Detection Methods for Current Signals Causing Errors in Static Electricity Meters

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***Abstract*—In recent years, the shift to Distributed Generation (DG) and the use of smarter domestic appliances has led to an increasing integration of power electronics (active infeed converters, power drive systems etc.) at the household level. However, the use of more power electronics results in the generation of highly distorted currents entering the distribution grid. Previous research shows that such current waveforms can cause large errors in static electricity meters. Thus, there is an imperative need to study the characteristics of these current waveforms and their impact on meter readings by performing extended measurements in households. Since it is not practical to store all the high granularity waveform data of such measurements, suitable detection methods and trigger levels need to be defined to only capture the potentially problematic current waveforms. In this paper, signal processing techniques (differentiation, Short Time Fourier Transform and Wavelet Transform) are applied to current signals in order to extract features suitable for use as a trigger. Results show that the Discrete Wavelet Transform and the filter with derivative method give the most promising results and work reliably even for very noisy signals.**

***Index Terms*—Power Quality, Static Meters, Short Time Fourier Transform, Wavelet Transform, Multiresolution Signal Decomposition.**

I. Introduction

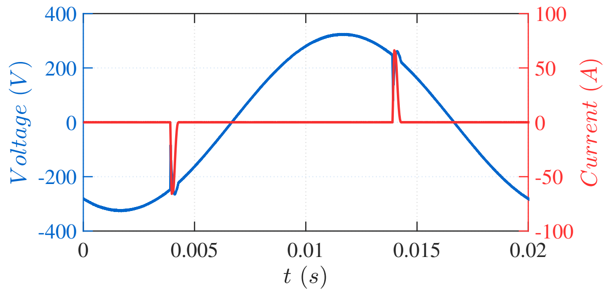
The increasing integration of Renewable Energy Sources (RES) and the emerging smart grid technologies, employing large amount of power electronics, have stressed the need for better control of the production and distribution of electricity. In that respect, traditional electro-mechanical electricity revenue meters are being replaced with static energy meters with communication capabilities for data transfer. Enhanced control in balancing power generation and load consumption is achieved and demand-response mechanisms arise, allowing residents to manage their energy consumption easier and more effectively. However, the use of more power electronics results in the generation of highly distorted currents, entering the distribution grid. In addition to the generated high frequency harmonics (between 2-150 kHz), some of these currents are characterized by sharp transitions with very short rise times which can cause EMI [1], [2]. Such phenomena, mainly observed when non-linear, fast switching loads are connected, can result in large errors in static electricity meters.

In [3], [4] it is shown that, for three-phase energy meters, large deviations exist in certain cases. In both studies various loads were used, including an electric heater (resistive load), a string of CFL lamps and a string of LED lamps. These loads were controlled by a dimmer creating a phase-fired waveform, effectively suppressing the first part of each half-cycle to zero. Large negative errors were observed when the dimmer angle was set to 90°. However, the most erroneous cases with large positive errors were observed when the dimmer angle was set to 135°. For the aforementioned studies, static meters with different types of current sensors were used, such as current transformers, Hall sensors and Rogowski coils. Readings taken by meters with Rogowski coil sensors turned out to be dramatically higher compared with the electromechanical meter [3], [4]. As a measurement with a Rogowski coil results in a time derivative of the current, the measurement signal has to be integrated. In [3], [4] it is speculated that active integration is used instead of passive integration, and the input electronics are pushed in saturation caused by the short rise-time of the current.

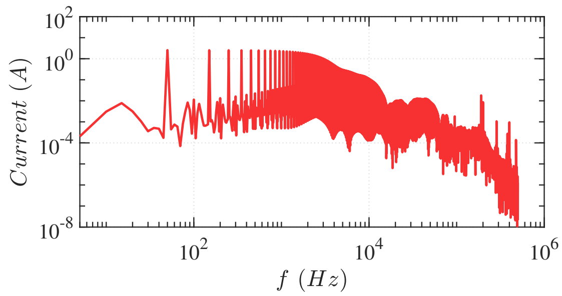
The voltage and current measurements shown in Fig. 1 correspond to one of the most disturbing signals, described in [4], for a combination of non-dimmable LED and CFL lamps, used with a dimmer set to 135°. The requirements for the static meters, as described in the standard EN 50470-3 [5], limits the rise time to be at least 0.2 ms. However, the rise time of the current signal depicted in Fig. 1a is less than 50 μs resulting in harmonics that extend up to many kHz (see Fig. 1b).

