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Fundamental Frequency Estimation in Power System through the Utilization of Sliding Window-LMS Method

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Abstract. Frequency estimation is a vital tool for many power system applications such as load shedding, power system security assessment and power quality monitoring. Moreover, the complexity and noisiness of modern power system networks have created challenges for many power system applications. Fast and accurate frequency estimation in the presence of noise is a challenging task. Sliding window with the complex form of least mean square (LMS) algorithm has been utilized in this study in order to improve the frequency estimation in noisy power system. Different simulation cases have been examined for signal with different signal to noise ratio (SNR) and to evaluate the performance of sliding window method for better frequency estimation. The results obtained show that the sliding window method with LMS is able to improve and enhance the frequency estimation even when the (SNR) is small compared to the existing LMS method.

Introduction

In power system, frequency estimation is an important task since it is generally used to indicate the system abnormal conditions. The imbalance between the system load and generation leads to variation in frequency. Furthermore, fault and overloaded system disturb the frequency in various levels. Therefore, understanding of the frequency deviations can describe the power system condition and hence, frequency estimation is vital tool involved in many applications in power system such as load shedding, power system security assessment and power quality monitoring. Fast and accurate frequency estimation is essential to maintain the system in normal operation. The common method used of frequency estimation is Zero-Crossing method [1-2]. However, this method is based on pure waveform but in reality the power system voltage signals is polluted signals due to the complexity of modern power system components and advance in technology of equipments involved in the system. Therefore, several methods has been introduced in the literature to cope with polluted signals such as least mean square (LMS), Phase-locked Loop (PLL), Fourier Transform (FFT), Weighted Least Square (WLS) technique, Kalman Filter, Adaptive Notch Filter, artificial neural network (ANN) as in [1-9] and Newton-type algorithms [10].The adaptive filter based on the LMS proposed in [1] should not be overlooked due to simplicity structure and low computational complexity of LMS.

LMS is the most popular adaptive algorithm and has been widely applied in many applications such as communication and digital signal processing. The LMS has been introduced by Widrow and Hoff [11]. However, LMS algorithm suffers from data-dependent behavior and sensitivity to the noise. Variable step size LMS introduced in [1] to increase the convergence rate of LMS has been adopted in this paper with moving average search direction (sliding window) in order to overcome the problem of LMS as well as to work with noisy signals that may appeared in modern power system environment.

A sliding window LMS-based adaptive filter of frequency estimation is proposed utilizing the three-phase voltages. A complex signal is obtained from the three-phase voltages by using $\alpha\beta$ transform [1], [12]. Then the instantaneous frequency estimation through the complex form of LMS in [1], [13] with a sliding window of input observations has been implemented. The performance of a sliding window LMS-based adaptive filter of power system frequency estimation has been examined in several cases through simulated and real data.

Background

Adaptive filter. An adaptive filter is a self-modifying filter that adjusts its parameters to minimize an error function (the difference between the desired value and the output of the adaptive filter in each iteration), [14].The basic configuration of an adaptive filter, operating in the discrete-time domain k is shown in Fig. 1.

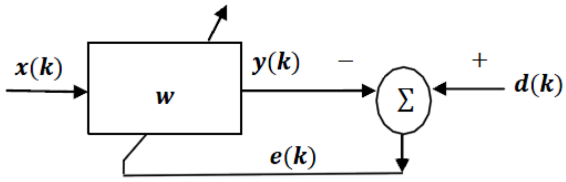

Fig.1. Adaptive filter

The input signal is given by $x(k)$ the reference signal or desired signal $d(k)$ represents the desired output signal (that usually includes some noise component), and $y(k)$ is the output of the adaptive filter, and hence the error signal is defined as

$$e(k) = d(k) - y(k) \tag{1}$$

LMS based fundamental frequency estimation. The three-phase voltages of a power system can be represented in continuous-time domain as:

$$V_a(t) = V_m \cos(wt + \emptyset) + \varepsilon_a(t) \tag{2}$$

$$V_b(t) = V_m \cos\left(wt + \emptyset - \frac{2\pi}{3}\right) + \varepsilon_b(t) \tag{3}$$

$$V_c(t) = V_m \cos\left(wt + \emptyset + \frac{2\pi}{3}\right) + \varepsilon_c(t) \tag{4}$$

