Design of an automated system for detection and classification of power quality disturbances

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Abstract—**Power quality (PQ) is one of the most significant issues in power monitoring systems and smart grids in recent years. Identifying disturbances has an important role in improving PQ. The intention of this paper is to improve the accuracy of the detection step in PQ disturbances. To do so an adaptive method called CEEMD (complete ensemble empirical mode decomposition) is used here for the first time. Here a new modified version of Hilbert Huang Transform (HHT) has been proposed for feature extraction. This version is combination of CEEMD and Hilbert Transform. The performance of the proposed method is compared with classical algorithms like HHT and MHHT (Modified HHT). Experimental results demonstrate the efficiency of the proposed method.**

Keywords-component; power quality; mode decomposition; Intrinsic mode functions (IMFs); disturbance.

I. INTRODUCTION

Electric power industry, includes electricity generation, transmission and distribution to the final consumer. Transmission from production to consumption depends on parameters such as production, demand and so on, which can leads to power quality loss. Some issues to decrease quality are switching large loads, welding equipment, capacitor switching and lightning. Lack of an appropriate control on these challenges can cause heavy damages to sensitive loads connected to the power grid, and can yields to customer dissatisfaction. In addition these disturbances occur in a fraction of a second. Therefore, recorded events in monitoring systems will generate huge volumes of data. Keeping all the generated signals in the personal computers is not possible. So the need of data compression is essential [1].

Power quality disturbances must be identified in order to compressing data, reduction of costs and diminution of adverse effects in monitoring and control system. Also continuous monitoring on these disturbances is a very important challenge [1]. Presence of disturbances can yield to non-stationary current and voltage signals. In non-stationary state, the main goal is to extract information such as amplitude, phase angle and frequency components of the signals. Block diagram of PQ disturbances identification and detection system is shown in Fig.1. As seen in Fig.1, in the first step, after receiving the input signal some preprocessing operations such as noise removal and normalization is done. Then in the second step, to analyze the enhanced signal some signal processing techniques will be used. These techniques are usually categorized into two main classes: non-model and model-based methods [1]. Non-model-based methods utilize one or more mathematical transforms like Wavelet Transform (WT), Stockwell Transform (ST) and etc..While Model-based methods are applied directly to the signal. In the feature extraction step, some features like statistical features, PQ indices and etc. are extracted. Finally extracted features are used in order to train a classifier for classifying the disturbances [1].

This paper is organized as follows: Section II presents the existing methods for PQ disturbances analyzing and feature extraction. Section III covers proposed approach, feature extraction technique, classification method and results. Section IV concludes the paper.

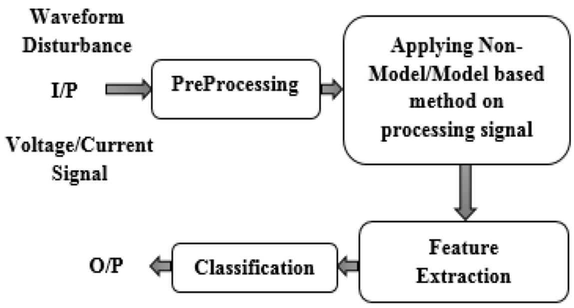

Figure 1- A block diagram of power quality recognition and classification system.

II. REALATED WORK

As mentioned before signal analysis methods for PQ disturbances are categorized into non-model-based methods and model-based methods. In the following these methods are described separately.

A. Non-model-based methods

In the non-model-based methods, the signal in time domain transfers into time-frequency or time-scale domain. According to the Hzynbrg's uncertainty principle, for a non-stationary signal, it's not possible to have a precise and simultaneous presentation of time and frequency. Thus, obtaining information about location and the time interval of power quality disturbances needs analytical methods that use information of both time and frequency or time and scale domains. Some of these methods are Short Time Fourier Transform (STFT), WT, ST, Gabor-Wigner Transform (GWT) and Hilbert-Huang Transform (HHT).

The Fourier Transform (FT) is the best technique to analyze signals in frequancy domain. Zhang et al. [2] extracted five distinct time-frequency statistical features of

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PQ disturbances using RMS[1] method and Discrete Fourier transform (DFT). Some of these features are: the per unit RMS value of the fundamental component, variation rate of the power signal's RMS values, oscillation number of the power signal's RMS values, THD[2] factor and LHD[3] factor. Gu and Bollen [3] analyzed PQ disturbances with STFT and WT. Results show that performance of WT is better than STFT. Also Tarasiuk in [4] proposed a combined method based on WT and Fourier spectrum analysis to obtained harmonics of the input signal and tracks it's position. For this purpose, first WT is applied on the input signal, then for reducing coefficients in each level of decomposition DFT is used. The fixed window size is an important issue in STFT that can cause problems in analyzing non-stationary signals.

