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Visualizing time-varying power quality indices using generalized empirical wavelet transform

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ABSTRACT

Tracking of instantaneous power quality (PQ) indices is very essential for better characterization of the time-varying voltage and current signals. This paper presents the estimation of time-varying PQ indices for accurate interpretation of disturbances using a generalized empirical wavelet transform (GEWT). This approach is based on adaptive segmentation of Fourier spectrum and followed by an appropriate filter design to extract the individual frequency components. The main emphasis of this work is to estimate the actual frequencies present in the signal by overcoming the problem of spectral leakage. A preliminary investigation of time domain amplitude variation of the signal helps in realizing the presence of low-frequency interharmonics and thereby permitting to extract the fundamental frequency component perfectly. Hence, the GEWT is employed to assess successfully all sorts of power signals having disturbances such as voltage fluctuation, sag, swell, interruption, transients, harmonics, and interharmonics. The robustness and applicability of the GEWT for PQ analysis have been verified by analyzing several distorted signals generated using PSCAD, recorded waveforms available in IEEE database and a few real signals. Finally, the estimated GEWT-based time-varying single phase PQ indices are compared with the indices obtained from IEC defined fast Fourier transform (FFT) and fast S-transform (FST).

1. Introduction

The persistent increase in the use of sophisticated fast control equipment, the integration of renewable energy sources and the complex interconnection of systems have elevated the rate of occurrence of power quality (PQ) disturbances in the network. Besides, the frequent variation of system load, energizing of capacitor bank and short circuit faults, etc. also create various PQ disturbances causing failure of end user equipment [1,2]. The deregulated electricity market provides flexibility for industries and consumers in choosing a utility, which provides a quality supply. Therefore, maintaining a high-quality power supply is one of the main objectives in the development of smart grid [3]. Continuous monitoring of power supply and its analysis [4] is a prerequisite for an appropriate remedial action to be taken for improving the power quality. The estimation of PQ indices is the quickest way to quantify the quality of supply and PQ disturbances [5]. The general steady state PQ indices [6] representing a windowed signal does not reflect the accurate time localization of power quality disturbances. Hence, it is essential to estimate the time-frequency based PQ indices for assessment of time-varying electrical disturbances. This necessitates a fast adaptive time-frequency technique to decompose the power system signal and estimate the time-varying signal parameters accurately. This accurate estimation helps in easy identification of the disturbance occurred and its source.

The most widely used frequency analysis technique to easily quantize the PQ signals is fast Fourier transform (FFT) [5,7]. The FFT is known for its computational efficiency and well suited to analyze the stationary signals but unable to provide temporal information of the spectral components. The later developed short time Fourier transform (STFT) overcomes this problem but has limitations of fixed time-frequency resolution, spectral leakage and picket fencing. Thus, the multi-resolution techniques like discrete wavelet transform (DWT), wavelet packet transform (WPT) have generally been applied for power quality assessment [8–11]. The wavelet based techniques decompose the distorted input signal into several scales, which contain a band of frequencies resulting in the inaccurate estimation of parameters of the fundamental frequency and interharmonics. Moreover, the predefined filters are not suitable to analyze all type of signals having disturbances, which occur in the

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real system. S-Transform is another widely used time-frequency analysis tool because of its frequency-dependent window and hence used for estimation of PQ indices [12]. The ST has many variants [13] based on the window selected, its shape and domain of analysis (time or frequency). One such approach is a recently proposed fast discrete S-transform (FST) [14]. The statistical signal processing techniques like Prony, Multiple Signal Classification (MUSIC), Estimation of Signal Parameters via Rotational Invariance Technique (ESPRIT) and few hybrid techniques [15–19] based on these are known for the accurate estimation of signal parameters even in the presence of noise. However, the computational burden [19] due to Eigen decomposition and matrix computations, limits their application in real-time. The other techniques, explored for PQ assessment are an artificial neural network, Kalman filtering, time–frequency–distribution technique [20–23]. Considering the advantage of FFT, efforts have been made for the development of new methods based on FFT for enhanced performance and robustness to analyze the non-stationary signals [24–28].

Recently proposed empirical wavelet transform (EWT) [29,30] has gained a greater attention for signal analysis in various applications because of its simple, fast and adaptive filter design procedure. The frequency estimation procedure of the EWT was modified in Ref. [31] to make it suitable for power quality analysis. It uses minimum magnitude and minimum frequency distance threshold (dF) for estimation of actual frequencies from the spectrum. The thresholds were conceived to estimate the interharmonics and harmonics present in the signal and thereby the PQ indices accurately. To assess the short duration PQ disturbances, it is preferred to consider the window length of 200 ms for a better frequency resolution of 5 Hz in accordance with IEC standard [7]. Consequently, the decrease in frequency resolution and an increase in spectral leakage due to the nonstationary signal may result in estimation of fake frequencies, if the thresholds are fixed irrespective of the signal. This results in an inaccurate estimation of time-varying indices, which limits its application for the assessment of PQ disturbance signals.

This paper aims for accurate assessment of the power system signals with a less computational burden, hence proposes a modified EWT approach termed as generalized empirical wavelet transform (GEWT) tailored for assessment of nonstationary signals containing disturbances. Based on the observation of signals reported in the literature [16–18,32,33] and the standards [6,7] the following two assumptions are made in this work. They are (i) any two consecutive frequencies present in the signal are at least 10 Hz separated except in the vicinity of the fundamental frequency (25 Hz–75 Hz). (ii) There are no frequencies between 45 and 55 Hz, other than the fundamental frequency (50 Hz). The major contributions of this work include an accurate extraction of the fundamental frequency component by estimating the interharmonics present around the fundamental, an adaptive Fourier segmentation based filter design and fast estimation of time varying indices. The novelty lies in estimating a new adaptive frequency distance threshold, which separates the fundamental frequency component from its adjacent interharmonic components. This is achieved by relating the amplitude variation of the signal to the interharmonics in the vicinity of the fundamental frequency. The GEWT significantly reduces the inaccuracies caused by spectral leakage with the adaptive frequency threshold followed by perfect segmentation of the Fourier spectrum. The time-varying single phase power quality indices presented in Section 3 of this paper are well known and can quickly quantize the disturbances. Further, the performance of the GEWT is compared with a widely used IEC defined FFT technique [7] and an ST variant, FST [14]. A rectangular time window of 200 ms duration is chosen for the analysis of time-varying waveforms in accordance with the IEC standard [7]. The results obtained are presented in Section 4, and finally, conclusions are given in Section 5.

