Real–Time Implementation and Comparison of Time–Varying Harmonic Measurement Methods

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Abstract—**Harmonics are an important issue in electric power systems. Therefore, real-time techniques to estimate and quantify harmonics and other indices directly related to waveform distortion are receiving increased attention. This paper presents and compares the outcome of three measurement techniques used to obtain the harmonic content of current and voltage measurements. For this study, Fast Fourier Transform (FFT), a model-based technique and a new approach based on the real wavelet transform of the analytic representation of distorted power signals are considered. The proposed methods are verified by real measurements on the in-house developed prototyping measuring platform. A DSP performance analysis is also given.**

Index Terms—**Harmonics, analytic signal, wavelet transform, Kalman filter, real–time system.**

I. NOMENCLATURE

AS: Analytic Signal
FFT: Fast Fourier Transform
DSP: Digital Signal Processor
DWT: Discrete Wavelet Transform
MUSIC: Multiple Signal Classification
PQ: Power Quality
SVD: Singular Value Decomposition
THD: Total Harmonic Distortion

II. INTRODUCTION

IN an ideal power system, voltage and current waveforms are pure sinusoids. However, in practice under different circumstances, voltage and current waveform distortions are created. These waveform distortions are further discussed in terms of harmonics, being integer multiples of the fundamental power frequency.

The waveform distortions are not a new phenomenon, being around since the first AC generator went on-line. However, the development of technology over decades (e.g. power electronic devices) has resulted in a rapid increase of harmonics within the power system.

In this paper the implementation and comparison of different signal processing techniques discussed to produce the harmonic signal content based on sampled data stream are presented. A special emphasis is given to a new approach based on the orthonormal real wavlet transform of analytic signals. To generate the analytic signal, two methods are given. The first method is based on Fast Fourier Transform, whereas the second is Finite Impulse Response filter based. The general structure of the DSP system, which is used for estimation of the harmonics performed in real-time, is also described. Finally, the on-line estimation of harmonics and other PQ indices directly related to waveform distortion by employing the signal processing as FFT, Wavelets and Kalman harmonics observer is performed.

III. SIGNAL PROCESSING TOOLS ON VOLTAGE AND CURRENT HARMONIC ESTIMATION

The harmonic currents and voltages are characterized by their frequency, amplitude and phase angle. Different signal processing techniques have been introduced as tools to estimate and calculate the above quantities. Some are revised below, but it should be mentioned that the listed methods are far from complete and each has its own advantages and drawbacks.

- In practical measurements, the standard method for studying and extracting the harmonic content of a signal (current and voltage) is based on the use of DFT through an implementation algorithm FFT [8]. The FFT performs well for estimation of periodic signals in steady state, but under certain conditions (e.g. picket-fence effect, leakage) it is known to loose accuracy.
- The short time Fourier transform (STFT), commonly known as a sliding window version of the FFT, has a fixed frequency resolution for all frequencies once the size of the window is chosen. It shows an easier and better interpretation in terms of harmonics [1].
- Wavelet Transforms have become more and more popular in extracting the harmonic contents included in a voltage or current waveform. For example, in [10] wavelet transforms are proposed to study power system transient harmonics distortion by decomposing the signal in different frequency subbands and study their characteristics separately. In [2], a combination of discrete and continuous wavelet analysis is used to quantify harmonic frequency amplitudes and phases whereas [3]

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and [11] propose the use of a wavelet packet transform. A new alternative technique [15], [16] based on the discrete wavelet transform (DWT) of an analytic complex representation of given real current and voltage signals, is presented. Since the (real) wavelet transform of a complex signal yields complex wavelet coefficients, the amplitude and phase (frequency) information provided in the analytic representation is preserved. Let *s(t)* be the analytic representation of the signal, then,

$$DWT_s\left(m,n\right)=\left\langle s,\Psi_{m,n}\right\rangle=\left(A,\phi\right) \tag{1}$$

Equation (1) defines the DWT of the analytical representation of the signal at scale *m* and time *n*. Applying (1) to the analytic representation of the voltage and current, yields

$$\begin{aligned} DWT_{u_a}\left(m,n\right)&=\left\langle u_a,\Psi_{m,n}\right\rangle=\left(U_a,\phi\right) \\ DWT_{i_a}\left(m,n\right)&=\left\langle i_a,\Psi_{m,n}\right\rangle=\left(I_a,\vartheta\right) \end{aligned} \tag{2}$$

