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A NEW METHOD FOR ESTIMATION OF MULTI-HARMONIC POWER SIGNAL PARAMETERS
NOVA METODA ZA ESTIMACIJU PARAMETARA SLOŽENO-HARMONIJSKOG ENERGETSKOG SIGNALA

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ABSTRACT

A systematic analytical procedure for simultaneous estimation of the fundamental frequency, the amplitudes and phases of harmonic waves was proposed in this paper, which enabled fast and precise estimation with a small numerical error. Individual sinusoidal components have been extracted from the input complex-harmonic signal with finite-impulse response (FIR) comb filters. The proposed algorithm is based on the application of partial derivate of the processed and filtered input signal, after which it is performed weighted estimation procedure to better estimate the size of the values of the fundamental frequency, amplitude and the multi-sinusoid signal phase. The designed algorithm can be used in the signal reconstruction and estimation procedures, spectral processing, in procedures for the identification of the system that is observed, as well as other important signal processing areas. Through the simulation check, the effectiveness of the proposed algorithm was assessed, which confirmed its high performance.

Keywords: *complex-harmonic signal, nominal frequency, Fourier coefficient estimation, signal parameters estimation, finite-impulse-response (FIR) comb filter.*

REZIME

U radu je predložena potpuno nova procedura za esimaciju kako frekvencije, tako i amplitude i faze harmonijskih komponenti energetskog signala koji je predmet procesiranja, kroz sistematski i analitički pristup. Postignuto je smanjenje kompleksnosti u procesiranju kroz potpuno nove svedene analitičke izraze, čime se omogućuje brza estimacija uz malu numeričku grešku. Ulazni naponski/strujni signal se kondicionira preko filtra koji potiskuje eventualno prisutne komponente koje su posledica spektralnog curenja (anti-aliasing filter) i dodaje mu se šumna (dithering) komponeta. Tako obrađen signal se uvodi u jedinicu za analogno-digitalnu konverziju koja se realizuje sa frekvencijom odmeravanja koja je višestruko veća od frekvencije definisane Nikvistovim kriterijumom (oversampling). Pojedinačne sinusne komponente su izdvojene uz upotrebu filtara sa konačnim impulsnim odzivom (FIR). Nakon ovako izvršene separacije pojedinačnih komponenti iz ulaznog složeno-harmonijskog signal, koji je opisan Furijeovim redom konačne dužine, prema predloženom konceptu obrade vrši se parcijalna derivacija procesiranih sinusnih komponenti. Posebno dizajniranim blokovima za diferenciranje realizuje se određivanje prvog i drugog izvoda svake od harmonijskih komponenti, u potpuno proizvoljnim vremenskim trenucima, čime se u potpunosti prati dinamika prostoperiodičnih komponenti ulaznog energetskog signala. Dodatnom estimacionom procedurom, zasnovanom na težinskim koeficijentima, a u cilju smanjenja neminovno prisutne greške u lancu obrade, realizuje se obračun frekvencije, amplitude i faze komponenti složeno-harmonijskog signala. Predloženi algoritam se može upotrebiti u procesu signalne rekonstrukcije, estimacije spektra, sistemskoj identifikaciji, kao i u drugim bitnim problemima vezanim za procesiranje signala. Rezultati simulacije su potvrdili efektivnost predloženog algoritma, kao i mogućnost njegove primene u on-line preračunavanjima.

Ključne reči: *frekvencijski ograničen signal, noseća frekvencija i estimacija Furijeovih koeficijenata, signalna rekonstrukcija, filter sa konačnim impulsnim odzivom-(FIR) filter*

INTRODUCTION

The mass application of electronics and systems based on the usage of semiconductors in the last few decades has led to an increase in the number of nonlinear loads in the power network *(Alhaj et al., 2013)*. Such loads lead to the appearance of distortion in the waveform as well as voltage and currents in the power supply system. For this reason, we can no longer talk about a pure sinusoidal, but about the function resulting in a combination of fundamental and higher harmonic components, which are the integer multiples of the fundamental harmonic. More (higher) harmonics become a source of many problems in the power system that reduces the efficiency of the system itself, its reliability and economy *(Alhaj et al., 2013; Petrovic, 2012a)*. In addition, eddy currents are inherent to higher harmonics, which increases losses that result in corona, skin effects, as the consequence that electrical parameters themselves directly depend on the value of the present frequency component. Higher harmonics also lead to overheating, frequent fuse blow, capacitors break-down, excess values of the neutral current, measuring inaccuracies, disrupting the function of the protective relays and inducing interference in the communications crossing switches, excess of neutral current, inaccuracy, disordering protection relays and induces interference in communication *(Arrillaga and Watson, 2003; Petrovic, 2012a)*.

