Discrete wavelet transform based classifier for PQ disturbance detection

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In this paper the Discrete Wavelet Transform (DWT) concept using multi-resolution signal decomposition (MSD) technique with Daubechies family db4 second order vanishing moment mother wavelet for detection of power quality (PQ) disturbances has been proposed and presented. The PQ disturbances are also classified by extracting energy distribution features from multi-resolution analysis (MRA) curve based on detailed energy distribution pattern (DEDP). The information obtained from detail squared wavelet transform coefficients (SWTC) of the disturbance signal at each wavelet decomposition level is utilized for plotting MRA curve. The proposed method algorithm has been verified by simulating various PQ disturbances and results are analyzed using Mathworks Matlab/Simulink. The classification and detection sensitivity of the proposed method is also verified and presented when signal to noise ratio (SNR) of 20 dB is superimposed during the duration of PQ disturbances. The proposed technique appears to be effective and accurate tool for the detection, localization and classification of PQ disturbances.

Keywords: Discrete wavelet transform (DWT), Energy distribution pattern, Squared wavelet transform coefficients (SWTC), Power quality.

Introduction

In an advanced deregulated power system structure, customers are mainly concerned with better power quality. In order to maintain the better power quality, it is necessary to detect, localize, classify as well as analyze the causes and sources of power quality disturbances. In literature, from the last fifteen years, a number of different approaches were proposed for power quality (PQ) signal analysis. 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 not capable to detect sudden or fast changes in waveform i.e. voltage dip, transients and voltage flickers, etc. The Fast Fourier transforms (FFT) has shown improved results for fixed frequency resolution for all frequencies and has shown its suitability for harmonic analysis. The FFT method has major drawbacks such as resolution, spectrum leakage as well as picket-fence effects.

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 above signal processing methods is the principle of Heisenberg in which one can’t 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. The STFT fixed resolution problems have been solved using wavelet transform 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. Wavelet Transform (WT) approach automatically adjusts the window width to give good time resolution and poor frequency resolution at high frequencies and good frequency resolution and poor time resolution at low frequencies. In discrete wavelet transform (DWT), signal is broken into multiple frequency bands, instead of a discrete number of frequency components as in discrete Fourier transform. The DWT has been successfully applied in the situations where the signal contains discontinuities and sharp spikes. The WT approach is also proposed for detection and
classification of various PQ events\textsuperscript{11}. The DWT coefficients have been presented as an input to the neural networks to classify PQ transients but it requires large memory space to store the learning data and also require more learning time\textsuperscript{12}. An effective MRA method has been presented for analyzing the power quality transients based on standard deviation and RMS value\textsuperscript{13}. The WT based de-noising techniques to remove noise effects on PQ disturbances is also proposed with comments that its effectiveness degrades with decrease in signal to noise ratio\textsuperscript{14-15}. 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\textsuperscript{16}. The PQ disturbance classification scheme is also performed with wavelet neural network (WNN)\textsuperscript{17}. A new time-frequency analysis Gabor-Winger transform (GWT) method is investigated for analysis of different PQ problems\textsuperscript{18}.

Even though there is lot of recent development in this area but still it is challenging. In this paper, multi-resolution signal decomposition (MSD) technique with DWT has been proposed to detect, localize and classify the various power quality disturbances with and without noisy environment. The PQ disturbances such as voltage sags, swells, harmonics, voltage flicker, low frequency and high frequency transients are generated using standard models and are simulated using Math-works MATLAB-7.0.\textsuperscript{14-16} The basic idea is to decompose a given disturbance signal into other signals that represent a smoothed version and a detailed version of the original signal. The detailed signal is a wavelet transform of the original signal that indicates the occurrence of the disturbance and the frequency content of the events. The proposed technique appears to be effective for detection and localization of power quality disturbances. The uniqueness of the squared SWTC, the detailed energy distribution pattern (DEDP) of MRA curves according to the Parseval’s theorem also has been studied. The presented approach can be used for automatically detection and location for various types of PQ disturbances if the analyzed information is given as an input to the artificial neural networks (ANN). The effectiveness of the proposed method under noisy environment for the detection and classification of PQ disturbances also has been presented.