The Wavelet Transform decomposes a signal into adequate frequency and time resolutions. In [5], Dehghani et al. used WT for identification and classification of disturbances. With the detail coefficients of first level, locations of disturbance occurrence are obtained. Then normalized energy of detail coefficients CD2 to CD6 of DWT and the RMS of input signal in three phases are used as parameters of feature vector. Oleskovics et al. in [6] presented a method for PQ detection with combining detail coefficients energy of 7 level WT decomposition.

The Stockwell Transform is a time–frequency tool which is the extension of WT and STFT. In [7], Huang et al. analyzed PQ signals by S-transform. Eighteen types of time–frequency features are extracted from the S-matrix. Then, after evaluating accuracy of classification with different features combinations, a selected subset with 2 features is taken as the input of the probabilistic neural network. Hajian et al. in [8] presented integrated approach using combination of DWT and hyperbolic ST for extracting spectral and statistical features. Hyperbolic S-Transform uses asymmetric Gaussian window instead of symmetric Gaussian window. In [9] Biswal et al. proposed a new method called Discrete Orthogonal S-transform (DOST). DOST increases computational speed of S-transform with changing sampling rate at different frequencies.

The Hilbert Huang Transform is a new data analysis tool which consists of two distinct processes: Empirical Mode Decomposition (EMD) and Hilbert Transform (HT). EMD decomposes input signal to Intrinsic Mode Functions (IMF). Each IMF represents mono-component signal inside the input signal. HT obtaines instantaneous amplitude and frequency curves for the IMFs. Shukla et al. [10] analyzed PQ disturbances by HHT. In this work feature vectors are obtained with IMF's energy and standard deviation of instantaneous amplitude (IA) and frequency (IF) curves. In [11] a method based on mathematical morphology and HHT is used to detect PQ disturbances. In [12] a EMD-based denoising is proposed for PQ evaluation. First a noisy signal is decomposed into N IMFs. Each IMF is denoised with a distinguished thereshold parameters. Finally HT employes to denoised IMFs for feature extraction. Because of EMD problems like mode mixing and spline fitting, [13] investigated Modified HTT (MHHT) for PQ analysis. MHHT presents a new version of classical EMD named Ensemble Empirical Mode Decomposition (EEMD). EEMD adds a white noise series to the targeted signal and decomposes the signal with added white noise into IMFs. Then it obtains the (ensemble) means of corresponding IMFs of the decompositions as the final result.

B. Model-based methods

In model based methods, input signal is modeled as a set of sinusoidal functions with distinct amplitudes and frequencies. These methods are applied directly on the input signal. The samples of these techniques are Kalman filter and Prony method [1]. In [14] Kalman filter beside DWT are used to extract signal parameters like amplitude and slope. In [15] Lobos et al. presented hybrid approach based on DWT and Prony method for detection of PQ disturbances in wind turbines power plants.

Some limitations of mentioned algorithms are as follows: (1) noise sensitivity of DWT and Prony, (2) time consuming of some curve fitting and optimization methods like Prony and Kalman filter, (3) the fixed window width in STFT and Gabor Transform (yielding lack of accurate and simultaneous representation of time and frequency), (4) limitation in handling effects of zero frequency or DC part and slow moving of window in high frequency in S-transform [1]. In contrast with aforementioned PQ analysis techniques, EMD is a self-adaptive and data driven method unfortunately EMD and modified EMD face with problems such as mode mixing which couldn't overcome this limitations perfectly. In this paper, we propose a new method based on EMD which can solve mode mixing problem.

III. PROPOSED APPROACH

In this section we introuduce a proposed method based on CEEMD. A new Modified Hilbert Huang Transform consists of two steps: CEEMD and HT. CEEMD like EEMD is a noise-assisted method. Similarly the method decomposes the signal with N different noise realizations but here the results are averaged after each component is found. After finding IMFs, HT obtains instantaneous amplitude and frequency of each IMF. CEEMD algorithm is explained in the next section.

