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Detection, localization, and classification of power quality disturbances using discrete wavelet transform technique

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Modern spectral and harmonic analysis is based on Fourier based transforms. However, these techniques are less efficient in tracking the signal dynamics for transient disturbances. Consequently, The wavelet transform has been introduced as an adaptable technique for non-stationary signal analysis. Although the application of wavelets in the area of power engineering is still relatively new, it is evolving very rapidly. The application of the wavelet transform in detection, time localization, and classification of power quality disturbances is investigated and a new identification procedure is presented. Different power quality disturbances will be classified by a unique energy distribution pattern based on the difference of the discrete wavelet coefficients of the analyzed signal and a pure sine wave. Verification of the proposed algorithm was done by simulating different disturbances and analyzing the results.

تستخدم أجهزة القياس والمراقبة على الشبكات الكهربية حاليا تقنيات تعتمد على تحليل فورير التوافقي، هذه التقنيات أقل كفاءة في تحديد المزعجات التى تشغل حيزا زمنيا قصيرا. من هذا تم تقديم التحليل المويجى كطريقة متكيفة لتحليل المزعجات قصيرة الزمن. رغم أن هذه الطريقة حديثة الا ان استخدامها في مجال القوى الكهربية تتطور سريعا. طريقة استخدام هذه الطريقة في اكتشاف وتحديد وتصنيف مزعجات القوى الكهربية ستوضح، وسيتم تقديم طريقة جديدة لتصنيف المزعجات. هذه الطريقة تعتمد على رسم مميز يستنتج من الفرق بين معاملات التحليل المويجى للإشارة المحللة والموجة الجيبية. التحقق من جدوى الطريقة النمقدمة سيتم عن طريق محاكاة مزعجات القدرة المختلفة وتحليل النتائج.

Keywords: Wavelet transform, Non-stationary signals, Power quality, Disturbance identification

1. Introduction

Power Quality is an issue of increasing concern both to the utilities and their customers. A power quality problem can be described as any variation in the electrical power service, such as voltage sags and swells, interruptions, transients, harmonics, notches, and fluctuations, resulting in miss-operation or failure of end-use equipment. To analyze these electric power system disturbances, data is often available as a form of a sampled time function that is represented by a time series of amplitudes. When dealing with such data, the Discrete Fourier Transform (DFT) based approach is most often used. The implementation of the DFT by various algorithms has been constructed as the basis of modern spectral and harmonic analysis. The DFT yields frequency coefficients of a signal, which represents the projection of orthogonal sine and cosine basic functions. Such transforms have been successfully applied to stationary signals where the properties of the signals do not vary with time. However, for non-stationary signals, any abrupt change may spread all over the frequency axis. Consequently, the Short Time Fourier Transform (STFT) uses a (time-frequency) window to localize -in time- sharp transitions is used for non stationary signals. However, the STFT uses a fixed time-frequency window, which is inadequate for the practical power system disturbances encountering a wide range of frequencies. Under this situation, the Fourier techniques are less efficient in tracking the signal dynamics. Therefore, an analysis adaptable to non-stationary signals is required instead of Fourier-based methods.

The Wavelet Transform (WT) technique, recently proposed in the literature as a new tool for monitoring power quality problems [1], has received considerable interests in fields such as signal processing, voice communications, and image compression [2,3]. The WT is well suited to wide-band signals that may not be periodic and may contain both sinusoidal and non sinusoidal components. This is due to the ability of wavelets to focus on short time intervals for high frequency components and long time intervals for low frequency components.

This paper introduces an approach that utilizes the wavelet multi-resolution signal decomposition in the detection, localization, and classification of power quality disturbances. Programs to simulate disturbances such as short duration voltage variations; including sags, swells, and interruptions, harmonics in a power system, notches, and capacitive switching transients are all formulated in MATLAB code according to IEEE standards [4]. Detection and Localization are performed in the wavelet domain rather than the time domain or the frequency domain. Different power quality disturbances will be classified by a unique energy distribution pattern according to Parseval's theorem rather than constructing time-frequency picture of the distorted signal and comparing the energy distribution of the distortion at different frequency bands and at certain time [5].

