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A SIMPLE ALGORITHM FOR SIMULTANEOUS SINE SIGNAL PARAMETERS ESTIMATION

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This paper presents a new algorithm based on the use of partial derivatives of the processed signal and the weighted estimation procedure to estimate the fundamental frequency, the amplitude and the phase of sinusoidal signal. The proposed algorithm is able to estimate the signal parameters simultaneously, supposing the time-varying frequency. The simulation results verify the effectiveness of the proposed algorithm.

Keywords: parameters estimation, sine signal, partial differentiation, oversampling, finite-impulse response (FIR) digital differentiator

1 INTRODUCTION

Literature on electrical parameter measurement techniques for power system applications is both voluminous and generally accessible. The estimation of the parameters (*eg*, frequencies, magnitudes, and phases) of periodic signals buried in noise is important in many practical applications of signal processing, system identification and control system design. The magnitude estimation of a power system signal has been an important area of research for the past few decades, and the methods have almost been standardized for the signals with known frequencies. The electrical parameter measurement of a fixed-frequency signal is a straightforward task [1, 2]. However, if the frequency is not known a priori, accurate measuring of the amplitude and phase becomes a very difficult. Various numerical algorithms for power measurements are sensitive to frequency variations. Typical examples are algorithms based on fast Fourier transform (FFT) or the least-mean-square (LMS) technique and on the assumption that the system frequency is known in advance and constant (50 or 60 Hz) [3, 4].

In an electric power system, an increase or decrease in frequency occurs due to disturbances in the power system. Large blocks of load are connected or disconnected, or large sources of generation go offline. Frequency variations are much more likely to occur for the loads that are supplied by a generator isolated from the utility systems (islands). Any frequency deviation from the nominal value of 50 or 60 Hz can substantially degrade the performance of the measurement devices that operate based on assumption of constant frequency.

Spectrum estimation of discretely sampled processes is usually based on procedure employing the fast Fourier transform (FFT). The FFT is a computationally efficient algorithm for computing discrete Fourier transformation (DFT). However, although the FFT is quite efficient under fixed- frequency conditions, it does not offer very good performance unless the sampling frequency and the fundamental frequency of the signal are synchronized. It is well known that FFT loses its accuracy under desynchronization and nonstationary conditions, whereas the fundamental/harmonic frequency may vary over time. These errors appear due to the orthogonal finite-impulse-response (FIR) filters having different magnitude gains at frequencies other that the nominal power frequency [3] and because the frequencies of harmonics are equal to zero of the frequency response of the FIR filter whit rectangular window, which is used in the DFT algorithms. These performance limitations are particularly troublesome when analyzing short data records, which frequently occur in practice because many measured processes are brief.

To better satisfy the periodicity requirement of the FFT process, time-weighting functions, called windows and/or correction interpolation algorithms are used [4]. In this way, however, the error can only be reduced but not removed. If a window is not used, then the synchronization to the grid fundamental frequency is mandatory. Unfortunately, phase-locked loop (PLL), as a traditional synchronization method, has a rather long response time, particularly in the presence of the transient phenomena on the input signal, such as the power supply frequency variations or the phase jumps.

In addition to the disadvantages related to the synchronization of the sampling frequency with the frequency of the signal, the FFT has disadvantages caused by frame implementation. Thus, the FFT processes entire frames of data and cannot provide in-between data. If the calculation is done in a sliding mode, *ie* the FFT is repeatedly applied to a frame of N elements computing of the last N-1-shifted elements of the previous frame and a single new element, then FFT requires intensive computational effort, which complicates its integration in low-cost microcontrollers.