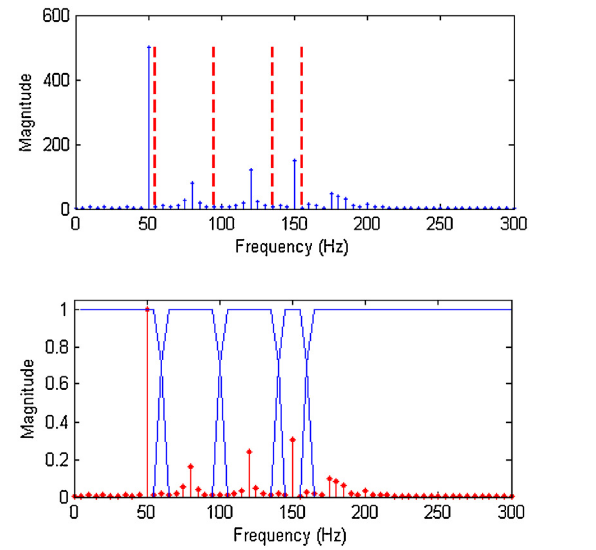

Fig. 1. (a) Segmented Fourier spectrum (b) spectrum with its corresponding wavelet filters.

2. Methodology

2.1. Empirical wavelet transform

This section presents a brief review of the empirical wavelet transform (EWT) [29,30] proposed by J. Gilles. It first estimates the frequencies $f = \{f_i\}_{i=1,2,\ldots,N}$ present in the signal $x(n)$ from the Fourier spectrum. Then, segment the Fourier spectrum by finding the local minima Ω_i between two consecutive frequencies f_i, f_{i+1} that separate the components perfectly as shown in Fig. 1(a). These boundaries based on the location of local minima provide better segmentation of the spectrum in the case of spectral leakage [30]. Considering these boundaries and frequency information, N wavelet filters (one low pass filter and N-1 band pass filters) are designed in the frequency domain as shown in Fig. 1(b) using a scaling function $\phi_1(\omega)$ and empirical wavelets $\psi_i(\omega)$ defined as

$$\phi_1(\omega) = \left\{ \begin{array}{ll} 1 & \text{if } |\omega| \le (1-\gamma)\Omega_1 \\ \cos\left(\frac{\pi}{2}\beta\left(\gamma, \omega, \Omega_1\right)\right) & \text{if } (1-\gamma) \le \Omega_1 \le |\omega| \le (1+\gamma)\Omega_1 \\ 0 & \text{otherwise} \end{array} \right\} \quad (1)$$

and

$$\psi_i(\omega) = \left\{ \begin{array}{ll} 1 & \text{if } (1+\gamma)\Omega_i \le |\omega| \le (1-\gamma)\Omega_{i+1} \\ \cos\left(\frac{\pi}{2}\beta\left(\gamma, \omega, \Omega_{i+1}\right)\right) & \text{if } (1-\gamma)\Omega_{i+1} \le |\omega| \le (1+\gamma)\Omega_{i+1} \\ \sin\left(\frac{\pi}{2}\beta\left(\gamma, \omega, \Omega_i\right)\right) & \text{if } (1-\gamma)\Omega_i \le |\omega| \le (1+\gamma)\Omega_i \\ 0 & \text{otherwise} \end{array} \right\} \quad (2)$$

where $\beta(\gamma, \omega, \Omega_i) = \beta\left(\frac{1}{2\gamma\Omega_i}\left(|\omega| - (1-\gamma)\Omega_i\right)\right)$ is an arbitrary function, fulfilling the properties given in Ref. [29]. The parameter, γ ensures minimal overlap between two consecutive frequency components in a transition band and its selection is based on the boundaries estimated. Therefore, for a particular frequency of consideration its filter will not overlap with the content of other significant frequencies present around in the spectrum. With these set of filters, the approximation and detail coefficients are obtained using the EWT as defined below

$$EWT(1, n) = IFFT\,(X(\omega)\phi_1(\omega)) \quad (3)$$

$$EWT(i, n) = IFFT\,\left(X(\omega)\psi_i(\omega)\right) \quad (4)$$

Thus, the adaptive filters extract the time-varying mono-frequency components, allowing it to use for analyzing the PQ signal.

The EWT based approach employed in Ref. [31] involves estimation of frequencies considering only the significant peaks present in the Fourier spectrum of the signal. This is achieved using a minimum magnitude and minimum frequency distance threshold (dF). For most of the non-stationary signals, it has been observed that any two frequencies present in the signal are separated by at least 10 Hz, except the vicinity of the fundamental frequency. Thus, fixing the minimum frequency distance threshold (dF) as 10 Hz helps in the estimation of all actual harmonics and interharmonics but the fundamental component extracted may be incorrect. Therefore, the thresholds particularly chosen for analyzing the harmonics and interharmonics signals may give erroneous results, if the analyzed signal contains any other disturbance. This is the consequence of utilizing the fixed dF for estimation of frequencies near the fundamental from the spectrum containing spectral leakage. It is really difficult to identify from the Fourier spectrum that whether the peaks existing near the fundamental frequency correspond to the actual low-frequency interharmonics or spectral leakage of the fundamental due to a disturbance. Thus, using the same fixed frequency threshold, $dF = 10$ Hz will estimate false frequencies in case of voltage interruption, sag, swell, voltage fluctuation, and interharmonics. This can be overcome by pre-estimating a new frequency threshold adaptively, according to the genuine low-frequency interharmonics present around the fundamental as explained in the next subsection. The new threshold (dFF) will help in estimation of genuine frequencies present around the fundamental frequency and the fixed 10 Hz frequency threshold for estimation of rest of the harmonics and interharmonics.

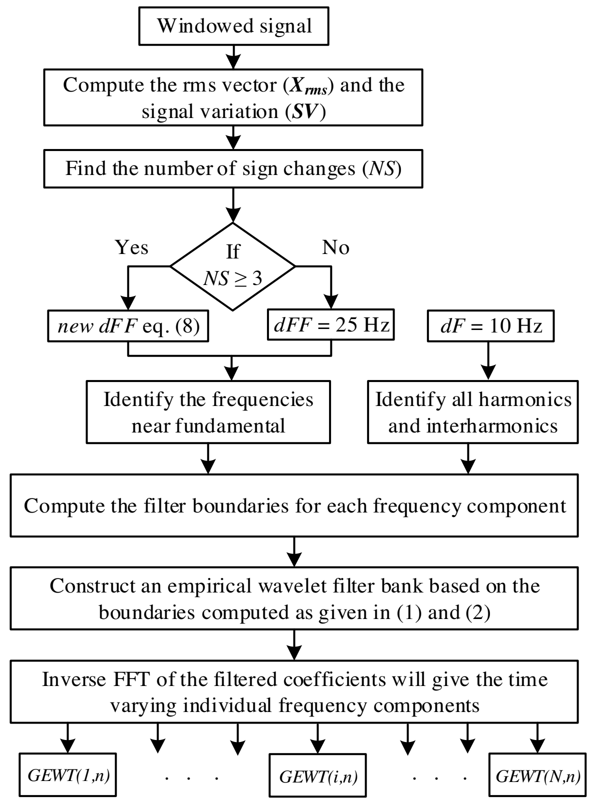

Fig. 2. Flowchart of the GEWT.