2. The proposed algorithm

The wavelet analysis procedure adopts a wavelet prototype function, the analyzing wavelet or the mother wavelet. Temporal analysis is performed by shifting a contracted, high-frequency versions of the mother wavelet, while frequency analysis is performed with dilated, low-frequency versions of the same wavelet. Any signal can be represented in terms of a wavelet expansion or series (similar to Fourier series) using coefficients in a linear combination of the wavelet functions at different scales. The selection of the mother wavelet is not a trivial issue. Different mother wavelets exist with various characteristics. Success of a given wavelet basis in a particular application does not mean that this set is efficient for other applications [6].

Let ψ(t) represents the mother wavelet as a function of time, then the daughter wavelets are generated from the mother wavelet by means of scaling and translation as shown in eq. (1):

$$\psi_{s,\tau}(t) = \frac{1}{\sqrt{s}}\,\psi\left(\frac{t-\tau}{s}\right), (s > 0). \quad (1)$$

Where S is the scaling parameter, used to perform stretching and compression operations on the mother wavelet, and τ is the translation parameter, used to obtain the time information of the signal to be analyzed. In this way, a family of scaled and translated wavelets is created and serves as the base, the building blocks, for representing the signal [7]. The Continuous Wavelet Transform (CWT) for a signal $X(t)$ is defined as follows:

$$CWT(s,\tau) = \frac{1}{\sqrt{s}}\int_{-\infty}^{+\infty} x(t)\,.\,\psi^*\left(\frac{t-\tau}{s}\right) dt \ . \quad (2)$$

It is noted that the CWT must be defined in terms of the mother wavelet. That is, one does not merely discuss the wavelet transform of a function, one must discuss the wavelet transform of a function with respect to a particular mother wavelet. Let $x(t)$ be the signal to be analyzed. Once the mother wavelet is chosen, the computation starts with s=1 and the continuous wavelet transform is computed for all values of s. For convenience, the procedure will start from scale s=1 and will continue for the increasing values of s, i.e., the analysis will start from high frequencies and proceeds towards low frequencies. This first value of s corresponds to the most compressed wavelet. It should be as narrow as the highest frequency component that exists in the signal. As the value of s increases, the wavelet dilates. As a result, for every scale and for every time interval, one point of the translation-scale plane is computed. The computations at one scale construct the rows of the translation-scale plane, and the computations at different scales construct the columns of the translation-scale plane.

It is necessary to discretize the CWT for digital computational purposes. The main idea of the discrete wavelet transform DWT is as follows: A time-scale representation of a digital signal is obtained using digital filtering techniques. Filters of different cutoff frequencies are used to analyze the signal at different scales. 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. After the filtering, half of the samples can be eliminated by subsampling [8]. This constitutes one level of decomposition. This decomposition halves the time resolution since only half the number of samples now characterizes the entire signal. However, this operation doubles the frequency resolution, since the frequency band of the signal now spans only half the previous frequency band, effectively reducing the uncertainty in the frequency by half.

The DWT of the original signal is obtained by concatenating all coefficients starting from the last level of decomposition. Fig. 1 illustrates this procedure with three decomposition levels [9]. Any change in the smoothness of the signal can be detected and localized at the finer resolution levels. As far as detection and localization are concerned, the first finer decomposition levels of the distorted signal are normally adequate to detect and localize this disturbance.

However, the other coarser resolution levels are used to extract more features that can help in the classification process.

The proposed classification process depends on *Parseval's theorem*, which states that: "The energy that a time domain signal contains is equal to the sum of all energies concentrated in the different resolution levels of the corresponding wavelet transformed signal". This can be mathematically formulated as follows:

$$\sum_{k=1}^{N} |f(k)|^2 = \sum_{k=1}^{N} |a_J(k)|^2 + \sum_{i=1}^{J}\sum_{k=1}^{N} |d_i(k)|^2 . \qquad (3)$$

The left-hand side of eq. (3) expresses the total energy of the discrete time domain signal *f, N* is the number of samples. The right-hand side of the equation consists of two parts; the energy concentrated in the level *J* of the approximated version of the signal *(a)* + The energy concentrated in the detailed versions of the signal *d*, from level 1, to level *J*.