Wavelet Transform(WT): A New Signal Processing Tool

In WT, the time (space) analysis of the distorted signal is performed with high frequency contracted version of the mother wavelet and the frequency analysis is performed with dilated low frequency version of the mother wavelet. Hence, the wavelet transforms can be defined by the following equation,

\[
\Psi_{x}(a,q) = \langle x(t), \Psi_{a,q}(t) \rangle = \int_{-\infty}^{\infty} x(t) \Psi_{a,q}(t) dt \tag{1}
\]

where, \(\Psi_{a,q}(t) = |a|^{-1/2} \psi \left( \frac{t-q}{a} \right) \) and \(\Psi(t)\) is mother wavelet, the transformed signal is a function of two variables, \(a \in R, a \neq 0\) is the dilation (scale) parameter, and \(q \in R\) is the translation parameter.

Discrete Wavelet Transform (DWT): A Brief Review

It is the digital representation of the CWT and is able to analyze the local discontinuities of the PQ disturbance signal. The DWT which is dyadic orthonormal wavelet transform is not continuously scalable but the dilation and translation parameters vary in discrete steps over a real line \(R\). With a special choice of scale and translation parameters, the redundancy can be suppressed\textsuperscript{8}.

In DWT, the mother wavelet in equation (1) is discretized in \(a\) and \(q\). A DWT gives a number of wavelet coefficients as per number of the discrete steps according to the dilation \(m\) and translation \(n\) integers. Hence wavelet coefficient can be described by two integers \(m\) and \(n\). It can be done by selecting \(a = a_{0}^{m}\) and \(q = nq_{0}a_{0}^{m}\), where \(a_{0}\) and \(q_{0}\) are fixed segmentation step sizes for the scale and translation width \(a_{0} > 1, q_{0} > 0, m, n \in Z\). Then the discretized mother wavelet in terms of new parameters are given by the following expression,

\[
\Psi_{m,n}(t) = \frac{1}{\sqrt{a_{0}^{m}}} \Psi \left( \frac{t-nq_{0}a_{0}^{m}}{a_{0}^{m}} \right) \tag{2}
\]

Hence the corresponding DWT coefficients are given by the following equation

\[
DWT_{\Psi^{x}}(m,n) = \langle x, \Psi_{m,n} \rangle = \int_{-\infty}^{\infty} x(t) \Psi_{m,m}(t) dt \tag{3}
\]
By careful selection of \( a_0 \) and \( q_0 \), the family of dilated mother wavelets constitutes an orthonormal basis of \( L^2(R) \). The general choice is \( a_0 = 2 \) and \( q_0 = 1 \), so that the sampling of the frequency axis corresponds to dyadic-orthonormal sampling. The DWT is called a dyadic-orthonormal wavelet transform which can be implemented by filter bank techniques called as the MSD technique, to decompose a signal into scales with different time and frequency resolution. The DWT analyzes the signal at different frequency bands with different resolutions by decomposing the signal into a smooth (coarse) approximation and detail information. DWT employs two sets of functions, called scaling functions and wavelet functions, which are associated with low pass and high pass filters, respectively. The decomposition of the signal into different frequency bands is simply obtained by successive high pass and low pass filtering of the time domain signal \(^6-17\).

**Multi-resolution Signal Decomposition: A Proposed Algorithm**

Let the original discrete-time signal \( c_0(n) \) is first passed through a half band equivalent high pass filter with impulse response \( g_d(n) \) and its equivalent low pass filter mirror version impulse response \( h_d(n) \). After the filtering, half of the samples can be eliminated according to the Nyquist’s frequency rule (half the sampling frequency), since the signal now has a highest frequency of \( \pi / 2 \) radians instead of \( \pi \). The signal can therefore be down sampled by 2, simply by discarding every other sample. 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 (blurred) version of the original signal and \( d_1(n) \) is the detailed representation of the original signal. This constitutes first level of decomposition. After each level of filtering and sub-sampling, there are half the numbers of sample with half time resolution and half the frequency with double frequency resolution. The process iterates by adopting \( m-1 \) level of coefficient of approximation to calculate \( m \) level approximation and detailed wavelet coefficients. The smoothed i.e. approximate (blurred) and the detailed coefficients are obtained recursively in the same way for all decomposition levels from the input signal. Mathematically it can be expressed by the following equation,

\[
c_m(n) = \sum_k h_d(k-2n) \cdot c_{m-1}(n)
\]  

...(4)

\[
d_m(n) = \sum_k g_d(k-2n) \cdot c_{m-1}(n)
\]  

...(5)