Where, V_m is the peak value of fundamental component, ε is the noise process, ∅ is the phase of fundamental component, and w is the angular frequency of the voltage signal ($w = 2\pi f$) with system frequency f. The complex form of signal derived from the three-phase voltages is obtained by αβ transform [1] as follow:

$$\begin{pmatrix} V_\alpha(t) \\ V_\beta(t) \end{pmatrix} = \sqrt{\frac{2}{3}} \begin{pmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & -\frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{pmatrix} [(V_a(t) \quad V_b(t) \quad V_c(t))]^T \tag{5}$$

A complex voltage $V(t)$ can be obtained from the above as the following:

$$V(t) = V_\alpha(t) + jV_\beta(t) \tag{6}$$

The voltage $V(t)$ can be modeled as

$$V(t) = Ae^{j(wt+\emptyset)} + \varepsilon(t) = \hat{V}(t) + \varepsilon(t) \quad , \qquad A = \sqrt{V_\alpha(t)^2 + V_\beta(t)^2} \tag{7}$$

$$V(t) = Ae^{j(wt_0)}e^{j(wt-wt_0+\emptyset)} + \varepsilon(t) \tag{8}$$

$$\hat{V}(t) = e^{j(wt_0)}\hat{V}(t - t_0) \tag{9}$$

$$\hat{V}(t) = W\hat{V}(t - t_0) \tag{10}$$

$$\theta = e^{j(wt_0)} \tag{11}$$

$$e(t) = V(t) - \hat{V}(t) \tag{12}$$

$$\theta = \theta + \mu e \hat{V}(t - t_0)^* \qquad , \ * \text{ is the conjugate} \tag{13}$$

$$\theta = e^{j(wt_0)} = \cos(wt_0) + j\sin(wt_0) \tag{14}$$

$$\sin(wt_0) = \mathrm{Im}(\theta) \quad \longrightarrow \quad wt_0 = \sin^{-1}[\mathrm{Im}(\theta)] \tag{15}$$

$$f_0 = \frac{1}{2\pi t_0}\sin^{-1}[\mathrm{Im}(\theta)] \qquad w = 2\pi f_0 \tag{16}$$

Based on [1], [15] and [16] the step size $\mu(t)$ for each iteration has been updated as following:

$$\mu(t+1) = \lambda\mu(t) + \gamma p(t)p(t)^* \tag{17}$$

*is the conjugate used to work with complex LMS
and $p(t)$ is used to control the update of the step size

$$p(t) = \delta p(t-1) + (1-\delta)e(t)e(t-1) \tag{18}$$

δ is a positive weighting parameter between $0 < \delta < 1$ that governs the time average of $e(t)e(t-1)$, $0 < \lambda < 1$ and $0 < \gamma$ the step size is limited between μ_{max} and μ_{min} to control the mean square error [15-16].

Sliding window learning (SW). SW training algorithms, also known as high order training algorithms which use the system input/output observations from previous input/output data until the current input/output data to perform instantaneous learning; typically the model weights are updated using information obtained from store of (L) previous training vectors [17,18].

$$X = [x_1, x_2, x_3, \dots x_L] \quad , \quad Y = [y_1, y_2, y_3, \dots y_L] \tag{19}$$

$$S = \begin{bmatrix} x_1, x_2 \dots x_{L-1}, x_L \\ y_1, y_2 \dots y_{L-1}, y_L \end{bmatrix} \tag{20}$$

S is store of the data depend on the model structure and in this paper *S* contain only input .Given (L) vector data store and the current data points x_t, this algorithm computes a moving average search direction for (LMS) as the following:

$$\mathrm{MA}_t = \frac{\alpha}{L}\sum_{i}^{L} e_i S_i + (1-\alpha)e_t S_t \tag{21}$$

$$0 < \alpha < 1$$

The weighting factor α controls the contribution of the current vector to the moving average search In this paper the moving average to update the weights of Eq. (13) for frequency estimation based on the previous information obtained from store of (L) previous training vectors is given as follow:

$$W = W + \frac{\mu\alpha}{L}\sum_{i}^{L} e_i \hat{V}(t-t_0)^*{}_i + (1-\alpha)e_t \hat{V}(t-t_0)^*{}_t \tag{22}$$