Since this is a complex number, it is possible to denote U_a and I_a as amplitudes and ϕ and ϑ as phase angle of the voltage and current, respectively. This information is further used to define the THD index or other power related quantities (e.g. instantaneous active and reactive power). The THD of the voltage is

$$THD_{(u)}=\frac{\sqrt{\sum_m\sum_n\left\|DWT_{u_a}\left(m,n\right)\right\|^2}}{\sqrt{\sum_n\left\|DWT_{u_a}\left(m_0,n\right)\right\|^2}} \tag{3}$$

with *n* the time parameter and m_0 the scale covering the fundamental. The same definition can be applied to the current.

- Another advanced technique for signal components estimation is the Kalman filter. This technique is defined as a state space model for tracking amplitude and phase of the fundamental frequency and its harmonics and was proposed, among others, in [4], [5].
- Other approaches for measuring harmonics are: linear least square, Singular Value Decomposition (SVD) and Prony [12], [13], Multiple Signal Classification (MUSIC) [14], statistical analysis [6], Finite Impulse Response (FIR) comb filter [7].

IV. EXPERIMENTAL MEASUREMENT OF TIME–VARYING HARMONICS

In order to evaluate the accuracy and the real-time behavior of the three main signal-processing tools (Fourier, Wavelets and Kalman filter) related to the estimation of the harmonic content of the current/voltage signals, a set of tests with on-line further computation are performed and compared.

A. Experimental measurement system overview

Their specific architecture and high performance make DSP technology suitable to implement a wide variety of measuring algorithms for real-time applications with high bandwidth requirements. Therefore, the classification measurement application is implemented using an in-house DSP-based real–time platform. It features a Texas Instruments (TI) ‘C6711 DSK, a Field Programmable Gate Array (FPGA) based measurement daughtercard and a data acquisition system (voltage and current measurement modules).

To maintain modularity and to achieve a high degree of flexibility, at the software side, TI Code Composer Studio (CCStudio), MATLAB/Simulink with RTW toolbox and in-house DSK_RTW package are used. The latter is an open framework in which MATLAB/Simulink generated code from the RTW toolbox can be run on a TI ’C6711 DSK. Furthermore, the tool relies on the TI operating system (DSP/BIOS) for different tasks and supports Simulink External Mode features, which allows on-line parameter changes. Concerning TI DSP/BIOS, different modules (i.e. Execution Graph, Statistics View, CPU Load graph), providing detailed information in real-time about the running algorithms (tasks), are supported.

For a full discussion of the measurement platform, the reader is referred to [8].

B. General remarks

Before presenting the experimental result, some general remarks are to be made:

- All methods are implemented on the measuring platform introduced above, after validation of the proposed techniques through simulation. Thanks to the rapid-prototyping setup of the system this is a straightforward operation, using little time in the overall design process.
- The loads, used in the measurements, comprise a mix of incandescent and compact fluorescent lamps (CFL) and a rectifier with a resistive/inductive load. There are summarized in Table I.

TABLE I: LOAD CLASSIFICATION

Type	Load
(1)	Rectifier with a resistive/inductive load (R=70, L=0.15)
(2)	Rectifier with a resistive/inductive load (R=85, L=0.15)
(3)	Rectifier with a resistive/inductive load (R=60, L=0.15)
(4)	Mix of incandescent and compact fluorescent lamps

- The voltages and currents are sampled at 6.4 kHz, so that 128 samples/period are acquired when the fundamental frequency is 50 Hz.
- As a reference, the [1]PM6000 power analyzer (Fourier-based) is used.

C. Experimental Results

The tests are mainly done at two distribution grid voltages: 230/240 V rms. Only the first 15 (odd) harmonics are considered. Techniques to estimate the harmonic magnitudes (rms value) and other related indices are further discussed. First, the experimental results regarding the harmonic FFT based estimation are introduced.