In this work, the Daubechies mother wavelet is used for analysis of PQ disturbances. The choice of analyzing mother wavelet plays very important role in the detection and classification accuracy. It is generated with the help of Wave Lab. The Daubechies family wavelet filter is an appropriate choice as a mother wavelet for analysis PQ disturbances. As compared to other wavelets, the has shorter filter length as well as shorter computational time and good compact support in real time applications \(^3-17\). If \( g_d(n) \) and \( h_d(n) \) are of four coefficient then it is called as Daubechies wavelet with four coefficients or Daub4 and other choices of filter coefficient are possible such as ones with 6, 8, 10 coefficients. This is done through digital filtering techniques called sub-band coding.

The three level of multi-resolution signal decomposition based on DWT is shown in Fig. 1. Here reference frequency is 50 Hz and the sampling frequency is \( f_s \). The DWT provides a very effective data reduction scheme. The frequency range at each level of MSD for approximate is \( 0 - f_s / 2^{n+1} \) and that for the detail signal is \( f_s / 2^{n+1} - f_s / 2^{n} \) where \( n \in (0,1,2,...) \) is the level of decomposition.

**Power Quality Disturbance Detection**

A pure sine wave with frequency 50 Hz and magnitude at 1.0 p. u. as well as other power quality disturbance such as high frequency, low frequency transients, harmonics, voltage sag, swells and flicker are generated using model equations with the help of Math works MATLAB-7.0.\(^{14-17}\). All the input signals are generated with total 660 samples for five cycles.
(132 samples per cycle). Its recording time is 0.1 seconds hence sampling frequency of the signal is 6.6 KHz (i.e.660/0.1=6.6 KHz). Even though ten levels of distorted signals MSD has been carried out using db4 mother wavelet but only four levels of MSD are shown here during the detection. For more critical analysis, ten level decomposition is done for obtaining detailed energy distribution to classify different disturbances.

**Pure Sine Wave Case**

Fig. 2(a) shows four finer level detail signal decomposition of pure sine wave, it is observed that the squared DWT detailed signal coefficients $d_1 - d_3$ plots are smooth and there is no detection and localization as the signal to be decomposed does not contain any abnormal situation. Any sudden changes in magnitude of signal can be detected and localized in time domain due to changes in the magnitude of these coefficients.

**Voltage Sags**

Fig. 2(b) shows the four finer level detail signal decomposition of the voltage sags in pure sine wave. The voltage sag was started at 0.025 seconds and the total duration of sag was 0.05 seconds. From the signal decomposition waveform it is observed that the squared DWT detailed signal coefficients $d_1 - d_2$ at first two finer levels in the vicinity of sample points 70 and 42 can locate and detect voltage sags efficiently. The $d_3$ and $d_4$ locate and detect low frequency components of the voltage sags as the high frequency components have been extracted. The duration of the sag can be determined for any nature. It is observed that the maximum value of energy content in the detailed energy distribution MRA curve is decreased.

**Voltage Swells**

Fig. 2 (c) shows the four finer level detail signal decomposition of the voltage swells in pure sine wave.
The voltage swell was started at 0.025 seconds and the total duration was 0.05 seconds. From the signal decomposition waveform it is observed that the squared DWT detailed signal coefficients $d_1 - d_3$ at first three finer resolution levels in the vicinity of sample points 70, 42 and 22 respectively can locate and detects voltage swells efficiently. The $d_4$ locates and detects low frequency component of the voltage sags as the high frequency components have been extracted. It is observed that the maximum value of energy content in the detailed energy distribution MRA curve is increased with respect to the swell magnitude.

**Harmonics**

Fig. 2 (d) shows the four finer level detail signal decomposition of harmonics in pure sine wave. The harmonics were generated at 0.05 seconds and the total duration was 0.025 seconds. Even though harmonics is steady state power quality event, from the signal decomposition waveform it is observed that the squared DWT detailed signal coefficients $d_1 - d_2$ at first two finer resolution levels in the vicinity of sample points 125 and 65 can locate and detects harmonics efficiently. The $d_3$ and $d_4$ do not locate and detect correctly but indicate harmonic content duration. It is observed that the maximum value of energy contents in the detailed energy distribution MRA curve is decreased slightly compared to pure sine wave case. The energy content in the detail energy distribution MRA curve at lower levels (high frequency left side) and higher levels (low frequency right side) fluctuates according to the harmonic content in the original power frequency signal.