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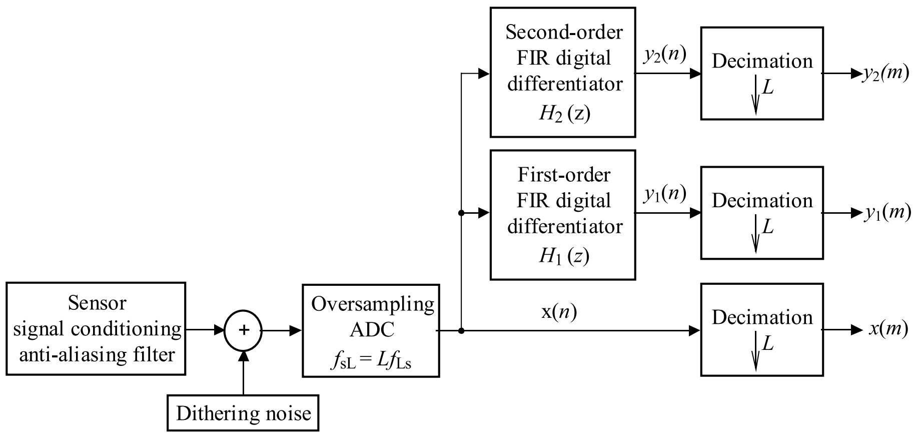

Fig. 1. Proposed system for signal reconstruction based on first and second-order differentiators in the over-sampling system

A Newton-type recursive numerical algorithm that also considers the system frequency as an unknown signal model parameter to be estimated has been proposed in [5]. It simultaneously estimates the frequency and spectra of the power system. This approach solves the problem of sensitivity to frequency variations. By the introduction of power frequency in the vector of unknown model parameters, the signal model becomes nonlinear, so strategies of nonlinear estimation are used. The recursive algorithm form is improved with a strategy of sequential tuning of the forgetting factor. By this, the proposed algorithm convergence and accuracy are significantly improved.

If the generator and the acquisition device are not synchronized, then the FIR filter with optimized frequency responses, which do not need synchronization, can be designed by the least-square (LS) technique [6]. In this case, the computational load is higher than in the synchronized case. The LS design method for large-order filters requires a considerable amount of computation that may not be completed within the available time that is one sampling interval. Thus, these filters cannot efficiently be online adapted during frequency deviations. If we want to avoid the burden of these calculations, than a proper tabulation of the weights can be applied.

In this paper, a simple new technique for simultaneous estimation of local system frequency and amplitude and phase with wide frequency variation range is presented. What are needed for a realization of the proposed algorithm are only the value of sample of processed signal and its first and second derivation values. The framework consists of an over sampling analog-to-digital conversion unit with a dithering process and a higher order finite-impulse response (FIR) digital differentiator followed by a decimator. Therefore, the derived algorithm is very simple and requires modest resources for implementation.

Unlike the IEEE standard that was analysed in [7], 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 harmonic will invariably be contaminated by the errors of the phases and amplitudes from previous steps.

2 SUGGESTED METHOD OF PROCESSING

Let us assume that the measured signal (arbitrary voltage or current) is profiteered to minimize and eliminate the impact of the noise and higher harmonic components. The following observation model should be used

$$x(t) = X\sin(\omega_i t + \phi_i) \tag{1}$$

where X is the magnitude of the processed signal. By differentiating the signal (1) we ge

$$\begin{aligned} &\frac{\mathrm{d}x(t)}{\mathrm{d}t}\Big|_{t=t_n} = \frac{\mathrm{d}X\sin(\omega_i t + \phi_i)}{\mathrm{d}t}\Big|_{t=t_n} = y_1(t_n) = y_1[n] \\ &\Rightarrow y_1(t_n) = \omega_i X\cos(\omega_i t_n + \phi_i)\,, \end{aligned} \tag{2}$$

$$\begin{aligned} &\frac{\mathrm{d}^2x(t)}{\mathrm{d}t^2}\Big|_{t=t_n} = \frac{\mathrm{d}^2X\sin(\omega_i t + \phi_i)}{\mathrm{d}t^2}\Big|_{t=t_n} = y_2(t_n) = y_2[n] \\ &\Rightarrow y_2(t_n) = -\omega_i^2 X\sin(\omega_i t_n + \phi_i)\,. \end{aligned} \tag{3}$$

Here, t_n is the time moment in which the differentiation of the input analogue signal is done, and it is completely arbitrary. Based on the obtained differential values-samples, the unknown signal parameters can be calculated as

$$\begin{aligned} f_i &= \frac{1}{2\pi}\sqrt{\left|\frac{y_2(t_n)}{x(t_l)}\right|}\,, \\ \phi_i &= \operatorname{arctg}\Big(\frac{x(t_n)}{y_1(t_n)}2\pi f_i\Big) - 2\pi f_i t_n\,, \\ X &= \frac{x(t_n)}{\sin(2\pi f_i t_n + \phi_i)}\,. \end{aligned} \tag{4}$$