A. CEEMD

CEEMD is an adaptive and non-linear signal processing method that is a modified version of EMD and EEMD [16]. Issues such as the existence of oscillations with very disparate amplitude in a mode, or the presence of very similar oscillations in different modes, called as "mode mixing", led to changes in EMD. Therefore to overcome these problems, In [17] Wu et al. presented EEMD method. It performs EMD over an ensemble of the signal plus Gaussian white noise. Idea of EEMD is based on the dyadic filter bank behavior of white Gaussian noise in EMD [17]. Independent decomposition of different version of noisy signals yields residual signals that have no dependency to each other. Therefore different realizations of noisy signal may produce different number of modes. To solving these

[1] root-mean-square
[2] Total Harmonic Distortion (THD)
[3] Lower Harmonic Distortion(LHD)

issues, another approach of EMD called CEMMD proposed by Patrick Flandrin and et al. [16]. Their approach solves mode mixing problem in EMD and different number of modes in EEMD. CEEMD algorithm is summarized as follow [16]:

1. Generate I different noisy realizations of original signal $x^i[n] = x[n] + \varepsilon_0 \omega^i[n]$ where $\omega^i[n], (i = 1,...,I)$ are different realizations if white Gaussian noise and $\varepsilon_0 > 0$
2. Decompose $x^i[n]$ $(i = 1,...,I)$ by EMD to obtain the first EMD mode and residue as Eq (4):

$$\begin{aligned} \widetilde{IMF_1} &= \frac{1}{I}\sum_{i=1}^{I} IMF_1^i[n] = \overline{IMF}_1[n] \\ r_1[n] &= x[n] - \widetilde{IMF}_1[n] \end{aligned} \tag{4}$$

3. Decompose realizations of $r_k[n] + \varepsilon_k E_k(\omega^i[n])$ for $(i = 1,...,I)$ until their first mode, so define IMF $(k+1)$ as (5):

$$\widetilde{IMF}_{k+1}[n] = \frac{1}{I}\sum_{i=1}^{I} (r_k[n] + \varepsilon_k E_k(\omega^i[n])) \tag{5}$$

4. Calculate the resiude signal for $k = 1,2,\dots,K$ Eq (6):

$$r_{k+1}[n] = r_k[n] - \widetilde{IMF}_{k+1} \tag{6}$$

If residual signal can be decomposed (the residue has at least two exterma point), perform step 3 and 4, $k = k + 1$.

5. Calculate the final residue as Eq. (7):

$$R[n] = x[n] - \sum_{k=1}^{K} \widetilde{IMF}_k[n] \tag{7}$$

B. Hilbert Transform

One of the most important signal processing purposes is finding the relation between real and imaginary parts of a signal is. This issue can be solved by using HT. HT is one of the mathematical transformations that shifts signal phase by 90 degree without changing in amplitude. Indeed positive frequencies shift -90 degree and negative frequencies shift +90 degree. The Hilbert Transform of $X(t)$ is calculated as Eq. (8) [18]:

$$Y(t) = h(t) * X(t) = \frac{1}{\pi}\int_{-\infty}^{+\infty} \frac{X(t)}{t-\tau} d\tau \tag{8}$$

$X(t)$ and $Y(t)$ are real and imaginary parts of an analytic signal $Z(t)$ in Eq. (9) [18]:

$$\begin{aligned} &Z(t) = X(t) + jY(t) = a(t)e^{j\phi(t)} \\ &a(t) = \sqrt{X^2(t) + Y^2(t)}, \phi(t) = \arctan(\frac{Y(t)}{X(t)}) \end{aligned} \tag{9}$$

In Eq. (9) $a(t)$ and $\phi(t)$ are respectively amplitude and phase of analytic signal. So instantaneous frequency is given by Eq. (10) [18]:

$$f(t) = \frac{1}{2\pi}.\frac{d\phi(t)}{dt} \tag{10}$$

Therefore, the Hilbert Transformation computes corresponding frequency and amplitude for each extracted modes [18].

C. Feature Extraction

Typically PQ disturbances include two categories: amplitude-based disturbances and frequency-based disturbances. Amplitude-based disturbances consist of sag, swell, interruption and voltage flicker and Frequency-based disturbances include transient and harmonic. Feature vector could be obtained by statistical information such as minimum, maximum, average, norm, standard deviation, skewness, kurtosis, crest factor and form factor from instantaneous amplitude and frequency curves of each mode. In Table 1, we explain mathematical equations of extracted features for an arbitrary vector X whose dimension belongs to $X \in R^{1\times N}$.

Table 1- Extracted features in proposed method.