**Flicker**

Fig. 2 (e) shows the four finer level detail signal decomposition of voltage flicker in pure sine wave. The voltage flicker started at 0.025 seconds and the total duration was 0.05 seconds. From the signal decomposition waveform it is observed that the squared DWT detailed signal coefficients $d_1 - d_3$ at first three finer levels in the vicinity of sample points 80, 42 and 22 can locate and detect voltage flicker efficiently. It is observed that the maximum value of energy content in the detailed energy distribution MRA curve is decreased. The energy content in the detailed energy distribution curve at higher levels at low frequency (right side) fluctuates according to the flicker content in the original power frequency signal.

**High Frequency Transients**

Fig. 2 (f) shows the four finer level detail signal decomposition of high frequency transients in pure sine wave. The transients were started at 0.04 seconds and the total duration was 0.04 seconds. From the signal decomposition waveform it is observed that the squared DWT detailed signal coefficients $d_1 - d_2$ at first two finer levels in the vicinity of sample points 130 and 65 can locate and detects HF transients efficiently. It is observed that the maximum value of energy content in the detailed energy distribution MRA curve is not changed compared to pure sine wave case. The energy contents in the MRA curve at higher levels (low frequency contents) fluctuates according to the frequency and magnitude of transients in the power frequency signal. Similar analysis is carried out for low frequency transients (LFT). The energy distribution in the MRA curve of all above power quality events at ten levels is shown in Table 1.

**Feature Extraction for Classification of Various PQ Disturbances**

The suitable feature extraction using signal processing technique for classification of PQ problems is very important. The different levels of wavelet coefficients over the scales can be interpreted as uneven distribution of energy across the multiple frequency bands. This distribution forms patterns that have been found to be useful for classifying between different power quality events. If the selected wavelet and scaling functions form an orthonormal (independent and normalized) set of basis, then the parseval theorem relates the energy of the signal to the values of the coefficients. Hence the total energy of the discrete time domain signal can be separated as per the following expression,

$$
\int|x(t)|^2 \, dt = \sum_{k} |A_j(k)|^2 + \sum_{j=0}^n \sum_{k} |D_j(k)|^2 \quad \ldots (6)
$$

where first term in right hand side of the equation shows the energy content in the approximated signal in all $j^{th}$ levels while the second term shows the energy distribution in the detailed versions of the signals at $j^{th}$ levels for $n$ number of samples. These squared wavelet coefficients are useful features for identifying power quality events. Instead of using the maximum or average values, the energy distribution pattern in the wavelet domain can be computed as sums of the squared coefficients$^{13}$. Fig.3 shows the energy distribution pattern during MSD for six commonly encountered power quality events. The
difference between these patterns based on energy content can be one of the best features for classification of power quality events. From the Fig. 3 and Table 1, based on the important energy distribution features, the power quality events can be classified as follows: It is observed that the harmonics, low frequency transients and high frequency transients have more energy distribution variations during 1-5 levels of MSD. It is also observed that all the power quality events have maximum energy distribution at 6th MSD level. The level where the peak energy distribution occurs depends on the number of samples per cycle and corresponding sampling frequency. During the 6th MSD level highest to lowest energy distribution in events are as follows: voltage swells, voltage flicker, harmonics, low frequency transients, high frequency transients followed by the voltage sags. As compared to other disturbances the high frequency transients has highest energy distribution at 1st and 2nd levels, low frequency transients at 3rd level, harmonics during 4th and 5th levels, voltage swells during 6th and 7th levels, voltage flicker at 8th level and voltage sags during 9th and 10th levels. During the levels 1st - 3rd only swells and sag energy content decreases compared to others and for transients there is a random variations. Energy contents in all signal including sine wave increases from 4th - 6th levels and decreases during 6th - 8th levels. The rate of increase of energy contents of harmonics has highest value during 4th - 5th levels, swells during 5th - 6th levels. All signals energy contents increases during 8th - 9th levels and decreases during 9th - 10th levels. It can be observed that when power quality distorted signal contains high frequencies, then at low levels energy distribution