Simulation and Discussion

The simulation of power system frequency estimation through the utilization of sliding window LMS has been done by using MATLAB program M file during several conditions that can be found in real system. The parameters in Eq. (17) and Eq. (18) are set based on [1], [15] and [16]. Which are $\beta = 0.99, \lambda = 0.97, \gamma = 0.01, \mu_{max} = 0.18, \mu_{min} = 0.0001$ and sampling frequency 5KHz. The initial value of μ and p highly influence the performance of the estimator for instance if the initial value of (p) is large that lead to larger(μ) and faster convergence speed and vice versa. But the large value of (p) makes the estimator fast and sensitive to the noise and lead to oscillation in the estimator. Therefore, the sliding window method which is introduced in this paper aims to cope with noisy signal and improve the performance of the estimator by maintaining fast convergence with less sensitive to the noise even when the noise to ratio SNR is small

Noiseless signal. When the system is noiseless or the signal is pure sine wave, the greater value of $(\boldsymbol{p})$ make the convergence faster and not lead to oscillation. Fig. 2 and Fig. 3 Show the convergence rate to the fundamental frequency with large and small initial value of$(\boldsymbol{p})$

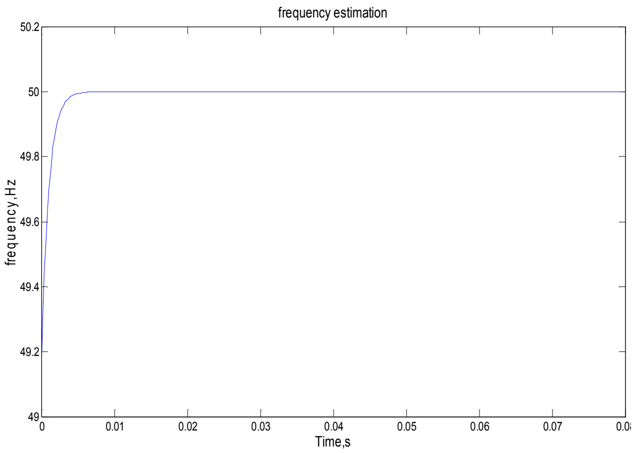

Fig.2 Estimation of the fundamental Frequency with LMS when p initialized in small value

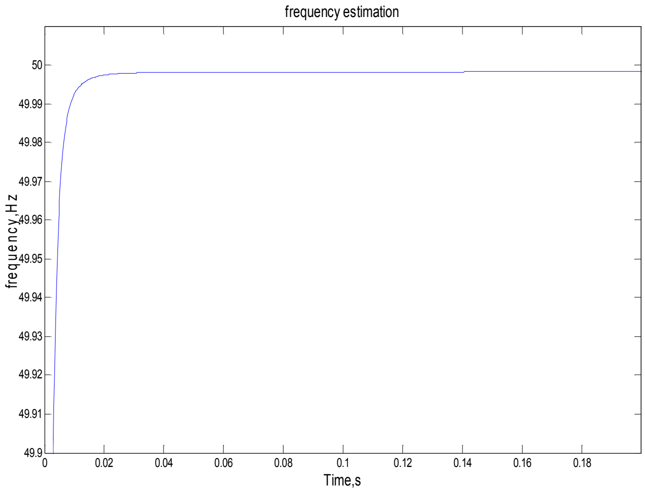

Fig.3 Estimation of the fundamental frequency when p initialized in large value

Fig. 2 and Fig. 3 show the estimation of the fundamental frequency for three phase voltage signal with noise free contain fundamental frequency equal to (50 Hz), for a small and large value of (p) respectively. It can be seen from Fig. 2 is that the estimator couldn't converge to the fundamental frequency, which is (50 Hz), while converge after (53) iteration when large value for (p) applied as in Fig. 3 which mean that large initial value of (p) make the estimator fast but unfortunately sensitive to noisy signal.

Signal with noise. In general, the noise influences the performance of LMS estimator. Furthermore, to evaluate the performance of the estimator of a noisy signal, different noise to signal ratio SNR is added to each phase signal with (50 Hz) fundamental frequency initialized at 49Hz. Fig. 4 shows the performance of LMS with large value of (p) with (SNR = 20 dB).