Extracted Feature	Mathematical Formula
Minimum	$\min(X)$
Maximum	$\max(X)$
Average	$\mu_c = \frac{1}{N}\sum_{j=1}^{N} X_j$
Norm	$\sqrt{\sum_{j=1}^{N} X_j^2}$
Standard Deviation	$\sigma_c^2 = \frac{1}{N}\sum_{j=1}^{N}(X_j - \mu_c)^2$
Skewness	$skewness = \sqrt{\frac{1}{6N}}\sum_{j=1}^{N}(\frac{X_j - \mu_c}{\sigma_c})^3$
Kurtosis	$kurtosis = \sqrt{\frac{N}{24}}\{\frac{1}{N}\sum_{j=1}^{N}(\frac{c_{lj} - \mu_c}{\sigma_c})^4 - 3\}$
Crest Factor	$crest \quad factor = \frac{X_{peak}}{rms_c}$
Form Factor	$form \quad factor = \frac{\mu_c}{rms_c}$

D. Least Squares Support Vector Machine (LSSVM)

The least squares version of the SVM classifier is obtained by reformulating the minimization problem. LSSVM simplifies the problem via equality constraint and least squares. Therefore, unlike solving quadratic system in classical SVM, LSSVM solves linear equations. Hence LSSVM reduces computation difficulty. LSSVM formulation can be implicitly corresponds to a regression interpretation as Eq. (11) [19]:

$$\begin{aligned} &\min \ J(\omega,b,e) = \frac{1}{2}\|\omega\|^2 + \gamma\frac{1}{2}\sum_{i=1}^{N}\xi_i^2 \\ &s.t. \ y_i[\omega^T\varphi(x_i) + b] = 1 - e_i \ ,\forall i \end{aligned} \tag{11}$$

In Eq. (11) ξ_i is slack variable, $\gamma \geq 0$ is a tuning parameter that regulizes the sum squared error. When γ value is increased, it prevents increasing model complicity and when γ value is decreased, it allows increasing training errors of model [19].

Lagrangian of Eq. (11) is defined as Eq. (12) [19]:

$$L(\omega,b,e;\alpha) = J(\omega,b,e) - \sum_{i=1}^{N} \alpha_i \{y_i[\omega^T \varphi(x_i) + b] - 1 + e_i\} \quad (12)$$

Where $\alpha_i \, (i = 1,...,N)$ are Lagrange multipliers. Conditions for optimality are attained as Eq. (13) [19]:

$$\begin{gathered} L(\omega,b,e;\alpha) = J(\omega,b,e) - \sum_{i=1}^{N} \alpha_i \{y_i[\omega^T \varphi(x_i) + b] - 1 + e_i\} \\ \frac{\partial L}{\partial \omega} = 0 \rightarrow \omega = \sum_{i=1}^{N} \alpha_i y_i \varphi(x_i) \quad \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{i=1}^{N} \alpha_i y_i = 0 \\ \frac{\partial L}{\partial e_i} = 0 \rightarrow \alpha_i = \gamma e_i \quad \frac{\partial L}{\partial \alpha_i} = 0 \rightarrow y_i[\omega^T \varphi(x_i) + b] - 1 + e_i = 0, i = 1,..., N \end{gathered} \quad (13)$$

Eq. (11) to (13) reform optimization problem as Eq. (14) [19]:

$$\begin{bmatrix} 0 & y^T \\ y & \Omega + I/\gamma \end{bmatrix} \begin{bmatrix} b \\ \alpha \end{bmatrix} = \begin{bmatrix} 0 \\ 1_v \end{bmatrix} \quad (14)$$

$$\Omega_{ij} = y_i y_j \varphi\,(x_i)^T \varphi\,(x_j) = y_i y_j K\,(x_i, x_j) \quad i, j = 1,..., N$$

$$y = [\ y_1;\ ...;\ y_N\ ],\ 1_v = [\ 1;\ ...;\ 1\ ]$$

Thus, the final form of LSSVM prediction function will be obtained as Eq. (15) [19]:

$$f(x) = \sum_{i=1}^{N} \alpha_i K(x, x_i) + b \quad (12)$$

E. Simulation And Result

In order to generate PQ disturbances, their parametric equations are simulated in Matlab software version 8.3. The generated database contains normal voltage signals, sag, swell, interruption, voltage flicker, oscillatory transient and harmonic disturbances. Each type of the disturbances consists of 40 samples with fundamental frequency 50Hz and 12 periods.

Fig.2 up to Fig.13 show the extracted IMFs by CEEMD and EMD for various types of disturbances. As the results show, it is understandable that CEEMD separates components of signals much better than EMD.