According to the above issues, accurate harmonic estimation is crucial in order to eliminate the harmful effects of unwanted harmonic components, and thus reduce unwanted losses, while enabling the delivery of power of satisfactory quality. Several different techniques for estimating harmonic components that exist in a processed energy signal have been described in the literature. Fast Fourier transform (FFT) is generally the most commonly used and proposed technique for this purpose; however, FFT has several disadvantages and limitations that result from spectral leakage and picket fence and aliasing effects *(Chang et al., 2000)*. In order to overcome these shortcomings in the current application of the FFT algorithm, many other algorithms have been proposed over the last two decades that are generally divided into two major groups: parametric and nonparametric *(Alhaj et al., 2013; Jain et al., 2011).* Nonparametric algorithms include the application of adequate wavelet transformation, Hilbert-Huang transformation, Chirp z-transformation and FFT. Parametric algorithms refer to procedures that use the Kalman filter, ANN and Adaline algorithm. As modern energy systems become more complex, with increasing process dynamics and very noisy, rapid monitoring and evaluation of harmonic components in this environment becomes more than a challenging task. The parametric and recursive algorithm should be able to cope with the system in the existence of a strong noise signal. The papers *(Macias and Exposito, 2006; Chen et al., 2010)* propose a model for estimating harmonic components based on the Kalman filter (KF) which allows monitoring of time-varying parameters depending on the value of the present noise, without prior knowledge of the characteristics of the process and noise, thus giving great importance to modelling state variables *(Jain et al., 2011).* Artificial neural networks-ANNs, such as BPN and RBFNN, have also been proposed in *(Wu et al., 2008; Chang et al., 2010).* However, apart from the large amount of data they require in their realization, and also in order to perform the training of the network itself, due to the dynamics of the signal in the power system and the very time-varying characteristics of present non-linear loads. All of this makes it difficult to condition layer structures in real time *(Jain et al., 2011; Chang et al., 2010).* A linear adaptive neural network- Adaline is firstly proposed in *(Sarkar et al., 2011).* This is a simple type of neural network with fast convergence that can be used for online monitoring of time-varying harmonic components but is sensitive to the presence of harmonics that are not included in the Adaline model *(Jain et al., 2011).*

Algorithms that are structurally recursive Newton-type algorithms have been proposed in *(Terzija 2003, Dash and Hasan, 2011; Petrovic and Rozgic, 2018),* starting from the assumption that the assumed carrier signal frequency is an unknown parameter, enabling the simultaneous estimation of the spectrum and frequency of the power signal. In this way, it is possible to overcome the problem of sensitivity of the estimation algorithms to frequency variation. The signal model used by these algorithms is nonlinear, so a nonlinear estimation is performed, and the algorithms are of a recursive type. In practical applications, sequential tuning must be performed with the forgetting factor, which leads to much better convergence and increases the accuracy of the algorithm.

If there is no synchronization between the generator and the acquisition device, then the design of FIR filters with optimized frequency responses, which do not require synchronization, is performed using the least squares (LS) technique *(Sidhu, 1999; Petrovic, 2012a).* In this way, the computational load is higher than in the situation when synchronization is achieved. The LS design method for high-order filters requires a significant amount of calculation that may not be completed within the available time equal to the duration of one sampling period. Therefore, these filters cannot be effectively adapted to the network in a situation where the carrier frequency varies. In order to reduce the requirements for the necessary recalculations, the appropriate tabulation of the weights can be applied.

In the proposed paper, a new method for simultaneous estimation of the amplitude, frequency and phase of a processed complex-harmonic power signal is presented. For the realization of the proposed algorithm, only the value of the samples of the processed signal and the values of the first and second derivatives of that same sample value are needed. The system by which such processing can be realized requires an analog-to-digital conversion unit with a dithering process, a finite-impulse-response (FIR) comb filter and a higher-order FIR digital differentiator followed by a decimator. The proposed method can be applied in the case when the fundamental frequency signal (input signal) has a range limited to the bandwidth of the first harmonic component. Unlike the existing algorithms for parameter estimation, the algorithm proposed here can perform signal parameter estimation at the same time, assuming that the frequency changes over time. The simulation results confirm the efficiency of the proposed algorithm. The described method can be applied in precise measurements of important electrical quantities such as RMS measurements of periodic signals, power and energy *(Petrovic, 2012a).*

Unlike the IEEE standard that was analysed in *(Arpaiaet al., 2001),* the algorithm proposed in this paper is significantly more stable and free of the propagation error. Namely, when using the procedure prescribed by the standard, the amplitude errors of the fundamental will propagate through the method since the amplitudes are used to reconstruct the detected sine wave and obtain the results before they are used to determine the next harmonic parameters. Overall, the frequency and amplitude errors from the first calculation are propagated to the higher harmonics and the calculation of the nth harmonic will invariably be contaminated by the errors of the phases and amplitudes from previous steps.

MATERIAL AND METHOD

Starting from the assumption that the input signal that is the subject of processing according to the proposed algorithm, is spectrally limited to the first M harmonic components and possesses a basic harmonic component of frequency f. Such a signal can be represented as the sum of Fourier components *(Petrovic, 2012a)*:

$$x(t) = \sum_{k=1}^{M} X_k \sin(k\omega t + \phi_k) \tag{1}$$

where $\omega=2\pi f$ represents the angular frequency in radians per second, X_k is the amplitude value of the *k*th harmonic, φ_k, is the phase angle of the *k*th harmonic in radians, M is the number of harmonic components in the input signal, and t is time in seconds.