Figure 1 shows a proposed scheme to obtain the first and second-order derivate in an oversampling system. As shown in Fig. 1, a sensor picks the signal of interest, which will be conditioned via a signal conditioning circuit (amplifier) and band limited by anti-aliasing filter. Then, the conditioned analog signal x(t) is added with dithering noise, so that the combined signal can be fed to an ADC unit at an over sampling rate of $f_{sL} = Lf_s$ Hz (samples/s), where f_s and L denote the minimum sampling rate (Nyquist sampling rate) and the over sampling factor, respectively. Each digital sample $x[n]$ is encoded using N_q bits. The first and second-order derivates of the digitized signal are then obtained using the first and second-order FIR digital differentiators at the over sampling rate [5], which have a transfer functions designed as $H_1(z)$ and $H_2(z)$. After decimating the obtained first and second-order derivative signals $y_1[n]$ and $y_2[n]$ by a factor L, we finally achieve the desired first and second-order derivate signals $y_1[m]$ and $y_2[m]$ at the Nyquist rate of f_s Hz. Since the impact of the digital differentiator on the over sampling rate reshapes the spectrum of quantization noise, eventually resulting in its being pushed toward the high-frequency range and filtered at the same time, we can expect an improvement of signal-to-quantization-noise ratio (SQNR) for the estimated derivative signal after decimation.

The anti-aliasing filter (Fig. 1) has a bandwidth of $f_s/2$ Hz. Although adding the dithering noise raises the average spectral noise floor of the original input signal, the dithering process forces the quantized error to lose its coherence with the original input signal so that the spectrum of the quantization noise becomes white and flat. Hence the over sampling technique can be applied effectively to compensate for the degraded SQNR and continue to improve the SQNR by further increasing the sampling rate. The typical amount of random wideband dithering noise, which can be provided by the noise diode or noise generator ICs 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 kth-order differentiator $H_k(z)$ is

$$H_k\left(e^{j\omega}\right)=\begin{cases} 0\,, & \text{for } -\pi \le \omega \le -\omega_{\max}\,, \\ (j\omega/\omega_{\max})^k & \text{for } -\omega_{\max} \le \omega \le \omega_{\max}\,, \\ 0 & \text{for } \omega_{\max} \le \omega \le \pi \end{cases} \tag{5}$$

where $\omega = 2\pi f/f_{sL}$ is the normalized digital frequency 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 over sampling system, $\omega_{\max} \ll \pi$, and $H_k\left(e^{j\omega}\right)$ is normalized to have a unit gain at $\omega_{\max}$. With the ideal frequency domain specification, the kth-order differentiator can be designed and implemented. The effective method for designing a FIR digital differentiator using the Fourier transform design is proposed in [8].

2.1 Recursion of FIR Differentiator Coefficients

Considering an ideal frequency response $H_k\left(e^{j\omega}\right)$ of the kth-order digital differentiator in (5), we can determine the noncausal FIR differentiator coefficients with the kth-order derivate as

$$h_k[n] = \frac{1}{2\pi}\int_{-\omega_{\max}}^{\omega_{\max}} H_k\left(e^{j\omega}\right)e^{jn\omega}\mathrm{d}\omega\,, \quad \text{for } -M \le n \le M \tag{6}$$

where M is the positive integer for truncating the obtained differentiator coefficient sequence so that there are $N = 2M+1$ coefficients in total. Note that $\omega_{\max}$ denotes the stop frequency edge. For a full-band differentiator, $\omega_{\max} = \pi$ radians. By substituting (5) in (6), we obtain

$$h_k[n] = \frac{1}{2\pi}\int_{-\omega_{\max}}^{\omega_{\max}} \left(j\omega/\omega_{\max}\right)^k e^{jn\omega}\mathrm{d}\omega\,, \quad -M \le n \le M\,. \tag{7}$$

