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ANALYSIS OF POWER QUALITY EVENTS USING WAVELETS

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Abstract

Wavelets are prominently used for Power Quality (PQ) signal analysis, the features that are computed from wavelet sub bands are informative for detection and classification. Energy levels of non-stationary events that occur in PQ signal computed considering wavelet sub bands suffer from shift variant property and hence use of dual tree complex wavelets that supports shift invariance property is used for PQ event analysis. In this paper, PQ event algorithm is developed considering dual tree wavelets and the results are compared with wavelets. Various PQ signals with non-stationary events are analyzed and the shift invariant property of dual tree wavelets is demonstrated to be advantageous in terms of event classification. Dual Tree Complex wavelet Transform (DTCWT) energy levels are capable of differentiating between multiple events as well as different types of sags, swells, harmonics, interrupts and flicker. The classification accuracy using DTCWT energy bands is improved by more than 90%. DTCWT filters selected in this paper are suitable for PQ event detection as well as classification.

Keywords

PQ Event, DWT, DTCWT, Wavelets, Decomposition, Shift Invariance

1. Introduction

In modern years power quality has become a major issue for both utilities and customers. Power quality problem is mainly due to increase in use of nonlinear and power electronically switched loads, lighting controls, computer and data processing equipment's, industrial plants rectifiers and inverters and unbalanced power system as well. PQ events like sag, swell, transients, harmonics and flicker are the most common types of disturbances that occur in a power line (Surajit. Chattopadhyay, Madhu chhanda, Mitra, 2016). Sophisticated equipment's connected to the power line are prone to these disturbances and get damaged due to disturbances. Thus, it is required to estimate the presence of disturbance, and classify, characterize the disturbances. In order to perform the tasks such as detection, classification and characterization, it is required to understand the basic properties of PQ events and their properties. A number of techniques have been investigated in the literature for the classification of different types of power quality events. Among these techniques, the Fourier Transform (FT) is usually used to obtain harmonic information of the signals. However, using the FT alone is inadequate for feature extraction due to the transient nature of most power quality signals where time information is required for analyzing such signals. To overcome the inadequacy of the Fourier transform (Gu Y. H. and Bollen, M. H. J., 2000) the short-time Fourier transform (STFT) technique was adopted for detecting and characterizing power quality disturbances in the time–frequency domain (Haibo He, and Janusz A. Starzyk 2006). Fourier Transform, Short Time Fourier Transform, Continuous Wavelet Transform, and S-Transform have been extensively used for PQ analysis (Murat Uyar et.al 2008). These techniques also combined with ANN, fuzzy logic, genetic algorithm and Support Vector machines (SVM) have been used to classify and characterize power line disturbances (Karthik Thirumala, 2016), (Pallavi R. Kamthekar, 2017). Detect and analyze the voltage sags and transients by the use of continuous wavelet transform proposed decision tree using inductive learning method (Olivier Poisson, 2000). Wavelet transform been used to capture and detect type of PQ disturbance (T. K. Abdel-Gali 2004). In (Saeed Al shahrani, Maysam Abbod, Basem Alamri, 2016) (Muhammad Ijaz, Md Shafiullah, M. A. Abido, 2015) proposed Discrete Wavelet Transform (DWT) and Artificial Neural Network (ANN) based PQ event classifier by decomposing the input data into sub band and have used feature vectors for ANN classifier. Limitations of DWT have been addressed by (Panigarhi.b.K. Anant Baijal, Krishna Chaitanya P, 2010).

PQ event such as sag and swell are identified by voltage fluctuations with minimum deviations in terms of frequency from 50Hz. To differentiate between voltage swell and sag, the intensity in energy bands are considered in most of the literature reported. Voltage rise or voltage dips resulting in voltage swell and voltage sag respectively Based on the literature review power signal events such as swell, sag, transients are the major event that have been analyzed using wavelets. Selection of wavelets for PQ signal analysis is one of the primary objectives that are presented in this paper. Mathematical modeling of PQ events and generation of synthetic power signal that comprises of PQ events plays a vital role in evaluation of wavelet properties for PQ signal analysis. Mathematical modeling of PQ signals is presented in section 2. Analyze the properties of PQ events in DWT and DTCWT in section 3. Feature extractions are carried out with wavelets in section 4. Further results and discussion are explained in section 5.

