Power System Harmonics Estimation using Sliding Window Based LMS

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Abstract— **The widespread use of power electronics devises and nonlinear loads in power system grids is increasing in the last decades leads to rise of harmonic in power system signals. Great damage to power system gird can happen due to harmonics. Thus it is important to precisely estimate the harmonics components that may help to avoid its harmful effect of the electrical grid performance. The more common algorithm that has been used to estimate the harmonic component is the Fast Fourier Transform (FFT), however FFT has few limitations, furthermore, modern power system network getting complex and noisy. Therefore, fast and accurate harmonic estimation in the presence of noise is needed. Sliding window based least mean square (LMS) algorithm is introduced in this paper to estimate the harmonic components in noisy environment. The result shows that the sliding window method able to give a good estimation to the harmonic component even when the signal to noise ratio (SNR) is 0 dB.**

I. Introduction

In recent decades, widespread use of the power electronics technology has increased the nonlinear loads in the power system grid , the nonlinear loads leads to distortion in power system voltage and current waveforms which are not pure sinusoids represented as a combination of the fundamental frequency with large-wavelength components which are integrated numerous of fundamental frequency generally known as harmonics. Harmonic is a source of several problems in power system grid and have considerable impact on power system efficiency, performance reliability and economic operation of the grid ,moreover, the eddy current loss, corona loss , skin effect and electrical parameters directly related to frequency and therefore, to the harmonic. Harmonic cause overheating, frequent fuse blowing, capacitor failures, excessive neutral currents, metering inaccuracy, disturb the protective relay functions and communication interference[1-4].Therefore, accurate harmonic estimation is a very important to eliminate the harmful effects of harmonics, avoids the unwanted losses and maintains the delivered power with high quality which recommended in some standards such as IEEE 519–1992 harmonic control standard and IEC 61000 Limitation of emission of harmonic current standards [5-7]. Several techniques have been proposed in the literature on harmonic estimation. Fast Fourier transforms (FFT) most commonly used around last several years, however, (FFT) has several disadvantages and restrictions which are Spectral leakage, aliasing and picket fence effect [8-12]. As a result of (FFT) drawbacks many algorithms are introduced in the last two decades which categorized to parametric and nonparametric algorithm [13]. Nonparametric algorithm such as Wavelet transforms Hilbert-Huang transform,
Chirp z-transform and (FFT). Parametric algorithm such as kalman filter, (ANN) and ADLINE. Modern power system girds getting more complex, dynamic and noisy, thus, fast tracking and estimating harmonic component in this environment is challenging task, parametric and recursive algorithm introduced to cope with noisy system. In [14-18] is presented harmonic estimation model based on kalman filter (KF), (KF) has the capability to track time divers noisy parameters nevertheless a prior knowledge of the noise and the process is required , furthermore , the modelling of Kalman filter State variable is essential [13]. Artificial neural network ANN (BPN) and ANN (RBFNN) are also introduced in [19-27]. However, it needs a large number of data and difficult to collect sufficient training signal data due to the dynamic power system signal and highly time-varying behavior of the nonlinear loads which make it difficult to adjust the layer structure effectively in an online manor [13], [27]. A linear adaptive neural network called ADALINE presented in [28- 30] is a simple type of neural network with fast convergence can be used for online tracking of time variably harmonic however sensitivities to the harmonics that is not included in ADALINE model [13].

In this paper, a new algorithm for the estimation of harmonics amplitude and phases using least mean square (LMS) with sliding window is introduced to work with noisy system and to give a good estimation in different signal to noise ratio SNR. Because of its simplicity The LMS is the most popular algorithm and has been widely applied in many areas such as communication and digital signal processing adaptive algorithm. However, the LMS algorithm suffers from slow convergence, data-dependent behavior and sensitive to the noise to increase the convergence rate of LMS and to work with noisy data moving average search direction (sliding window) is introduced in this paper to improve the performance of the LMS as well as the estimation of harmonic in noisy system that can be found in modern power system environment.