In order to study the characteristics of these current waveforms and their impact on meter readings extended on-site measurements at real metering connection points need to be performed to capture potentially problematic currents of the type thought to cause meter errors. Since it is not practical to store all the data of such measurements, suitable detection methods and trigger levels need to be defined for capturing only the current waveforms causing the meter errors. Thus, algorithms suitable for detecting such waveforms are developed and tested on a known disturbing current signal.

In Section II the Short Time Fourier Transform and the Wavelet Transform, suitable for processing non-stationary signals, are briefly described. Four detection methods are presented in Section III and tested on a disturbing current waveform. In Section IV a sensitivity analysis is performed for the choice of the mother wavelet used in the discrete wavelet transform, which turned out to be the most promising detection method. Section V gives the conclusions.



(a)



(b)

Fig. 1. (a) Voltage and current waveforms for a combination of non-dimmable LED and CFL lamps, used with a dimmer set to 135° and (b) the harmonic content of the current signal.

II. Processing of non-stationary signals

It is often useful to apply mathematical transformations to time domain waveforms, in order to extract more features and analyse certain characteristics of the signals. Power system voltage and current waveforms vary with time, so processing methods suitable for the analysis of non-stationary signals, in particular the Short Time Fourier Transform (STFT) and the Wavelet Transform, are described in this section.

A. Short Time Fourier Transform

The STFT is used to decompose the non-stationary signal in time-frequency components, since the frequency content of the signal is changing with respect to time [6], [7]. For a given signal *x(n)* the discrete STFT is defined as:

$$X_n(e^{j\omega_k}) = \sum_m x(m)w(n-m)e^{-j\omega_k m} \quad (1)$$
$$k = 0,\ 1, ...,\ N-1$$

where k and n denote the frequency band and time instant respectively, ω_k is the frequency in radians and $w(m)$ is a selected symmetric window function.

Using the STFT, it is possible to estimate the frequency contents of data as a function of time using sliding window functions. Since the derivation of the Discrete Fourier Transform (DFT) strictly requires the signal $x(n)$ to be periodic, special care should be taken for the choice of the window function in order to minimize possible leakage of signal components from the neighbouring frequency bands. The main disadvantage of this method is related to the time-frequency resolution constraint, i.e. the product of the time resolution and the frequency resolution is constrained by the uncertainty principle (Parceval's theorem) [7], [8]. The STFT assumes local periodicity within a continuously translated time window, thus the time period of each window fixes the frequency resolution.

Multiple resolutions in time and frequency are needed when power signals containing a fundamental frequency superimposed with transients are studied. More specifically, fine time resolution for short duration and high frequency signals, and fine frequency resolution for long duration and lower frequency signals are desirable. This provides accurate location of the transient component while simultaneously retaining information about the fundamental frequency and its low-order harmonics [9].

B. Wavelet Transform

The disadvantage of STFT concerning the fixed time-frequency resolution can be overcome with the use of the Wavelet Transform. The wavelet transform analysis is sensitive to signals with irregularities and is an appropriate tool to detect and localise power quality disturbances [10].

The Continuous Wavelet Transform (CWT) of a signal $x(t)$ is defined as:

$$CWT_\psi x(a,b) = W_x(a,b) = \int_{-\infty}^{+\infty} x(t)\psi^*_{a,b}(t)dt \quad (2)$$

where the asterisk denotes a complex conjugate and

$$\psi_{a,b}(t) = |a|^{-1/2}\,\psi\left(\frac{t-b}{a}\right) \quad (3)$$

is the mother wavelet and a, b are the dilation and translation parameters. Fig. 2 demonstrates how the frequency resolution changes with respect to time by expanding and contracting the mother wavelet using parameter a while parameter b allows the various scale wavelets to be moved across the time axis. Here lies the main difference between the Wavelet Transform and STFT since for the latter the tiling of the time-frequency plane (window) is fixed where short duration window generates low time uncertainty and major frequency uncertainty, and vice versa. Thus, in power quality analysis, long duration disturbances have higher frequency and lower time resolution while fast disturbances have increased time and decreased frequency resolution [11].