2. PQ Signals With Mathematical Modeling

Verification of software reference models for PQ analysis requires PQ signals, which are generated using software programs. Mathematical equations are used to generate PQ Synthetic signals. Synthetic signals generated need to have all the properties of a real-time signal and should match the real-time signal in all aspects (Dugan, R. C. Mc Granaghan M. F., Santoso, S. and H. W. Beaty 2003). Development of software programs to generate PQ signal disturbances are governed by IEEE standard definitions for PQ events like voltage sag, voltage swell, Harmonics, Transient, Interrupts etc as given in Table 1.

Table 1: *Mathematical Models of PQ Signals*

PQ disturbances	Model	Parameters
Normal	$x(t)=\sin(\omega t)$	
swell	$x(t)=A(1+\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$ $t_1<t_2, u(t)= 1, t\geq 0 \quad 0, t<0$	$0.1\leq\alpha\leq 0.8$ $T\leq t_2-t_1\leq 9T$
Sag	$x(t)=A(1-\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.1\leq\alpha\leq 0.9; T\leq t_2-t_1\leq 9T$
Harmonic	$x(t)=A(\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+ \alpha_5$ $\sin(5\omega t)+ \alpha_7\sin(7\omega t))$	$0.05\leq\alpha_3\leq 0.15$, $0.05\leq\alpha 5\leq 0.15$ $0.05\leq\alpha_7\leq 0.15, \sum\alpha_i^2=1$
Outage	$x(t)=A(1-\alpha(u(t-t_1)-u(t-t_2)))\sin(\omega t)$	$0.9\leq\alpha\leq 1; T\leq t_2-t_1\leq 9T$

Sag with harmonic	$x(t)=A(1-\alpha(u(t-t_1)-u(t-t_2)))$ $(\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+\alpha_5\sin(5\omega t))$	$0.1\leq\alpha\leq0.9, T\leq t_2-t_1\leq 9T$ $0.05\leq\alpha_3\leq0.15$, $0.05\leq\alpha5\leq0.15$; $\sum\alpha_i^2=1$
Swell with harmonic	$x(t)=A(1+\alpha(u(t-t_1)-u(t-t_2)))$ $(\alpha_1\sin(\omega t)+\alpha_3\sin(3\omega t)+\alpha_5\sin(5\omega t))$	$0.1\leq\alpha\leq0.9, T\leq t_2-t_1\leq 9T$ $0.05\leq\alpha_3\leq0.15$, $0.05\leq\alpha5\leq0.15$; $\sum\alpha_i^2=1$
Interruption	$x(t)=A(1-(u(t_2)-u(t_1)))\cos(\omega t)$	
Transient	$x(t)=A[\cos(\omega t)+k\,\mathrm{cxp}(-(t-t_1)/\tau)$ $\cos(\omega_n(t-t_1))(u(t_2)-u(t_1))]$	$K=0.7$ $\tau=0.0015$ $\omega_n=2\pi f_n$ $900\leq f_n\leq1300$
$x(t)$- PQ signal, A-Amplitude(constant), ω_n-angular frequency, t-time, α_n-time duration of event occurrence (constant), T-time duration, f_n-frequency, K-constant, τ-constant		

3. PQ Events Analysis Using Wavelets

PQ events that have been modeled based on mathematical models are generated in MATLAB. PQ event is generated by setting the event intensity, event duration, frequency bands, event start and stop time and event type. For analysis, the MATLAB model that processes the input signal to compute wavelet sub bands processes the input signal by considering 1024 samples per frame. The sub bands that are computed by considering 1024 samples will have 512 samples of low pass and high pass coefficients at level 1. Further the low pass sample comprising of 512 samples are further decomposed into 256 samples of low pass and high pass coefficients at level 2. The process is continued until the desired levels of DWT coefficients are required. From the sub bands computed, energy levels from each sub band is computed and is analyzed for its properties. Figure 1 presents the flow chart for PQ event analysis. In this work, both DWT and DTCWT transforms are considered to analyze the properties of PQ events. As the PQ events considered for analysis are generated from synthetic signal, the results will be able to evaluate the properties of wavelet transforms and wavelet filters. The purpose of this approach is to evaluate and select appropriate wavelet transform and wavelet filter that can be used of PQ analysis.