The performance of a sliding window LMS-based adaptive filter for power system harmonic estimation is examined in several cases with different noise to signal ratio (SNR).

II. BACKGROUND

A. Least Mean Square Algorithm (LMS)

It is mostly a celebrated algorithm that is used widely in different applications due to its simplicity, low computational complexity and robustness. The simplicity of LMS comes from the fact that it does not require matrix inversion and the update of kth coefficient requires only one multiplication and one addition [31].

The steps of the LMS algorithm for an Nth-order FIR adaptive filters is given as follows.

Parameters: M= filter order, μ= step size
Initialization: $w_0=0$
Computation: for k =0, 1, 2…

$$y(k) = w^T x(k) \quad (2)$$
$$e(k) = d(k) - y(k) \quad (3)$$
$$W(k) = w(k-1) + \mu e(k) x(k) \quad (4)$$

Where the step size μ calculated by:

$$0 < \mu < \frac{2}{\lambda_{max}} \quad (5)$$

λ_{max} is the largest eigenvalue of the input signal due to the difficulty of determination of the step size μ that is a trade-off between the steady-state excess error and the speed of convergence [32].

B. LMS based harmonic estimation

Let the voltage or current waveforms of the known fundamental angular frequency ω assumed as the sum of harmonics of unknown magnitudes and phases as follows

$$y(t) = \sum_{n=1}^{N} A_n \sin(\omega_n t + \emptyset_n) + A_{dc}\exp(-\alpha_{dc} t) + \varepsilon(t) \quad (6)$$

Where N is the number of harmonics. $\omega_n = n2\pi f_0$, f_0 is fundamental frequency, is the dc $A_{dc}\exp(-\alpha_{dc}t)$ offset decaying term

In discretization form with sampling period T Eq. (6) Become as

$$y(k) = \sum_{n=1}^{N} A_n \sin(\omega_n kT + \emptyset_n) + A_{dc}\exp(-\alpha_{dc} kT) + \varepsilon(kT) \quad (7)$$

Using Taylor series expansion for the dc decaying term $A_{dc}\exp(-\alpha_{dc}t)$
And retaining only first two terms of the series yields

$$y_{dc} = A_{dc} - A_{dc}\alpha_{dc} kT \quad (8)$$

Replacing (8) in (6) Eq. (7) Become as follow
Type equation here.

$$y(k) = \sum_{n=1}^{N} A_n \sin(\omega_n kT + \emptyset_n) + A_{dc} - A_{dc}\alpha_{dc} kT + \varepsilon(kT) \quad (9)$$

$\omega_n = n2\pi f_0$, For estimating the amplitude and phases for each component Eq. (9) can be written as

$$y(k) = \sum_{n=1}^{N}[A_n \sin(\omega_n kT)\, A_n cos\emptyset_n + A_n\cos(\omega_n kT)\, A_n sin\emptyset_n] + A_{dc} - A_{dc}\alpha_{dc} kT + \varepsilon(kT) \quad (10)$$

In general form Eq. (10)

$$y(k) = X(k)W \quad (11)$$

$$X(k) = [\sin(\omega_1 kT)\ \cos(\omega_1 kT) \ldots \sin(\omega_n kT)\ \cos(\omega_n kT) 1 - kT]^T \quad (12)$$

The unknown parameter vector

$$W(k) = [\, W_1(k) \ldots W_{2n-1}(k) \ \ldots\ W_{2n+2}(k)\,]^T \quad (13)$$

$$W = [\, A_1 cos\emptyset_1\ A_1 sin\emptyset_1\ A_2 cos\emptyset_2\ A_2 sin\emptyset_2 \ldots \ldots A_n cos\emptyset_n\ \ A_n sin\emptyset_n\ \ A_{dc}\ \ A_{dc}\alpha_{dc}\,] \quad (14)$$