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[1] PM6000 power analyzer is a trademark of the Voltech Instruments Inc. manufacturer

1) *Harmonic estimation Fourier-based*

The voltages and currents measurement data are obtained from a load type (1) connected to a single–phase system. Different scenarios for extracting the harmonic spectrum are used, reflecting the data block size for the analysis:

- The series cover exactly one, two and eight grid frequency periods, i.e. all computations are performed on 128, 256, and 1024 samples, respectively.
- A sliding window (e.g. rectangular, triangular, Hanning) with a length of two (40 ms or 256 samples) or eight cycles (200 ms or 1024 samples) and no overlap.

The on-line harmonic components and the rms values calculation are compared in Fig. 2 and Table II.

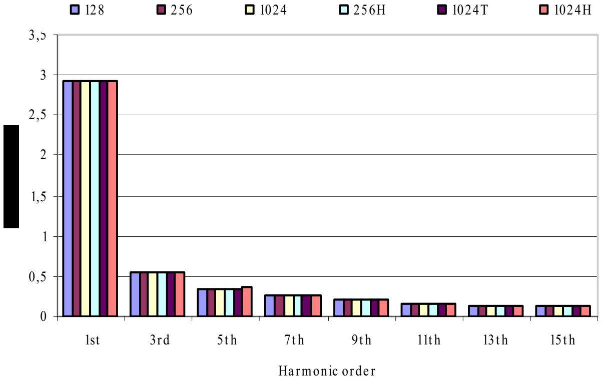

Fig. 2: Harmonic amplitude estimation by using FFT method based

TABLE II: COMPARISON OF HARMONIC MEASUREMENT RESULTS FFT-BASED

Method	Current		
	$I_{rms}^{(*)}$ [A]	$I_1^{(*)}$ [A]	$THD_{Is}^{(*)}$ [%]
$FFT_{N=128}$	3.03	2.935	25.97
$FFT_{N=256}$	3.034	2.938	25.85
$FFT_{N=1024}$	3.034	2.936	26.03
$FFT_{N=256H}$	3.034	2.936	26.06
$FFT_{N=1024H}$	3.037	2.938	26.14
$FFT_{N=1024T}$	3.033	2.935	26.04

(*)The on-line calculated values are compared to data obtained with a PM6000 Universal Power Analyser (3.036 A, 2.936 A and 26.1% respectively).

As seen, similar results are obtained. Regarding the computational complexity, the STS module and the variation of CPU load at a clock frequency of 150 MHz are used for monitoring (Table III).

TABLE III: COMPUTATIONAL COMPLEXITY BY MEANS OF CPU USE AND STS PROCESSING STATISTIC

Method	Computational effort (STS [ms] /CPU [%])
$FFT_{N=128}$	0.64 / 9.4
$FFT_{N=1024}$	5.06 / 18.3
$FFT_{N=1024W}$	5.33 / 18.7

As expected, when the calculation of harmonic content is performed over one cycle (on 128 samples), less time and computational effort are required, increasing with the number of samples.

2) *Harmonic estimation Wavelet based*

For the method based on the (real) wavelet transform of the analytic representation of the signals, the following main items need to be considered:

- the type of the (real) wavelet transform should be orthonormal;
- the wavelet (filter) order, generally related to the frequency separation characteristic of the selected wavelet: good frequency separation reduces the amount of leakage energy to the adjacent frequency bands;
- the number of levels, related to the input frame size, e.g., if the number of input samples is $N=2^D$ then a maximum of D levels can be performed; the wavelet levels are from 0 to D-1 and the scaling level is 0^*.
- the analytic signal (AS) approximation method: two methods, referenced to as AS-FFT and AS-FIR [15], are given.

All features above have an impact on the performance and the accuracy of harmonic measurements and consequently, need to be chosen careful. The signals are sampled at 128 (2^7) points per the fundamental cycle (50 Hz). A five (wavelet) level and one approximation (scaling) level are chosen. Such a choice gives the opportunity of including the fundamental in the subband located at the lowest frequency (2^*). A load type (4) is used.

First, the results obtained by applying the wavelet transform of the analytic representation of measured signal (the current), with AS approximation via FFT, are highlighted. Table IV shows the rms value of each output band when three orthonormal wavelets (i.e. Daubechies, Symlets, and Coiflets) with different number of coefficients are used.