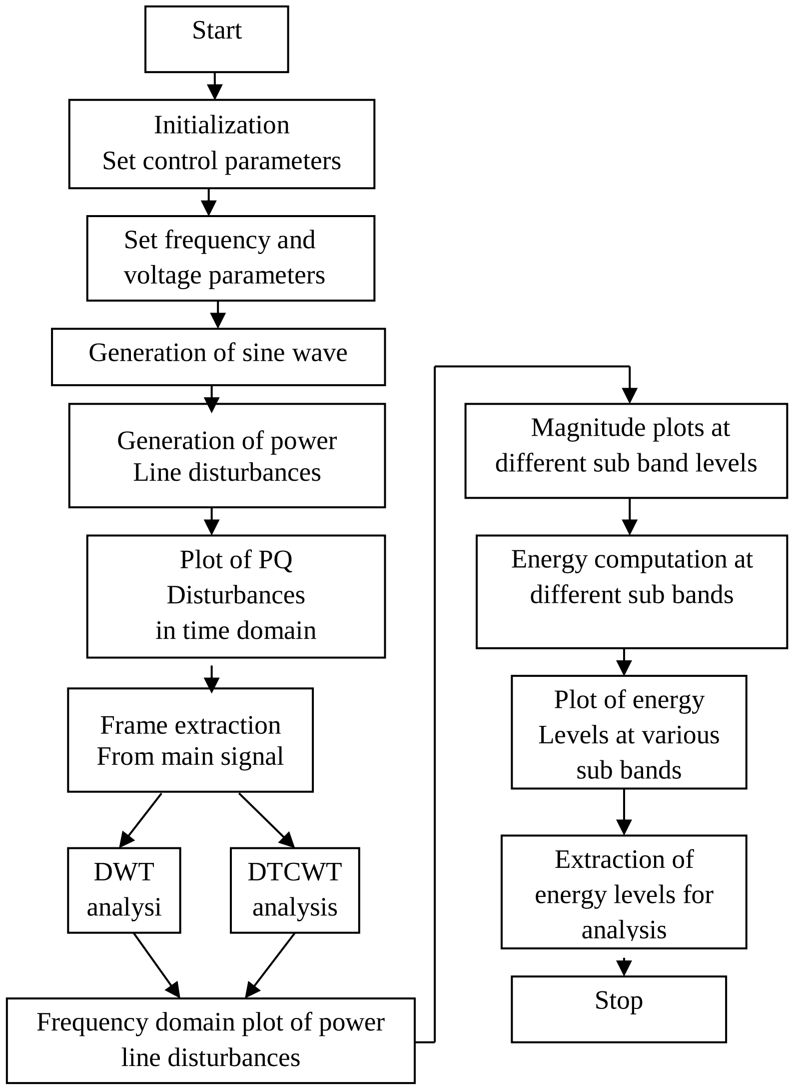

Figure 1: *Flow chart for energy computation of PQ signals using various techniques*

4. Feature Detection Using DWT And DTCWT

Swell and Sag are the two events that occur very frequently, that have distortions in voltage levels of PQ signal. With frequency remaining similar for both swell and sag, it is required to differentiate between these events by considering wavelet sub bands. Flicker, transients and harmonics not only affect voltage but also affect the PQ signal frequency. It is an easier task to differentiate between flicker, transient and harmonics considering the wavelet sub bands as wavelet provides localization with regard to time-frequency.

Figure 2 shows the decomposition process using DWT. With DWT being replaced with DTCWT, the decomposition levels are as shown in Figure 3. Where there are both real and imaginary trees that compute successive coefficients at each levels of decomposition. Where G and H are represented as a low pass and high pass filter respectively.

