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Integrated DWT–FFT approach for detection and classification of power quality disturbances

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ABSTRACT

The signals in the electrical power system always have some power quality disturbances and noise contents which is the biggest obstacle in detection and time localization. In this paper, an integrated rule based approach of discrete wavelet transform – fast Fourier transform is proposed. For the detection of power quality disturbance present in the input signal, the input waveform is processed by discrete wavelet transform. The discrete wavelet coefficients are used to calculate average energy entropy of squared detailed coefficients feature. The various power quality disturbances are initially detected and then classified into four main categories as disturbances related to sag, swell, interruption and harmonics using this feature. Further classification of each main category is done using fast Fourier transform features. The total twelve types of power quality disturbances including seven basic and five combinations which are very close to real situations, are considered for the classification which are generated by parametric equations. Also four another cases are considered by adding noise to four basic disturbances sag, swell, harmonics and flicker. All sixteen cases are simulated using Mathworks Matlab R2008b. The performance of classifier is tested for 150 test signals for various durations with different disturbances with and without noise. The developed classifier is able to achieve 99.043% accuracy. From the simulation results, it can be seen that the proposed approach is effective for the detection and classification of various power quality disturbances.

Introduction

The ability of an equipment or system to function satisfactorily in its electromagnetic environment without introducing intolerable electromagnetic disturbances to anything in that environments is called power quality (PQ) [1]. The interest in PQ has been increased enormously since 1995 due to many reasons. All power equipments have become less tolerant to bad power quality. With the power system deregulation, there has been an increased need for study of various PQ issues since electricity consumers are demanding better power quality. The analysis of sources of PQ disturbances is an important task in order to understand the behaviors of the power system, to identify and implement an effective mitigation measures.

In recent years, the researchers have studied and proposed various methods for analysis, detection and classification of various PQ issues. The Fourier transform (FT) is used to process and analyze the stationary signals only. The FT is time independent and tells about frequency contents in the signal. The Discrete Fourier transform (DFT) is used for analysis of frequency content in steady state periodic signal and is suitable for harmonic analysis. However it is not capable to detect sudden or fast changes in waveform i.e. voltage dip, transients and voltage flickers, etc. The DFT has major drawbacks such as resolution, spectrum leakage as well as picket-fence effects [1]. The basics of wavelets and wavelet transform can be referred in [2]. The short time Fourier transforms (STFT) has the limitation of the fixed window width, hence it is inadequate for the analysis of the non-stationary PQ disturbances. The problem of all above signal processing methods are the principle of Heisenberg's uncertainty in which one cannot know what spectral components exist at what instance of time. The unique features that characterize power quality disturbances and techniques to extract from recorded disturbances are also presented [1,3]. The STFT fixed resolution problems have been solved using wavelet transform (WT) approach which does not need to assume the signal conditions. This makes it highly suitable for tracing changes in signal including fast changes in high-frequency components. The WT approach automatically adjusts the window width to give good time resolution and poor frequency resolution at high

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frequencies and good frequency resolution and poor time resolution at low frequencies [3,4]. The unique features that characterize power quality events and methodologies to extract them from recorded voltage or current waveforms using Fourier and wavelet transforms. Converter operation, transformer energization, and capacitor energization (which includes normal, back-to-back, and restrike on opening energization), representing three common power quality events at the distribution level, are presented [5]. The discrete short-time Fourier transform (STFT) is used for the time–frequency domain; dyadic and binary-tree wavelet filters for the time-scale domain. Dyadic wavelet filters are not suitable for the harmonic analysis of disturbance data. With a properly chosen window size, discrete STFT is also able to detect and analyze transients in a voltage disturbance [6]. The wavelet transform was introduced as a method for analyzing electromagnetic transients associated with power system faults and switching [7]. In their method, authors provide information related to the frequency composition of a waveform, it is more appropriate than the familiar Fourier methods for the non-periodic, wide-band signals associated with electromagnetic transients. It appears that the frequency domain data produced by the wavelet transform may be useful for analyzing the sources of transients through manual or automated feature detection schemes. The basic principles of wavelet analysis are set forth, and examples showing the application of the wavelet transform to actual power system transients were presented. The WT based on line disturbances detection and characterization of transients in transformers using DWT was also presented [8,9]. The basic ideas of discrete wavelet analysis for power quality detection is used, in which a variety of actual and simulated transient signals are then analyzed using the discrete wavelet transform that help demonstrate the power of wavelet analysis [10].

The continuous wavelet transform to detect and analyze voltage sags and transients is used. A recursive algorithm is used and improved to compute the time–frequency plane of these electrical disturbances. The characteristics of investigated signals were measured on a time–frequency plane. Detection and measurement results are compared using classical methods [11]. The DWT is used to extract the features of transients caused by the load/capacitor switching. The wavelet coefficients are then served as inputs to the hybrid self-organizing mapping neural network for detecting/identifying switching types and phase angles [12]. An effective MRA method has been presented for analyzing the power quality transients based on standard deviation and RMS value. The WT based de-noising techniques to remove noise effects on PQ disturbances is also proposed but it is also mentioned that its effectiveness degrades with decrease in signal to noise ratio [13,14]. The squared wavelet transform coefficients (SWTC) based approach and its effectiveness for detection and localization of transients due to load and capacitor switching is also presented [15].

A new time–frequency analysis Gabor–Winger transform (GWT) method is investigated for analysis of different PQ problems. Using this GWT only the beginning of PQ disturbances is detected [16]. An energy difference of multi-resolution analysis method is proposed for PQ disturbances detection and classification [17]. Hybrid signal processing combined with machine intelligence, WT based feature extraction approach, multi-resolution signal decomposition (MSD) technique, WT based de-noising, S-transform integrated with neural network, optimal feature selection methods and PQ events using WT and least squares support vector machines have been proposed for PQ events identification, detection and classification [18–22]. A prototype wavelet-based neural network classifier for recognizing PQ disturbances is implemented and tested under various transient conditions [23]. A noise-suppression scheme of noise-riding signals and an energy spectrum of the WTC in different scales calculated as well as the neuro-fuzzy classification system is then used for fuzzy rule construction and signal recognition [24]. The concept of DWT for feature extraction of power disturbance signal combined with artificial neural network and fuzzy logic incorporated as a powerful tool for detecting and classifying PQ problems. In this a different type of univariate randomly optimized neural network combined with DWT and fuzzy logic to have a better PQ disturbance classification accuracy is implemented [25].

Even though there has been lot of development in this area but still it is challenging and needs to be studied. The conventional analyzing methods does not provide clear and sufficient information on the time domain. In this paper, DWT based MSD technique with percentage energy entropy of squared detailed coefficient (EESDC) feature extraction method to detect, localize and for an automatic classification of PQ disturbances an integrated DWT–FFT approach with and without noisy environment is proposed. The paper is organized as follow. In Section "DWT and multi-resolution signal decomposition (MSD) analysis", DWT and multi-resolution analysis concepts are presented. The DWT algorithm implementation and PQ disturbance detection is presented in Sections "Application of DWT algorithm for PQ disturbance detection" and "Power quality signal disturbance detection" respectively. Various feature selected are discussed in Section "Feature extraction using DWT for classification of PQ disturbances". In Section "Performance of DWT based MRA under noisy environment", the proposed method performance is analyzed under noisy environments. Integrated approach of DWT–FFT is implemented in Section "Rule based system for an automatic classification of PQ disturbances". The proposed method comparison is discussed in Section "Performance comparison of proposed method" followed by conclusion in Section "Conclusions".