In order to extract a single sinusoidal signal, the frequency response of the filter must have zeros at the frequencies of the harmonics that are expected to be present in the processed signal and a unit gain at the fundamental frequency. If the frequency is not constant, then the filter parameters must be adjusted online during the process of the frequency estimation. In order to ensure satisfactory measurement, it is necessary to monitor the frequency of the system and apply certain corrections to the measurement algorithms and input filters. The block diagram of the adaptive algorithm that applies FIR comb filters is given in Fig.1 *(Petrovic, 2012a).*

The FIR comb filters *(Kusljevic, 2008; Petrovic, 2012a)* consist of second-order modules that eliminate dc component and harmonic frequencies and have unity gain at the fundamental frequency. The complete filter is realized as a cascade of all these modules. The second-order section that rejects the dc component and the frequency fS/2 (fS is the sampling frequency) and has a unity gain at the frequency of the kth harmonics fk=kf1 is given by the following transfer function:

$$H_{0k}(z) = \frac{1 - z^{-2}}{\left|1 - z_k^{-2}\right|} \tag{2}$$

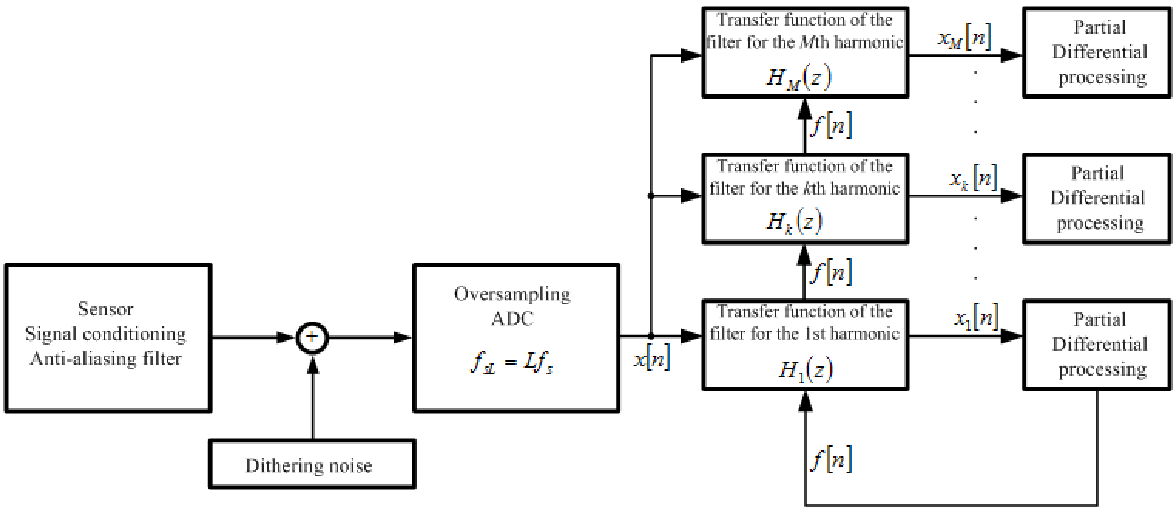


Fig. 1. Block diagram of the estimation algorithm with FIR comb filters.

where $\left|1-z_k^{-2}\right| = 2\sin(k\omega_1 T), z^{-1} = e^{-j\omega}, \omega = 2\pi f / \omega_S,$, $z_1^{-1} = e^{-j\omega_1}, \omega_1 = 2\pi f_1 / \omega_S$, f_1 is the fundamental frequency (ω_S is the sampling frequency), and $z_k^{-1} = e^{-jk\omega_1}$.

The section that rejects the harmonics $\omega_i = i\omega_1$, and has unity gain at frequency $\omega_k = k\omega_1$ is shown as:

$$H_{ik}(z) = \frac{1-2\cos(\omega_i T)z^{-1} + z^{-2}}{\left|1-2\cos(\omega_i T)z_k^{-1} + z_k^{-2}\right|} \tag{3}$$

where the gain $\left|1-2\cos(\omega_i T)z_k^{-1} + z_k^{-2}\right| = 2\left|\cos(k\omega_1 T) - \cos(i\omega_1 T)\right|$, $i = 1,2,3,...,M, i \neq k$, is used to adjust the gain for the *k*th harmonic. $M = [f_S / 2f_1]$ is the maximum integer part of $f_S/2f_1$, which is equal to the number of sections in the cascade. The transfer function of the filter for the *k*th harmonic is given as *(Petrovic, 2012a)*:

$$H_k(z) = H_{0k}(z)\prod_{\substack{i=1\\ i\neq k}}^{M} H_{ik}(z) \tag{4}$$

If the transfer function is determined with (4), then it practically applications uncontrolled phase shift on the basic frequency is appear. As some applications we need to provide an additional phase shift from $\pi/2$ (for example, in measuring the reactive power), this can be achieved using the adaptive phase shifter *(Kusljevic, 2008, Petrovic, 2012a)*. The estimation algorithm that is proposed is very simple because it uses closed-form solutions for calculating filter coefficients. The number of sections in the cascade realization and the length of the data window can be changed during the measurement depending on the frequency changes.

The filters (4) have nonunity gains at frequencies that differ from the nominal power system frequency, and for this reason, during the estimation process, we must perform adaption of their responses. This DFT modification with the FIR filter gives suppression of all signal harmonics, which causes the leakage effect, but because the FIR filter is adaptive, its coefficients depend on the estimation of the actual frequency. The accuracy of such an algorithm depends on the accuracy of frequency estimation.