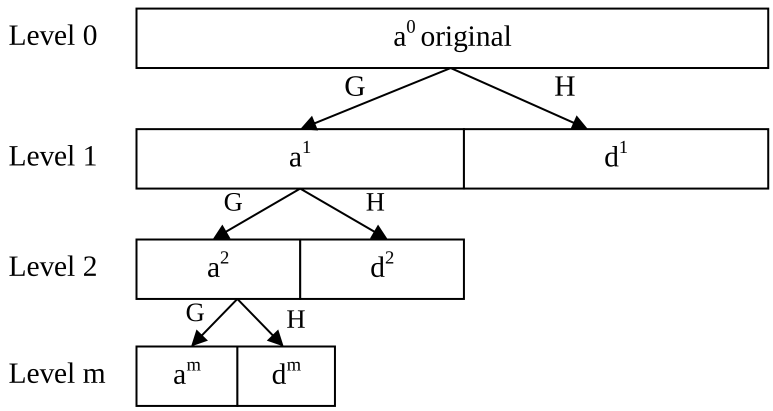

Figure 2: *DWT Decomposition levels*

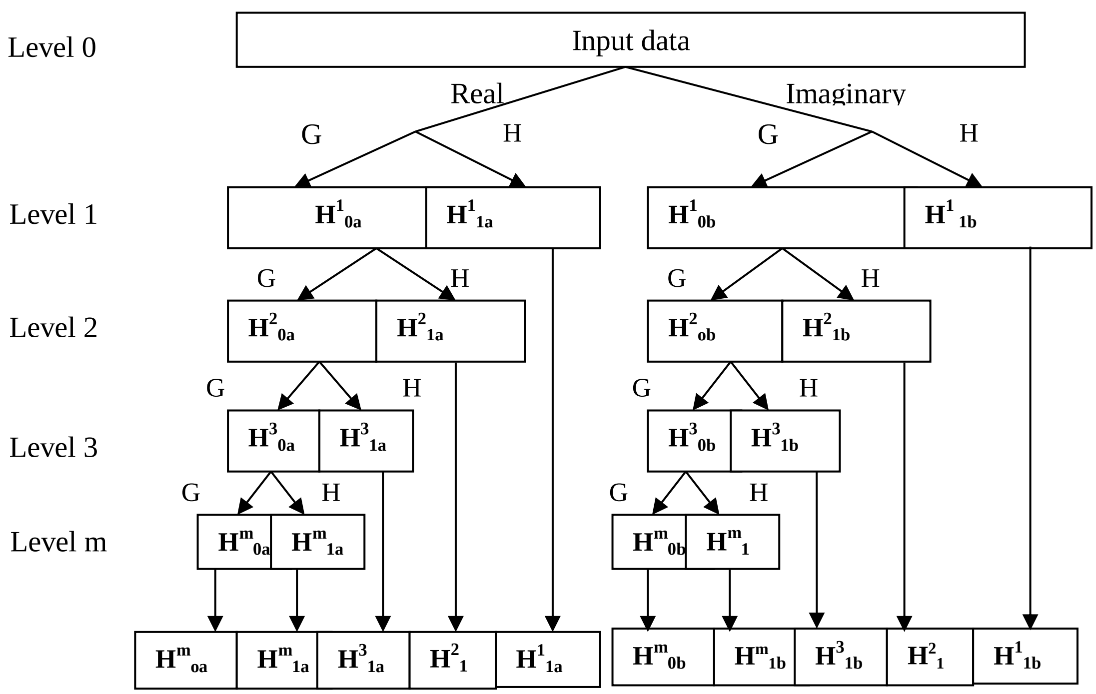

Figure 3: *DTCWT Decomposition levels*

By considering two levels of decomposition, DWT generates two high pass sub band and one low pass sub band. DTCWT generates two low pass sub bands (Real and Imaginary) and four high pass sub bands (two real and two imaginary) at two levels of frequency resolutions. The low pass sub band after two levels of decomposition captures sampling frequency(fs) in the range fs/4-fs/8, the two higher sub band capture frequency in the range fs/2-fs/4 and fs/2-fs. Figure 4 presents the method used for analysis of wavelets for PQ analysis. The input signal is decomposed considering both DWT and DTCWT, from the sub bands obtained the approximation and detail sub bands are separated for analysis. From the sub bands, threshold levels are set to extract maximum features that can improve classification process.