Using Eq. (4)

$$W(k) = W(k-1) + \mu e(k) X(k) \quad (15)$$

$$A_n = \sqrt{W_{2n}(k)^2 + W_{2n-1}(k)^2} \quad (16)$$

$$\emptyset_n = \tan^{-1}\frac{W_{2n}(k)}{W_{2n-1}(k)} \quad (17)$$

$$A_{dc} = W_{2n+1} \quad (18)$$

$$\alpha_{dc} = \frac{W_{2n+2}}{W_{2n+1}} \quad (19)$$

C. Sliding window learning (SW)

SW training algorithms, also known as high order training algorithms, use a sliding Window of system input/output observations to perform instantaneous learning .That can be applied when the data is highly correlated or noisy; typically the model weights are updated using information obtained from store of (L) previous training vectors [33].

$$X = [x_1, x_2, x_3, \ldots\ x_L] \quad (20)$$

$$Y = [y_1, y_2, y_3, \ldots\ y_L] \quad (21)$$

$$S = \begin{bmatrix} x_1, x_2 \dots x_{L-1}, x_L \\ y_1, y_2 \dots y_{L-1}, y_L \end{bmatrix} \quad (22)$$

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:

$$MA_t = \frac{\alpha}{L}\sum_{i}^{L} e_i S_i + (1-\alpha) e_t S_t \quad (23)$$

$$0 < \alpha < 1$$

The weighting factor α controls the contribution of the current vector to the search direction

Eq. (4) Updated as the following using sliding window

$$W(k) = W(k-1) + \mu \frac{\alpha}{L}\sum_{i}^{L} e_i S_i + (1-\alpha) e_t S_t \quad (24)$$

Using data store management called first in first out (FIFO) to manage the L vector of data store which when the new samples are obtained the oldest data in the store L will be replaced by the new data, therefore, the sliding window training use not only the current samples but also the previous samples, the store S for harmonic estimation include only input which

$$S = [x_1, x_2 \dots x_L] \quad (25)$$

III. SIMULATION AND DISCUSSION

To evaluate the performance of the sliding window LMS algorithm in estimating the harmonic amplitude and phase angle the simulation is done using MATLAB m file environment for different signal to noise ratio (SNR). Simulation of Several cases is shown below to explain the performance of (SW) for harmonic estimation under noisy system.

A. Simulation of Several cases

1) Signals corrupted with random noise and Decaying DC Component

To evaluate the performance of the proposed sliding window LMS algorithm in estimating harmonic amplitudes and phases in noisy system based on [34-36] the signal having fundamental frequency of 50 Hz with higher harmonics of the 3rd, 5th, 7th, 11th and a slowly decaying DC component is generated using MATLAB M file program. This kind of signal is typical in industrial load comprising power-electronic converters and arc furnaces [34-36].

$$y(t) = 1.5\sin(wt + 80^0) + 0.5\sin(3wt + 60^0) + 0.2\sin(5wt + 45^0) + 0.15\sin(7wt + 36^0) + 0.1\sin(11wt + 30^0) + 5\exp(-5t) + \varepsilon(t) \quad (26)$$

$\varepsilon(t)$ is Random noise with different noise to signal ratio added to signal, all the amplitudes given are in per unit

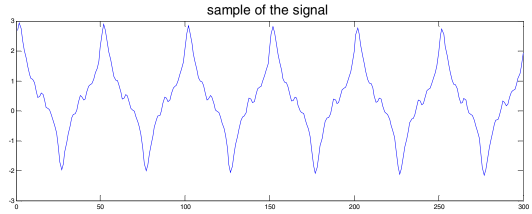

Fig. 1 Harmonic signal

Estimating of phase and amplitude of the signal in Fig. 2 with different noise to signal ratio using LMS and sliding window LMS fundamental frequency amplitude and phase are taken as examples for 40 and 10 *dB SNR* while fundamental frequency amplitude, phase and third harmonic amplitude, phase are taken for 0 *dB SNR* fundamental and third harmonic are taken as an example to their higher value of the signal