To optimise computational efficiency, the mother wavelet may be dilated and translated discretely by selecting a and b such that:

$$\psi_{m,n}(t) = a_0^{-m/2}\psi\left(\frac{t-nb_0a_0^m}{a_0^m}\right) \quad (4)$$

and the corresponding Discrete Wavelet Transform (DWT) is given by:

$$DWT_\psi x(m,n) = \int_{-\infty}^{+\infty} x(t)\psi^*_{m,n}(t)dt \quad (5)$$

With appropriate selection of a_0 and b_0 it is possible to have an orthonormal wavelet transform and use the multiresolution

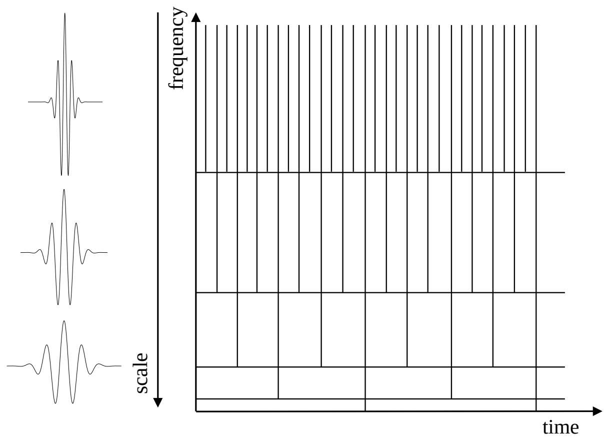


Fig. 2. CWT time-scale plane.

signal decomposition (MSD) technique [11]. By using the MSD technique, the input signal is decomposed into two other signals; one is the smoothed version of the initial signal (which can be further decomposed), and the other is the detailed version of the initial signal that contains the sharp edges, transitions, and jumps.

A recorded digitized time signal, $c_0(n)$, is decomposed into its detailed, $d_1(n)$, and smoothed, $c_1(n)$, wavelet coefficients using a bandpass filter, $g(n)$, and a lowpass filter, $h(n)$, respectively.

$$c_1(n) = \sum_k h(k-2n)c_0(k) \tag{6}$$

$$d_1(n) = \sum_k g(k-2n)c_0(k) \tag{7}$$

Higher-order decompositions are then performed in a similar manner taking the smooth wavelet coefficients, $c_1(n)$, as the signal to be decomposed again into smooth, $c_2(n)$, and detailed, $d_2(n)$, wavelet coefficients. The procedure is shown in Fig. 3. At each decomposition level, the lengths of the wavelet coefficients are half of the length of the signal in the previous level [12], [13]. This scaling provides the DWT with logarithmic frequency coverage in contrast to the uniform frequency coverage of the STFT.

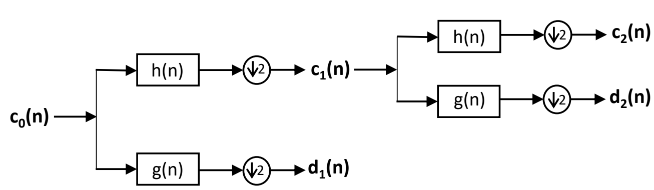


Fig. 3. A two level signal decomposition of $c_0(n)$ into $c_2(n)$, $d_2(n)$ and $d_1(n)$.

In most publications the highest frequency band is used to detect sudden changes in the waveform. This filter has the shortest filter length and thus gives the best time localization. Different authors use different mother wavelets. The two most commonly used ones are the Morlet wavelet and the Daubechies wavelet. A problem in the practical implementation of the wavelet-based triggering method is the noise in the filter outputs when using actual measurements.

III. Detection algorithms comparison

In order to detect current waveforms causing meter errors, four methods are developed and tested on the disturbing current signal depicted in Fig. 1a:

1) Since the rise time of the current waveform might be related to the cause of false static meter readings [1], [3], [4] the most straightforward indicator to detect such wave shapes is the calculation of their derivatives. Thus, the first method is the calculation of the $\mathrm{d}I/\mathrm{d}t$.
2) Furthermore, due to the steep rise of the current waveform higher frequency harmonics are created. Thus, the second method to be tested is the Short-Time Fourier Transform (STFT).
3) For the same reason, the wavelet transform is tested using the continuous formulation (CWT).
4) Accordingly, the discrete wavelet transform (DWT) is tested.