Estimation of the frequency of the complex-harmonic signal, using the finite number of noisy samples-results of discrete measurements, is an important task of both theoretical and practical aspects. This problem was the focus of research in the long period of time, and it was currently actual *(Wu and Wang, 2005; So et al., 2005; Klein, 2006; El-Shafey and Mansour, 2006; Trapero et al., 2007)* since it is used in a wide range of applications in many fields such as control theory, relaying protection, intelligent instrumentation of power systems, signal processing, digital communications, distribution automation, biomedical engineering, radar applications, radio frequency, instrumentation and measurement. We will list some of the well-known procedures for this issue: adaptive notch filter, time frequency representation based method, phase locked loop based method, eigensubspace tracking estimation, extended Kalman filter frequency estimation. Requirements set in front of the frequency estimator, which directly affects and the solution vary, but typical issues are accuracy, processing speed or complexity and ability to handle multiple signals.

By differentiating the *k*th harmonic component of the signal (1) after filtering (Fig. 1), we obtain the following functional relations *(Petrovic, 2012a)*:

$$\frac{d(x_k(t))}{dt} = \frac{d(X_k \sin(k\omega t + \phi_k))}{dt}\Big|_{t=t_n} = y_{1k}(t_n) = y_{1k}[n] \Rightarrow$$
$$y_{1k}(t_n) = k\omega X_k \cos(k\omega t_n + \phi_k) \tag{5}$$

$$\frac{d^2(x_k(t))}{dt^2} = \frac{d^2(X_k \sin(k\omega t + \phi_k))}{dt^2}\Big|_{t=t_n} = y_{2k}(t_n) = y_{2k}[n] \Rightarrow$$
$$y_{2k}(t_n) = -k^2\omega^2 X_k \sin(k\omega t_n + \phi_k) \tag{6}$$

where t_n is the completely arbitrary (irregularly spaced samples) time moment in which the differentiation is done. Fig. 2 shows the configuration (scheme) which is provided a determination of the first and second-order derivate in an oversampling system.

Based on the obtained differential values-samples, the signal parameters can be determined as:

$$f_k(t_n) = kf(t_n) = \frac{1}{2\pi}\sqrt{\left|\frac{y_{2k}(t_n)}{x_k(t_n)}\right|}$$
$$\phi_k(t_n) = \text{arctg}\left(\frac{x_k(t_n)}{y_{1k}(t_n)} 2k\pi f(t_n)\right) - 2k\pi f(t_n) t_n \quad (7)$$
$$X_k(t_n) = \frac{x_k(t_n)}{\sin(2k\pi f(t_n) t_n + \phi_k(t_n))}$$

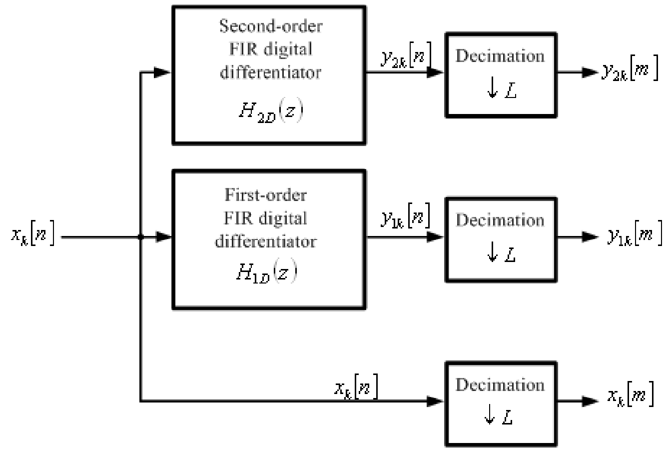


Fig. 2. A proposed system for signal reconstruction based on first and second-order differentiators in the oversampling system

A sensor shown in Fig. 1 picks the signal who is the subject of processing, conditioning its value via conditioning circuit (amplifier) and band-limited anti-aliasing filter. After that, the analog signal *x(t)* is added with dithering noise, so that the combined signal can be fed to an ADC unit at an oversampling rate of $F_{sL}=Lf_s$ Hz (samples/s), where f_s and *L* denote the minimum sampling rate (in accordance with Nyquist sampling rate) and the oversampling factor, respectively *(Petrovic, 2012a)*. Each digital sample $x_k[n]$ is encoded using N_q bits, while the first and second-order derivates of the digitized signal are obtained using the first and second-order FIR digital differentiators, which have transfer functions designed as $H_{1D}(z)$ and $H_{2D}(z)$. The obtained first and second-order derivative $y_{1k}[n]$ and $y_{2k}[n]$ after decimation by a factor *L*, allow us to determine the desired first and second-order derivate signals $y_{1k}[m]$ and $y_{1k}[m]$ at the Nyquist rate of f_s Hz. The digital differentiator on the oversampling rate reshapes the spectrum of quantization noise, resulting in its being pushed toward the high-frequency range and filtered at the same time. In accordance with this, we can expect an improvement of signal-to-quantization-noise ratio (SQNR) for the estimated derivative signal after decimation *(Petrovic, 2012a)*.