Through the simulation tests, the Daubechies wavelet with 40 coefficients (Db_{40}) presents the best results, being able to quantify the rms value of the current of several harmonics within each frequency band. It is worthwhile to mention that as the number of coefficients increases, more accurate measurements for harmonic estimation are obtained. Therefore, Daubechies wavelet with 40 coefficients (Db_{40}) is further taken as reference point for the on-line harmonic estimation experiments (Table IV).

TABLE IV: COMPARISON OF HARMONIC MEASUREMENT USING DWT (5-LEVELS), WITH AS APPROXIMATION VIA FFT

Method	Frequency band (Hz)					
	0-100	100-200	200-400	400-800	800-1600	1600-3200
Db_6	1.053	0.161	0.204	0.133	0.120	0.092
Db_{20}	1.056	0.165	0.204	0.129	0.121	0.081
$\mathbf{Db_{40}}$	1.055	0.166	0.210	0.112	0.123	0.082
$Coif_5$	1.052	0.166	0.207	0.125	0.119	0.086
Sym_8	1.054	0.164	0.200	0.133	0.121	0.092
Sym_{20}	1.052	0.165	0.203	0.131	0.119	0.086

However, the DWT provides non-uniform frequency bands, which implies that at a higher level of decomposition, the frequency band becomes wider and covers more harmonic components (e.g. the 5th and 7th harmonics are together part of frequency band: 200~400 Hz, 9th, 11th, 13th, 15th of 400~800 Hz and so on).

To overcome this limitation, for example, the DWT expanded to the wavelet packet transform (WPT) can be used. Similar to the DWT algorithm, the input signal is decomposed into uniform frequency bands. Thus, the WPT algorithm has the capability to measure the rms value of the signal of individual harmonic components.

The outcomes are presented in Table V along with the estimated results from FFT (calculated over 1024 samples).

TABLE V: COMPARISON OF HARMONIC MEASUREMENT RESULTS USING AS ($FFT_{N=128}$)-WPT (5-LEVELS) AND FFT (CALCULATED OVER 1024 SAMPLES)

Method	Current							
	1st	3rd	5th	7th	9th	11th	13th	15th
WPT (Db40)	1.05	0.16	0.12	0.06	0.04	0.03	0.03	0.01
FFT N=1024	1.05	0.16	0.12	0.06	0.04	0.02	0.02	0.01

Comparing the results obtained from both, AS (FFT)-WPT and FFT, respectively no major differences are seen. The main quantities are calculated (Table VI).

TABLE VI: COMPARISON OF MAIN QUANTITIES HARMONIC MEASUREMENT RESULTS USING AS ($FFT_{N=128}$)-DWT AND AS ($FFT_{N=128}$)-WPT (5-LEVELS)

Method		Current		
		$I_{rms}^{(*)}$ [A]	$I_1^{(*)}$ [A]	$THD_{Is}^{(*)}$ [%]
AS ($FFT_{N=128}$)	DWT_{Db40}	1.094	1.055	27.57
	DWT_{Coif5}	1.093	1.052	28.0
	DWT_{Sym20}	1.093	1.052	27.91
	WPT_{Db40}	1.080	1.055	21.91

(*)The values are compared to data obtained by using $FFT_{N=1024}$ method (1.079 A, 1.054 A and 21.73% respectively).

The results show that the values computed using DWT method are fairly alike. However, some disagreements in the results appear regarding WPT approach. The small differences between both techniques are the consequences of the signal decomposition (asymmetrical and symmetrical) and their related leakage problems. Note that only first 15th odd harmonics are considered. Thus, for an asymmetrical decomposition (DWT) only the data of the first three wavelet levels and the scaling level are taken into account for the rms calculations and some leakage can occur to the rms values at some frequency bands. Concerning the symmetrical (WPT) one, the rms value of each harmonic component can be computed, leading to less leakage problems and therefore, more accurate results.

Besides creating the AS via FFT, an alternative way is proposed based on the FIR filter. The study uses a filter length of 60. In [15] the AS-FIR based algorithm proves to perform better for lower sampling frequencies (e.g. f_s=1600 Hz instead of f_s=6400 Hz), as also demonstrated through measurements (Table VII).