The voltage and current measurements of Fig. 1a have a sampling rate of 1 MHz and the acquisition window is 10 power cycles. To imitate conditions existing in actual field measurements, white Gaussian noise is added in the studied current waveform, where the signal to noise ratio is chosen as 20 dB.

The first derivative of the current waveform is shown in Fig. 4. Using the differentiation method, the current spikes are clearly depicted in their derivatives, where at the time of the steep transitions the derivative magnitudes are significantly higher (see Fig. 4a). However, when noise is added in the current measurement, it is impossible to detect the spikes since it is highly sensitive and imbedded with noise (see Fig. 4b). In order to suppress the noise a Gaussian filter is applied to the current signal and then the derivative is calculated. As presented in Fig. 4c, when the current waveform is filtered using the Gaussian filter, the first-order derivative succeeds in capturing the current transitions.

For the STFT, a window of one power cycle is used (which translates into a frequency step of 50 Hz) with a slide step of 1% of the power cycle. To minimize leakage a hamming window is chosen and at the end the harmonic content magnitude is scaled according to the window length and amplification. The frequency content of the current waveform through time is shown in Fig. 5. From the higher frequency content disturbances are visible between 0 s and 0.005 s and between 0.01 s and 0.015 s which correspond to the fast current transitions. However, it is not possible to accurately localize the disturbance since its spectrum is spread in a wide time period. The main disadvantage of this method is related to the time-frequency resolution constraint.

For the CWT, the Morlet wavelet is chosen as mother wavelet and 148 scales were used for the calculations. The CWT of the noisy current waveform is presented in Fig. 6.

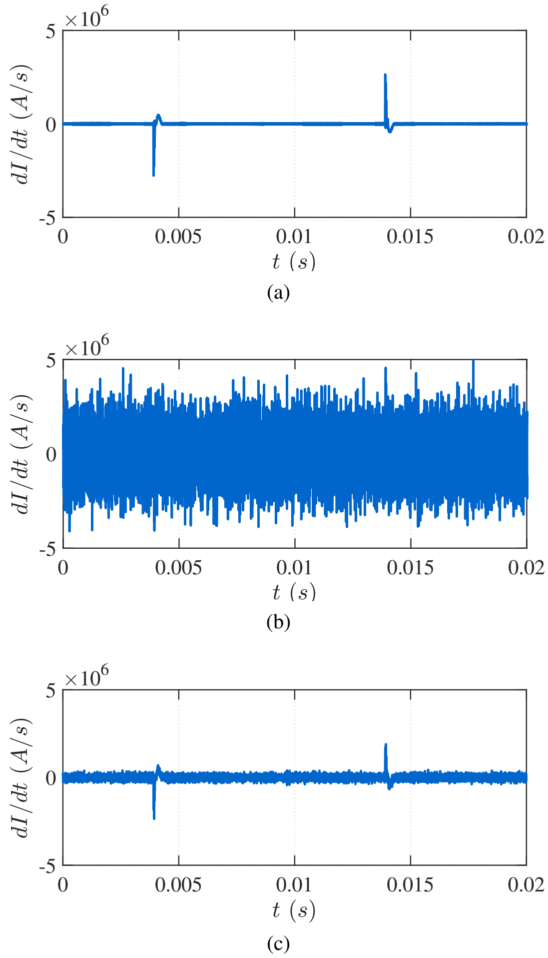


Fig. 4. First derivative of the current waveform (a) without noise, (b) with white Gaussian noise and (c) when a Gaussian filter is applied to the noisy current signal.