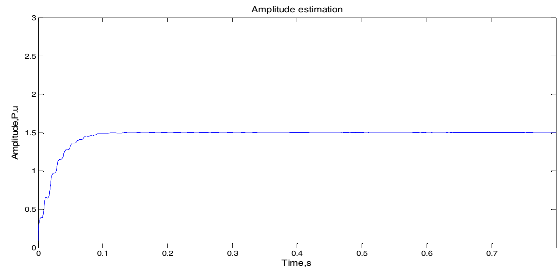

Fig.2 Estimation of the fundamental frequency amplitude with LMS

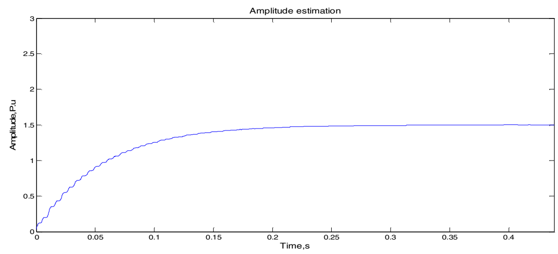

Fig.3 Estimation of the fundamental frequency amplitude with sliding window L=5

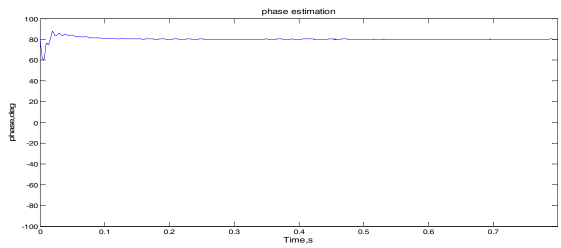

Fig.4 Estimation of the fundamental frequency phase angle with LMS

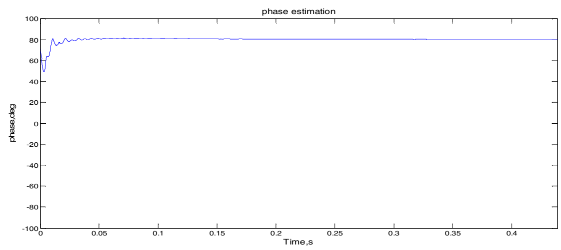

Fig.5 Estimation of the fundamental frequency phase angle with sliding window L=5