DWT and multi-resolution signal decomposition (MSD) analysis

The DWT uses the wavelet function (ψ) and scaling function (ϕ) to perform simultaneously the multi-resolution analysis (MRA) and reconstruction of the distorted signal. The DWT automatically makes narrow window size for high frequency and wide window size for low frequency. This feature of DWT make it possible to maintain an optimum time–frequency resolution at all frequency intervals.

MSD analysis

The recursive mathematical representation of MSD is given below:

$$A_j = D_{j+1} \oplus A_{j+1} = D_{j+1} \oplus D_{j+2} \oplus \cdots \oplus A_n \tag{1}$$

where, A_{j+1} is the approximated (smooth) signal at scale $j+1$, D_{j+1} is the detailed version for displaying all types of transient phenomena of the signal at scale $j+1$, $\oplus$ denotes an orthogonal summation, n represents the signal decomposition levels.

Modeling of DWT and MSD

A DWT gives a number of wavelet coefficients as per the number of discrete steps according to the dilation m and translation n integers. The wavelet coefficient can be described by two integers m and n. It can be done by selecting $a = a_0^m$ and $q = nq_0a_0^m$, where a_0 and q_0 are fixed segmentation step sizes for the scale and translation with $a_0 > 1$, $q_0 > 0$, $m, n \in z$ and z is the set of positive integers. The mother wavelet in DWT is given by [1],

$$\psi_{m,n}(t) = \frac{1}{\sqrt{a_0^m}}\psi\left(\frac{t - nq_0a_0^m}{a_0^m}\right) \tag{2}$$

and the corresponding DWT is given by

$$DWT_{\psi}f(m,n) = \langle f(t), \psi_{m,n} \rangle = \int_{\infty}^{-\infty} f(t)\psi^{*}_{m,n}(t)\,dt \quad (3)$$

The scaling factor a_0^m and the shifting factor $nq_0a_0^m$ are functions of the integer parameter $m(m = 0, 1, 2, \ldots)$, where m and n are scaling and sampling numbers respectively. We normally choose $a_0 = 2$, so that the sampling of the frequency axis corresponds to dyadic sampling. For the translation factor we choose $q_0 = 1$ for dyadic sampling of the time axis. With the appropriate choice of a_0 and q_0, an elegant algorithm is obtained and is multi-resolution signal decomposition technique. The discrete wavelet function ψ and scaling function ϕ can be defined as [2,17],

$$\psi_{j,n}(t) = 2^{j/2}\sum_n d_{j,n}\psi(2^j t - n) \quad (4)$$

$$\phi_{j,n}(t) = 2^{j/2}\sum_n c_{j,n}\psi(2^j t - n) \quad (5)$$

where, d_j is the detailed wavelet coefficient at scale j and c_j is the scaling coefficient at scale j.

For calculating DWT coefficients for each level requires more processing and large data information results in huge memory space requirements. Hence to have an efficient signal analysis, if the scaling and shifting based on the multiples of 2 are selected. The signals are decimated by 2, simply by discarding every other signal samples. From the MSD technique, the decomposed signals at scale 1 are $c_1(n)$ and $d_1(n)$, where, $c_1(n)$ is the smoothed version of the original signal, $d_1(n)$ is the detailed representation of the original signal and, $c_0(n)$ is the signal to be decomposed. This constitutes first level decomposition. The approximate and the detailed coefficients are obtained recursively in the same way for all decomposition levels from the input signal $c_{j-1}(n)$. Mathematically it can be expressed by the following equations [2,9],

$$c_jn = \sum_k h(k - 2n)c_{j-1} \quad (6)$$

$$d_jn = \sum_k g(k - 2n)c_{j-1} \quad (7)$$

where, c_j is the coefficients of the approximate signal at level j and d_j represents coefficients of the detailed signal at level j [1,4].

The high pass and low pass filters are not independent of each other, and they are related by [2],

$$g(n) = (-1)^n h(L - 1 - n) \quad (8)$$

where, $g(n)$ is the high pass filter (HPF), $h(n)$ is the low pass filter (LPF), and L is the filter length. Let the original distorted signal sampling frequency range is $0 - f_{sp}$. The typical three level of MSD based on DWT is shown in Fig. 1. Here reference frequency is 50 Hz and the sampling frequency is f_{sp}. The frequency range at each level of MSD for approximate signal is $0 - \frac{f_{sp}}{2^{n+1}}$ and that for the detailed signal is $\frac{f_{sp}}{2^{n+1}} - \frac{f_{sp}}{2^n}$ where n is the level of decomposition.

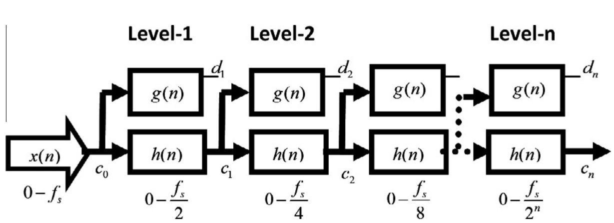

Fig. 1. Typical three level MSD based on DWT.

Application of DWT algorithm for PQ disturbance detection

The MSD can be implemented by set of successive filter banks in which the wavelet acts as a high pass filter ($g_d(n)$) and the scaling function acts as a low pass filter ($h_d(n)$). The choice of analyzing mother wavelet plays very important role in the detection and classification accuracy. From the various studies and research, it has been observed that the different wavelets families have been used for multi-resolution signal decomposition analysis and feature extraction of distorted signals. For testing the performance of various feature vector extracted, the families of daubechies have been used and tested. After studying and comparing performances of Daubechies family wavelets, the *db*4 has more efficient in feature extraction and hence is used as a mother wavelet for PQ disturbance signal analysis. The various wavelets used in signal processing application are Daubechies, Symlets, Coiflets and Haar wavelets. Table 1 shows the various features of wavelets used in application [17]. In this *DL* is the number of decomposition levels. The Daubechie's family wavelet filter *db*4 is an appropriate choice as a mother wavelet for analysis of PQ disturbances because of larger energy contents at each level. As compared to other wavelets, the *db*4 has shorter filter length, shorter computational time as well as good compact support in real time applications [19].

Power quality signal disturbance detection

A pure sine wave with frequency 50 Hz and magnitude at 1.0 p.u. as well as 11 other PQ disturbances such as voltage sag, swell, harmonics, interruption, sag + harmonics, swell + harmonics, flicker, high frequency transients (HFT), low frequency transients (LFT), capacitor switching, load switching and 4 other signals with 20 dB peak magnitude noise are generated using parametric equations [19,22] and Mathworks Matlab simulation software. The power quality disturbance signal generation models and their control parameters are shown in Table 2. All other PQ signal combinations can be generated using these basic models. Squared wavelet transform coefficients are very powerful in detecting power quality

Table 1
Characteristics of various wavelets.

Name of wavelet	Compact support	Support width	Symmetry	Filter length
Daubechies	Yes	$2DL - 1$	Far from	$2DL$
Symlets	Yes	$2DL - 1$	Near from	$2DL$
Coiflets	Yes	$6DL - 1$	Near from	$6DL$
Harr	Yes	1	Yes	2

Table 2
Power quality disturbance signal modeling and its controlling parameters.