Since the anti-aliasing filter (Fig. 1) possess bandwidth of $f_s/2$ Hz, and how added the dithering noise raises the average spectral noise floor of the original processed signal, this process forces the quantized error to lose its coherence with the input signal so that the spectrum of the quantization noise becomes white and flat *(Petrovic, 2012a)*. This is exactly the reason why we use the oversampling technique can effectively compensate degraded SQNR and continue to improve the SQNR by increasing the sampling rate. The typical amount of random wideband dithering noise usually has a root-mean-square (RMS) level equivalent to 1/3- to 1-least significant bit (LSB) voltage level. An ideal frequency response of the *k*th-order differentiator $H_{kD}(z)$ is designated as *(Petrovic, 2012a)*:

$$H_{kD}\left(e^{j\omega_c}\right) = \begin{cases} 0, & for \quad -\pi \le \omega_c < -\omega_{\max} \\ \left(j\omega_c / \omega_{\max}\right)^k & for \quad -\omega_{\max} \le \omega_c \le \omega_{\max} \\ 0, & for \quad \omega_{\max} < \omega_c \le \pi \end{cases} \quad (8)$$

where $\omega_c = 2\pi f / f_{sL}$ is the continuous frequency of the digital signal in radians, while $\omega_{max} = 2\pi(f_s/2)/f_{sL} = \pi/L$ is the maximum normalized digital frequency of the sensor signal in radians. In the oversampling system, $\omega_{max} << \pi$, and $H_{kD}(e^{j\omega_c})$ is normalized to have a unit gain at ω_{max}. The effective method for designing a FIR digital differentiator using the Fourier transform design, properties of FIR differentiator coefficient is proposed in *(Tan and Wang, 2011; Petrovic, 2012a)*.

Aware of the fact that in process of the determination of the samples $x_k(t_n)$, $y_{1k}(t_n)$, and $y_{2k}(t_n)$ exists the error in the practical applications, we must conduct the best estimation of the given values in accordance with the criterion assumed. One of the well-known ways to realize such an estimation procedure is to recalculate the values $x_k(t_n)$, $y_{1k}(t_n)$, and $y_{2k}(t_n)$, through *N* arbitrary passages, forming series $x_k(t_n)_i$, $y_{1k}(t_n)_i$, and $y_{2k}(t_n)_i$ (i=1,...,N, k=1,2,…,M). In such an organized procedure, it takes that samples $x_k(t_n)$, $y_{1k}(t_n)$, and $y_{2k}(t_n)$ taken at the same points in time during the detected period of the processed signal. Also are assumed that the random errors Δ_n of measurements are unbiased and not mutually correlated, $E(\Delta_i)=0$ and have the same variance $\text{var}(\Delta_i)=\sigma^2$. In this situation, it is possible to use the weighted average procedure for decreasing random errors in the determination of observed values. The averages $\hat{x}_k(t_n), \hat{y}_{1k}(t_n), \hat{y}_{2k}(t_n)$ of the values $x_k(t_n)$, $y_{1k}(t_n)$, and $y_{2k}(t_n)$ are calculated as *(Petrovic, 2012a)*:

$$\hat{x}_k(t_n) = \frac{\sum_{i=1}^{n_{x_k}} w_{xi} x_k(t_n)_i}{\sum_{i=1}^{n_x} w_{x_k i}}$$
$$\hat{y}_{jk}(t_n) = \frac{\sum_{n=1}^{n_{y_{jk}}} w_{y_{kj}i} y_{jk}(t_n)}{\sum_{i=1}^{n_{yj}} w_{y_{jk}i}}; \; j=1,2 \quad (9)$$
$$\sum_{i=1}^{n_{x_k}} w_{x_k i} = \sum_{i=1}^{n_{y_{1k}}} w_{y_{k1}i} = \sum_{i=1}^{n_{y_{2k}}} w_{y_{2k}i} = N$$

where $w_{x_k i}, w_{y_{1k}i}, w_{y_{2k}i}$ are non-negative weights of series $x_k(t_n)$, $y_{1k}(t_n)$, *and* $y_{2k}(t_n)$. The $n_{x_k}, n_{y_{1k}}, n_{y_{2k}}$ defines the numbers of different values in the above series through *N* passages. The number of passages *N* in a practical application of the proposed algorithm depends on the required processing speed - larger *N* allows a more precise estimation of the signal parameters. The estimation of the value of samples $\hat{x}_k(t_n), \hat{y}_{1k}(t_n), \hat{y}_{2k}(t_n)$ it is necessary to perform the re-calculation of the unknown amplitudes and phases, for all harmonic components of the limited periodical signal, was evaluated by the process of measures. Based on such certain values of Fourier coefficients, it is possible to calculate the effective signal value, active power and energy. After the calculations are conducted, we can restart the sampling of the input signal.

RESULTS AND DISCUSSION

The proposed algorithm was tested by simulation in the MATLAB program package. The first and second derivation of a complex input signal was performed with an 8-bit ADC resolution and an oversampling factor *L* of 256. The dithering noise of $\sigma_d = (1/3)\mathrm{LSB}$ is added to the processed signal before oversampling. In this way, a multi-sinusoidal input signal was oversampled with 4096*L* samples.

First, the processed modulated sinusoid test signal was processed (a change of steps of 50 to 49.8 Hz on T = 0.06 s). The sinusoid signal was added white noise with SNR = 60 dB. The test was developed with a distorted source voltage (10% of third, 5% five, 3% of the seventh and 2% of the eleventh harmonious). The phase corners of each accordion are randomly selected. The results obtained confirm a good dynamic response to the change algorithms and frequency accuracy. The proposed algorithm is capable of adjusting the time variations of the electrical signal characteristics over time. It was noted that except for a short passage at the time of the step, the algorithm effectively follows variations in the frequency. As shown in Figure 3, we received a technique that provides a precise frequency assessment by an error in the range of 0.001 Hz.