Using integrations by parts, we achieve

$$h_k[n] = \frac{(j\omega)^k}{jn\omega_{\max}^k}e^{jn\omega}\Big|_{-\omega_{\max}}^{\omega_{\max}} - \frac{k}{n\omega_{\max}^k}\int_{-\omega_{\max}}^{\omega_{\max}} (j\omega)^{k-1}e^{jn\omega}\mathrm{d}\omega\,. \tag{8}$$

Replaying (8) in (7), it leads to the general recursion

$$h_k[n] = \frac{(j\omega)^k}{jn\omega_{\max}^k}e^{jn\omega}\Big|_{-\omega_{\max}}^{\omega_{\max}} - \frac{k}{n\omega_{\max}^k}h_{k-1}[n]\,. \tag{9}$$

It is possible realize (9) in the following recursion. For n=0

$$h_k[0] = \frac{1}{2\pi}\int_{-\omega_{\max}}^{\omega_{\max}} \left(j\omega/\omega_{\max}\right)^k\mathrm{d}\omega = \begin{cases} \frac{j^k\omega_{\max}}{\pi(k+1)}\,, & \text{for } k = \text{even}\,, \\ 0 & \text{for } k = \text{odd}\,. \end{cases} \tag{10}$$

For $n \neq 0$ and $k = \text{even}$ (the even-order derivative)

$$h_k[n] = \frac{j^k\sin(n\omega_{\max})}{n\pi} - \frac{k}{n\omega_{\max}}h_{k-1}[n]\,. \tag{11}$$

For $n \neq 0$ and $k = \text{odd}$ (the odd-order derivative)

$$h_k[n] = \frac{j^{(k-1)}\cos(n\omega_{\max})}{n\pi} - \frac{k}{n\omega_{\max}}h_{k-1}[n]\,. \tag{12}$$

Note that the recursion starts from a low-pass filter

$$h_0[n] = \frac{\sin(n\omega_{\max})}{n\pi}\,. \tag{13}$$

Therefore, starting form (13), we can compute the noncausal coefficients of FIR digital differentiators by applying (10) and (11) for the second-order derivate or (10) and

(12) for first-order derivate. We can shift the noncausal filter coefficients by M samples to obtain the causal differentiator coefficients. In order to reduce the ripple effect [5] due to truncation of the filter sequence, a window function is finally applied to achieve the windowed filter coefficients. The FIR digital differentiator design procedure is summarized as follows.

- Given the length of the FIR digital differentiator with $N = 2M + 1$ (odd integer number) and the kth-order derivate, compute the noncausal filter coefficients $h_k[n]$ using (10), (11) or (12), and (13) for $n = 0, 1, 2, \ldots, M$.
- Apply the window function to achieve the windowed filter coefficients for $n = 0, 1, 2, \ldots, M$:

$$\overline{h}_k[n] = h_k[n]w[n]\,. \tag{14}$$

- Use the coefficient symmetric properties to acquire the other half of differentiator coefficients. For $k = \text{even}$

$$\overline{h}_k[n] = \overline{h}_k[-n] \text{ for } n = -1, -2, \ldots, -M\ ,. \tag{15}$$

- For $k = \text{odd}$

$$\overline{h}_k[n] = -\overline{h}_k[-n], \text{ for } n = -1, -2, \ldots, -M\,. \tag{16}$$

- Obtain the causal differentiator coefficients

$$h_k[n] = \begin{cases} \overline{h}_k[n-M]\,, & n = 0, 1, \ldots, M-1\,, \\ \overline{h}_k[M-n]\,, & n = M, M+1, \ldots, 2M+1\,. \end{cases} \tag{17}$$

2.2 SQNR

The quantization noise is assumed to be white and uniformly distributed in the quantization interval. However, in many cases, this is not true. For example, quantizing a sinusoidal signal results in a situation where the quantization noise has a correlation to the quantized sinusoid. This will cause degradation in the performance of SQNR in the over sampling system. The overcome this shortcoming, a dithering process, otherwise known as white Gaussian noise with an RMS level between 1/3- and 1-LSB voltage, is added to the analog signal before over sampling. With the dithering process, we can achieve an approximate flat quantization noise spectrum.