2.2. Generalized empirical wavelet transform

The GEWT aims at decomposing the power system signal into fundamental frequency and distortion components. It is a known fact that the existence of low-frequency interharmonics around the fundamental will cause amplitude variation of the signal. Therefore, their presence can be investigated from the time-domain amplitude variation rather than relying only on the frequency domain information. Thus, an extensive study has been carried out to relate the amplitude variation of a signal to the frequencies present in it and thereby estimate the new frequency threshold (dFF). It has been realized that a signal containing an interharmonic frequency, f_i in the range of 25–75 Hz will cause a significant amplitude variation at a rate of $|50 - f_i|$ Hz (for the 50 Hz system). Therefore, the dFF can be obtained from the signal RMS variation vector ($\boldsymbol{SV}$) by calculating the number of sign changes (NS) of the $\boldsymbol{SV}$ as follows.

First, compute the root mean square (RMS) value for each fundamental cycle of the input signal defined as

$$X_{rms}(n) = \sqrt{\frac{1}{S}\sum_{i=(n-1)S+1}^{nS} x(i)^2} \tag{5}$$

where n represents order number of signal cycles, S is the number of samples in a cycle and $x(i)$ is the sampled signal. The signal RMS vector $\boldsymbol{X_{rms}}$ having ten values calculated for a 200 ms duration input signal is

$$\boldsymbol{X_{rms}} = [X_{rms}(1), \ldots, X_{rms}(n), \ldots, X_{rms}(10)] \tag{6}$$

Then the signal variation ($\boldsymbol{SV}$) [34], which reflects the low-frequency interharmonics, is obtained by shifting the RMS vector to the zero-axis by deducting with its mean as

$$\boldsymbol{SV} = \boldsymbol{X_{rms}} - mean\ (\boldsymbol{X_{rms}}) \tag{7}$$

Thereafter, the number of sign changes (NS) is calculated for the signal RMS variation ($\boldsymbol{SV}$), which confirms the existence of low-frequency interharmonics. For a 50 Hz signal of 200 ms duration, the $NS < 3$ indicates that no interharmonics exist in the signal near fundamental frequency and the peaks in the spectrum are spectral leakage of the fundamental frequency due to nonstationary behavior. Hence, the dFF is chosen as 25 Hz to extract the fundamental component accurately. On the other hand, for a signal containing any interharmonics between 25 Hz–75 Hz, NS is found to be in the range of 3–9 for which the dFF should be chosen between 0 and 25 Hz to avoid the overlap of these interharmonics with the fundamental frequency component. Therefore, the dFF is correlated to the NS using the following equation

$$dFF = (quot(NS, 2) + rem(NS, 2) - 1)\,\Delta f \tag{8}$$

where Δf is the frequency resolution, which is 5 Hz in this work, $quot(NS, 2)$ is the quotient of NS and 2, $rem(NS, 2)$ is the remainder of NS and 2.

The novelty of the GEWT lies in pre-estimating the dFF based on the signal amplitude modulation. This new dFF, which is not pre-defined, enables the analysis of all sort of nonstationary voltage and current signals. The estimation of dFF is entirely based on the amplitude modulation of the signal and is independent of change in sampling frequency or time window length. This procedure really helps in confirming whether the peaks in the spectrum near the fundamental are due to spectral leakage or the actual frequencies.

Thereafter, the GEWT utilizes this adaptive dFF and 2% of the fundamental frequency magnitude as the minimum magnitude threshold for estimation of genuine frequencies in the range of 25 Hz–75 Hz. Besides, rest of the frequencies present in the signal are estimated using $dF = 10$ Hz as frequency threshold and the 2% magnitude threshold. The obtained frequencies are first sorted and then used for segmentation of the Fourier spectrum. Later, a set of empirical wavelet filters is designed accordingly to extract the time domain mono-frequency components. The flowchart, illustrated in Fig. 2 describes the step by step procedure for estimation of new frequency threshold (dFF) and the GEWT. For a distorted input signal

$x(n)$ containing N frequency components, the $GEWT(i, n)$ corresponds to the *nth* sample of the extracted *ith* frequency component. Since the modes extracted, contain only one frequency component, the Hilbert transform (HT) can be utilized to estimate the instantaneous frequency and amplitude information.

The HT [32,35] of a real-valued function $GEWT(i, t) = a_i \sin(2\pi f_i t - \phi_i)$ computes its complex conjugate $GEWT_H(i, t)$ determined by

$$GEWT_H(i, t) = \frac{1}{\pi} p.v. \int_{-\infty}^{+\infty} \frac{GEWT(i, \tau)}{t - \tau} d\tau \tag{9}$$

where $(p.v.)$ is the Cauchy principal value of the singular integral. This orthogonal imaginary part of the original real signal is essential to define its instantaneous phase. Thus, the obtained analytic signal corresponding to $GEWT(i, t)$ is defined as

$$GEWT_a(i, t) = GEWT(i, t) + j(GEWT_H(i, t)) = IA(i, t)e^{j\theta_i(t)} \tag{10}$$

The instantaneous amplitude and phase are

$$\begin{aligned} \mathrm{IA}(i, t) &= \sqrt{GEWT(i, t)^2 + GEWT_H(i, t)^2}, \\ \theta_i(t) &= \tan^{-1}\left(\frac{GEWT_H(i, t)}{GEWT(i, t)}\right) \end{aligned} \tag{11}$$

Instantaneous frequency can be obtained from the phase function as

$$IF(i, t) = \frac{1}{2\pi} \frac{d\theta_i(t)}{dt} \tag{12}$$

Thus, the HT easily estimates the instantaneous parameters $IF(i, n)$ and $IA(i, n)$ of the signal $GEWT(i, n)$. However, the accuracy of these parameters depends on how narrow band-passed the signal is.

3. Time-varying power quality indices

Time-varying PQ indices are the time-frequency distribution-based indices, which describe the quality of nonstationary current or voltage signal. The indices are computed for each sample (n), giving information of the signal with respect to the time, hence termed as instantaneous PQ indices [12,36]. However, the estimation is after an estimation delay of time taken for data accumulation (i.e., 200 ms) and the computational time. The instantaneous frequency variation, instantaneous distortion energy index and instantaneous K-factor help in the assessment of transient disturbances [36]. The PQ indices described in this paper are for the single phase voltage and current signals.

3.1. Instantaneous root mean square (iRMS)

It is one of the most basic and important indices useful for power computations, which is obtained from the instantaneous amplitude of all frequency components present in the signal [12].

$$X_{rms}(n) = \sqrt{\frac{1}{2} \sum_{i=1}^{N} IA(i, n)^2} \tag{13}$$

where N is the total number of frequencies present in the input signal and $IA(i, n)$ represents instantaneous amplitude of *ith* frequency component.