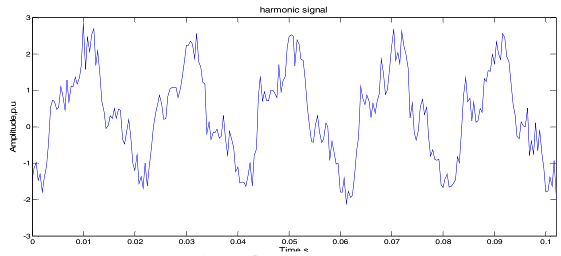

Fig.6 Harmonic signal with 10 dB

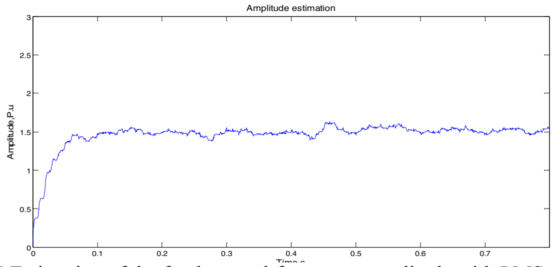

Fig.7 Estimation of the fundamental frequency amplitude with LMS

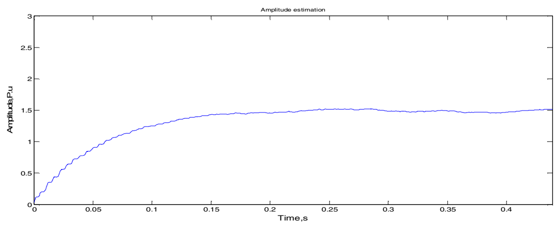

Fig.8 Estimation of the fundamental frequency amplitude with sliding window L=5

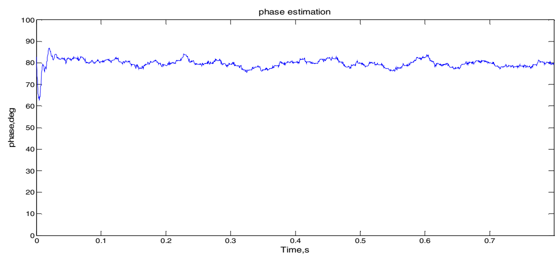

Fig.9 Estimation of the fundamental frequency phase angle with LMS

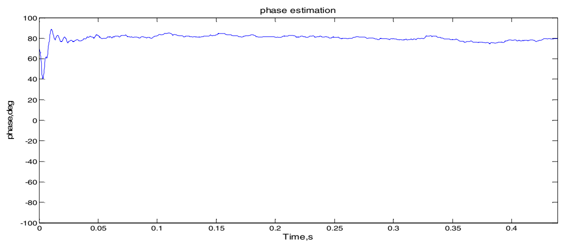

Fig.10 Estimation of the fundamental frequency phase angle with sliding window L=5

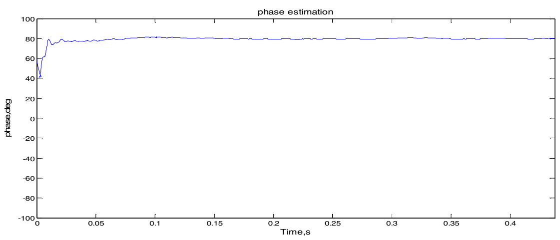

Fig.11 Estimation of the fundamental frequency phase angle with sliding window L=10

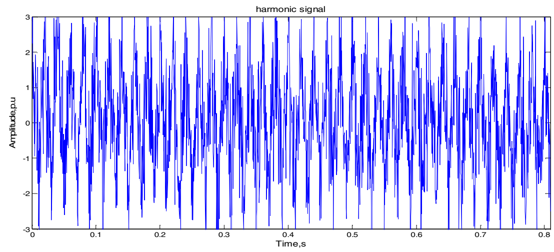

Fig.12 Harmonic signal with 0 dB

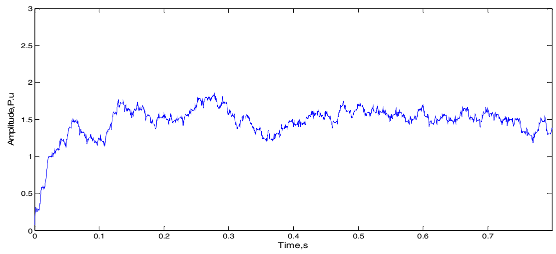

Fig.13 Estimation of the fundamental frequency amplitude with LMS

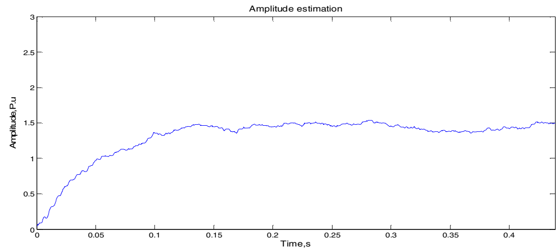

Fig.14 Estimation of the fundamental frequency amplitude with sliding window L=5

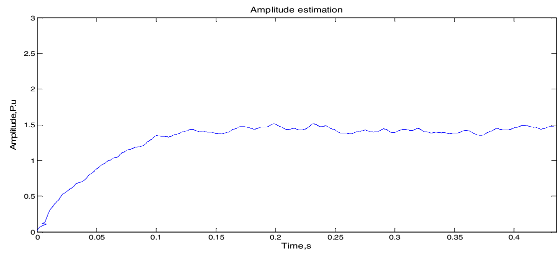

Fig.15 Estimation of the fundamental frequency amplitude with sliding window L=20