In practical applications, the transition band for differentiator has a roll-off curve so that more high-frequency edge will be filtered. Hence, using the ideal frequency response for our SQNR analysis will result in a lower SQNR value if there is no desire for signal components around the cut-off frequency edge. It was assumed that the over sampling system has the N_q-bit ADC resolution, and the sampling rate in the data acquisition system can be increased by the user to achieve a desired over sampling rate. Consider adding a dithering noise $w_a[n]$ to the analog signal $x_a[n]$. After ADC, the quantized signal $x[n]$ is

$$x[n] = Q\big(x_a[n] + w_a[n]\big) = x_a[n] + w_a[n] + e[n]\,. \tag{18}$$

Here $Q(\ )$ is N_q-bit uniform quantizer, while $e[n]$ is the quantization noise, which is assumed to be white and uniformly distributed with its power given by

$$\sigma_q^2 = \frac{\big(X/2^{N_q-1}\big)^2}{12}\,. \tag{19}$$

Now, it is possible define the quantization error as the difference between the quantized signal and analog signal samples without dithering. Taking the mean-square expectation of this difference, we can determine the power of quantization error

$$\sigma_{qd}^2 = E\big\{\big(x[n] - x_a[n]\big)^2\big\} \tag{20}$$

where $E(\ )$ is the mean-square expectation operator. If we assume that the dithering noise and quantization noise are uncorrelated, the power of quantization error with the dithering process can be expressed as sum of the dithering noise power σ_d^2 and the quantization noise power σ_q^2. After over sampling and differentiation, the power of the in-band quantization error for the frequency ranging from $-\omega_{\max}$ to $\omega_{\max}$ can be approximated using the ideal transfer function of the kth-order derivative differentiator

$$\sigma_{\text{in-band}}^2 = \int_{-\omega_{\max}}^{\omega_{\max}} \frac{\sigma_{qd}^2}{2\pi}\Big|H_k\big(e^{-j\omega}\big)\Big|^2 \mathrm{d}\omega = \frac{\omega_{\max}}{\pi(2k+1)}\Big(\frac{X^2 2^{-2N_q-2}}{12} + \sigma_d^2\Big). \tag{21}$$

Substituting $\omega_{\max} = 2\pi f_{\max}/f_{sL} = \pi/L$ in (21) the SQNR can be expressed as

$$SQNR = \frac{12L(2k+1)2^{2N_q-2}/X^2}{1 + 12\cdot 2^{2N_q-1}\sigma_d^2/X^2}\sigma_k^2 \tag{22}$$

where σ_k^2 is the power of the kth-order derivative signal $y_k[m]$. Consider a sinusoidal signal (1), we can determine the power of the kth-order derivative signal as

$$\sigma_k^2 = \frac{1}{2}\Big(\frac{X\omega_i^k}{\omega_{\max}^k}\Big)^2 = \frac{X^2}{2}\Big(\frac{f_i}{f_{\max}}\Big)^{2k}. \tag{23}$$

The spectrum of quantization error over all the frequency range is flat due to dithering. At a higher sampling rate, the spectrum of in-band signals becomes relatively narrow, and as result, the quantization error has a tendency to correlate with the quantized signal, consequently, the spectrum of the derivative signal contains significant low-frequency noise components, which cannot be further removed via differential filtering. With the dithering process, the spectrum of quantization error is always white and relatively flat so that the SQNR can continuously be