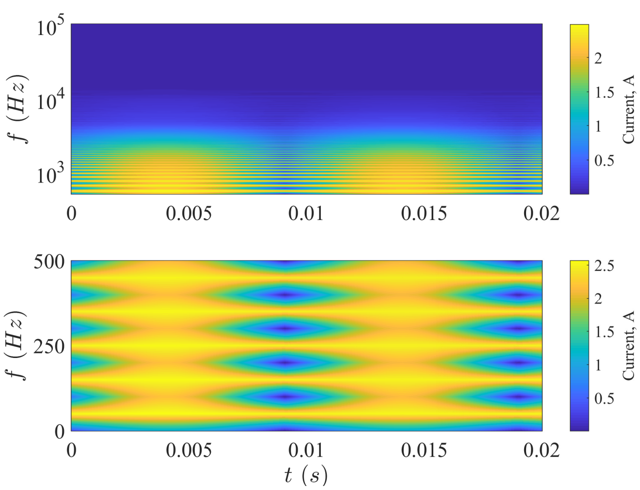


Fig. 5. Frequency spectrum with respect to time of the current waveform with white Gaussian noise.

It is clear that the use of the wavelet transform can localize the disturbances more accurately in time compared with the STFT. This is due to the multiresolution characteristic of the wavelet transform.

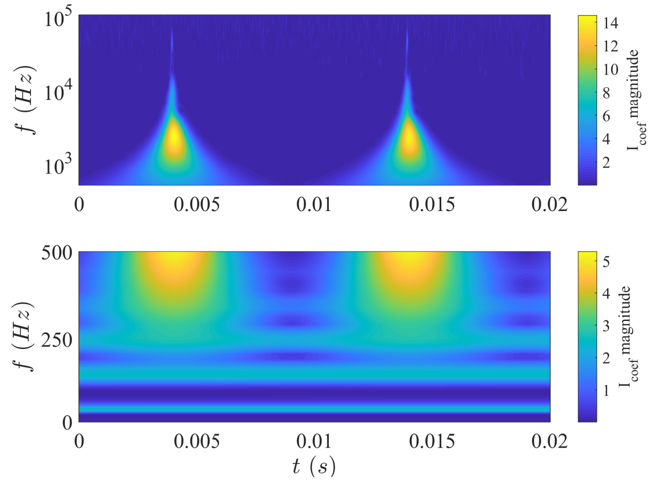


Fig. 6. Continuous wavelet transform of the current waveform with white Gaussian noise.

Since the CWT is achieved by dilating and translating the mother wavelet continuously, it generates substantial redundant information and requires high computational time. Therefore, instead of continuous dilation and translation, it is preferable that the mother wavelet is dilated and translated discretely by selecting appropriate dilation and translation parameters. For the DWT, the Daubechies wavelet with two filter coefficients (db2) is used as mother wavelet and a four-level decomposition is performed. In Section IV, a comparison of the performance between various mother wavelets is conducted.

The DWT coefficients of the current waveform with the addition of white Gaussian noise is shown in Fig. 7. Each coefficient is related to a frequency band where for d_1 is 250-500 kHz, for d_2 is 125-250 kHz, for d_3 is 62.5-125 kHz and for d_4 is 31.25-62.5 kHz. As described in [14], using the Taylor series approximation it is proved that the wavelet transform reacts the most to the gradient of the signal. Thus, the wavelet transform is sensitive to signal irregularities similar to the sharp edges of the current shown in Fig. 1a but insensitive to the steady-state behaviour of the signal. The first two detailed coefficients d_1 and d_2 are very noisy but the disturbances start to become detectable for both d_3 and d_4. The higher level detailed coefficients are capable of detecting the timings of the fast sharp current rise (having high $\mathrm{d}I/\mathrm{d}t$), making clear that DWT is suitable for detecting these kind of disturbances.

In order to enhance the magnitude of the associated disturbance coefficients and to suppress the magnitude of the noise-related coefficients, all wavelet transform coefficients are squared [12]. The result for squared d_4 is shown in Fig. 8. In this case, the detection of the disturbances becomes clear. Thus, it can be concluded that the use of squared wavelet coefficients (of higher scale) for noisy signals is a strong indicator for disturbance detection.

