the contour and standard deviation of the phase contour. So, there are nine features for a signal as we used three IMFs for one signal and three parameters have been calculated for one IMF. The extracted features using wavelet transform of IMFs have been used for PQ event classification. Four classes of PQ disturbances have been used for simulations. They are:

1. $C_1$ representing Sag
2. $C_2$ representing Swell
3. $C_3$ representing Harmonic
4. $C_4$ representing Transient.

TABLE I
Classification Result Using EMD and Hilbert Transform Method

| Case | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|---|---|---|---|---|
| $C_1$ | 97 | 1 | 2 | 4 |
| $C_2$ | 3 | 95 | | 2 |
| $C_3$ | | 2 | 95 | |
| $C_4$ | | 2 | 3 | 95 |
| Classification Efficiency in % | 97 | 95 | 95 | 95 |
| Error Efficiency in % | 3 | 5 | 5 | 5 |
| Overall Efficiency in % | | | | 95.50% |

These are shown in Figs. 2-5. We used KNN classifier and compared the proposed WT based analytic signal method with HT based method for classifier efficiency. Tables I and II shows the classifier efficiency for Hilbert method and wavelet method respectively.

$$\text{Overall Efficiency} = \frac{\text{Number of events classified correctly}}{\text{Total number of event}}$$

## VI. Conclusions

The wavelet based method presents better classification accuracy as compared to Hilbert transform based method. This is due to time frequency localization property of the wavelet

TABLE II
CLASSIFICATION RESULT USING EMD AND WAVELET TRANSFORM METHOD

| Case | $C_1$ | $C_2$ | $C_3$ | $C_4$ |
|---|---|---|---|---|
| $C_1$ | 97 | 3 | | |
| $C_2$ | 3 | 97 | | 4 |
| $C_3$ | | | 100 | |
| $C_4$ | | | | 96 |
| Classification Efficiency in % | 97 | 97 | 100 | 96 |
| Error Efficiency in % | 3 | 7 | 0 | 9 |
| Overall Efficiency in % | | | | 97.5% |

transform. Also, some noise may be present in the PQ events. In that case also, due to localization characteristic of wavelet, it provides accurate calculation of instantaneous parameters as compared to Hilbert transform. The time and frequency localization properties of wavelet helps in noise detection, when the signal energy is small and noise is wide band and has short duration. These properties of wavelets helps to preserve the desired signal.

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