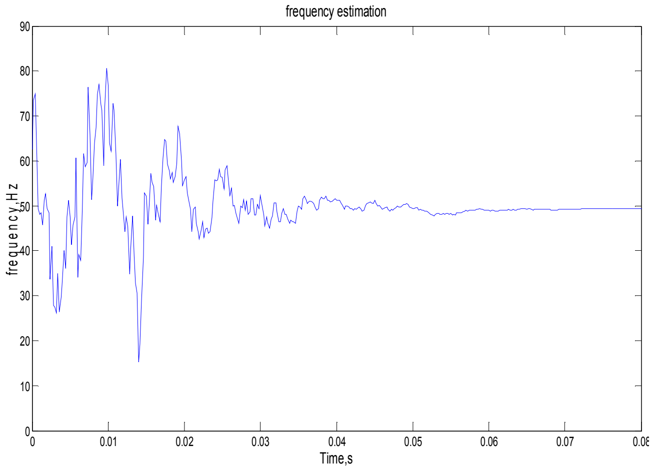

Fig .4 Estimation of the fundamental frequency with LMS when SNR = 20dB

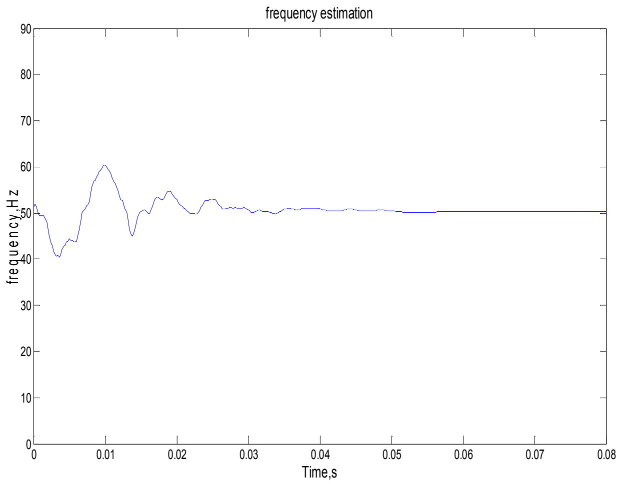

Fig.5 Estimation of the fundamental frequency with SW- LMS when SNR=20dB

It can be seen from Fig. 4, the noise influences the LMS estimator. In order to reduce the influence of the noise as well as to maintain the robustness and fast convergence of the estimator, the sliding window method is utilized. Fig. 5 shows the performance of L = 5 window size sliding window, which is applied to 20 SNR noise ratios. The sliding window-LMS can improve the estimator performance in a noisy system. The results obtained in the Table. I, II and III shows the mean, standard deviation and maximum value to the error between desired frequency (50 Hz) and the estimator output frequency to each iteration for (400) input samples with different SNR ratio.

Table.I FREQUENCY ESTIMATION FOR 20 SNR

Estimator performance in 20 SNR			
Algorithm	Std	Mean	Max
LMS	7.2568	0.098	34.7641
SW=3	2.5273	0.7457	8.4119
SW=5	2.6644	0.5533	9.5164
SW=7	2.9283	0.3684	11.0256
SW=10	2.8889	0.4572	9.9539

Table.II FREQUENCY ESTIMATION FOR 30 SNR

Estimator performance in 30 SNR			
Algorithm	Std	Mean	Max
LMS	3.0894	0.3438	8.7739
SW=3	0.9375	0.3823	2.0517
SW=5	0.9451	0.4104	2.0152
SW=7	0.9410	0.4077	1.9516
SW=10	0.9489	0.4326	1.9140

Table.III. FREQUENCY ESTIMATION FOR 40 SNR

Estimator performance in 40 SNR			
Algorithm	Std	Mean	Max
LMS	0.8929	0.0190	3.2292
SW=3	0.3447	0.0572	1.1393
SW=5	0.3591	0.0745	1.2094
SW=7	0.3576	0.0545	1.1981
SW=10	0.3669	0.0395	1.1833

From the results obtained from Tables I-III the sliding window LMS gives better performance with noisy signals than LMS as it has lower standard deviation for all sliding window size with different SNR as known low standard deviation indicates that the data points tend to be very close to the mean. In addition, a lower maximum error for sliding window size equal to 10 for 30 and 40 SNR ratios. While the sliding window equal to 3 has a lower maximum error at 20 SNR. Sliding window with size equal to 5 has almost medium maximum error in the three SNR ratios.

Signal with dynamic frequency change. To represent the worst case condition for dynamic frequency change, the frequency is assumed to be randomly and uniformly varying between 48Hz and 52 Hz after 100 iteration from the initializing the estimator for 10 iteration.