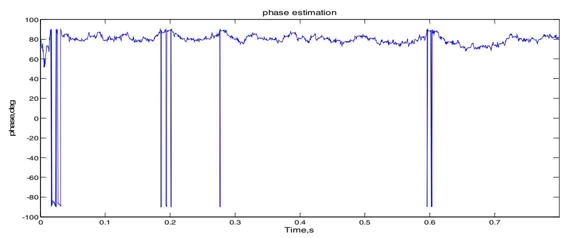

Fig.16 Estimation of the fundamental frequency phase angle with LMS

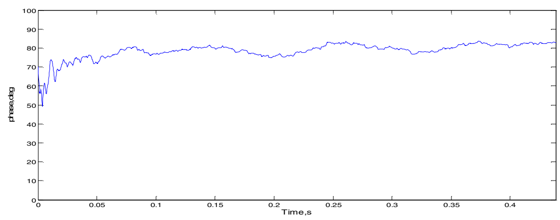

Fig.17 Estimation of the fundamental frequency phase angle with sliding window L=5

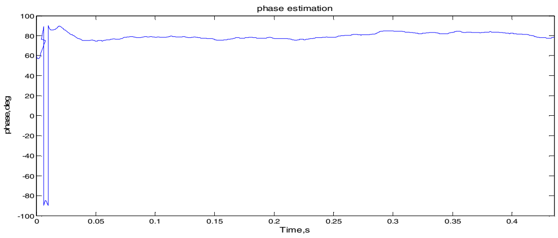

Fig.18 Estimation of the fundamental frequency phase angle with sliding window L=20

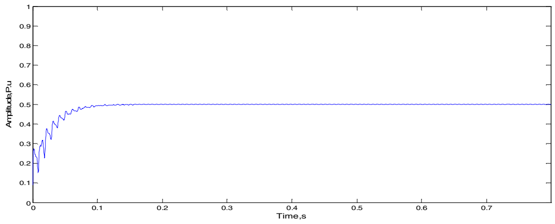

Fig. 19 Estimation of the third harmonic amplitude using LMS with the noise free signal

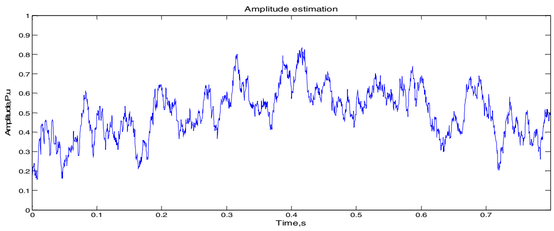

Fig.20. Estimation of the third harmonic amplitude using LMS with 0 dB SNR

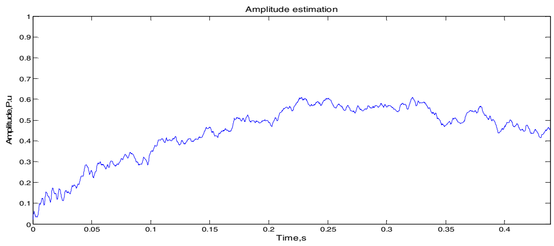

Fig.21 Estimation of the third harmonic amplitude with sliding window L=5

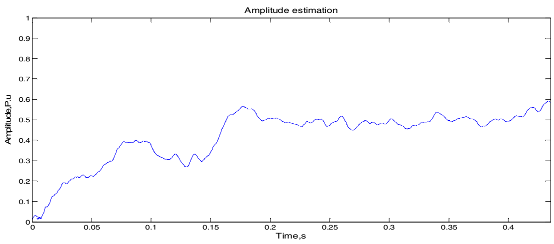

Fig.23 Estimation of the third harmonic amplitude with sliding window L=22

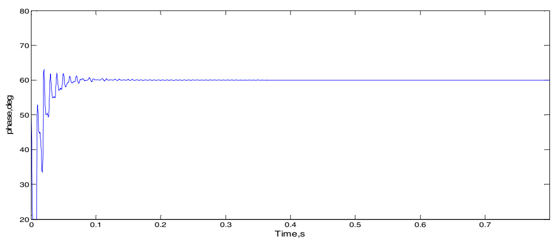

Fig.23 Estimation of the third harmonic phase angle using LMS with the noise free signal