PQ disturbances	Models	Parameters
Sine-wave	$x(t) = A\sin(\omega t)$	$A = 1.0$, $f = 50$ Hz
Voltage sag	$x(t) = A\sin(\omega t) \times [1 - \alpha(u(t - t_1)) - u(t - t_2)]$	$0.1 < \alpha < 0.9$
Voltage swell	$x(t) = A\sin(\omega t) \times [1 + \alpha(u(t - t_1)) - u(t - t_2)]$	$0.1 < \alpha < 0.8$
Harmonics (HR)	$x(t) = A\sin(\omega t) + \alpha_3\sin(3\omega t) + \alpha_5\sin(5\omega t)$	$0.1 < \alpha_3 < 0.2$ $0.05 < \alpha_5 < 0.1$
Voltage flicker	$x(t) = A\sin(\omega t)[1 + \beta\sin(\gamma wt)]$	$0.1 \leqslant \beta \leqslant 0.2$ $0.1 \leqslant \gamma \leqslant 0.2$
High frequency transient (HFT)	$x(t) = A\sin(\omega t) + \alpha e^{-t/\lambda}\sin(bwt)$	$20 \leqslant b \leqslant 80$ $0.1 \leqslant \lambda \leqslant 0.2$ $0.1 \leqslant \alpha \leqslant 0.9$
Low frequency transient (LFT)	$x(t) = A\sin(\omega t) + \alpha e^{-t/\lambda}\sin(bwt)$	$5 \leqslant b \leqslant 20$ $0.1 \leqslant \lambda \leqslant 0.2$ $0.1 \leqslant \alpha \leqslant 0.9$

events disturbance. Therefore, squaring wavelet transform coefficients improves the detection accuracy if the wavelet transform coefficients are inadequate to indicate the disturbance features.

All the input signals are generated with total 1280 samples for five cycles (256 samples per cycles). It's recording time is 0.1 s hence sampling frequency (f_{sp}) of the signal is 12.8 kHz. The reference frequency is 50 Hz. Even though ten level distorted signals MSD has been carried out using *db*4 mother wavelet but only four levels of MSD are shown here during the detection. For feature extraction and for more critical analysis, ten level decomposition is done for classification purpose of PQ disturbances. Figs. 2–7 show four level squared discrete wavelet transform coefficients (DWTC) decomposition for detection of voltage sag, voltage swell, harmonics, voltage interruption, sag + harmonics and capacitor switching respectively. The starting ($t_s = 0.025$ s) and ending ($t_e = 0.075$ s) duration for all PQ disturbances are same (i.e. time duration (t_{td}) = ($t_e - t_s$)). The total 16 PQ signals are modeled and processed but only following six signals detection have been shown.

Fig. 2 shows that the squared DWT detailed signal coefficients DWTC-1 and DWTC-2 at first two finer levels in the vicinity of sample points 160 and 82 can locate and detect voltage sag efficiently. The DWTC-3 and DWTC-4 locate and detects low frequency components of the voltage sags as the high frequency components have been extracted. Fig. 3 shows the four finer levels of detail signal decomposition of the voltage swell in pure sine wave. From the signal decomposition waveform, DWTC-1, DWTC-2 and DWTC-3 in the vicinity of sample points 160, 82 and 40 respectively can locate and detect voltage swells efficiently. Fig. 4 shows the four finer levels of detailed signal decomposition of harmonics in pure sine wave. Even though harmonics is steady state power quality event, from the signal decomposition waveform it is observed that the squared DWT detailed signal coefficients DWTC-1 and DWTC-2 at first two finer resolution levels in the vicinity of sample points 160 and 80 can locate and detect harmonics efficiently. The DWTC-3 and DWTC-4 does not locate and detect correctly but indicates harmonic content duration in the signals. The voltage interruption detection is shown in Fig. 5. From the signal decomposition

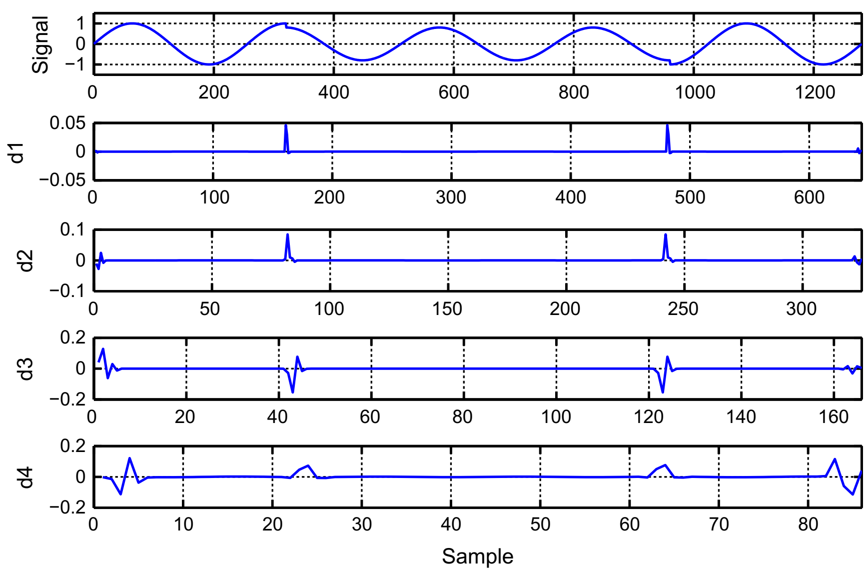

Fig. 2. Four level squared DWTC decomposition for detection of voltage sag.

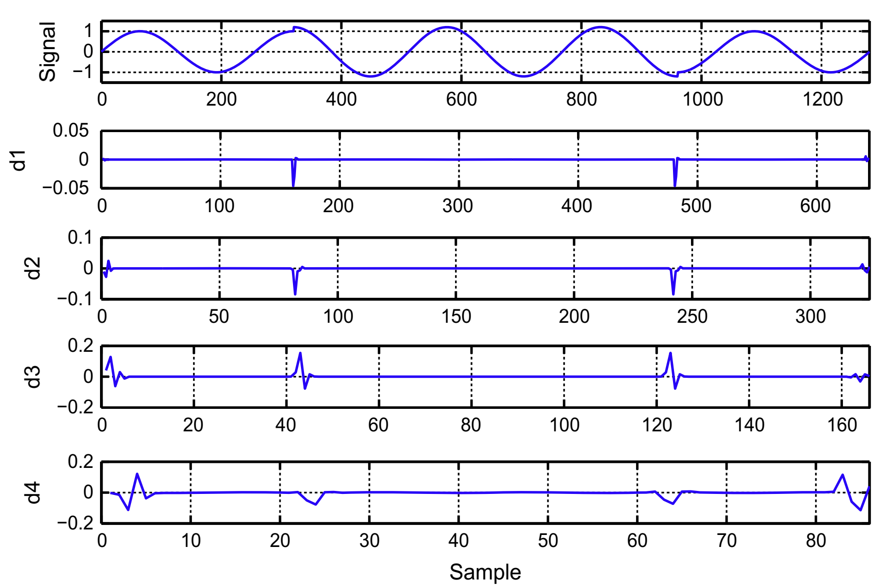

Fig. 3. Four level squared DWTC decomposition for detection of voltage swell.