3.2. Instantaneous fundamental amplitude (iFA)

This index is very important in the identification of magnitude related disturbances like voltage sag, voltage swell, and interruption. It is obtained from the HT of the extracted time-varying fundamental frequency component of the signal.

$$iFA(n) = IA(i, n) \ \forall f_i \approx 50 \text{ Hz} \tag{14}$$

3.3. Instantaneous frequency variation (iFV)

It helps in exploring the localization of frequency related disturbances like transients, harmonics and voltage fluctuation. The frequency of each component is weighted by its instantaneous energy reflecting dominant frequency component of the signal or higher value for a disturbance with high frequencies [36].

$$iFV(n) = \frac{\sum_{i=1}^{N} IF(i, n) IA(i, n)^2}{\sum_{i=1}^{N} IA(i, n)^2} \tag{15}$$

where $IF(i, n)$ is the instantaneous frequency of the *ith* frequency component obtained from the HT.

3.4. Instantaneous total harmonic distortion (iTHD)

The most common index to assess the harmonic power relative to the fundamental frequency component is the total harmonic distortion (THD), its instantaneous computation is achieved as

$$iTHD(n) = \frac{\sqrt{\sum_{i=2}^{N} IA(i, n)^2}}{IA(1, n)} \tag{16}$$

where $IA(1, n)$ is assumed to be fundamental frequency component.

3.5. Instantaneous normalized distortion energy index (iNDEI)

This PQ index is a fraction of the disturbance energy to the total energy of the signal [36]. Here, it is assumed that $IA(1, n)$ represents the fundamental frequency component of the signal.

$$iNDEI(n) = \frac{\sqrt{\sum_{i=2}^{N} IA(i, n)^2}}{\sqrt{\sum_{i=1}^{N} IA(i, n)^2}} \tag{17}$$

3.6. Instantaneous K-factor (iKF)

It measures disturbance content of the signal in terms of squared normalized frequencies weighted by its energy [36]. It is similar to *iFV* but it has more sensitiveness to frequencies as it is proportional to its square. For a normal signal, the value remains one.

$$iKF(n) = \frac{\sum_{i=1}^{N} IF_N(i, n)^2 IA(i, n)^2}{\sum_{i=1}^{N} IA(i, n)^2} \tag{18}$$

where $IF_N(i, n) = IF(i, n)/50$

3.7. Instantaneous form factor (iFF)

iFF is defined as the ratio of *iRMS* of the signal to the inst. mean value of the signal [12].

$$iFF(n) = \frac{X_{rms}(n)}{\frac{2}{\pi}\sum_{i=1}^{N} IA(i,n)} \tag{19}$$

4. Results and discussion

In order to evaluate the performance of the GEWT for estimation of time-varying PQ indices, a variety of synthetic signals having disturbances have been considered for the analysis with fundamental frequency variation of ±0.2 Hz and SNR of 25 dB. The GEWT has also been tested on a few signals containing oscillatory transient, voltage sag and swell generated from test systems [37] simulated in PSCAD, IEEE test waveforms [38] and six practical signals acquired using OROS-34 data acquisition card (DAQ). However, due to space constraint, the results of only five case studies including one synthetic, a recorded voltage sag waveform from IEEE database, and three practical signals are presented in this paper. All the synthetic, as well as PSCAD signals are sampled at the rate of 10 kHz and a rectangular sliding window of 200 ms duration without an overlapping has been considered for the analysis [7]. The study is conducted in the MATLAB hosted on a desktop PC with Intel Core i3 3.1 GHz processor and 2 GB RAM.

The accuracy of the GEWT-based PQ indices have been verified with the true values in addition to the values obtained with the well-known FFT [7] and a recent technique, FST [14]. For estimation of the time-varying indices, it is really essential to extract the time information of all frequency components. Hence, to extract the indices using FFT, harmonic and interharmonic grouping is performed first in accordance with the IEC definitions [7] for all frequencies. Then, inverse FFT is computed for each subgroup to obtain the time domain components. Further, to validate the accuracy of the extracted GEWT components, the relative root mean square error (RRMSE) is computed for the windowed signal, $x(n)$ as

$$RRMSE = \frac{\sqrt{\frac{1}{N}\sum_{n}(x(n)-x_r(n))^2}}{x_{rms}} \times 100 \tag{20}$$

where x_{rms} is RMS value of the original input signal and $x_r(n)$ is the reconstructed signal obtained as $x_r(n) = \sum_{i=1}^{N} GEWT\,(i,n)$.

4.1. Case study-1: voltage fluctuation and harmonic signal

This section presents the analysis of a synthetic voltage fluctuation signal added with a white Gaussian noise of 25 dB SNR. The signal also contains a few harmonics and an interharmonic, whose parameters are listed in Table 1.

$$x(t) = \left(\left(1+a_1\sin(2\pi f_1 t-\theta_1)\right)\left(a_2\sin(2\pi f_2 t-\theta_2)\right)\right) + \sum_{i=3}^{8} a_i\sin(2\pi f_i t-\theta_i) + \zeta(t) \tag{21}$$

The presence of subharmonic components results in amplitude variation of the signal as seen in Fig. 3(a). The flicker frequency of 20 Hz will result in interharmonics at 30 and 70 Hz near the fundamental, for which the *NS* is obtained to be 7. Thereby, the estimated new frequency distance threshold, *dFF* is 15 Hz, which allows detection of two interharmonics along with the fundamental. The