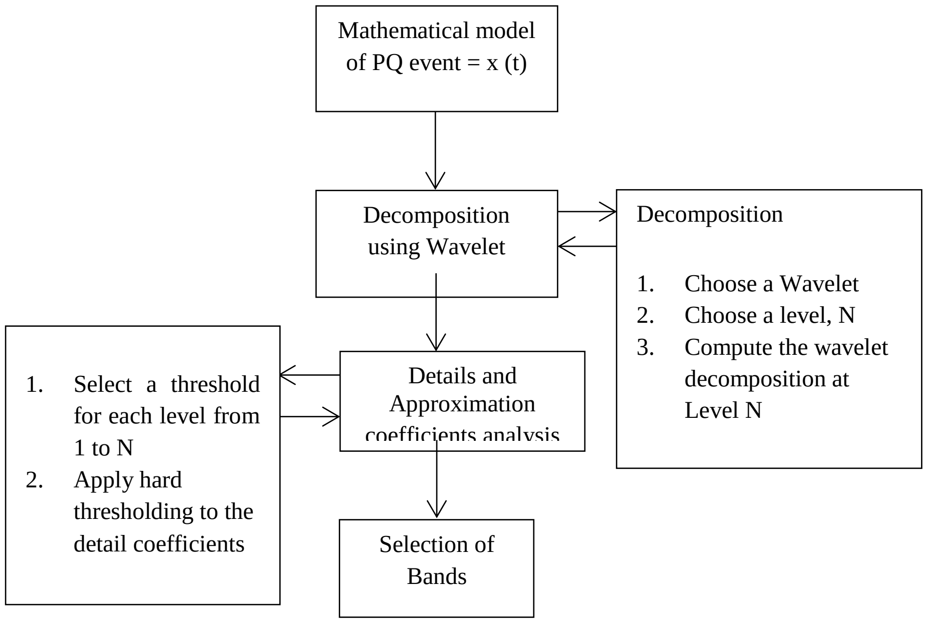

Figure 4: *Method for DWT and DTCWT based PQ analysis*

Table 2 below presents the frequency bands in which PQ events occur as per the mathematical model developed.

Table 2: *Frequency bands of PQ events*

Bands	Frequency range	PQ events
Band 1	31.21- 62.5	Sag/ Swell
Band 2	62.5 - 125	Sag/ Swell with harmonics
Band 3	125- 250	harmonics
Band 4	250 - 500	harmonics
Band 5	500 - 1000	Transients
Band 6	1000 - 2000	flicker

5. Result and Discussion

Figure 5 below presents the two level decomposition of PQ signal with swell event considering DWT and DTCWT. The swell event occurs in the range of 300 to 600 time duration with voltage increase by 20% than average RMS levels. The wavelet decomposition generates three sub bands, one low pass and two high pass bands. The low pass band at level 2 is similar to the input signal with only difference in time interval. The level 2 sub band exists between 0 to 250 time interval, and the original signal is between time intervals 0 to 1024. Level 1 high pass sub band which is between 0 to 500 time interval captures the sudden jump in swell at both ends which and is denoted with a short impulse at time duration 150 and 300 samples. The level 2 high pass sub band comprising of samples between 0 to 250 samples captures both the PQ signal and the event. Localizing the swell event from level 2 high pass band becomes complex. Considering DTCWT for PQ signal analysis, at level 2 DTCWT decomposition six sub bands are obtained. At level 2, two low pass sub bands with time duration 0 to 250 samples representing real and imaginary components. At level 2, two high pass sub bands with time duration 0 to 250 representing real and imaginary components. Similarly at level 1, two high pass sub bands between time duration 0 to 500 representing real and imaginary sub bands.