The proposed classification method is done using unique patterns. The difference between the discrete wavelet coefficients of the analyzed signal and a pure signal at each level will be computed, and the result will be divided by the total energy of the corresponding pure signal for normalization purposes, and then multiplied by 100 to have a percentage ratio as shown in eq. (4):

$$\%dif(i) = \frac{energy(i) - energy(pure)}{total\ energy} * 100 . \qquad (4)$$

Where i is the wavelet transform level. The unique pattern is then plotted with the percentage difference as the y-axis, and the resolution level as the x-axis. The energy of the distorted signal will be partitioned at different resolution levels in different ways depending on the power quality problem at hand; hence, each power quality problem is characterized by a unique energy distribution plot.

3. Applications

Detection, localization and identification of disturbances are done by simulating, according to IEEE standards [4], different disturbance signals and analyze these signals using MATLAB graphic user interface toolbox

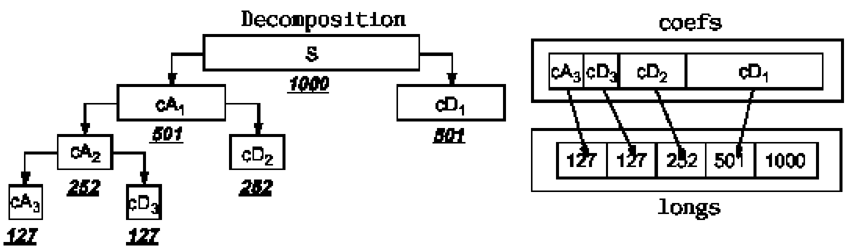

Fig. 1. Multiple decomposition of wavelet analysis.

(for detection and localization) using Daub4 mother wavelet and 12 resolution levels [6]. Identification is done using our proposed method formulated as a MATLAB code. 18 different disturbances were simulated including voltage sags at different durations and magnitudes, i.e, 4 cycles, 50%, capacitor switching at 1000 Hz, notches, voltage swells at different durations and magnitudes, harmonic contents, and a combination of the above [10]. Three cases (sag at 4 cycles, 50%, swell at 6 cycles, 120% and capacitor switching at 1000 Hz) are shown in figs. 2, 3 and 4.

In all the studied cases, the maximum energy distribution occurs at the tenth level of resolution, which corresponds to around 50 Hz. This is determined by the number of samples representing the signal. The first resolution levels of decompositions of figs 2-a, 3-a, 4-a hardly show any non-zero coefficients due to absence of frequency components at these high frequencies. Higher resolution levels, corresponding to lower frequencies, start to pick up the disturbance. Figs. 2-a, 3-a show the start and the end of a transient phenomenon. This could be attributed to a short duration disturbance; sag, swell, or an interruption. However, we still need further information for precise identification. Fig. 4-a shows the start of a transient phenomenon that decays gradually with time. This may give sense to some sort of discharging or decaying transient, involving capacitor energization. Figs. 2-b, 3-b show the standard energy distribution among various decomposition levels of the detailed versions of test signal. The decomposition starts with the highest frequency tending to capture any transient variation or discontinuity of the signal, as we step up with the resolution levels, the wavelet stretches trying to pick up lower frequencies. The bulk energy is concentrated in the 7th through the 11th levels. After this level, the wavelet dilates more and more to search for any sub-power frequencies, which obviously do not exist. Referring to figs 2-b, 3-b, the percentage energy deviation from a pure sine wave, in case of sag or swell, is proportional to the magnitude and the duration of the sag or swell respectively. This suggests an identification patterns for these disturbances.

For fig. 4-b, we have a peak at the fifth resolution level (corresponding to 1000 Hz), identification of the frequency can be used to locate the switching source.

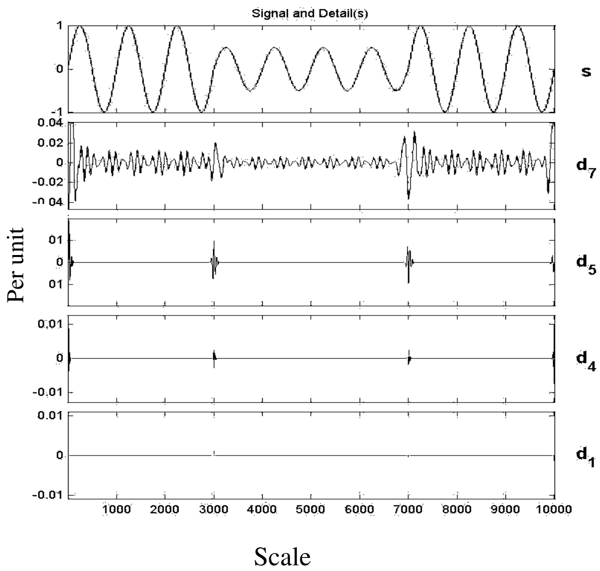

Fig. 2-a. Wavelet analysis of the sagged wave, 4 cycles, 50%.