<table>
<thead>
<tr>
<th>Type of Signals</th>
<th>$E_{D1}$</th>
<th>$E_{D2}$</th>
<th>$E_{D3}$</th>
<th>$E_{D4}$</th>
<th>$E_{D5}$</th>
<th>$E_{D6}$</th>
<th>$E_{D7}$</th>
<th>$E_{D8}$</th>
<th>$E_{D9}$</th>
<th>$E_{D10}$</th>
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<tr>
<td>Pure Sine Wave</td>
<td>0.00016753</td>
<td>0.007399</td>
<td>0.091039</td>
<td>0.17352</td>
<td>7.2597</td>
<td>238.25</td>
<td>121.43</td>
<td>8.2932</td>
<td>24.578</td>
<td>19.124</td>
</tr>
<tr>
<td>Voltage Sag</td>
<td>0.021553</td>
<td>0.019746</td>
<td>0.14008</td>
<td>0.21504</td>
<td>7.1733</td>
<td>197.78</td>
<td>101.62</td>
<td>8.7324</td>
<td>26.105</td>
<td>19.28</td>
</tr>
<tr>
<td>Voltage Swell</td>
<td>0.021553</td>
<td>0.01974</td>
<td>0.14088</td>
<td>0.21679</td>
<td>8.0715</td>
<td>287.32</td>
<td>145.08</td>
<td>8.0138</td>
<td>23.101</td>
<td>18.969</td>
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<td>Harmonics</td>
<td>0.0014225</td>
<td>0.022196</td>
<td>0.32363</td>
<td>7.6894</td>
<td>22.215</td>
<td>238.78</td>
<td>124.24</td>
<td>7.1287</td>
<td>20.389</td>
<td>19.75</td>
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<td>Flicker</td>
<td>0.010915</td>
<td>0.015907</td>
<td>0.10984</td>
<td>0.20856</td>
<td>7.5503</td>
<td>263.44</td>
<td>133.93</td>
<td>8.9723</td>
<td>25.434</td>
<td>19.034</td>
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<td>High Frequency</td>
<td>14.858</td>
<td>0.075899</td>
<td>0.16726</td>
<td>0.17208</td>
<td>7.2437</td>
<td>238.29</td>
<td>121.47</td>
<td>8.2687</td>
<td>24.496</td>
<td>19.137</td>
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<tr>
<td>Transient</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low Frequency</td>
<td>0.008747</td>
<td>0.66027</td>
<td>11.584</td>
<td>2.887</td>
<td>7.1206</td>
<td>238.66</td>
<td>121.81</td>
<td>8.0489</td>
<td>23.736</td>
<td>19.262</td>
</tr>
</tbody>
</table>

Fig. 3—Comparison of energy levels in sine wave and other power quality disturbances during MSD

Table 1—Energy Levels in Sine Wave and Other Power Quality Disturbances
variation is more and when the signal disturbance contains low frequencies obviously at higher levels there is more energy distribution variations. From the detailed energy distribution curve top section is a good indicator to classify sags and swells as well as left and right bottom parts are good indicators for classifying high frequency and low frequency disturbance signals.

The Performance of DWT Based MRA under Noisy Environment

A band limited spectrum noise caused by non-linear electrical and electronic load switching is always present in an electrical power system signals. In this case, we have considered signal to noise ratio (SNR) 20 dB as a band limited spectrum noise contaminated (superimposed) during disturbance duration. The value of signal to noise ratio can be calculated using the following expression,

$$SNR(dB) = 10\log\left(\frac{P_{sp}}{P_{np}}\right)$$  

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 DEDP has been analyzed under noisy environment conditions for pure sinusoidal signal and voltage sags, swells, harmonics as well as voltage flicker developed in pure sinusoidal signal.

Detection and Classification of PQ disturbances during Noisy Environment

When the voltage sag, swells, flicker and harmonics are created in the sinusoidal signal, it not only detects disturbances with slight degradation 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 $d_1$ and $d_2$. 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. The Fig. 4 shows the DEDP of various disturbances in the MRA curves for each decomposition level when a 20dB band limited spectrum noise is superimposed during the duration of disturbances to verify 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, the noisy environment have affected DEDP of MRA curves. For a sinusoidal signal with noise, energy distribution at highest value is concentrated towards low frequency region. Other disturbances such as sag, harmonics and flicker with 20 dB noise contamination, DEDP greatly affected and 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 6th MSD level. The
highest energy distribution during 6th MSD for sinusoidal
signal, voltage sag, swells and flicker increases and for
harmonics, it decreases slightly. Hence based on the
analysis of DEDP of MRA curves, we can say that the
proposed MSD based DWT method is not that much
sensitive to the noise but has performed accurately under
noisy environments.