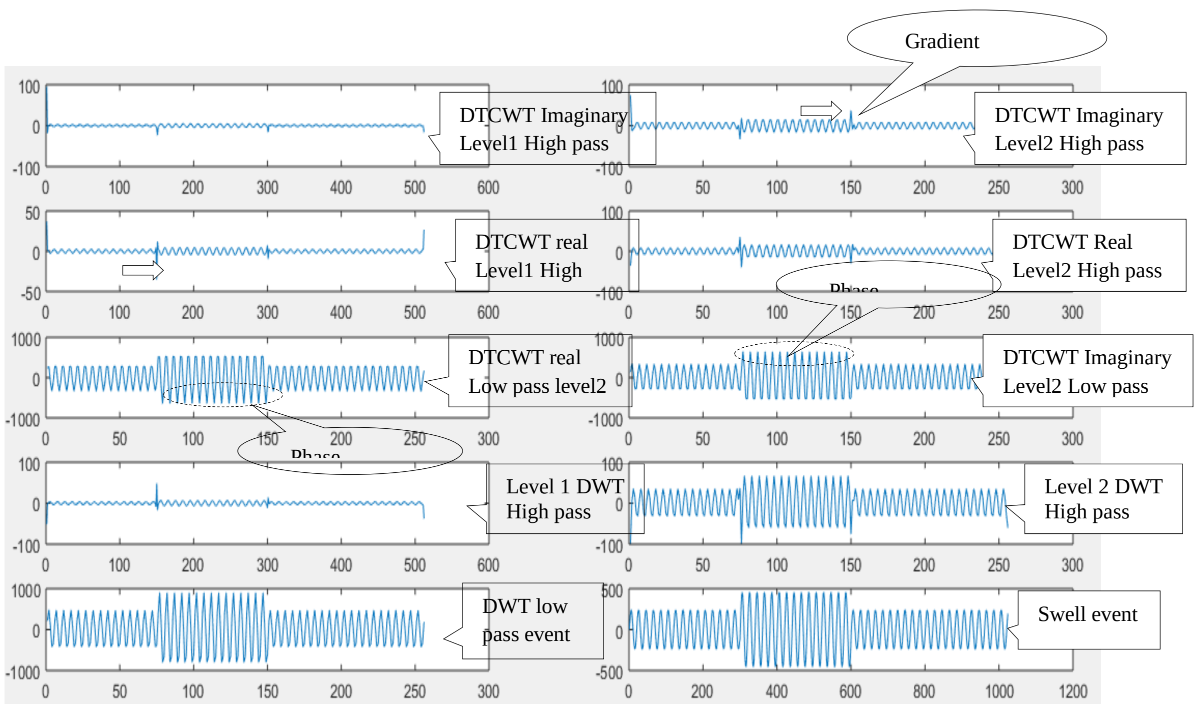

Figure 5: *Swell Analysis using DWT and DTCWT sub bands*

Considering the two low pass sub bands the envelope of the signals are similar to the PQ event considered for analysis. There exists a phase shift between the two low pass sub bands. The two high pass sub bands at level 1 capture the swell event start and end points and is seen at time intervals 150 and 300 sample time intervals. Comparing the short duration impulses at time interval 150 from level 1 real and imaginary sub band, the short duration impulse has higher positive intensity as the sort duration pulse at 150th location from imaginary component has higher negative intensity. This indicates phase shifts that exist between real and imaginary components. The intensity levels of short duration impulses indicate the presence of PQ event disturbances. The high pass sub bands at level 2 also capture the PQ events and are observed with short impulse at time locations 75^{th} and 150^{th} intervals. Comparing the short duration impulses captured by DWT and DTCWT sub bands, the information or intensity levels of these short impulses are significant in DTCWT bands and hence support event detection and event characterization.

The short duration discontinuities that exist in the input signal are captured in the form of impulses in high pass DWT and DTCWT sub bands at level 2. In addition to event occurrence time and intensity level that can be captured from DWT and DTCWT sub bands, the gradient of event occurrence or the direction in which the event occurs is captured by considering the phase information that can be computed from real and imaginary sub bands.