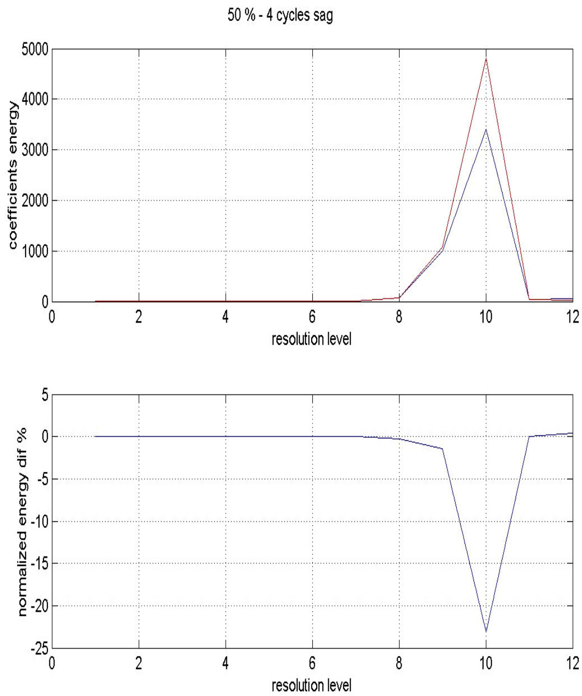

Fig. 2-b. Energy distribution among various resolution levels compared with pure sinewave (upper plot).

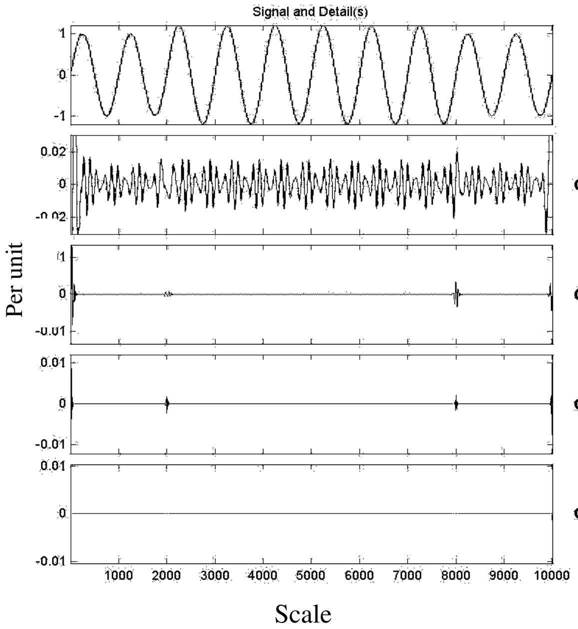

Fig. 3-a. Wavelet analysis of the swelled wave, 6 cycles, 120%.

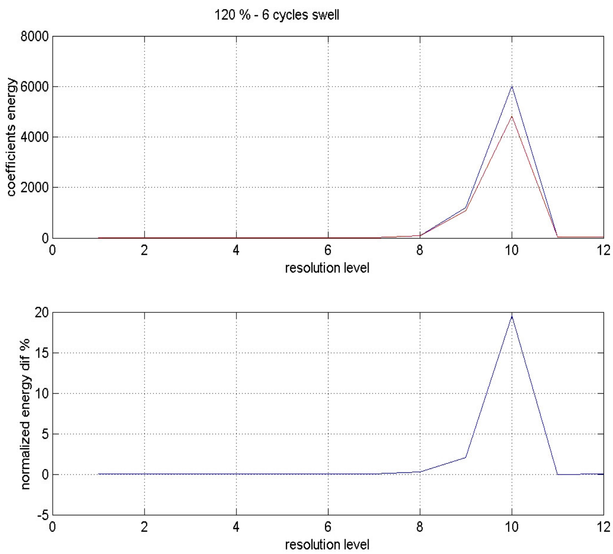

Fig. 3-b. Energy distribution among various resolution levels compared with pure sinewave (lower plot).