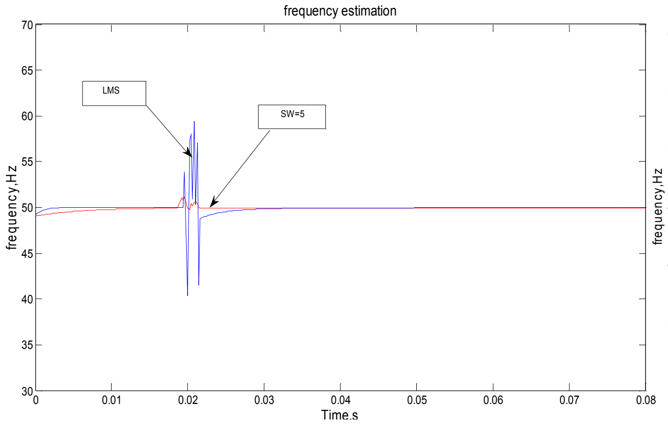

Fig.6 SW and LMS dynamic change

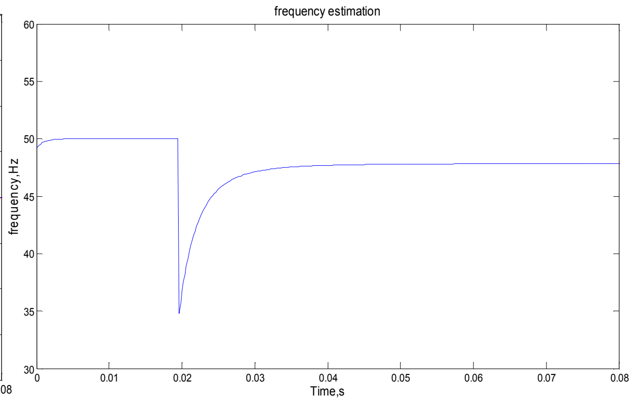

Fig.7 LMS sudden frequency change

Fig.6 shows the comparison between SW and LMS when dynamic change in the signal happen clearly more damping in LMS than that in sliding window

Signal with sudden frequency change. The frequency is assumed to suddenly change from 50Hz to 48Hz after100 iteration from the beginning of the estimation. Fig.7 shows the LMS performance when the signal faced frequency change with noise free signal. It can be seen from Fig.7 that the LMS has fast response to the change in the frequency when the signal is free from the noise. But in the real case the signal will be with noise, which can affect the performance of LMS. Fig.8 shows the performance of LMS and SW with noisy signal. The sliding window LMS frequency estimation can perform better than LMS frequency estimation when sudden frequency change happens and the signal is contaminated with noise.

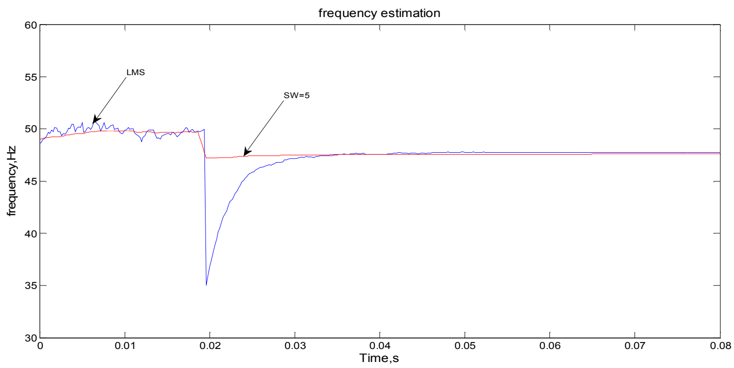

Fig .8 LMS and SWLMS sudden frequency change with noisy signal

Signal with harmonic. The presence of harmonic in the signal influences the performance of LMS as well as sliding window LMS. However, $\boldsymbol{\alpha\beta}$ transform eliminates the third harmonic and is not influencing the performance of the estimator. but the fifth and above harmonic order can influence the performance, thus low pass filter Butterworth with cut off frequency of 200 Hz suggested in [1] and [19] as pre-filtering. Moreover, the signal that is used for frequency estimation is transmission a bus voltage and usually the fifth and higher harmonic order less than 1 % where no need for pre-filtering [1].