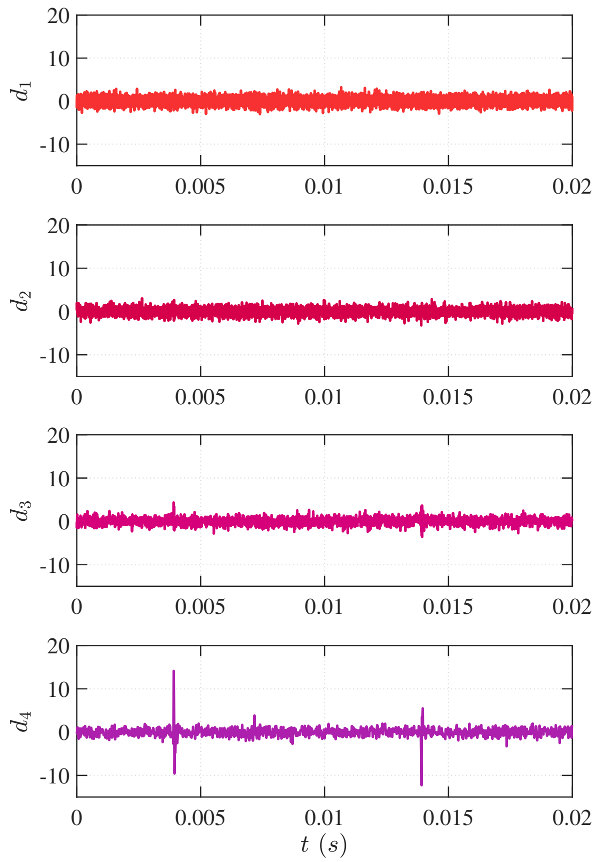


Fig. 7. Discrete wavelet transform of the current waveform with noise, where d1-d4 are the level 1-4 wavelet detailed coefficients.

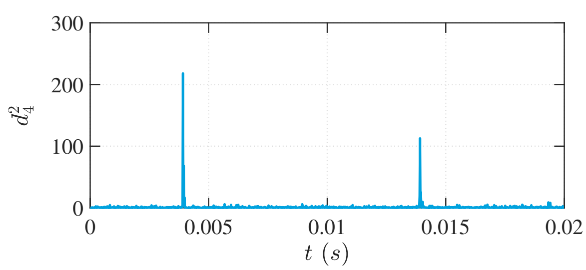


Fig. 8. Squared wavelet detailed coefficients at level 4 for the current waveform with noise.

Since the processing of the waveforms and possible disturbance detection should be performed in real time the computation time required by each transform is of utmost importance. For this study, the signal processing is performed in Matlab2018a software using a data window of 10 power cycles with a sampling frequency of 1 MHz. Table I shows the computational time needed for each method, as calculated by Matlab's "*tic toc*" function.

As expected, the derivative is the fastest method while the CWT is by far the slowest. The DWT is more optimized since it does not contain all the redundant information of CWT and thus, its computational time is approximately 100 times less than the one of CWT. More specifically, DWT requires

TABLE I
COMPARISON OF COMPUTATIONAL TIME NEEDED FOR EACH TRANSFORMATION METHOD USING A DATA WINDOW OF 10 POWER CYCLES WITH A SAMPLING FREQUENCY OF 1 MHZ.

	Filtered derivative	STFT	CWT	DWT
Computational time (s)	0.0087	0.7630	2.7405	0.0262

26.2 ms to analyse a 10 cycle (200 ms) window waveform which makes it a realistic method for real time processing of waveform data. It is observed that the calculation of the filtered derivative is approximately three times faster than the calculation of the discrete wavelet transform.

IV. SELECTION OF MOTHER WAVELET

In power quality disturbance detection, the disturbances can be classified into two categories, i.e. fast and slow transients. In the fast transient case, the waveforms are characterized with sharp edges, rapid changes, and short duration while in the slow transient case, the waveforms are characterised with a slow change or smooth amplitude change. The choice of a mother wavelet for the DWT and its performance depend on the type of disturbance to be analysed [10]. In Section III db2 was chosen as mother wavelet because Daubechies functions (with 2 or 4 filter coefficients) are the most commonly used in literature when analysing power quality disturbances [10], [12]. Since the choice of the mother wavelet strongly affects the magnitudes of the detailed coefficients, it is important to thoroughly investigate the behaviour of the various mother wavelets.