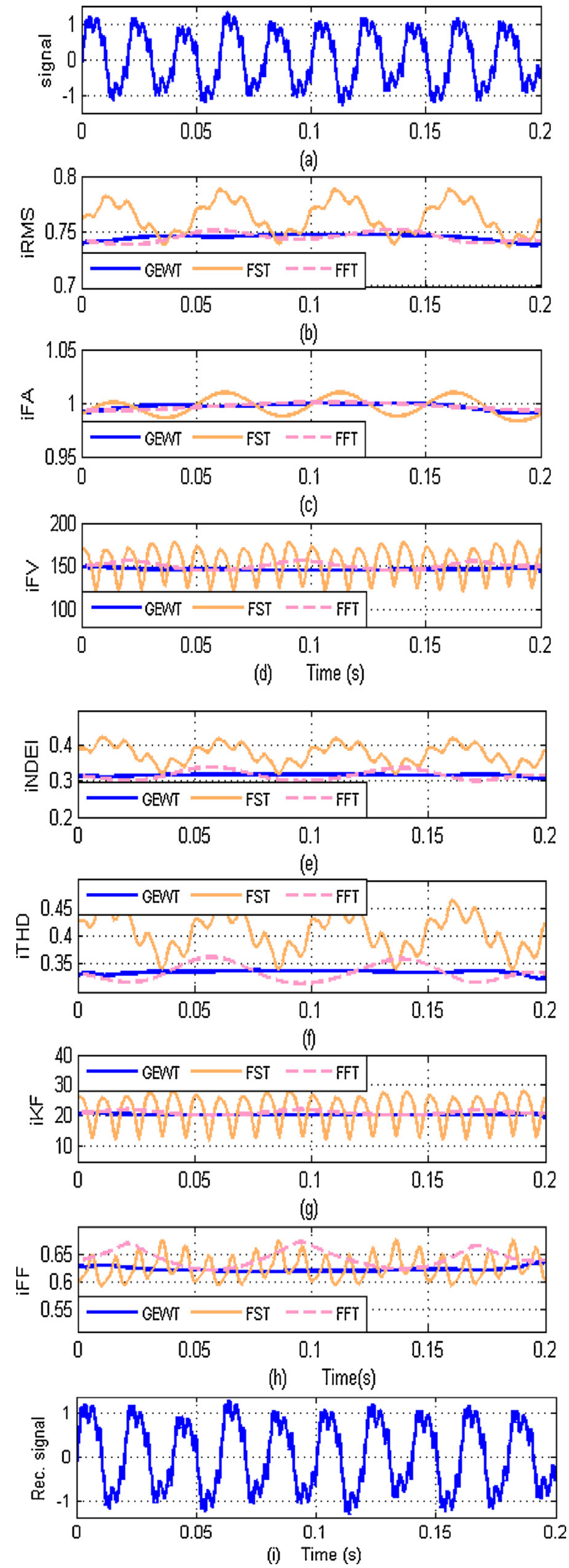

Fig. 3. Analysis of voltage fluctuation and harmonic signal and its indices.

Table 1
Parameters of the synthetic signal.

Spectral components	Actual values			Estimated values			Relative error (%)		
	a_i	f_i (Hz)	θ_i (deg)	a_i	f_i (Hz)	θ_i (deg)	a_i	f_i	θ_i
1	0.15	20	0	0.0746	29.89	0.045	0.533	−0.302	–
				0.0752	70.09	0.08	−0.266	0.148	–
2	1.0	50.2	0	0.9992	50.183	0	0.08	0.033	0
3	0.09	17	0	0.091	16.84	0.016	−1.11	0.941	–
4	0.2	150	30	0.1999	150	31.4	0.05	0	−4.66
5	0.15	250	135	0.1501	249.99	135	−0.067	0.004	0
6	0.12	350	60	0.12	350	61.5	0	0	−2.5
7	0.1	550	0	0.1	550	0	0	0	0
8	0.08	650	45	0.08	650.07	45.8	0	−0.011	−1.77

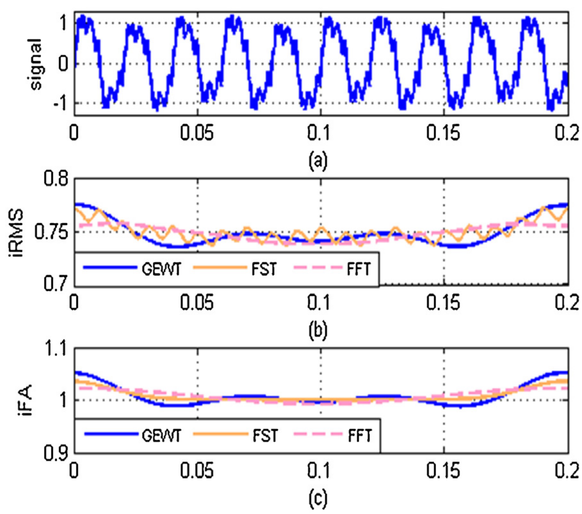

Fig. 4. Analysis of 33 Hz voltage fluctuation and harmonic signal, and its indices.

other threshold, dF = 10 Hz helps in estimating the additional subharmonic frequency 17 Hz and all the harmonics as reported in Table 1. It also shows that the estimated parameters of all spectral components are close to the actual values and the maximum relative error is noticed to be 1.11% for the amplitude, 0.941% for frequency and 4.66% for the phase angle. The reconstructed signal, shown in Fig. 3(i) contains all frequency components, and thus the RRMSE of the GEWT is noticed to be 0.0349%, which is negligible. It is evident from Fig. 3(c) that the *iFA* estimated using the GEWT is absolutely constant as the segmentation is perfect, separating the fundamental frequency from the interharmonics. Since the amplitude of each mono-frequency component is almost constant for the complete window length, the overall signal RMS, *iRMS* is also constant as shown in Fig. 3(b). It can be noticed from Fig. 3(d)–(h) that the rest of GEWT-based indices are also constant since the amplitude of flicker frequencies and the harmonics are same throughout the window i.e., stationary. Hence, FFT also extracts the indices accurately with very less error but the FFT-based *iTHD* and *iFF* vary over the true value as the two subharmonics (17 Hz and 30 Hz) are treated as a single component. Similarly, the FST-based indices fluctuate due to an overlap of flicker frequency components with the fundamental frequency component.

To verify the accuracy of the proposed approach on a voltage fluctuation signal characterized by a non-synchronized frequency, it has been tested on a signal characterized by a flicker frequency of 33 Hz. The signal, shown in Fig. 4(a) also has five frequently occurring odd harmonics that are used in the previous signal. The results, shown in Fig. 4 indicate that the GEWT-based indices are constant as expected. Since the signal contains only one subharmonic, there are no chances of overlapping of frequency components using the IEC defined FFT approach and therefore, the FFT-based indices coincide with the GEWT-based indices. In contrary, except the *iRMS* and *iFA*, all other FST based indices are improper.

4.2. Case study-2: voltage sag signal

To verify the ability of the GEWT for non-stationary signals, it has been tested on 60 Hz recorded waveforms provided by IEEE 1159.2 [38]. This case study presents the analysis of a phase-a voltage signal (wave 7) sampled at 15.36 kHz [38], which contains sag for duration of around 38 ms as shown in Fig. 5(a). The extracted time domain components are perfect such that the total reconstructed signal, shown in Fig. 5(i) has characteristics almost same as that of the original signal, thus the RRMSE is 0.0849%. The *iRMS* and *iFA* shown in Fig. 5(b) and (c) clearly replicate the voltage sag and its intensity with the lowest magnitude of 0.18 pu identified at 72.7 ms. The *iFA* value obtained is quite accurate and can be used to identify the starting instant of the sag and its duration based on a magnitude threshold of 0.9 pu. The start time, end time and thereby the duration estimated is 94% accurate. The GEWT-based indices *iFV*, *iNDEI*, *iTHD* and *iKF*, shown in Fig. 5 remains constant throughout the window except for the event duration since the recorded signal has slight distortion at the beginning and end of the event. It is also evident that the indices estimated using GEWT are superior to that of the FFT and FST-based indices with better time localization of the voltage sag and its magnitude.

4.3. Case study-3: measured voltage signal

This test case presents an analysis of a voltage signal acquired from a distribution system of an academic institution [39]. The acquired 50 Hz voltage signal, shown in Fig. 6(a) is sampled at 6.4 kHz. Since the measurements of IEC defined FFT technique is better for the stationary signals, it is taken up as a reference to demonstrate the ability of GEWT. The analysis reveals that the measured signal does not contain any interharmonics but has only harmonics up to 11th order. Hence, all the GEWT-based and FFT-based indices are constant as shown in Fig. 6, which confirms that performance of the GEWT is exactly same as the FFT. Most of the FST-based indices fluctuate around the true values due to an overlap of frequency domain windows. The RRMSE of the measured voltage signal is obtained as 0.0021%.