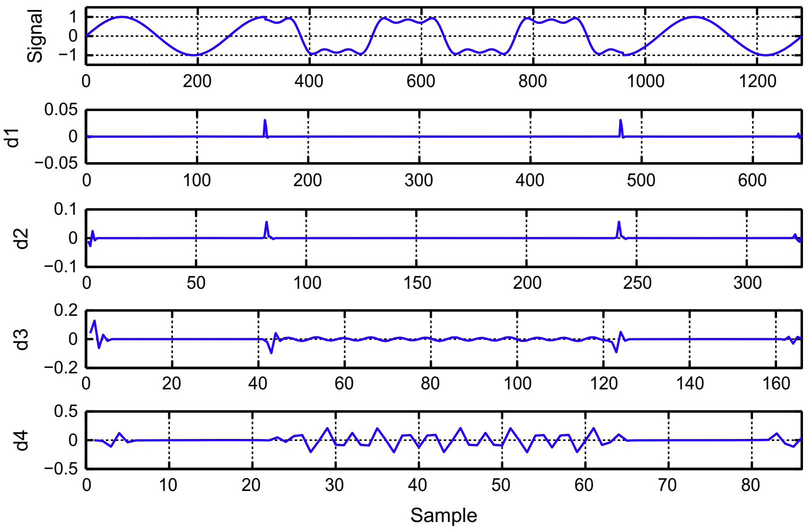

Fig. 4. Four level squared DWTC decomposition for detection of harmonics.

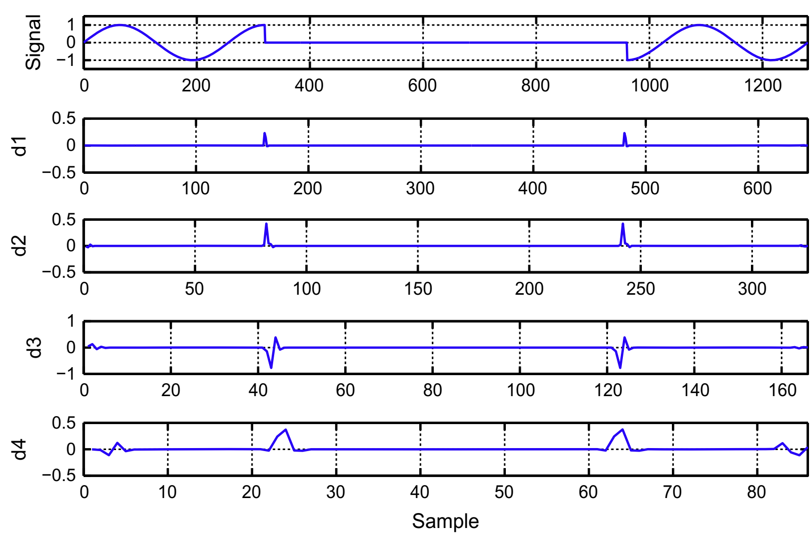

Fig. 5. Four level squared DWTC decomposition for detection of interruption.

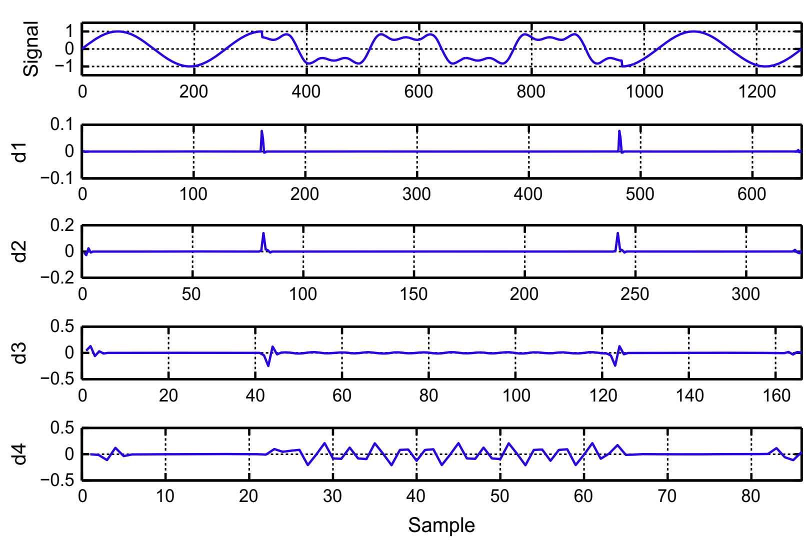

Fig. 6. Four level squared DWTC decomposition for detection of sag + harmonics.

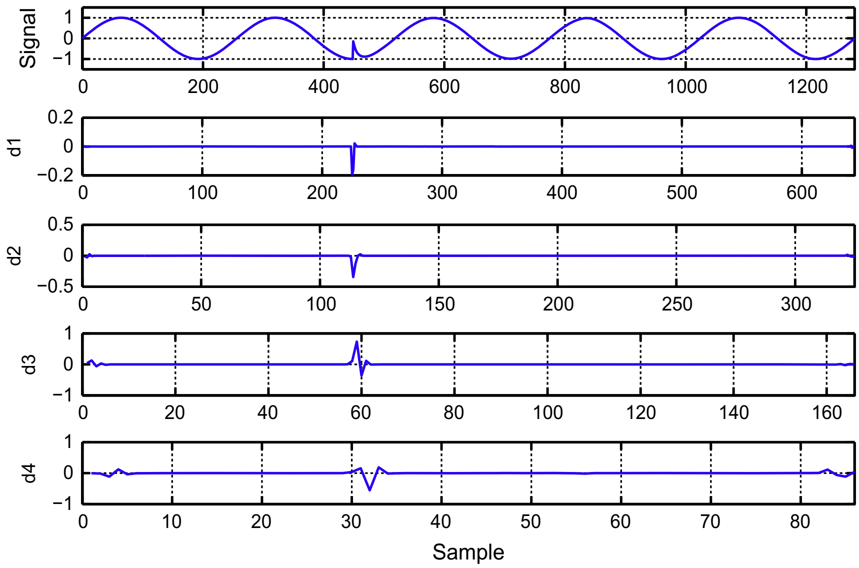

Fig. 7. Four level squared DWTC decomposition for detection of capacitor switching.

waveforms, it is observed that the squared DWT detailed signal coefficients DWTC-2 and DWTC-3 in the vicinity of sample points 80 and 40 can locate and detect interruption efficiently. Figs. 6 and 7 show the four finer levels of detail signal decomposition of sag + harmonics and capacitor switching in pure sine wave. From the signal decomposition waveforms, it is observed that the squared DWT detailed signal coefficients DWTC-2 and DWTC-3 in the vicinity of sample points 80 and 40 can locate and detect these two PQ disturbances efficiently. The energy distribution in the MRA curve for 12 PQ disturbances at ten levels is shown in Table 3.

Feature extraction using DWT for classification of PQ disturbances

Feature extraction is the process of transforming original disturbed time domain signal into a new signal form, from which a suitable feature can be extracted for classification of PQ disturbances. The energy distribution of a distorted signal can be used as a discriminatory feature for classification. The proper feature extraction is the key for an efficient classifier performance. To get efficient performance of classifier, it is an important to get a useful feature vector which can reduce the data size and helps in indicating and recognizing the main characteristics of the signal.

Application of Parseval's theorem in DWT for PQ classification

In DWT, signal energy at each level of the wavelet transform coefficients (WTC) can be separated in time and frequency domains. Hence the relationship between the energy in PQ signal $f(t)$ each scale of the WTC can be calculated using the Parseval's theorem by using the following expression [17,23]:

$$1/N\sum^{t}|x[t]|^2 = \sum_{j=1}^{N}|A_{i,j}|^2 + \sum_{j=1}^{N}|D_{i,j}|^2 \quad i = 0, 1, 2, \ldots, l \tag{9}$$

The first term on the right site of Eq. (9) consists an average power of the approximated version of the decomposed signal and the second term denotes the detailed version of the decomposed signal. The second term in the equation contents maximum required information hence can be used to extract features from distorted PQ signals.