Figs. 5-a, 5-b could be used as a classification pattern for notching, furthermore, the number of tics could be counted, and we can reveal that this is the result of a 6 or a 12 pulse converter, moreover, the firing angle of the thyristor could be anticipated from the time series corresponding to the wave length (20 msec ~ 360° ~ 1000 sample points in our procedure). Figs. 6-a and 6-b (lower plot) show "knee" or peak other than the tenth level. This is the area of high order harmonics

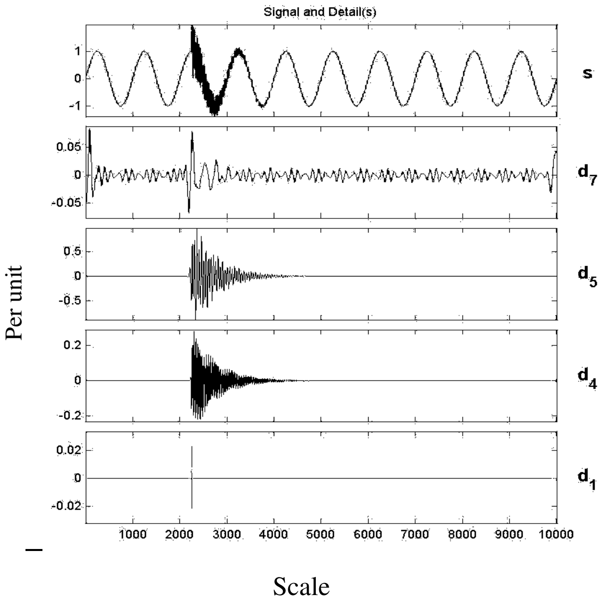

Fig. 4-a. Wavelet analysis of capacitor switching wave, at 1000 Hz.

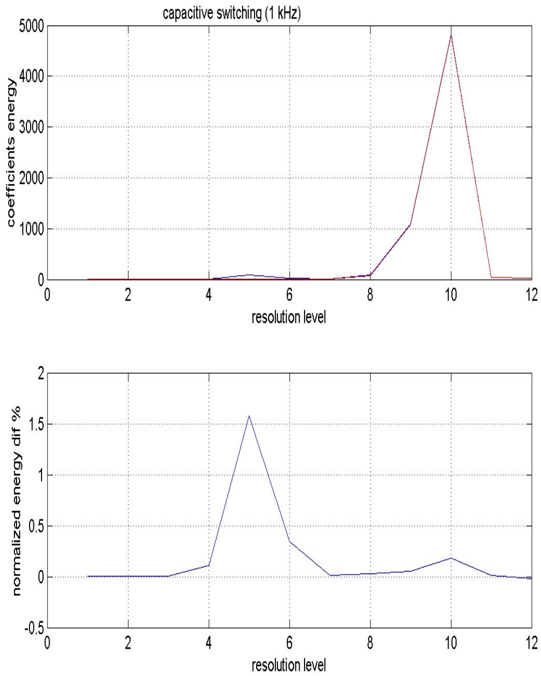

Fig. 4-b. Energy distribution among various resolution levels.

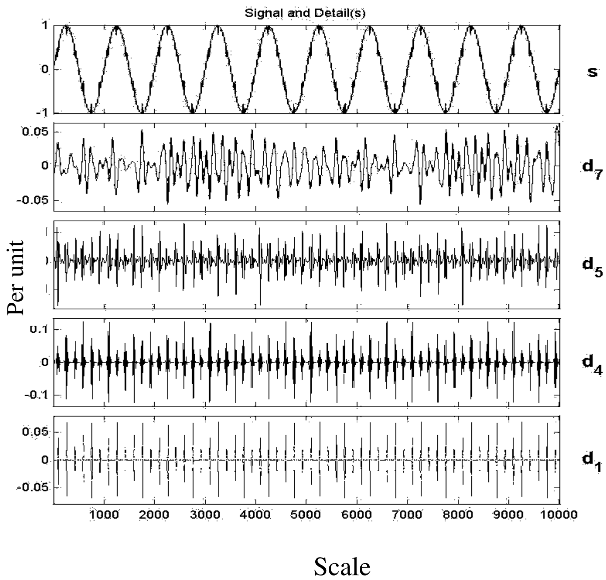

Fig. 5-a. Wavelet analysis of 6 notch, 30 degree converter wave.