The first test was conducted in the way that an input-frequency modulated sinusoidal test signal (step frequency change from 50 to 49.8 Hz at t=0.06 s) was processed, while a white noise with SNR=60 dB is super pointed on it. The distorted source voltage with the presence of 10% third, 5% fifth, 3% seventh and 2% eleventh harmonics was used during the simulation, while the phase angles are randomly chosen. The obtained results confirm a good dynamic response of the proposed algorithm in such an environment, and it is capable of adaptively tracking time variations of the characteristics of the power signal over time. It is observed that apart from a brief transient at the time of the step change, the algorithm effectively follows the variations in frequency, Fig. 3-algorithm provides accurate frequency estimation with an error lower than 0.001 Hz.

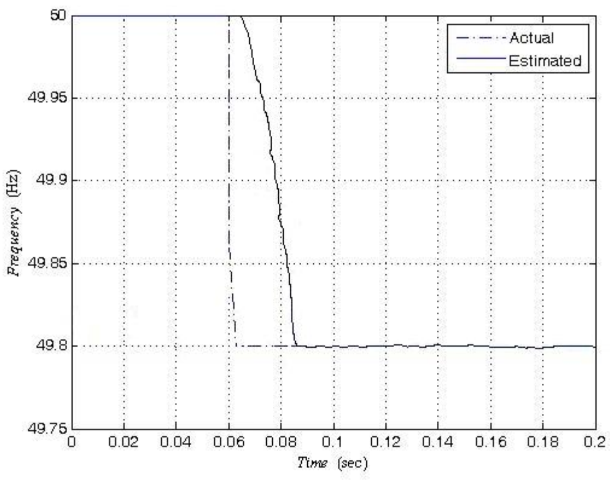


Fig. 3. Estimation for f=50 Hz for t<0.06 s and f=49.8 Hz for t>0.06 s with SNR=60 dB and with harmonics presence.

The ability of the frequency estimation over a wide range of frequency changes is investigated using sinusoidal test signals with the following time dependence $f(t) = 50 + 0.5\sin(10\pi t)$ as shown in Fig. 4. Good dynamic responses can be noticed. Considering the case simulates extreme conditions in a power system, the error can be accepted by most applications.

In order to examine the possibility of frequency estimation in a wide range of frequency changes, sinusoidal test signals with time dependence $f(t) = 50 + 0.5\sin(10\pi t)$ as shown in Fig. 4 was used. It can be stated that the proposed procedure has satisfactory dynamic responses, especially for the reasons that in this way we simulated extreme conditions in the power supply system. Estimation is acceptable for most practical applications.

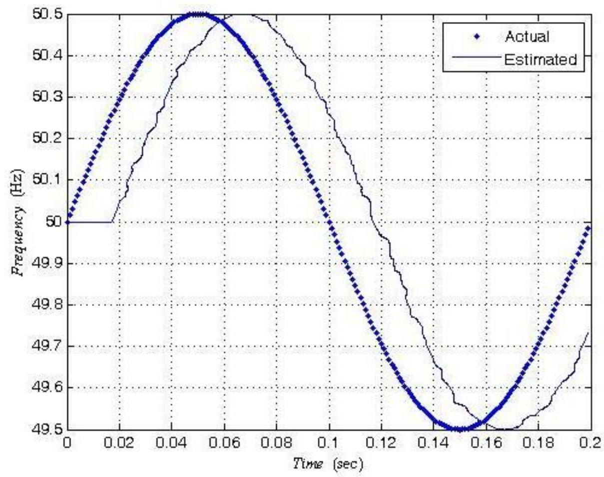


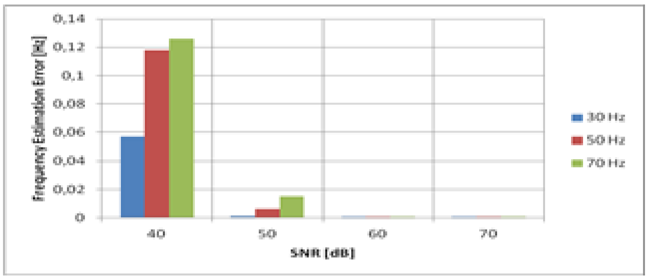
Fig. 4. Estimation for $f(t) = 50 + 0.5\sin(10\pi t)$ with SNR=60 dB with harmonics presence.

In order to achieve a better performance assessment of the proposed estimation algorithm, in the condition of the noisy processing, we added to the input signal an additive white noise of variable power. The random noise signal was used to obtain the prescribed value of the SNR, which is defined as SNR = $20\log\left(A/\sqrt{2}\sigma\right)$, where *A* is the magnitude of the signal fundamental harmonics, and σ is the noise standard deviation, Fig. 5 shows the maximum errors that are observed in the frequency and harmonious estimates when input signals of 30, 50, and 70 Hz having SNRs of 40, 50, 60, and 70 dB were used. It should be noted that, in practice, SNR on the power signal obtained from the power system is between 50 and 70 dB. It can be stated that in these noise levels, the proposed algorithm generates a very small error.