The comparison indicator between the mother wavelets is chosen to be the maximum squared magnitude of detailed coefficient d_4. Fig. 9 illustrates the maximum squared values of coefficients d_4 of the current waveform for the the Daubechies' (Fig. 9a), the Coiflets (Fig. 9b), the Symlets (Fig. 9c), and the biorthogonal (Fig. 9d) wavelet families [15]. Daubechies, Coiflets, and Symlets are orthogonal wavelets which can be entirely defined by the scaling filter (a low-pass finite impulse response filter). On the other hand, in biorthogonal wavelets, separate decomposition and reconstruction filters are defined. It is observed that the mother wavelet which produces the highest magnitude coeffcients is biorthogonal 1.5. The second best is db2, which was the one used in the previous analysis. With respect to computational time needed to perform DWT, all mother wavelets give similar results.

V. CONCLUSION

This paper evaluates the use of signal processing techniques to extract features from disturbing current signals that could be used as a waveform data capture trigger mechanism when to perform extended on-site measurements at meter connection points.

Four detection methods are compared both for their accuracy in detecting sharp transitions in a specific disturbing signal (used as an extreme example) in a noisy environment

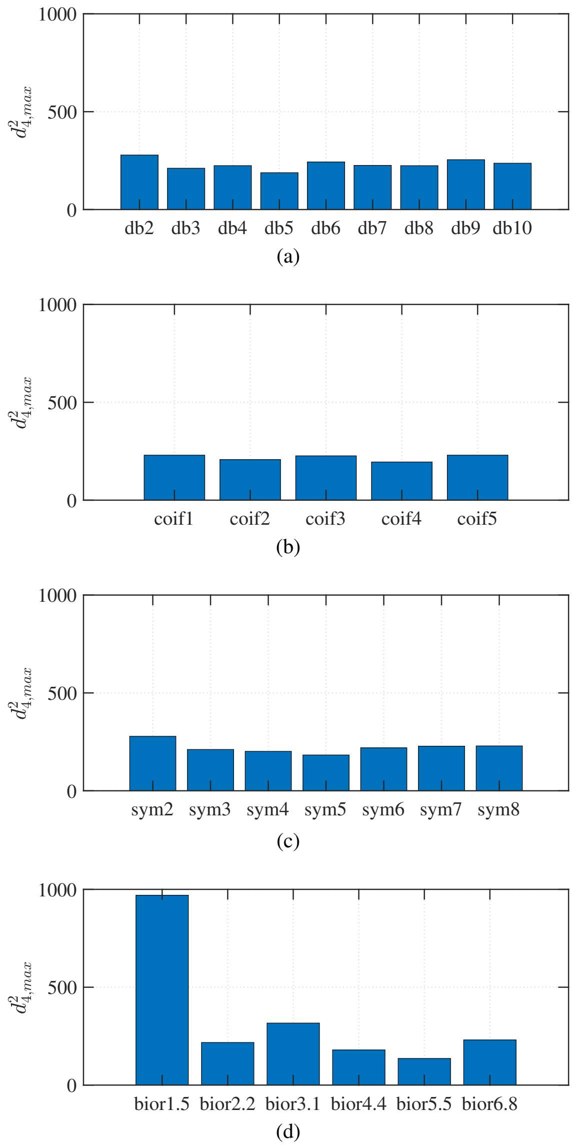


Fig. 9. Maximum value of wavelet coefficient D4 of the current waveform for (a) the Daubechies' (b) the coiflets (c) the symlets and (d) the biorthogonal wavelet family.

and for their computational time, since real time implementation is essential. It can be concluded that both the DWT and the Gaussian filtered derivative give the most promising results, since they can accurately detect the steep current fronts with high time accuracy even when high levels of white Gaussian noise are added in the measurements. Comparing the two methods, the calculation of the filtered derivative is approximately three times faster than the calculation of the DWT.

Finally, a sensitivity analysis for the mother wavelet, used in DWT, is performed to choose the most suitable mother wavelet for the studied type of disturbance using the maximum absolute magnitude of detailed coefficient d_4 as comparison indicator. Biorthogonal 1.5 and db2 resulted in the highest magnitudes while with respect to computational time all mother wavelets gave similar results.

Future work will focus on the application of the suggested detection algorithm on an extended set of test current waveforms, both problematic and non-problematic. The analysis will aim for the definition of a proper global trigger limit for one of the detailed wavelet coefficients to be able to identify the current waveforms which result in meter errors.

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