After features are extracted from IA and IF curves of decomposed signals, the results will be considered as input arguments of LSSVM classifier. If the size of feature vectors are not equal, empty features are filled with zeros. In Table.2 accuracy of proposed method is compared with some of the other methods. As you can see, accuracy of proposed method is more appropriate than others.

Classifier	Method	Accuracy
LSSVM	CEEMD	99.1%
Adaboost+Navie Bayes[13]	EEMD	96%
Fuzzy Expert System[14]	Kalman	92.3
Dempster-shafer[5]	wavelet	95.6%

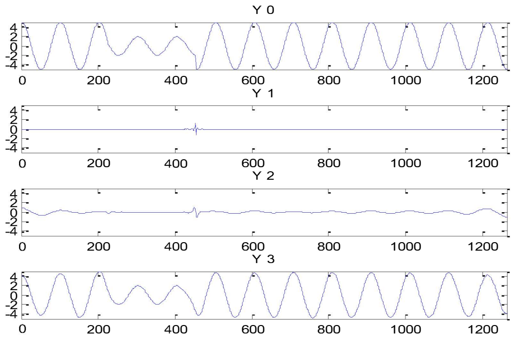

Figure 2- Sag intrinsic mode functions with CEEMD.

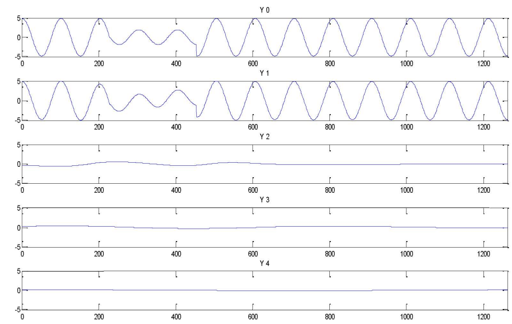

Figure 3- Sag intrinsic mode functions with EMD.

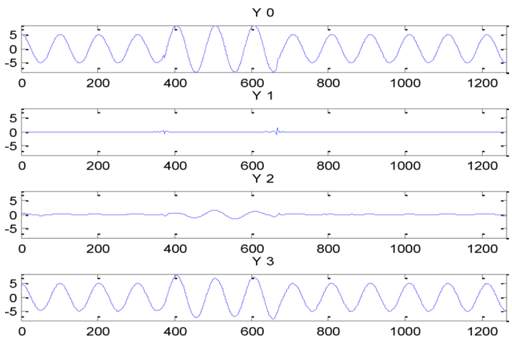

Figure 4- Swell intrinsic mode functions with CEEMD.

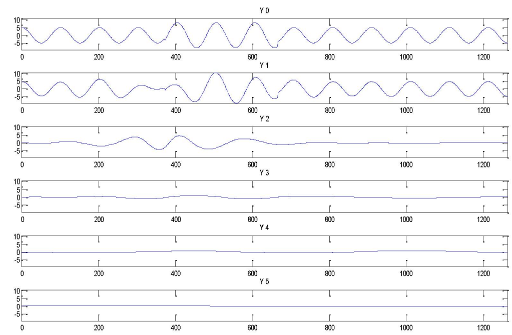

Figure 5- Swell intrinsic mode functions with EMD.

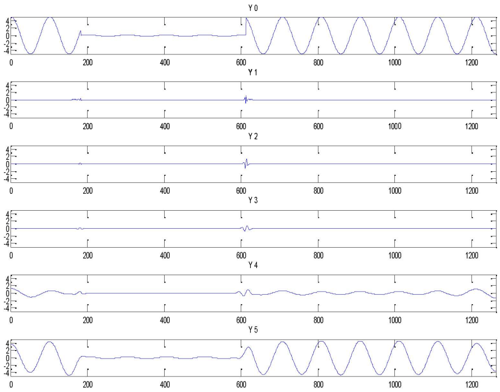

Figure 6- Interruption intrinsic mode functions with CEEMD.

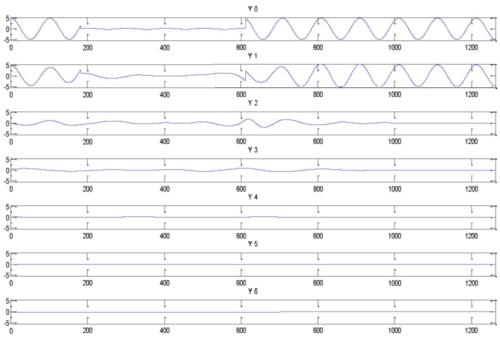

Figure 7-Interruption intrinsic mode functions with EMD.