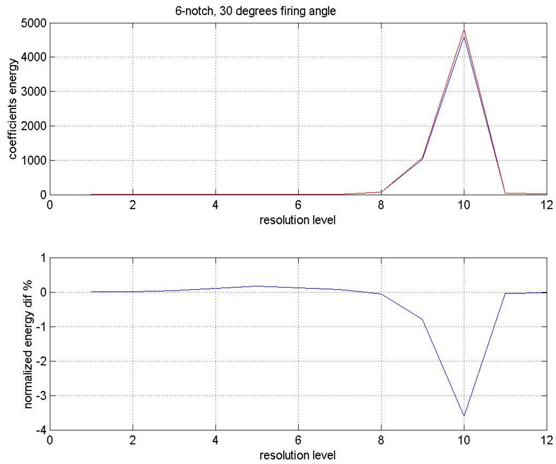

Fig. 5-b. Energy distribution among various resolution levels.

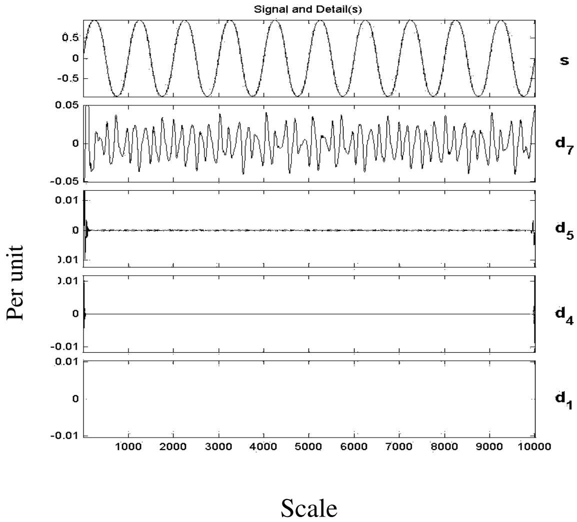

Fig. 6-a. Wavelet analysis of fundamental+5% 3rd harmonic wave.

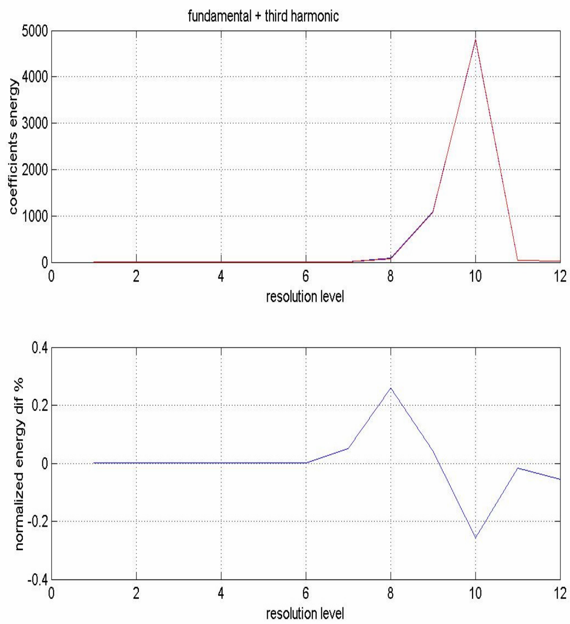

Fig. 6-b. Energy distribution among various resolution levels.

4. Conclusions

Wavelet transform is a powerful tool for non-stationary signals analysis. It provides time localization of the signal that will have a resolution that depends on the level in which they appear. Therefore, it is a good candidate for detection and localization of short time disturbances. The standard deviation of the wavelet transform coefficients at different resolution levels is used in this technique as a feature to classify different power quality problems.

A proposed procedure, depending on energy distribution difference between the analyzed wave and a pure sine wave, showed excellent on-line detecting and locating properties, plus the ability to fast classifying these disturbances in advantage of the current methods, which require either an Artificial

Neural complementing technique or massive extra calculations for the standard deviation of the wavelet transform coefficients in each decomposition level as a characteristic feature.

The main thrust to the wavelet technique as shown in this research work is its deficiency in handling steady state disturbances in the wavelet domain. This is most obvious in the case of harmonic distortions. As a remedy to this problem, combining Fourier analysis and wavelet technique would be the optimum solution. A prescanning of the waveform by a Fourier analyzer would detect the harmonic content in the waveform, and therefore applying the wavelet technique to pick non-harmonic distortions.

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