- **Shift Invariance Algorithm**

One of the important properties of DTCWT is that it support shift invariance. The input PQ signal with PQ event such as sag, swell, transient, harmonics and flicker occur at random intervals in real time. The feature detection algorithm need to detect the presence of event from the features detected from sub bands and also characterize the event by providing information on time of occurrence, event duration, intensity and gradient. In addition to characterization it is also required to classify the event accurately. Most of the classification algorithms that consider DWT features fail to classify the events if the event occurs at different time intervals. It is observed that DWT has limitations and is shift variant. In this section, discussions are presented on use of DWT and DTCWT for feature detection and classification demonstrating shift invariance property of DTCWT.

PQ signals with PQ event swell, sag, transient, flicker, harmonics, harmonics with swell and harmonics with sag have been generated that occur at different time intervals. The time shifted PQ events are processed by the mathematical model that computes DWT as well as DTCWT sub bands with four levels of decomposition. Energy levels based on signal norm at level-4 is computed by considering two different PQ signals that comprises of PQ event that occur at two different time intervals.

Test case 1 has two different PQ signals that comprises of PQ events that occur in the signal with time shift of 100 sample units are considered for analysis. Table 3 below presents the energy levels of all the events computed by considering energy levels in both DWT and DTCWT sub bands.

Table 3: *Test case 1*

PQ event	Transform technique	PQ signal Energy Level	PQ signal with shifted Energy level	Difference of Energy level	DTCWT Accuracy
Swell	DWT	3731077	3778023	46946	100 %
	DTCWT	4110185	4110185	0	
Sag	DWT	3563212	3523132	40080	99.94 %
	DTCWT	3875371	3875344	27	
Harmonics	DWT	3280722	3488025	207303	100 %
	DTCWT	3621293	3621293	0	
Transient	DWT	2928667	2761623	167044	100 %
	DTCWT	3621293	3621293	0	
Flickers	DWT	3071820	3068813	3007	86.04
	DTCWT	3371083	3371503	420	

PQ event swell is analyzed considering both DWT and DTCWT sub bands. The energy levels obtained are presented in the Table 3 from which it is identified that DTCWT energy levels are higher than DWT energy levels. Comparing the energy levels of PQ signals with time shifted PQ events the energy levels of DTCWT are equal and hence it is zero units. Considering the DWT energy levels of PQ signal with time shifted events there exist large difference in energy levels of 46946 units. The larger the differences in energy levels demonstrate the time shift property limitations of DWT. Sag events analyzed using DTCWT sub bands also exhibit minimum variations to an extent of zero units in energy levels for the PQ signal with time shifted PQ events.

For all events considering DTCWT sub bands will improve classification accuracy as the energy metric considered as one of the feature from DTCWT bands remains constant even if the PQ event occurs at different time intervals. Similarly it is observed for all other events that have been considered, from the results provided in Table 3 the following are the major observations made:

- DTCWT energy levels are greater than DWT energy levels for all PQ events and hence also help in accurate detection of QP events.
- DWT is shift variant and DTCWT is shift invariant and hence the classification algorithm that could be based on DTCWT features can provide more accurate results.

- The energy difference between DWT and DTCWT of swell and Sag PQ events computed by considering energy levels of 46946 and 40080 respectively. Hence it is easy to resolve between swell and sag events when DTCWT energy level is considered.
- Hence achieved the 100 % of accuracy in DTCWT.

6. Conclusion

DTCWT has advantageous over DWT as it supports shift invariant property. PQ events such as sag and swell occur in the similar frequency bands of 50Hz with only voltage fluctuations. Using DTCWT energy features for classification of sag and swell is demonstrated in this paper considering the energy levels in real and imaginary sub ands. In addition to shift invariant property supported by DTCWT, the gradient of events or the direction in which the events occur is also captured using DTCWT sub bands providing adequate information for characterization. 10-tap filter coefficients that support orthogonal property and used for DTCWT analysis. The first stage filter and the second stage filters are derived based on Kingsbury filters that are used to decompose the given PQ signal to more than 4 levels providing information of significant feature for detection, classification and characterization.

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