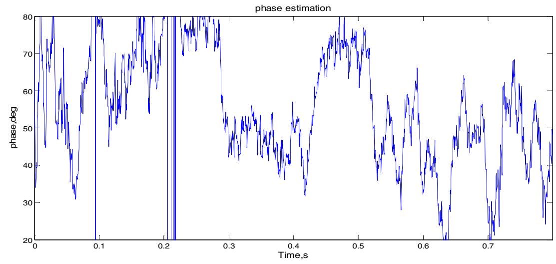

Fig.24 Estimation of the third harmonic phase angle using LMS with 0 dB SNR

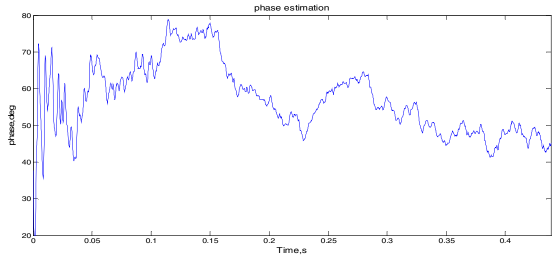

Fig.25 Estimation of the third harmonic phase angle sliding window L=5

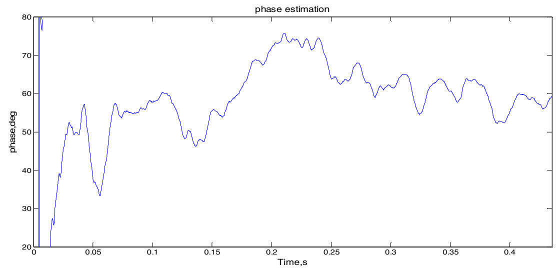

Fig.26 Estimation of the third harmonic phase angle sliding window L=20

From the Fig.1-26 above it can be shown that the performance of the sliding window LMS with different window size L for harmonic estimation in different signal to noise ratio is much better than LMS. Fig.2-5 show the tracking of the fundamental amplitude and phase using LMS and sliding window with L =5 in SNR equals to 40 dB which are almost the same performance with slightly faster in convergence for sliding window. However it can be clear from the rest of the figures the sliding window with different store size is more stable and robust against noise than LMS when the noise increases in signal. Fig.7-11 show the tracking of the fundamental amplitude and phase using LMS and sliding window with L =5 and 10 , SNR equals to 10 dB. Estimating using LMS exhibits oscillation while sliding window LMS smooth the estimation process. For the worst noise to ratio signal SNR case which 0 dB. Fig. 13-26 show not only the tracking of the fundamental amplitude and phase but also the estimating of third harmonic amplitude and phase. Whereas Fig.20 and 26 show the estimating of the third harmonic components in a noisy system using LMS and sliding window LMS ,LMS extremely more oscillation than the estimation of the fundamental components especially for the phase angle while sliding window reduce the oscillation, moreover, when the size the of storing large as in Fig.26 the oscillation will be reduced more but with consuming time which is impractical for online application ,therefore, small size of the store can give better estimation with acceptable computation time .

IV. CONCLUSION

Many algorithms have been introduced for accurate harmonic estimation in the past two decades. This paper presents a new approach for adaptive estimation of amplitude and phase angles of harmonics in power systems based on the concept of moving average search direction or sliding window least mean square algorithm to cope with the noise power system environment . The result shows strong convergence for sliding window with different windows size L using FIFO strategy for different signal to noise ratio. Furthermore sliding window technique with large size such as L=20 can give smoother estimation to the harmonics even when SNR =0 dB but with computation burden that is not desired in online estimation, therefore, small size can be suitable for online application.

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