The Parseval's theorem in the DWT application can be implemented by separating the total energy of the discrete time domain signal. This can be done using the following expression:

$$WD_i = \sum_{j=1}^{N}|D_{i,j}|^2 \quad i = 0, 1, 2, \ldots, l \tag{10}$$

and

$$WA_l = \sum_{j=1}^{N}|A_{i,j}|^2 \tag{11}$$

where, i, N are the wavelet decomposition level and the number of coefficients of detailed signal at each decomposition level respectively and WD_i, WA_l are the energy of the detailed coefficients (DC) at decomposition level i and the energy of the approximate

Table 3
Energy contents in sine wave and other PQ disturbances during ten level of decomposition.

Disturbances	E_{D1}	E_{D2}	E_{D3}	E_{D4}	E_{D5}	E_{D6}	E_{D7}	E_{D8}	E_{D9}	E_{D10}
Pure sine wave	0	0.002	0.0244	0.061	0.3958	11.5004	253.3528	532.1044	11.5621	1.2721
Voltage sag	0.006	0.0165	0.0861	0.077	0.4698	10.5253	208.6922	443.7847	11.8109	1.294
Voltage swell	0.0027	0.0086	0.0523	0.7115	3.128	31.7583	259.6248	557.1459	11.5976	1.2755
Harmonics	0.1496	0.3659	1.5670	0.4614	2.4175	15.5420	138.4195	252.2143	17.3980	1.4025
Voltage inter.	0.1496	0.3659	1.5670	0.4614	2.4175	15.5420	138.4195	252.2143	17.3980	1.4025
Sag + harmonics	0.0167	0.0427	0.1892	0.7382	3.3653	35.9010	212.5357	465.1683	11.8496	1.2922
Swell + harmonics	0.0007	0.0035	0.0388	0.7169	3.0558	28.5072	317.5508	665.2944	11.8048	1.2517
Voltage flicker	0.003	0.0093	0.0552	0.0696	0.4652	12.1738	287.3819	569.9398	13.2695	1.2829
HFT	1.1453	5.5246	0.0316	0.0793	0.3959	11.4724	253.2102	531.7553	11.6361	1.2666
LFT	0.0002	0.0065	0.3415	5.5611	1.2662	11.4396	252.4298	530.0656	11.9945	1.2414
Capacitor switch.	0.0654	0.1369	0.7184	0.4279	0.8847	11.6694	274.3894	480.8108	11.4855	1.7875
Load switch.	0.00395	0.01244	0.6345	2.3987	11.6789	20.2248	290.8095	275.432	64.1235	1.2254

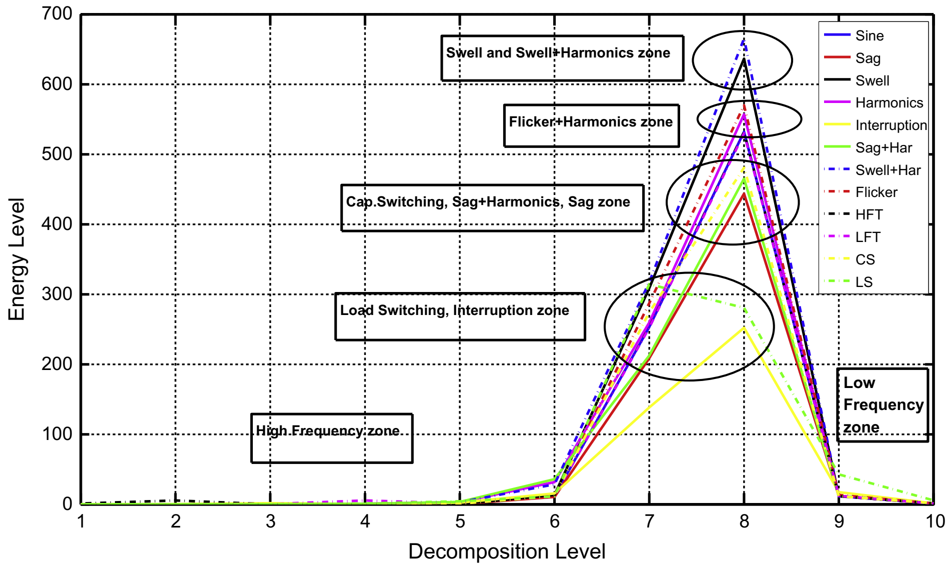

Fig. 8. MRA curve for the comparison of energy levels in sine wave and other power quality disturbances during MSD.

coefficients at MSD level l respectively. The energy contents in an approximate signal is neglected for feature extraction. Hence for a l level of MSD, $l+1$ dimensional feature vector can be extracted for feature analysis. The extracted feature helps in distinguishing the disturbance signal from each other. For distorted signal, it can be represented by the feature vectors given below:

$$Feature\,vector(WD_{DS}) = [WD1, WD2, \ldots, WD_l, WA_l] \tag{12}$$

and feature vector for pure sinusoidal signal can be expressed using the following expression:

$$Feature\,vector(WD_{PS}) = [WD1, WD2, \ldots, WD_l, WA_l] \tag{13}$$

The resultant feature vector can be obtained using the following expression:

$$\Delta W = (WD_{DS}) - (WD_{PS}) \tag{14}$$

The classification of PQ disturbances using MRA curves is shown in Fig. 8. Based on the energy distribution pattern it is very difficult to classify correctly all PQ disturbances. Hence other feature extraction methods like percentage average energy entropy difference of squared DC, percentage difference of average absolute sum of squared DC and only the sum of squared DC are extracted for classification of PQ disturbances. The squared wavelet coefficients were shown to be useful features for identifying and classifying power quality events. The energy entropy of approximate squared DC is neglected for further analysis. The percentage average energy entropy of squared DC can be extracted using the following expression,

$$\%W_{AVG-EE} = \frac{\Delta W}{WD_{PS}} \times 100 \tag{15}$$

where, $\%W_{AVG-EE}$ is the entropy difference of average energy distribution during PQ events and during pure sine waves, WD_{DS} is the average energy distribution during PQ disturbance and WD_{PS} is the average energy distribution in pure sine wave at all levels. The PQ disturbances are always non-stationary, imbalance with various frequency components and energy distribution. The energy entropy is used to extract significant features from different PQ disturbances. This extracted feature is used to distinguish various PQ disturbances [17,19]. The variations in average energy entropy for 12 types of disturbance signals are analyzed using *db*4 mother wavelet filters for ten level of decomposition is shown in Table 4. The classification bar chart based on this percentage energy entropy is shown in Fig. 9 for easier identification. Other feature extraction methods are given in next subsection.

Magnitude of an average absolute sum of detailed coefficients

The feature of percentage difference of average values of absolute sum of detailed signal coefficients are extracted from MSD. This can be calculated using following expression

$$\%W_{Absavg} = \frac{W_{DSabs} - W_{PSabs}}{W_{PSabs}} \times 100 \tag{16}$$

where, $\%W_{Absavg}$ is the percentage average difference of detailed coefficients during PQ events and during pure sine waves, W_{DSabs} is the average of absolute sum of DC during PQ disturbances and W_{PSabs} is the average of absolute sum of energy distribution in pure sine wave at all levels. The sum of DC is also calculated and it is shown in Table 5.