4.4. Case study-4: measured transient signal

A practical transient signal is acquired from a laboratory test setup shown in Fig. 7 at a sampling rate of 12.8 kHz, using a current probe (A622) and OROS-34 data acquisition card (DAQ). The nonlinear loads considered for the experiment are a laptop and a mobile. Initially, the only mobile is charging and then the laptop is

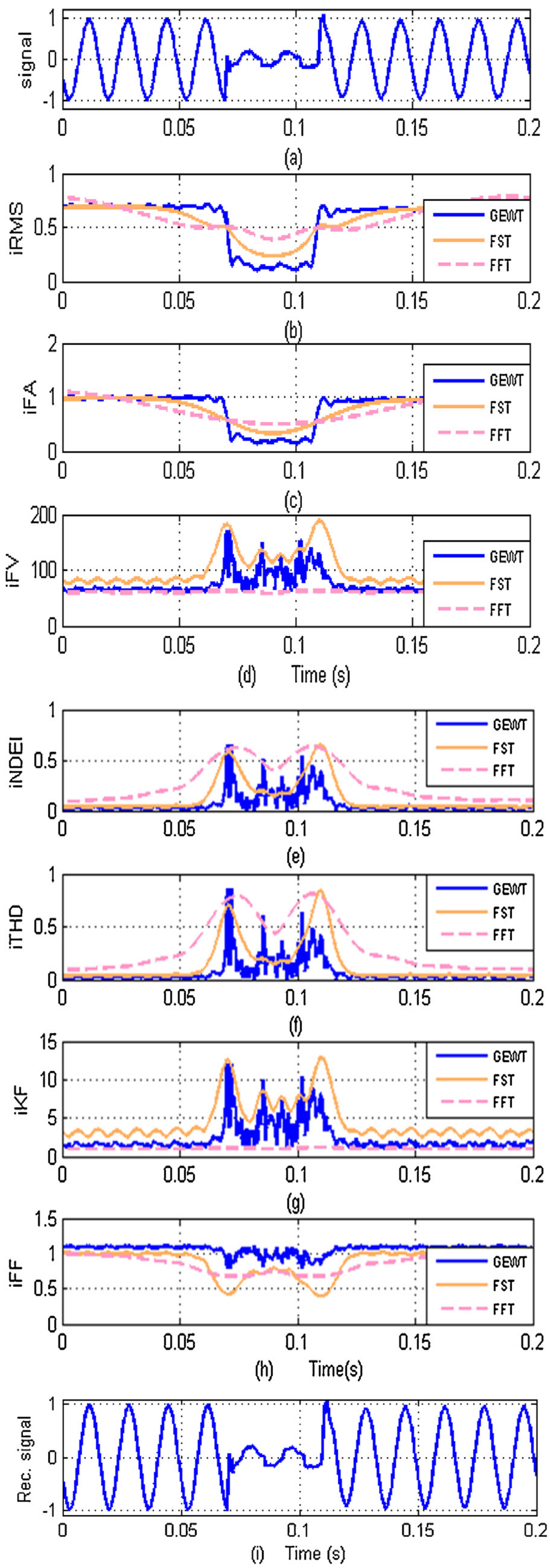

Fig. 5. Analysis of recorded voltage sag signal and its indices.

Table 2
Performance comparison in terms of computational time.

Signals of case study	Sampling frequency	Computational time (ms)		
		GEWT	Standard FFT	FST
1	10 kHz	26.47	16.89	21.7
2	15.36 kHz	31.72	25.49	16.2
3	6.4 kHz	15.137	8.73	11.15
4	12.8 kHz	70.88	45.43	57.74
5	12.8 kHz	44.13	24.85	22.39

also turned on, which caused a switching transient for the duration of around 1.6 ms as shown in Fig. 8(a). The GEWT has been applied to analyze and estimate the indices for quantizing the transient.

It can be noticed from *iFA* that the fundamental component amplitude increased with an increase in load. The signal contains high frequencies up to 3500 Hz during the transient, consequently, the GEWT-based *iFV*, *iTHD*, and *iKF* index values are very high during the transient. The significant rise in values of *iRMS*, *iFV*, *iTHD* and *iKF* for a short duration clearly indicate the presence of transient in the signal. The peak of *iFV* and *iKF* are relatively smaller than the actual frequency present, due to the fact that frequencies are weighted with their energies. Moreover, it is evident from the waveforms shown in Fig. 8 that the GEWT-based indices are better than the FFT and FST, which can extract time-varying features with exact instants of the transient. These indices permit us to record the initial time and duration of the transient occurred. It can be noticed from Fig. 8(i) that the reconstructed signal has slightly less transient factor than the actual intensity, thereby the RRMSE is obtained as 0.952%.

4.5. Case study-5: measured interharmonics signal

It is a known fact that the time-varying loads will generate interharmonics; one such load is a laser printer, which fluctuates regularly [33]. The current drawn by a laser printer is acquired for 10 s using the same DAQ at 12.8 kHz and later normalized as shown in Fig. 9(a) for further analysis. The obtained RRMSE of 0.1297% indicates that two or more frequency components are neither overlapped nor redundant. It is observed that the interharmonics of 35 Hz and 65 Hz are dominant than the odd harmonic components of 150 Hz and 250 Hz. The amplitude of fundamental frequency component and thereby the signal RMS is varying as noticed from the *iRMS* and *iFA*. The *iFV* and *iKF* indices remain almost constant as the interharmonics are present continuously for all the time. This proves that the GEWT is able to identify the interharmonics, sub-harmonics, and harmonics clearly. The GEWT- and FST-based indices are almost similar indicating that both the approaches are suitable for interharmonics. Whereas, the FFT-based *iNDEI*, *iTHD*, and *iFF* deviates from the true values due to spectral leakage effect of the time-varying signal.

Results of all the case studies revealed that the characteristics of the signal can be predicted by observing the GEWT-based time-varying PQ indices. The maximum RRMSE of the GEWT is noticed to be 1% for the transient signal. The standard FFT approach is better in analyzing the stationary signals but when the objective is to assess the non-stationary signals, it compromises the accuracy of the measurements. Especially, for signals like the voltage of wind turbine, arc furnace, and current of variable speed drive, cyclo-converters, arc furnace and rectifier interfaced nonlinear loads. The GEWT shows improved performance over the standard FFT and the FST for signals, which contain plentiful of interharmonics near the fundamental and harmonics.