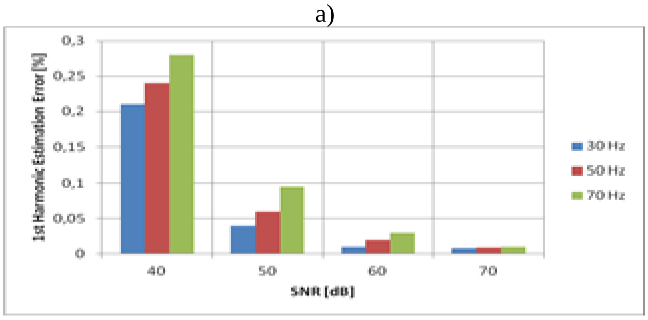
The statistical characteristics of the proposed estimator can be evaluated based on the samples generated in the simulation procedure, with the added noisy component. To assess the deterministic parameters, the most commonly used lower bound for the mean squared error (MSE) is the Cramer-Rao lower bound **(**CRLB), given by the inverse of the Fisher information *(Kay, 1988; Stoica et al., 2000; Belega et al. 2010)*. Fig. 6 shows MSE of the amplitudes after 10^5 simulations. The results clearly show that the proposed assessment scheme asymptotically reached the CRLB as in *(Belega et al. 2010; Pantazis et al., 2010; Petrovic and Damljanovic, 2017; Petrovic and Damljanovic, 2018)*.

The proposed algorithm was additionally tested using standard sigma-delta ADC with an effective resolution of 24 bit, and sampling rate f_S=1 kHz. The input signal with the fundamental frequency *f* = 50 Hz in process of the simulation was defined as:

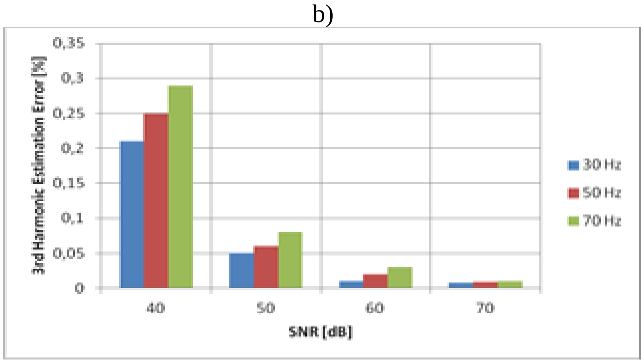
$$x(t) = 1\sin(2\pi ft + \pi) + 0.81\sin(4\pi ft + \pi/3) + 0.62\sin(6\pi ft)$$
$$+0.58\sin(8\pi ft + \pi/6) + 0.41\sin(10\pi ft + \pi/4)$$
$$+0.33\sin(12\pi ft + \pi/12) + 0.16\sin(14\pi ft) \quad (10)$$



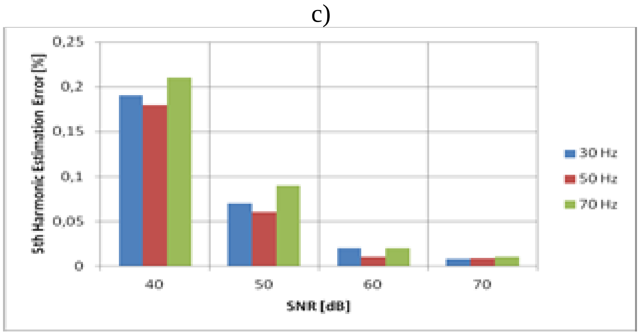
a)



b)



c)



d)

Fig. 5. Maximum estimations errors: a) frequency; b) 1st harmonic; c) 3rd harmonic; d) 5th harmonic

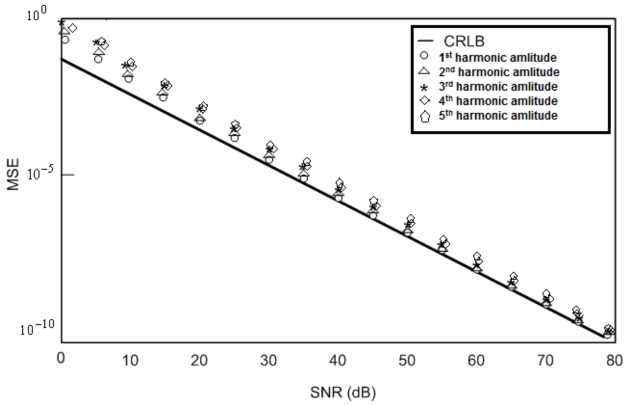


Fig. 6. MSE of the three harmonic amplitudes as a function of SNR.

The output PSD (Power Spectral Density) of the ideal thermal noise affected on the input signal defined in (10) possesses a clock jitter in the range of -100 to -170 dB. The signal-to-noise distortion ratio (SNDR) was ranged between 60 dB and 80 dB. The superposed noise and jitter will cause a relative error in the detection of the fundamental frequency of 0.01. In order to realize a comparison of such obtained simulation results, Figs. 7 and 8 show the maximum errors observed in harmonics magnitude and phase estimation for the signal defined in (10)) by the proposed reconstruction algorithm, FFT and continuous wavelet transformation (CWT) *(Tse and Lai, 2007)*. FFT was conducted with a sampling rate of 25kHz, data length equal to 25000, and in the time period of 1s.