Classification of PQ disturbances based on feature extraction without noise

Table 6 shows the classification performance of each method. It has been observed that the percentage average energy entropy of

Table 4
Average energy entropy difference of squared detailed coefficients.

Type of signal	Symbol	Sum of squared DC	Average of DC at 10 levels	% Average EE of DC
Pure sine wave	S1	810.275	81.0275	0.0
Voltage sag	S2	676.7625	67.67625	−16.78
Voltage swell	S3	972.5046	97.25046	20.0215
Harmonics	S4	865.3052	86.53052	6.7925
Voltage inter.	S5	429.9375	42.9938	−46.9392
Sag + harmonics	S6	731.0989	73.1099	−10.0769
Swell + harmonics	S7	1028.225	102.8225	26.898
Voltage Flicker	S8	884.6502	88.46502	9.179
HFT	S9	816.5173	81.65173	0.7790
LFT	S10	814.3464	81.43464	0.5111
Capacitor switch.	S11	782.3759	78.23759	−3.4915
Load switching	S12	660.7299	66.07299	−18.4474

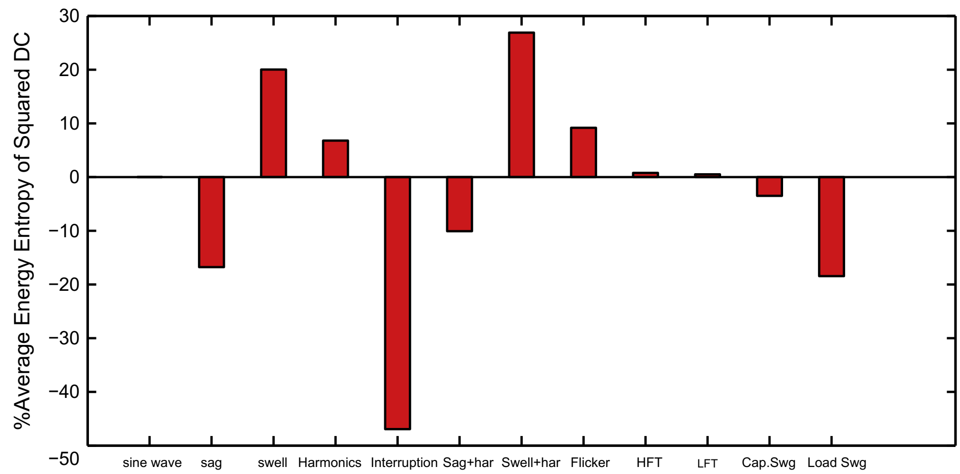

Fig. 9. Bar chart for percentage energy entropy of squared detailed coefficients.

Table 5
Average difference of absolute value of detailed coefficients.

Type of signal	Symbol	Sum of DC	Absolute sum of DC	Mean of DC	% Average EE of DC
Pure sine wave	S1	−26.7501	150.6545	15.0654	0
Voltage sag	S2	−23.3790	140.3335	14.0334	−6.8507
Voltage swell	S3	−30.1213	164.2116	16.4212	8.9988
Harmonics	S4	−22.3274	170.7359	17.0736	13.3295
Voltage inter.	S5	-9.8944	112.0392	11.2039	−25.6315
Sag + harmonics	S6	−18.9563	162.6429	16.2643	7.957
Swell + harmonics	S7	−25.6986	179.9686	17.9969	19.458
Voltage Flicker	S8	−28.7684	157.3978	15.7398	4.4760
HFT	S9	−26.7108	195.9694	19.5969	30.0788
LFT	S10	−26.9061	172.1208	17.2121	14.2487
Capacitor switch.	S11	−26.3268	153.7396	15.3740	2.0484
Load switching	S12	−23.6410	157.5196	15.7520	4.5571

Table 6
Classification of PQ disturbances.

Symbol	% Energy entropy of squared DC	Average absolute sum of DC	Sum of DC
S1	Classified	Classified	Classified
S2	Classified	Classified	Not classified
S3	Classified	Not classified	Not classified
S4	Classified	Not classified	Not classified
S5	Classified	Classified	Not classified
S6	Classified	Not classified	Not classified
S7	Classified	Not classified	Not classified
S8	Classified	Not classified	Not classified
S9	Not classified	Classified	Not classified
S10	Not classified	Classified	Not classified
S11	Classified	Not classified	Not classified
S12	Classified	Not classified	Not classified

squared DC feature extraction method is found to be an effective for PQ disturbance classification.

Performance of DWT based MRA under noisy environment

The signals in the real electrical power systems have always some noise contents due to non-linear loads and load switching. The classification sensitivity analysis of the proposed feature extraction method is done under noisy environments. An additive white Gaussian noise (AWGN) is considered in many research papers [17,19]. In this case, we have considered signal to noise ratio (SNR) of 20 dB peak amplitude noise and is mixed during the disturbance duration. The value of signal to noise ratio can be calculated using the following expression,

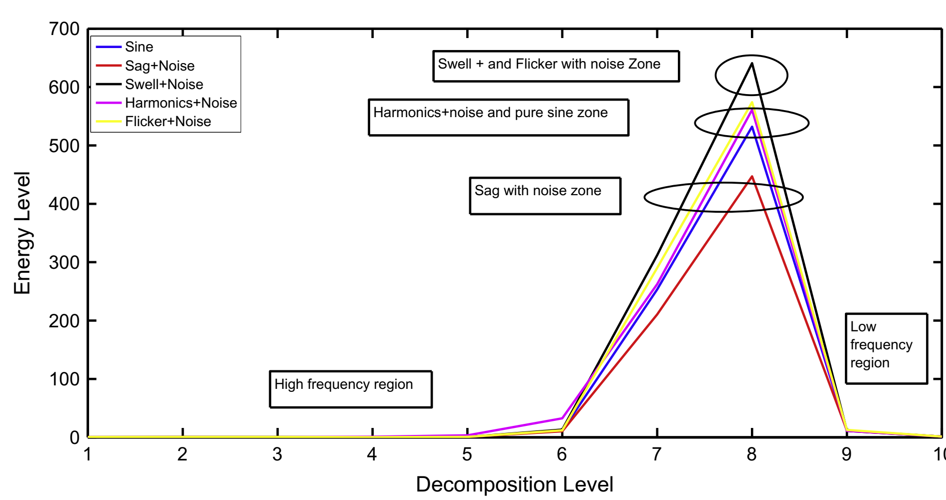

Fig. 10. MRA curve for the comparison of energy levels in sine wave and other power quality disturbances during MSD under noisy environment.

$$SNR = 10log_{10}\left(\frac{P_{sp}}{P_{np}}\right) \tag{17}$$

where, P_{sp} is the power of the signal and P_{np} is the noise power. The sensitivity of MSD based DWT method according to detailed energy distribution pattern (DEDP) has been analyzed under noisy environment conditions for pure sinusoidal signal and voltage sag, swell, harmonics as well as voltage flicker developed in pure sinusoidal signal.