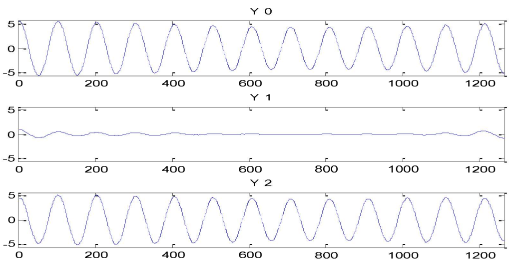

Figure 8- Voltage flicker intrinsic mode functions with CEEMD.

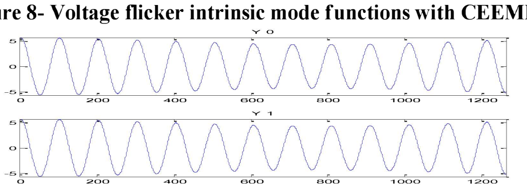

Figure 9- Voltage flicker intrinsic mode functions with EMD.

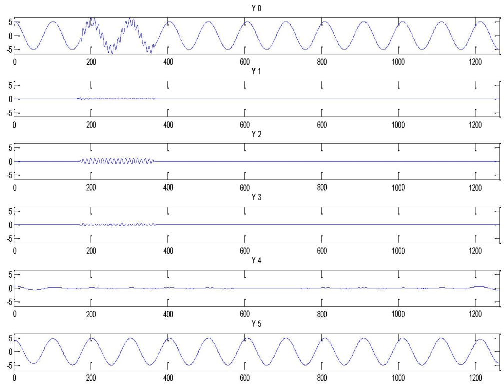

Figure 10- Oscillatory transient intrinsic mode functions with CEEMD.

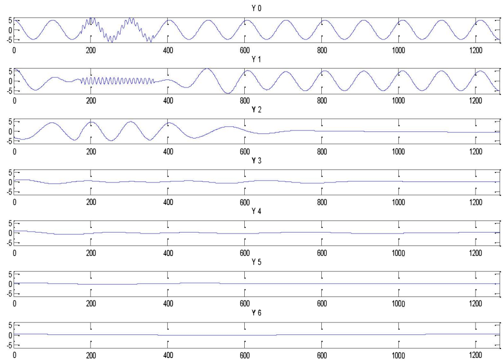

Figure 11- Oscillatory transient intrinsic mode functions with EMD.

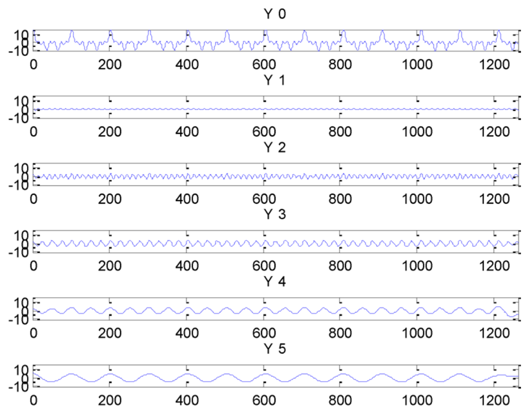

Figure 12- Harmonic intrinsic mode functions with CEEMD.

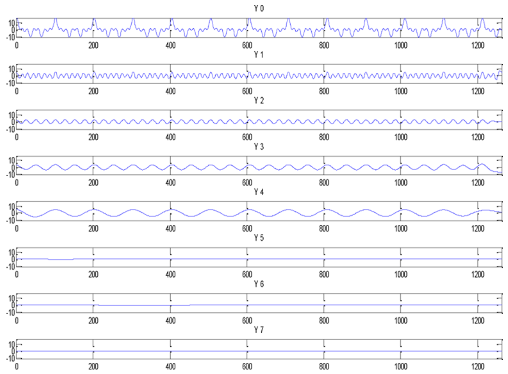

Figure 13- Harmonic intrinsic mode functions with EMD.

IV. CONCLUSION

In this paper, an algorithm based on CEEMD method have been proposed to detect power quality disturbances. CEEMD can improved the accuracy of the classical algorithms. This method overcomes the disadvantages of EMD and EEMD such as mode mixing and different number of IMFs. Here in contrast to other methods such as Wavelet Transform and S-Transform, there is no need for selecting basis functions or setting too many parameters to implement the algorithm, because CEEMD applies to input data adaptively.

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