TABLE VII: COMPARISON OF HARMONIC MEASUREMENT RESULTS USING ^{1}AS ($FIR_{N=60}$)-WPT (F_S=6.4 KHZ, 5-LEVELS) AND ^{2}AS ($FIR_{N=60}$)-WPT (F_S=1.6 KHZ, 3-LEVELS)

Method	Current							
	1st	3rd	5th	7th	9th	11th	13th	15th
^{1}WPT (Db40)	0.93	0.15	0.12	0.05	0.04	0.03	0.03	0.01
^{2}WPT (Db40)	1.05	0.16	0.13	0.07	0.04	0.02	0.01	0.01

Then, comparing the results obtained from the AS–FIR (Table VII) and the AS–FFT (Table V), the later performs better given more accurate results. Regarding computational complexity, the results of the monitoring are shown in Table VIII.

TABLE VIII: COMPUTATIONAL COMPLEXITY BY MEANS OF CPU USE AND STS PROCESSING STATISTIC USING WAVELET TRANSFORM AND ITS RELATED TECHNIQUES FOR HARMONIC ESTIMATION

Method		Computational effort (STS [ms] /CPU [%])
AS ($FFT_{N=128}$)	DWT_{Db6}	0.9 / 5.1
	DWT_{Db20}	2.01 / 11.1
	DWT_{Db40}	3.32 / 17.9
	WPT_{Db40}	6.16 / 32.7
AS (FIR_{60})	DWT_{Db40}	3.68 / 19.6
	WPT_{Db40}	6.43 / 33.35
DWT_{Db40}		1.55 / 9.1
WPT_{Db40}		3.04 / 16.2

Summarizing the type of the wavelet and especially the order, the number of levels, the way the signal is decomposed (asymmetric referenced as DWT and symmetric referenced as WPT) and the way of the analytic signal approximation (via FFT or FIR), all are important characteristics and have a major impact on identification and measurement of harmonic components and parameter algorithms.

3) *Harmonic estimation Kalman filter based*

The output of the Kalman filter is employed for tracking harmonics. It is worth to mention that the Kalman filter algorithm requires that the frequencies of harmonics (implicit the number of harmonics) and the measurement and model noise variance should be fully specified and fixed in advance (before the Kalman filter algorithm starts). Under such settings the accuracy, stability, convergence are just few aspects that need to be addressed. The Kalman estimator is obtained by using the Matlab function *kalman.m* given the discrete-time model and the variance data. Type (4) is used as load.

First, the impact of the modelling and measurement noise over the accuracy of the estimation are studied. In the application considered, several harmonics are estimated: all uneven up to the 7th harmonic. The variance of measurement noise is set to σ_r^2=0.2. Fig. 3 shows the estimated magnitudes of the fundamental and odd harmonics in time. The left column gives the measurement results when a small model noise variance σ_q^2=0.0001 is used, while the right column provides the results for a larger value σ_q^2=0.1.

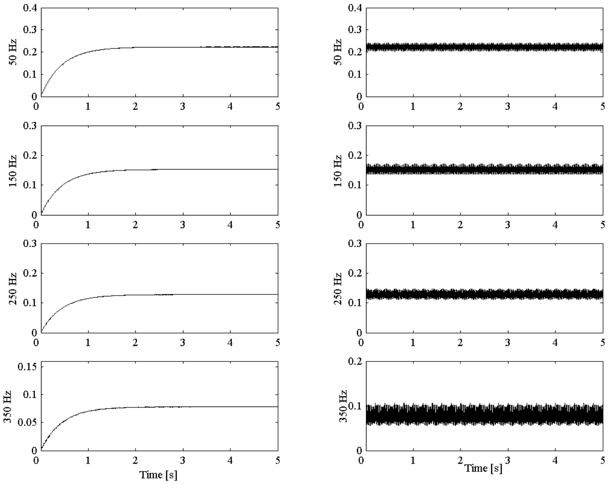

Fig. 3: Estimated harmonic amplitude using Kalman filter with measurement noise variance set to σ_r^2=0.2 and 2K=8 state-variables (1st, 3rd, 5th, and 7th harmonics considered). (left) Model noise variance σ_q^2=0.0001. (right) Model noise variance σ_q^2=0.1.