Detection and classification under noisy environment

When the voltage sag, swells, flicker and harmonics are generated in the sinusoidal signal, it not only detecting disturbances but also shows the presence of noise in the distorted signal by indicating small distortions during disturbance duration. For these disturbances, the detection is possible for first two finer levels of detailed signal coefficients (DWTC-1 and DWTC-2). It is observed that due to the presence of spectral noise, disturbance detection capability degrades slightly but still it finds effective. For a pure sinusoidal waveform with noise, it just indicates presence of noise by reflecting small distortions during all sample points. Fig. 10 shows the DEDP of disturbances in the MRA curves for each decomposition level when a 20 dB noise is superimposed on disturbances to find the disturbances classification capability of the proposed method. It is observed that as compared to the pure sinusoidal signal, the disturbances such as sag, swell, harmonics and flicker with noisy environment have affected DEDP of MRA curves.

The PQ disturbances such as sag, swell, harmonics and flicker with 20 dB noise contamination, DEDP is greatly affected and its energy magnitude has been increased in high frequency region as compared to low frequency region of MRA curves. It is also observed that all above disturbances have maximum energy distribution at 8th MSD level. The highest energy distribution during 8th MSD level for sinusoidal signal, voltage sag, swells and flicker have been increased and for harmonics, it has decreased slightly. Hence based on the analysis of DEDP of MRA curves, it can be seen that the proposed energy entropy of squared detailed coefficients (EESDC) method based on DWT is not that much sensitive to the noise but has performed detection and classification accurately under noisy environment also.

The classification of PQ disturbances based on percentage energy entropy of squared DC, percentage average absolute sum of DC and sum of DC are shown in Tables 7 and 8 respectively. The classification capability of each method is shown in Table 9.

Table 7
Classification of PQ disturbances using % energy entropy (EE).

Type of signal	Symbol	Sum of squared DC	Average of DC	Average EE differences	% Average EE differences
Sag + noise	S13	683.4225	68.3422	−12.6853	−15.1060
Swell + noise	S14	981.3277	98.1328	17.1053	21.16
Harmonics + noise	S15	874.3555	87.4356	6.4081	7.90
Flicker + noise	S16	893.1403	89.31403	8.28653	10.22

Table 8
Classification of PQ disturbances using absolute sum of detailed coefficients (DC).

Type of signal	Symbol	Sum of detailed coefficients	Sum of absolute value of DC	Mean of absolute of DC	% Difference of mean of DC
Sag + noise	S13	−22.9122	165.7050	16.5705	9.9901
Swell + noise	S14	−29.6545	189.4867	18.9487	25.7757
Harmonics + noise	S15	−21.8606	194.0254	19.4025	28.788
Flicker + noise	S16	−28.7684	182.9619	18.2962	21.4451

Table 9
Classification of PQ disturbances under noisy environment.

Symbol	% Energy entropy of squared DC	Average absolute sum of DC	Sum of DC
S13	Classified	Not classified	Not classified
S14	Classified	Not classified	Not classified
S15	Classified	Not classified	Not classified
S16	Classified	Not classified	Not classified

The bar chart for EESDC method is shown in Fig. 11 for easier identification.

Rule based system for an automatic classification of PQ disturbances

For more accurate detection and classification of PQ disturbances with and without noisy environments, feature extraction method based on DWT–FFT is proposed. A rule based system using the features of DWT and FFT is developed for the automatic classification and detection of various PQ disturbances. The minimum

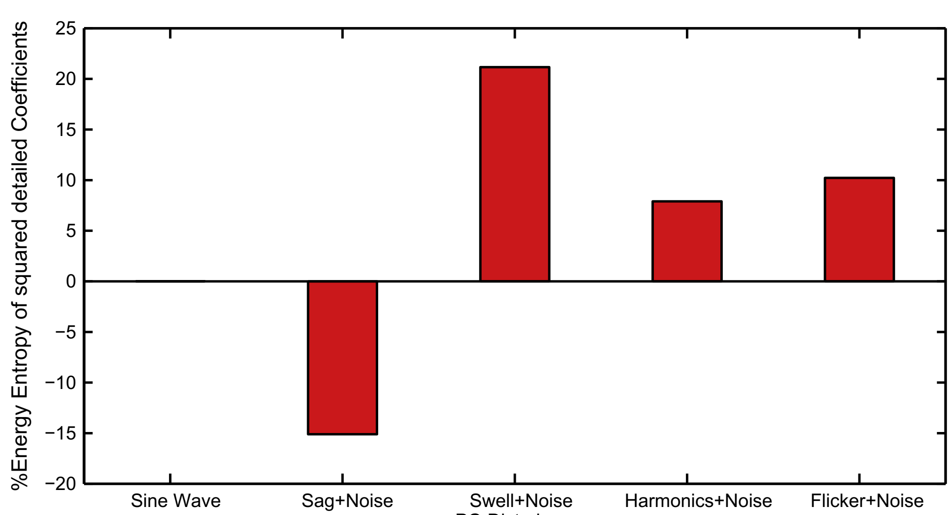

Fig. 11. Bar chart for percentage energy entropy of squared DC with noise.

Table 10
Minimum and maximum average detailed coefficients energy distribution for different PQ signals.

PQ disturbances	Average detailed coefficients energy distribution (maximum)	Average detailed coefficients energy distribution (minimum)
Pure sine	81.0275	81.0275
Voltage sag (10–90%)	43.5659	73.9928
Sag + harmonics	48.7582	79.4609
Sag + noise (20 dB)	43.8542	74.7128
Interruption	42.9938	43.4763
Voltage swell	163.1548	88.7802
Swell + harmonics	168.9331	94.3172
Swell + noise (20 dB)	177.9115	89.6081
Harmonics (<25%)	86.5301	81.0275
Harmonics + noise (20 dB)	87.4356	81.8014

and maximum of average detailed coefficient energy distribution up to 10th level of MSD is determined for unit amplitude of pure sinusoidal signal and sinusoidal signal with PQ disturbances which are given in Table 10. Fig. 12 shows the proposed integrated DWT–FFT flow chart of rule based system.

The algorithm steps based on DWT–FFT rule based system for an automatic classification and detection of PQ disturbances are given below.

1. The MSD of the signal is carried out using DWT.
2. The energy distribution of detailed coefficients at 10 levels is calculated.
3. Percentage average of squared detail coefficients at 10 levels is calculated.
4. By considering energy ranges of all PQ disturbances (minimum and maximum condition) given in Table 10, four non-overlapping regions are formed as,
   - For sag related disturbances (Pure sag, sag + harmonics and sag + noise) the region is $E_1 \in [E_{1L}, E_{1H}]$.
   - For interruption the region is $E_2 \in [E_{2L}, E_{2H}]$.
   - For swell related disturbances (Pure swell, swell + harmonics and swell + noise) the region is $E_3 \in [E_{3L}, E_{3H}]$.
   - For harmonic related disturbances (Harmonics and harmonics + noise) the region is $E_4 \in [E_{4L}, E_{4H}]$.
5. With constraints, the PQ disturbance is classified into four main categories given in step 4.
6. For further classification in each subgroup, FFT features are used considering the facts that,