The computational time of the proposed GEWT for estimation of time-varying indices of all the aforementioned signals has been reported in Table 2. It also presents the computation time of other

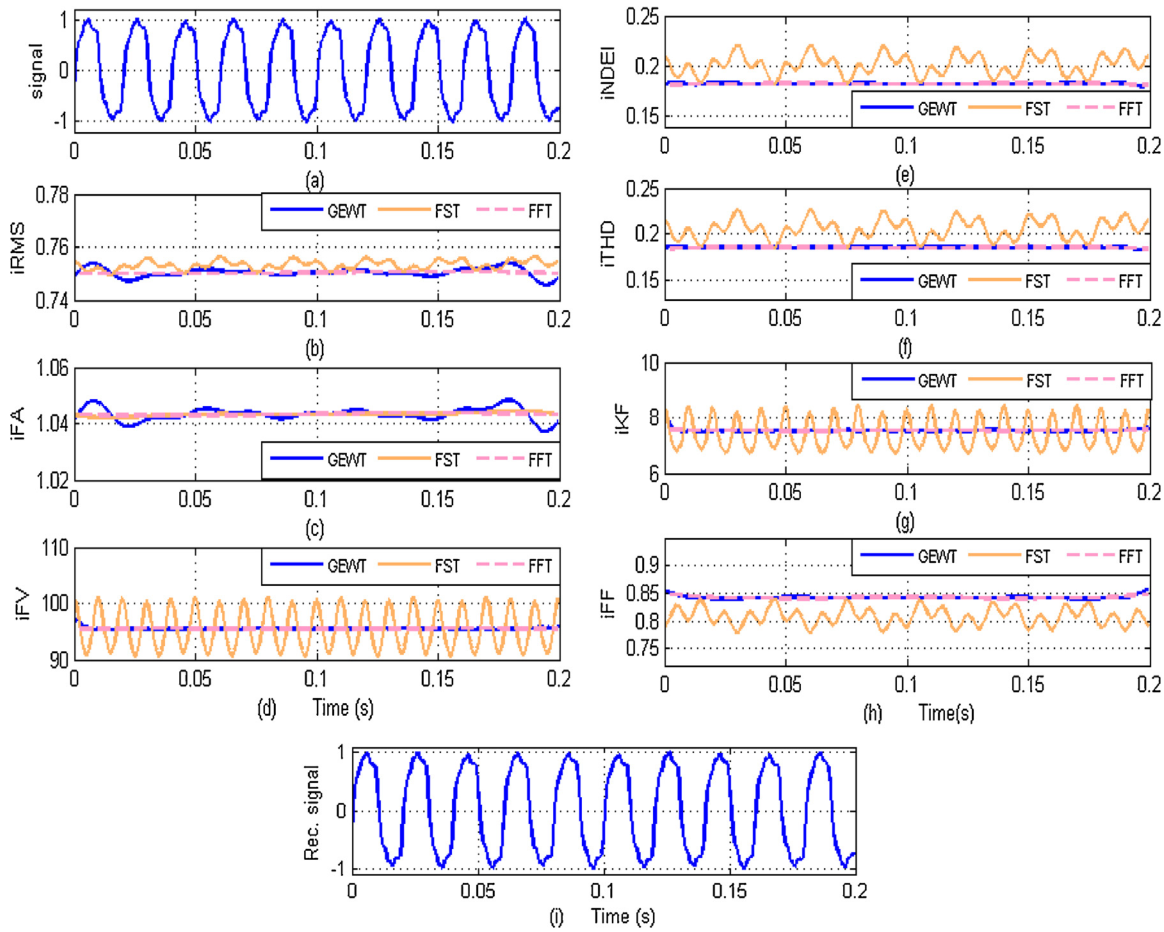

Fig. 6. A measured voltage signal and its indices.

two methods for comparison. The time taken by the GEWT for estimation of all the indices of the 10 kHz sampled signal is almost one fundamental time period. It can also be seen that for the third signal of 6.4 kHz sampling frequency, the total estimation time of the GEWT is 15.137 ms only whereas, the time increased to 31.72 ms for the 15.36 kHz voltage sag signal. In the next case of transient signal (case study-4), the computation time of the proposed method is 70.88 ms as the signal contains several frequency components due to the transient. On an average, time elapsed by the GEWT for estimation of time-varying PQ indices of a 200 ms signal, sampled at 10 kHz is around 46 ms. The maximum computational time for analyzing a 12.8 kHz signal with at most thirty frequencies is found to be 76.5 ms. From Table 2, it can be inferred that the computational time of the GEWT is almost twice that of the FFT and the FST, but is still less than the parametric methods. Since the complete estimation is finished well before the next window of the signal is available (i.e., 200 ms), the technique is suitable for online estimation of time-varying indices.

5. Discussion

The length of time window affects the performance of the GEWT in terms of both accuracy and computational time. The GEWT being an FFT-based algorithm, it holds the limitation of fixed time-frequency resolution. An increase in time window above 200 ms will give better frequency resolution but at the cost of increased non-stationary behavior and decreased time resolution. Also, the estimation delay will rise due to increased computational time and buffering time. The time window should be small such that the signal within the window is approximately stationary. On the other hand, the window below 200 ms fails in an accurate detection of interharmonics due to the poor frequency resolution and increased number of non-synchronized interharmonics.

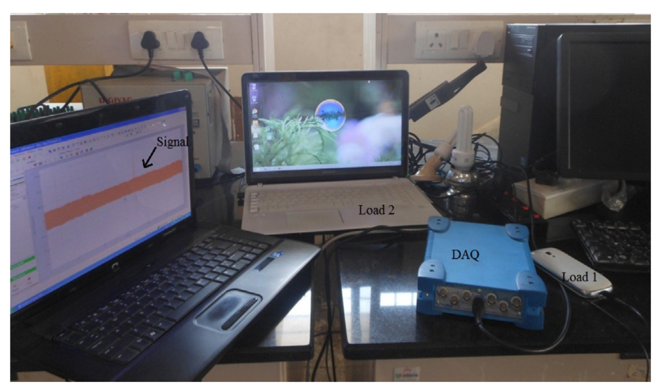

Fig. 7. Test setup for acquiring transient signal.

It can also be observed from the results that the proposed approach is fast but the computation time increases proportionally with either increase in the sampling rate or the number of filters designed. For instance, it has been found that the estimation time of the proposed approach for a 32 kHz sampled signal containing forty frequencies is approximately 383.59 ms. Limiting either of it will reduce the computation time but may also reduce the estimation accuracy. Thus, a tradeoff has been made by choosing sampling rate, not more than 15.6 kHz with at most thirty filters designed such