As seen, for small model noise variance (left side), the estimated harmonic magnitudes exhibit small fluctuations. However, this implies that the algorithm takes longer to converge, which for the case is not considered a problem.

Another aspect that needs to be considered is related to the Kalman filter order (or, the number of harmonics considered to be estimated). The noise parameters are set σ_r^2=0.1 and σ_q^2=0.0001 in order to ensure high accuracy.

Fig. 4 (top) shows the estimated magnitude of the current fundamental when the Kalman model only describes the fundamental frequency component (2K=2 state-variables). As seen the estimation performs not as good and the fundamental magnitude fluctuates in time.

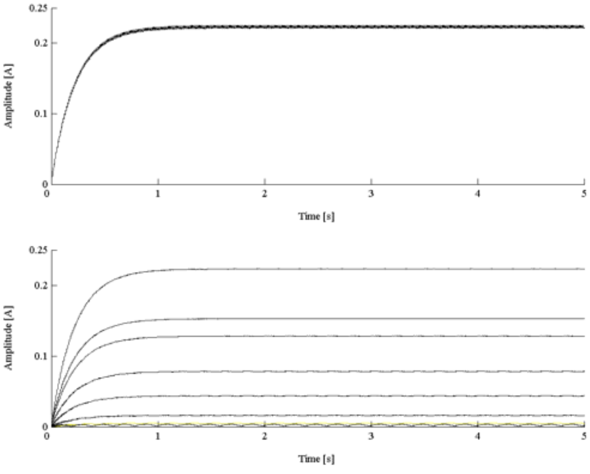

Fig. 4: Estimated harmonic amplitude using Kalman filter with the measurement noise variance σ_r^2=0.1 and the model noise variance σ_q^2=0.0001. Only the fundamental (2K=2) is estimated (top). The fundamental and the first 7 odd harmonics (2K=16 state-variables) are estimated (bottom).

In contrast, Fig. 4 (bottom) illustrates the estimated magnitude of the current fundamental when a higher order model is used (by adding the first seven odd harmonics (from 3rd to 15th) to the fundamental), implying 2K=16 state-variables. When plotting the response of the Kalman model, the improvement of the tracking performance is clearly visible. Even if only the estimate of the fundamental component is required, it is essential to estimate the most important harmonic components as well, improving the component tracking greatly.

On the other hand, by increasing the order of the filter, an increase in computational demand occurs too. The computational cost of estimating these harmonic components includes the addition of two states per harmonic (and one state for the dc component). By monitoring, the following results are obtained (Table IX).

As expected, the higher order Kalman filter model ($\text{Kalman}_{2K=16}$) requires the longest and highest computational effort, but it does not prevent the algorithm to run in real–time. Moreover, the tracking accuracy is superior, enhancing the method as a good candidate.

TABLE IX: COMPUTATIONAL COMPLEXITY BY MEANS OF CPU USE AND STS PROCESSING STATISTIC USING KALMAN FILTER FOR HARMONIC ESTIMATION

Method	Computational effort (STS [ms] /CPU [%])
$\text{Kalman}_{2K=2}$	0.49 / 13
$\text{Kalman}_{2K=8}$	0.55 / 30.7
$\text{Kalman}_{2K=16}$	0.68 / 73.6

It can be concluded that by using a Kalman filter the harmonic estimations are fairly accurate. However, if the parameters are not careful selected (state and measurement equations, and noise variance), the performance of Kalman filter can be poor, leading to large estimation errors.

4) Comparison overview

Based on the results presented above, a comparison of harmonic estimation measurement results based on all three techniques is given:

- FFT–a number of 128 samples per window with the calculation of the harmonic content every grid cycle (50 Hz) is set. The method is referenced to as '$\text{FFT}_{N=128}$'.
- WPT–applied to the analytic representation of measured signal (current), with AS approximation via FFT. A 5-level symmetric structure and the Daubechies with 40 coefficients (Db_{40}) wavelet function are chosen.
- Kalman filter–a model with 16–state variables and with the measurement noise variance set to σ_r^2=0.5 and the model noise variance set to σ_q^2=0.0001.