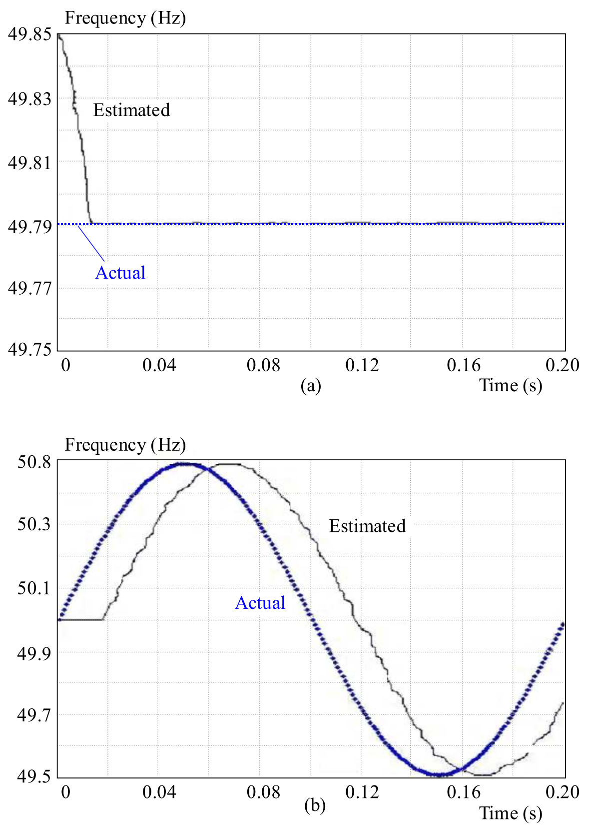

Fig. 2. Estimation for (a)– $f = 50$ Hz for $t < 0$ s and $f = 49.8$ Hz for $t > 0$ s with $SNR = 60$ dB and with harmonics presence; (b)– $f(t) = 50 + 0.5\sin(10\pi t)$ with $SNR = 60$ dB

improved by increasing the over sampling factor. Furthermore, assuming that, without the usage of the dithering process, the SQNR stops at the over sampling factor of L_N using (22), it is possible easily achieve the over sampling factor for the dithering process to reach the same SQNR, *ie* $L \geq \left(1 + 12\cdot 2^{2N_q-1}\sigma_d^2/X^2\right)L_N$. This relations show that an increased over sampling factor is required to overcome the disadvantage by using the dithering process. In (22), using $\sigma_d = \Delta V/3$ volts (equivalent to 1/3 LSB), where ΔV is the ADC resolution, and considering the signal's full range of $2X = 2^{N_q}\Delta V$ volts, we can obtain the relationship as $L = (7/3)L_N$.

Due to the presence of the error in determining the samples $x(t_n)$, $y_1(t_n)$, and $y_2(t_n)$ in the practical applications of the proposed algorithm we need to have the best estimate of the given values, according to the criterion assumed. This can be done by the means of recalculation of the values $x(t_n)$, $y_1(t_n)$, and $y_2(t_n)$, through W passages, (W is arbitrary). In this process we form series $x(t_n)_i$, $y_1(t_n)_i$, and $y_2(t_n)_i$ $(i = 1,\dots,W)$, as given in the proposed algorithm. The random errors ?n of measurements are unbiased, $E(\Delta_i) = 0$ have the same variance $\operatorname{var}(\Delta_i) = \sigma^2$, and are not mutually correlated. Under these assumptions, we can use the weighted average procedure for decreasing random errors in determination of observed values. The weighted average is used for measurements that are not correlated and have a varying degree of accuracy. The averages $\hat{x}(t_n), \hat{y}_1(t_n), \hat{y}_2(t_n)$ of the values $x(t_n)$, $y_1(t_n)$, and $y_2(t_n)$ are calculated as

$$\hat{x}(t_n) = \frac{\sum_{i=1}^{n_x} w_{xi}x(t_n)_i}{\sum_{i=1}^{n_x} w_{xi}}, \quad \hat{y}_1(t_n) = \frac{\sum_{n=1}^{n_{y1}} w_{y_1i}y_1(t_n)}{\sum_{i=1}^{n_{y1}} w_{y_1i}},$$

$$\hat{y}_2(t_n) = \frac{\sum_{n=1}^{n_{y2}} w_{y_2i}y_2(t_n)}{\sum_{i=1}^{n_{y2}} w_{y_2i}}, \tag{24}$$

$$\sum_{i=1}^{n_x} w_{xi} = \sum_{i=1}^{n_{y1}} w_{y_1i} = \sum_{i=1}^{n_{y2}} w_{y_2i} = W$$

where w_{xi}, w_{y_1i}, w_{y_2i} are non-negative weights of series $x(t_n)$, $y_1(t_n)$, and $y_2(t_n)$. The n_x, n_{y_1}, n_{y_2} defines the numbers of different values in above series through W passages.. The value of W will depend on the required speed of processing — the higher the W, the more precise the estimation of the value is.