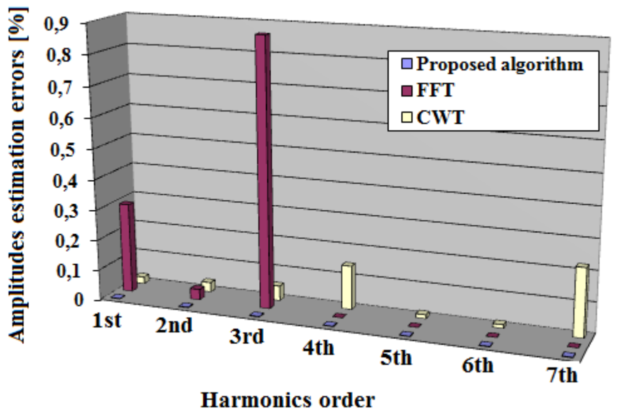


Fig. 7. Comparison of estimation errors observed in harmonics magnitude

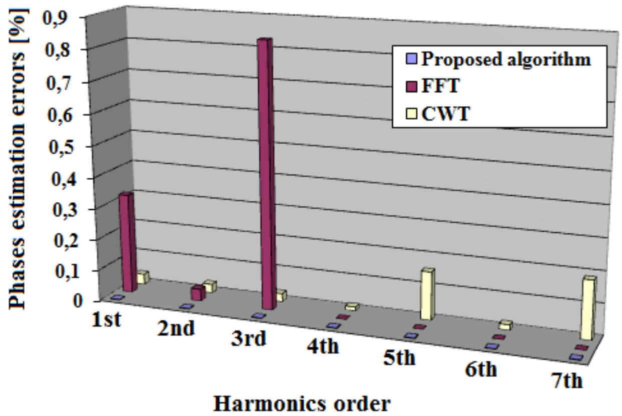


Fig. 8. Comparison of estimation errors observed in harmonics phase

In order to make clear the comparison among the different estimation procedures, Fig. 9 shows the power spectral density (PSD) of a 1s section of the processed signal (acquisition time), with parameters defined in (10). In order to minimize the leakage effect for FFT, the Hanning window has been applied.

The accuracy of the proposed algorithm is within the limits that are attained in processing a signal of form defined in (10), in *(Belega et al. 2010; Agrež, 2005; Petrovic and Stevanovic, 2011; Petrovic, 2015)*, and better than the one presented in *(Tse and Lai, 2007, Kuseljevic, 2010; Petrovic, 2012b; Petrovic, 2012c)*.

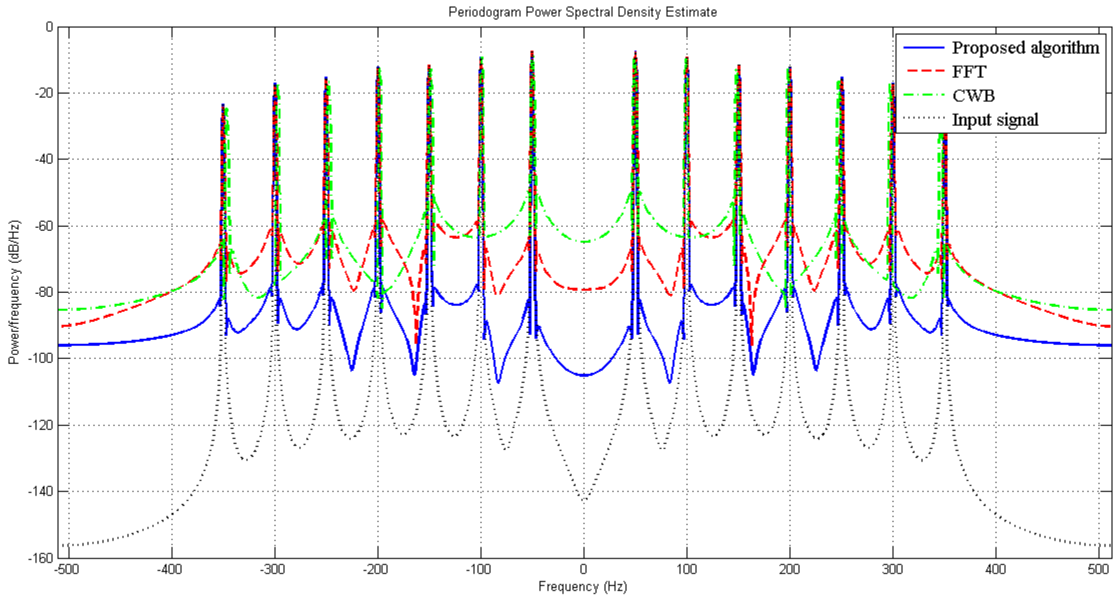


Fig. 9. Comparison among the different estimation techniques applied, with respect to PSD

CONCLUSION

The paper proposed and described a new procedure for the estimation of unknown parameters of the processed input multi-sinusoidal signal. Completely new and reduced analytical expressions are derived, which creates the possibility to perform calculations with a low numeric error. The proposed algorithm is able to simultaneously assess more parameters of signal-frequency, phases and amplitudes, assuming the time-varying frequency. Based on the identified parameters, we can determine all relevant values in the electric utilities (energy, power, RMS value). The measurement uncertainty is a function of the error in synchronization with fundamental frequency, due to no stationary nature of jitter-related noise, and white Gaussian noise, and an error that occurs in determining the value of samples. The simulation results show that the proposed algorithm can offer satisfactory precision in the estimation of periodic signals parameters in real power systems.

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