For practical reasons, the only first 7 odd harmonics (3, …, 15) are estimated and taken into account for the calculations of the harmonic parameters (e.g. THD). A load type (2) is used.

The on-line calculated values obtained using the above mentioned techniques are compared in Table X.

TABLE X: COMPARISON OF HARMONIC MEASUREMENT RESULTS USING FFT, AS (FFT)-WPT AND KALMAN FILTER

Method	Current		
	$I_{rms}^{(*)}$ [A]	$I_1^{(*)}$ [A]	$THD_{Is}^{(*)}$ [%]
$FFT_{N=128}$	2.595	2.530	23.10
AS(FFT)-WPT_{Db40}	2.597	2.533	22.76
$Kalman_{2K=30}$	2.594	2.531	22.52

(*)The on-line calculated values are compared to data obtained with a PM6000 Universal Power Analyser (2.603 A, 2.53 A and 23.3% respectively).

Figures 5 and 6 illustrate the corresponding spectrum and the THD values obtained by applying again those three measurement sources. The results show that the differences between the three estimates are minor.

Regarding the computational complexity of the methods used in the comparison, the FFT and Kalman filter method needs less time, whereas the Wavelet based the longest. On the other hand, higher computational effort (CPU load) is needed by Kalman filter method.

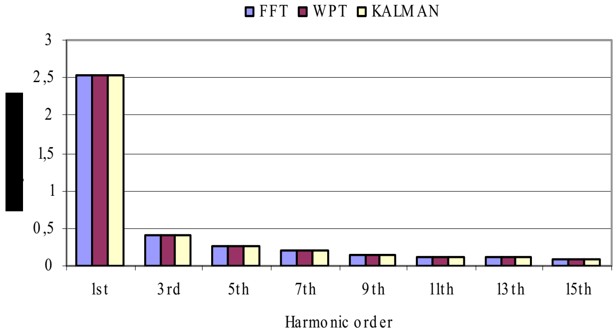

Fig. 5: Harmonic amplitude estimation by using FFT, AS (FFT)-WPT and Kalman filter techniques.

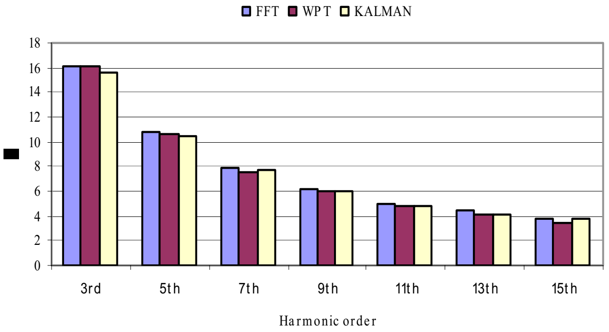

Fig. 6: Harmonic spectrum estimation by using FFT, AS(FFT)-WPT and Kalman filter techniques (base value=the fundamental).

Note that each method has its own characteristic parameters, needed to be assessed very carefully. A good choice verifies the above methods as suitable for the harmonic analysis.

V. CONCLUSIONS

Harmonic analysis is the main issue addressed in this paper. Different methods applied for quantifying waveform distortion are implemented and tested. Most studies obtain the harmonic content of a signal from a discrete Fourier transform (DFT) and related techniques (e.g. FFT, STFT), where a block of data (an integer number of cycles of the power-system frequency) is required for each estimate. Besides the DFT two other alternatives (Wavelet transform of analytic signals and Kalman filter) have been considered to estimate the spectral content of voltage and current signals.

The results show that the new algorithm (based on DWT or WPT) can separate harmonic components in the power system and compute the rms values of each harmonic. However, leakage occurs at some frequency bands, especially when DWT is used. In addition, the method can also be used in association with other power quality issues [15] and can form a basis for power definitions [16].

Kalman filters, the last method introduced for the harmonic estimation requires the frequencies of harmonics and noise variance to be pre-specified and fixed in advance, clearly being a drawback. However, by using a Kalman filter, the harmonic estimations are fairly accurate.

Generally, the experimental measurements demonstrate that, by selecting the right parameters the proposed techniques are suitable for the harmonic analysis under various operating conditions and their computational burden do not prevent them to run in real–time on a DSP based system.

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