3 SIMULATION RESULTS

The algorithm proposed in this paper is tested by the means of the input data obtained through computer simulation under several steady-states, dynamic, and transient operation conditions. The performance of the proposed power component estimation technique for several cases has been investigated.

It was performed as the first and second derivation of a sine signal with an 8-bit ADC resolution and an over sampling factor L of 256 and $\sigma_d = (1/3)LSB$ (dithering noise is added to the analog signal before over sampling). In this way it over sampled the sine signal with $4096\,L$ samples.

First, an input-frequency modulated sinusoidal test signal (step frequency change from 50 to 49.8 Hz at $t = 0$ s) was processed (Fig. 2a). A white noise with $SNR = 60$ dB was added to the sinusoidal signal. The proposed algorithm is capable of adaptively tracking time variations of the characteristics of the power signal over time. As shown in Fig. 2a, we have obtained a technique that provides accurate frequency estimation with error in the range of 0.001 Hz, similarly as results obtained in [9].

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. 2b. The good dynamic responses can be noticed. Obtained results are much better then the one presented in [10]. The arguments and conclusions of the preceding frequency-step-changing case are confirmed again in this experiment.

Additional testing of the proposed algorithm was carried out by simulation in the program package Matlab and SIMULINK. The effect of noise presence in the signal that contain noise. A sinusoidal 50 Hz input test signal with superimposed additive white centered Gaussian noise was used as input for the test. The random noise was selected to obtain a prescribed value of the SNR, which is defined as $SNR = 20\log(X/\sqrt{2}\sigma)$, where σ is the noise standard

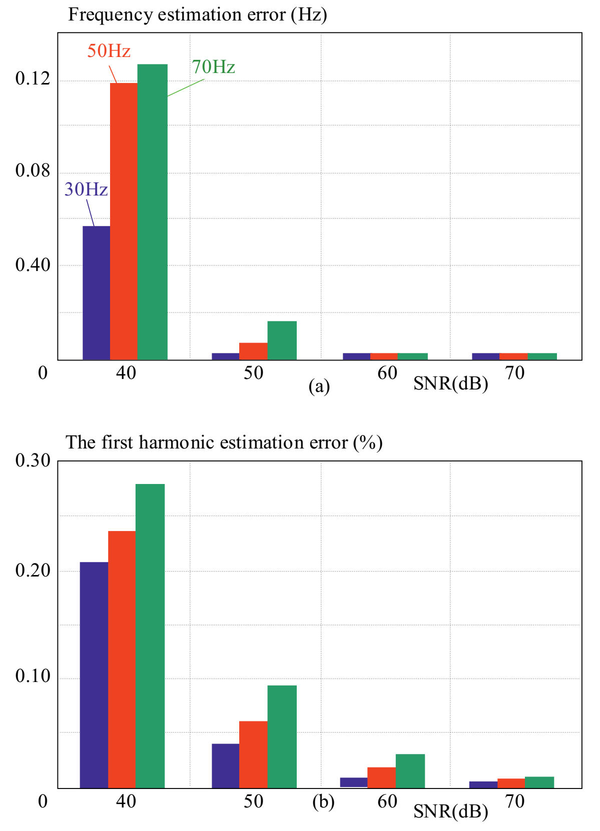

Fig. 3. Maximum estimations errors for noisy input signals

deviation. Figure 3 shows the maximum errors observed in frequency and harmonic magnitude 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, the SNR of the voltage signal obtained from a power system ranges between 50 and 70 dB. At this level of noise, very little error is expected with the proposed technique, as depicted in Fig. 3. Obtained results are better then the one presented in [11–13].

4 CONCLUSION

The estimation procedure proposed in this paper is a new complexity-reduced algorithm for estimation of the frequency and signal parameters. The proposed algorithm is able to estimate the signal parameters simultaneously, supposing the time-varying frequency. Based on the identified parameters of the input analogue signals, we can establish all the relevant values in the electric utilities (energy, power, RMS values). The simulation results show that the proposed algorithm can offer satisfactory precision in reconstruction of periodic signals in a real environment.

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