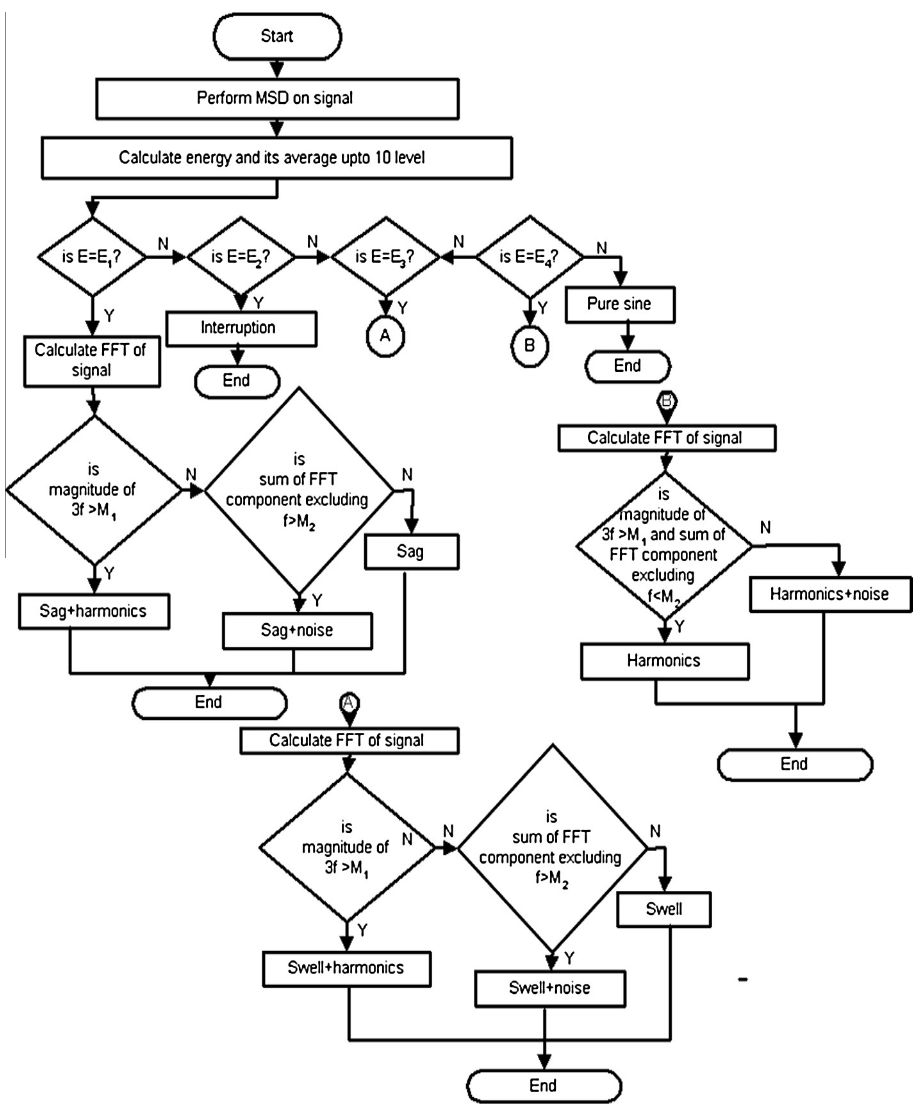

Fig. 12. Integrated DWT–FFT rule based system flow chart.

Table 11
The PQ events classification results of DWT–FFT rule based system.

PQ disturbances	No. of test carried out	% Classification accuracy achieved
Pure sine	150	100
Voltage sag	150	99.97
Sag + harmonics	150	100
Sag + noise	150	98.19
Interruption	150	100
Voltage swell	150	100
Swell + harmonics	150	98.57
Swell + noise	150	95.56
Harmonics	150	100
Harmonics + noise	150	98.14
Overall	–	99.043

(a) Pure sag/swell problem has only fundamental frequency component.
(b) The pure sag/swell plus harmonics has fundamental plus multiples of fundamental frequency components.
(c) Noise is distributed over a frequency range and has less magnitude at multiples of fundamental frequency as compared to harmonic case.

Table 11 shows the test results of the proposed rule based system. In this 150 cases of each class with different parameters were generated for analysis. It has been observed that the 99.043% correct classification rate is obtained for this 10 types of PQ disturbance signal. From Table 11, it is clear that all the tests are successful passed by proposed algorithm except voltage flicker.

Performance comparison of proposed method

In order to evaluate the performance of proposed method, comparison is made with method of Cho et al. [16]. This method uses Gabor–Wigner transform (GWT) method for detection of various PQ disturbances. It detects only the beginning of PQ disturbances but not its end. The proposed method detects beginning as well as ending of disturbance events with and without noisy environments and it also classifies various disturbances. It also removes the problem of window width for time–frequency analysis. The GWT based method is not used for the classification of PQ disturbances. The detail comparisons of results obtained using proposed method is tabulated in Table 12. In the proposed method, total sixteen PQ disturbances are generated and further processed using DWT based EESDC feature extraction method. The PQ disturbance classification accuracy is also improved by integrating features obtained from the DWT–FFT approach whose performance is totally noise independent. In order to assess the effectiveness of DWT–FFT method, a comparison in terms of % of the classification accuracy between the results of this work and results of classification in references [19,22,23,25] are made and all are presented in Table 13. With reference to Table 13, the classification performance of the proposed rule based method is better than the performance of the classification method proposed in references [19,22,23,25]. In the work of Uyar et al. [19], the disturbance classification is performed with wavelet neural network with noise level of both 20 dB, 30 dB, 40 dB and 50 dB. In the proposed method 20 dB peak magnitude noise is used to evaluate the performance of rule based system. The noise and noiseless distorted signal classification results in paper [22] are based on support vector machines and WT. The dB4 wavelet is selected to obtain various features and best one is selected based on classifying accuracy. In the work of references [23,25] wavelet-based neural network and DWT combined with expert system classifiers are proposed. The proposed method classifies and achieves 99.043% accuracy.

Table 12
Performance comparison (DT: detection; CL: classification; Y/N: yes/no).

PQ disturbances	DT [16]	CL [16]	Proposed DT	Proposed CL
Pure sine	Y	N	Y	Y
Voltage sag	Y	N	Y	Y
Voltage swell	Y	N	Y	Y
Harmonics	Y	N	Y	Y
Interruption	Y	N	Y	Y
Sag + harmonics	Y	N	Y	Y
Swell + harmonics	Y	N	Y	Y
Voltage Flicker	N	N	Y	Y
HF transients	N	N	Y	Y
LF transients	N	N	Y	Y
Capacitor switching	N	N	Y	Y
Load switching	N	N	Y	Y
Sag + noise	N	N	Y	Y
Swell + noise	N	N	Y	Y
Harmonics + noise	N	N	Y	Y
Flicker + noise	N	N	Y	Y

Table 13
Performance comparison for correct classification results.

PQ disturbances	This work	Ref. [19]	Ref. [22]	Ref. [23]	Ref. [25]
Overall	99.043%	95.71%	97.69%	98.19%	90%

Conclusions

This paper presents, DWT–FFT based integrated approach for detection and classification of various PQ disturbances with and without noisy environments. To check the classifier performance, various Daubechie's wavelet families are tested. The *db*4 wavelet was found to be an effective in its performance and hence has been chosen as a mother wavelet for further analysis. The analysis and the results presented in this paper clearly indicate the potential capability of the proposed EESDC method in detecting and classifying the PQ disturbances. In this, energy at each MSD level and the different frequency components contained in the PQ disturbances are used as a features to obtain high correlation. The proposed integrated approach is used to construct logistic rule for an automatic detection and classification of ten types of PQ disturbances. The classifier is tested for 150 test signals randomly generated for various durations with 20 dB peak noise level. It has been found that the DWT based feature extraction can effectively remove the redundancy available in time-domain data and hence effectively able to reduce the size of the classifier. The developed classifier based on DWT–FFT approach is able to achieve 99.043% accuracy with less computational complexity. The proposed technique also has potential and capability to implement for on-line real applications.

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