Signal from real data. The signal was collected from unbalanced voltage source of distribution system to examine the performance of SW-LMS under unbalanced voltage. The data was collected using fluke 1750 power quality analyser 8 channels with sample rate of 256/cycle. The three phase shape, magnitude and phase angles are given as in Fig.9

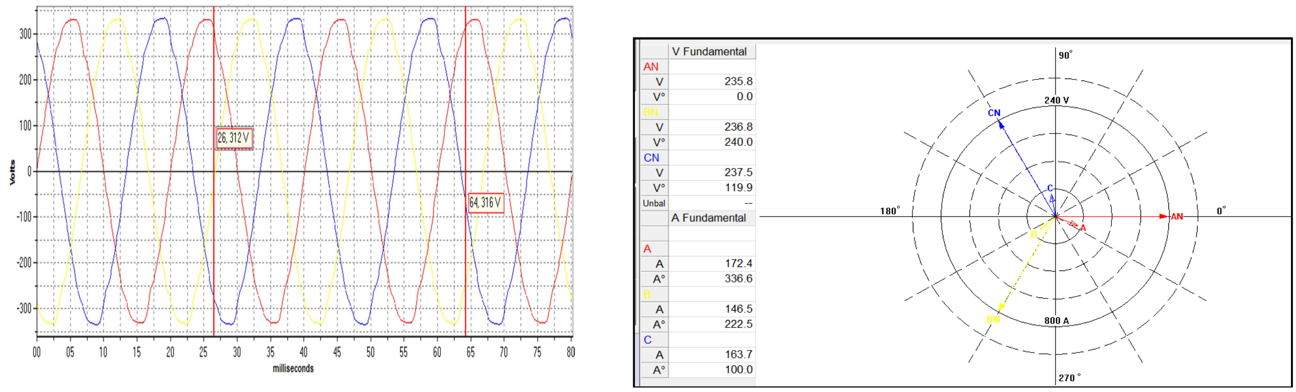

Fig.9. Three phase voltage from distribution system

The unbalanced three phase voltages is transformed to the complex form with noise of SNR 50 dB and then introduced to the LMS and LMS-sliding window estimator. The result of the estimation is shown in Fig. 10. And Fig.11

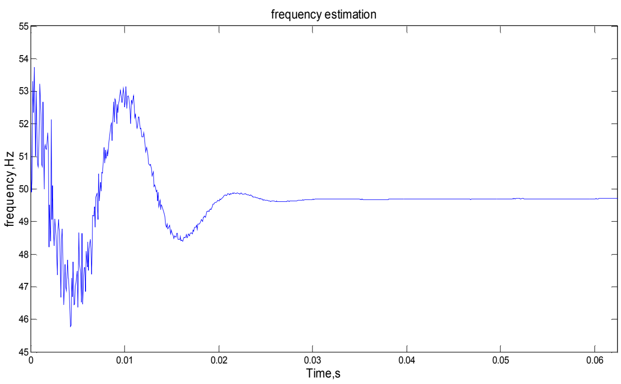

Fig .10. LM for unbalance and noisy three phase voltage

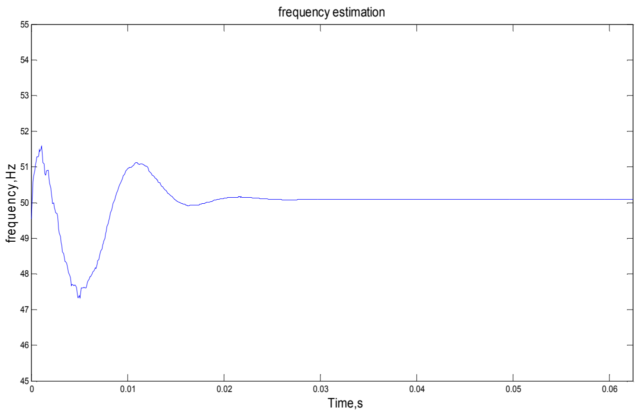

Fig .11.LMS-SW for unbalance and noisy three phase voltage with 5 window size

As shown in Fig.10 and Fig.11 the unbalanced condition of three phase voltage influence the performance of the estimator, however, the result obtained by sliding window estimator is better than LMS estimator. Furthermore, in the high voltage line which the estimation of the fundamental frequency done from its three phases voltage signal, the unbalance between phases is significantly smaller than that in distribution system while the data in this paper was taken from distribution system to show the performance of both method in highly unbalance signal.

Conclusion

Power system network become more complex and noisy system and accurate frequency estimation is challenging task. This paper presents the concept of moving average search direction or sliding window to cope with the noisy power system environment based on least mean square algorithm. The results show strong convergence for sliding window with different windows size L or SW for different signal to noise ratio. Furthermore, sliding window technique is tested to real unbalance three phase voltages from distribution system and gives better estimation than LMS.

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