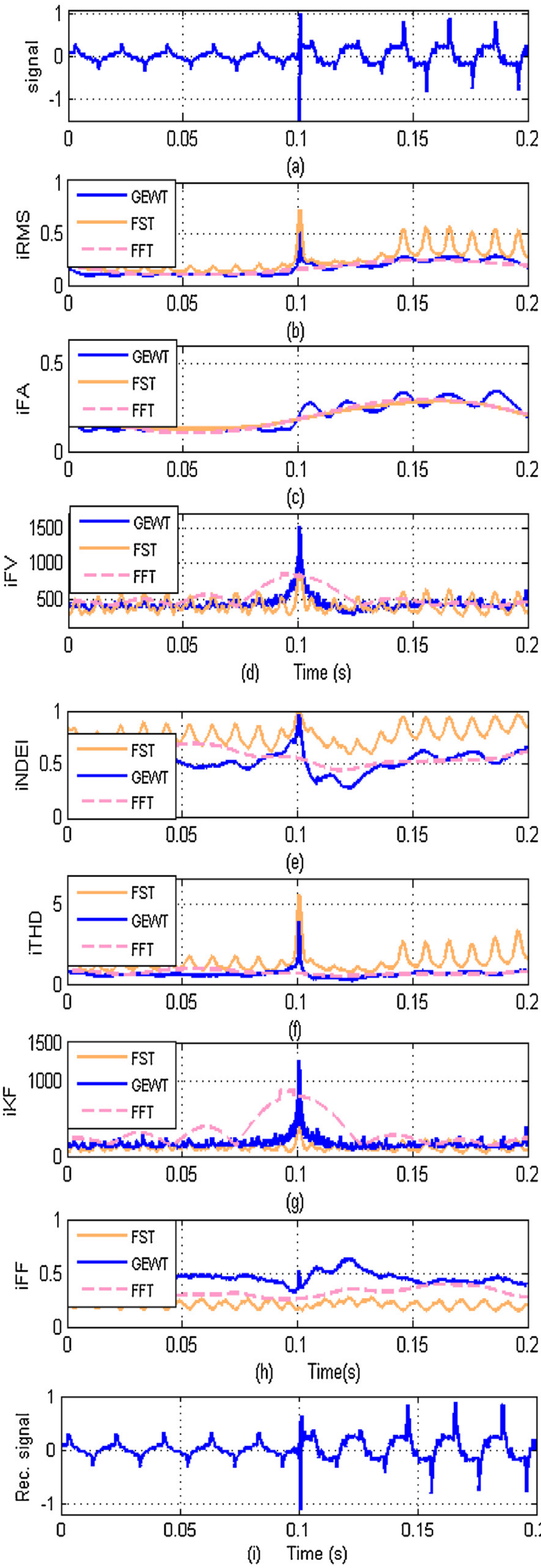

Fig. 8. Analysis of transient signal and its indices.

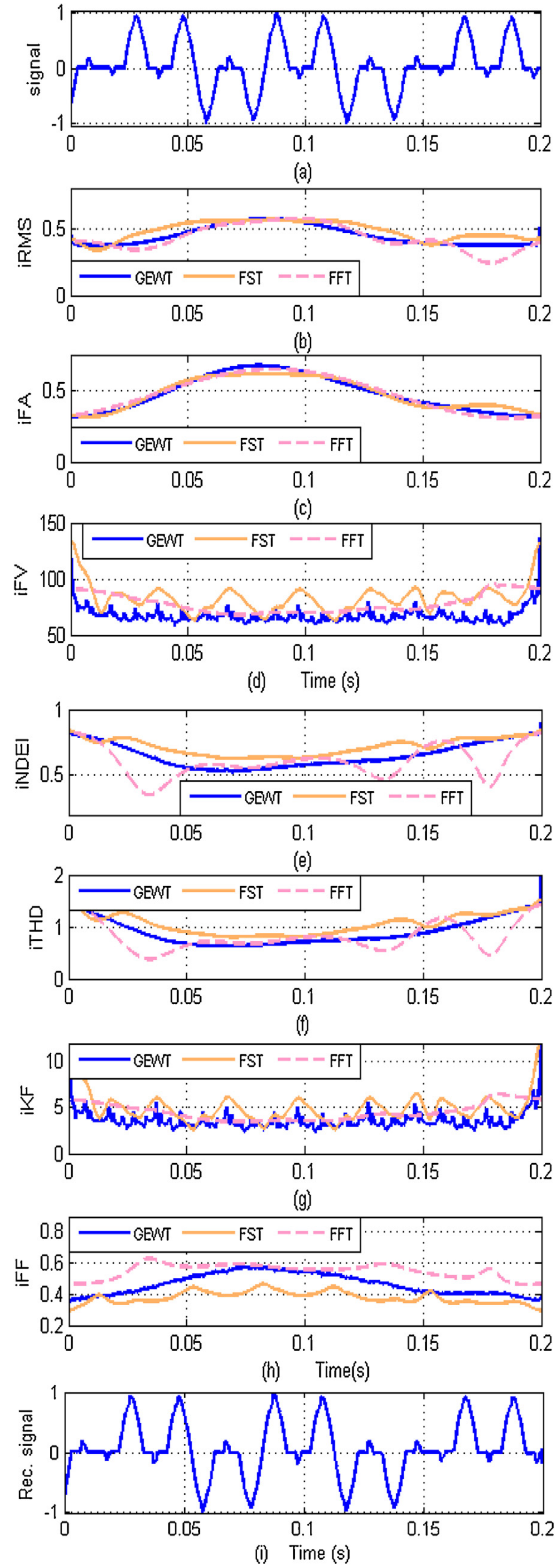

Fig. 9. Analysis of an interharmonic signal and its indices.

that all the remaining high-frequency components are included in the last distorted component. Thus, the achieved computation time is about 147.85 ms; this makes the proposed method feasible for online monitoring. The limitation of the GEWT is that the estimated NS may deviate from its true value if the windowed signal contains more than two disturbances. Therefore, the accuracy of the estimated indices may decrease for the three or more combined disturbances.

The advantages and highlights of the GEWT-based approach for estimation of time-varying PQ indices are summarized below

5.1. Completely adaptive

The accurate estimation of frequencies by overcoming the problem of spectral leakage is achieved with the help of adaptive frequency threshold (*dFF*). Further, the Fourier segmentation and the filter design are purely dependent on the spectral components creating the GEWT as completely adaptive.

5.2. Extraordinary for single disturbances

The GEWT method can assess all sorts of power signals having single disturbances by accurately estimating the time-varying PQ indices. These indices can be utilized to identify the type of disturbance and its duration of the occurrence. The accuracy of these indices plays a major role in the detection of disturbances with extreme intensities.

5.3. Computationally efficient

The GEWT, being a simple FFT-based adaptive filtering approach, is computationally fast. The hardware implementation on FPGA or DSP will further reduce the computational time making it suitable for online monitoring.

6. Conclusion

This paper presents the estimation of time-varying PQ indices using a generalized empirical wavelet transform (GEWT) for accurate assessment of PQ disturbances. The GEWT approach mainly aims to extract the actual fundamental frequency component from any distorted signal. The proposed frequency estimation procedure based on the information of low-frequency interharmonics provides better segmentation of Fourier spectrum minimizing the chances of overlapping. The performance of the GEWT has been verified by analyzing the known synthetic signals, a few disturbance signals generated in PSCAD, IEEE recorded waveforms and some measured signals. The results reveal that the GEWT outperforms the FFT in the assessment of non-stationary disturbance signals with actual intensity and better time instants. Also, GEWT is superior over FST in terms of transients, frequency deviation and nearest interharmonics. The analysis of practical signals proves that the GEWT can be successfully employed for real-time estimation of PQ indices.

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