**Performance Comparison of the Proposed Method**

To evaluate the performance of proposed method,
comparison is made between the results of this study
and the results obtained in \(^18\). The reference\(^18\) uses Gabor-
Wigner Transform (GWT) method for detection of various
PQ disturbances. This method detects only the beginning
of PQ disturbances but not end of it. The proposed
method detects beginning as well as ending of
disturbance events with and without noise and it also
classifies various other PQ disturbances. It also removes
the problem of window width for time-frequency analysis.
It can be used for the classification of PQ disturbances.
The detail comparisons of results obtained using proposed
method is presented in Table 2.

**Conclusions**

This paper presents the DWT based MSD techniques
with \(db4\) as a mother wavelet for detection and
classification of various PQ disturbances. The proposed
squared DWTC based MSD technique with its localized
properties has an ability to extract information from the
decomposed signals. It extracts and separates various
power quality events that are overlapped in both time
and frequency domain. The DEDP of MRA curve
indicates the distribution of energy in the power quality
disturbances at different frequency bands in time domain.
It is also analyzed that the power quality disturbances
have unique features of energy distribution deviations in
their MRA curves compared with standard sinusoidal
signal energy MRA curve. The analysis and the results
presented in the paper clearly indicate the potential
capability of the proposed method in detecting and
classifying the PQ disturbances is accurately even under
noisy environments. Under noisy conditions, the energy
distribution increases at high frequency region during low
decomposition levels. This feature of MRA curve can
be utilized as an input to an artificial neural network
(ANN) classifier for on-line classification of various PQ
disturbances but it requires large amount of data for
training. Hence DWT with MSD method is an emerging
tool for PQ disturbance analysis. The most important
advantage of the proposed method is the reduction of
data size, reduction in memory space, less preprocessing
needs and the network size. It also increases computation
speed for the classification of PQ disturbances.

**References**

1. Gu I Y H & Styvaktakis E, Bridge the Gap: Signal Processing for
   83-96.
2. Dugan R C, McGranagham M F, Santoso S & Beaty  H W,
   Characterization of distribution power quality events with fourier
   and wavelet transforms, *JIEEE Trans on Power Del*, 15(1)
5. Abdel- Galil T K, Kamel M, Youssef A M & Salama M M A,
   Power quality disturbance classification  using the inductive
   inference approach , *JIEEE Trans on Power Del*, 19
   domain analysis of voltage disturbances, *JIEEE Trans on Power Del*,
7. Robertson D C , Camps O I , Mayer J S & Gish Sr W B ,
   Wavelets and electromagnetic power system transients, *JIEEE
   disturbance detection for power quality applications, *JIEEE

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### Table 2—Performance comparison of the DWT based MSD method

<table>
<thead>
<tr>
<th>PQ Disturbances</th>
<th>Method in Reference(^18)</th>
<th>Proposed Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Voltage Sag</td>
<td>DT Y, CL N</td>
<td>DT Y, CL Y</td>
</tr>
<tr>
<td>Voltage Swell</td>
<td>DT Y, CL N</td>
<td>DT Y, CL Y</td>
</tr>
<tr>
<td>Voltage Flicker</td>
<td>DT Y, CL N</td>
<td>DT Y, CL Y</td>
</tr>
<tr>
<td>Harmonics</td>
<td>DT Y, CL N</td>
<td>DT Y, CL Y</td>
</tr>
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<td>Inter-harmonics</td>
<td>DT Y, CL N</td>
<td>DT Y, CL Y</td>
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<tr>
<td>HF Transients</td>
<td>DT Y, CL N</td>
<td>DT Y, CL N</td>
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<td>LF Transients</td>
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<td>DT Y, CL N</td>
</tr>
<tr>
<td>Sag+ NS</td>
<td>DT N, CL N</td>
<td>DT N, CL Y</td>
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<td>Swell+ NS</td>
<td>DT N, CL N</td>
<td>DT N, CL Y</td>
</tr>
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<td>Flicker+NS</td>
<td>DT N, CL N</td>
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</tr>
<tr>
<td>Harmonics +NS</td>
<td>DT N, CL N</td>
<td>DT N, CL Y</td>
</tr>
</tbody>
</table>

# DT- Détection, CL-Classification, Y- Yes, N-No, NS- Noise


