

AN ADAPTIVE LINEAR COMBINER FOR ON-LINE TRACKING OF POWER SYSTEM HARMONICS

P.K.Dash, D.P.Swain
Dept. of Electrical Engg,
Regional Engineering
College, Rourkela 769 008
INDIA

A.C.Liew
Dept. of Electrical Engineering,
National University of Singapore,
Republic of Singapore.

Saifur Rahman
Dept. of Electrical Engg.
Virginia Polytechnic Institute & State
University
U.S.A.

Abstract :

The paper presents a new approach for the estimation of harmonic components of a power system using a linear adaptive neuron called Adaline. The learning parameters in the proposed neural estimation algorithm are adjusted to force the error between the actual and desired outputs to satisfy a stable difference error equation. The estimator tracks the Fourier coefficients of the signal data corrupted with noise and decaying dc components very accurately. Adaptive tracking of harmonic components of a power system can easily be done using this algorithm. Several numerical tests have been conducted for the adaptive estimation of harmonic components of power system signals mixed with noise and decaying dc components.

Key words : Power system harmonics, Neural network, Adaline, Estimation.

1. Introduction

Estimation of the harmonic components in a power system is a standard approach for the assessment of the quality of the delivered power. There is a rapid increase in harmonic currents and voltages in the present AC systems due to large introduction of solid state power switching devices. Transformer saturation in a power network produces an increased amount of current harmonics. Consequently, to provide the quality of the delivered power, it is imperative to know the harmonic parameters such as magnitude and phase. This is essential for designing filters for eliminating and reducing the effects of harmonics in a power system. Many algorithms are available to evaluate the harmonics of which the Fast Fourier Transforms (FFT) developed by Cooley and Tukey[1,2] is widely used. Other algorithms include, recursive DFT, spectral observer, Hartley transform[3,4] for selecting the range of harmonics. The use of a more robust algorithm is described by Dash and Sharaf [5] and Girgis et al[6] which provides a simple linear Kalman filter for estimating the magnitudes of sinusoids of known frequencies embedded in an unknown measurement noise, which can be a mixture of both stochastic and deterministic signals.

In tracking harmonics for the large power system, where it is difficult to locate the magnitude of the unknown harmonic sources, a new algorithm based on learning principles is used by Hartana and Richards [7]. This method uses Neural networks to make initial estimates of harmonic source in the power system with nonlinear loads. To predict the voltage harmonics, Mori et.al, [8] have used the artificial neural network based on the backpropagation learning technique. An analog neural method of calculating harmonics is presented by S. Osowski [9] which basically uses the optimization technique to minimize error and this is an interesting application from the point of view of VLSI implementation.

The present paper proposes a new approach for the adaptive estimation of harmonics using a Fourier linear combiner. The linear combiner is realised using a linear adaptive neural network called Adaline[10]. An Adaline has an input sequence, an output sequence, and a desired response-signal sequence. It has also a set of adjustable parameters called the weight vector. The weight vector of the Adaline generates the Fourier coefficients of the signal using a nonlinear weight adjustment algorithm based on a stable difference error equation. This approach [11] is substantially different from the backpropagation approach and allows one to better control the stability and speed of convergence by appropriate choice of parameters of the error difference equation. Several computer simulation tests are conducted to estimate the magnitude and phase angle of the harmonic components from power system signals embedded in noise very accurately. Further, the estimation technique is highly adaptive and is capable of tracking the variations of amplitude and phase angle of the harmonic components. The performance of this algorithm is compared with the well-known Kalman filtering algorithm showing its superiority over the later in tracking power system harmonics on-line.

2. Problem formulation

Let us assume the waveform of the voltage or current of the power system with a fundamental angular frequency, ω , as the sum of harmonics of unknown magnitudes and phases. The general form of the waveform is

$$y(t) = \sum_{l=1}^N A_l \sin(l\omega t + \phi_l) + \epsilon(t) \quad (1)$$

where the A_l 's and ϕ_l 's are the amplitude and phase of the harmonics, respectively; N is the total number of harmonics, and $\epsilon(t)$ is the noise and t is the instant of measurement.

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The discrete-time version of the signal represented by equation (1) is

$$y(k) = \sum_{l=1}^N A_l \sin\left(\frac{2\pi l k}{N_s} + \phi_l\right) + \epsilon(k) = \sum_{l=1}^N A_{ld} \cos \phi_l \cdot \sin \frac{2\pi l k}{N_s} + \sum_{l=1}^N A_{lq} \sin \phi_l \cdot \cos \frac{2\pi l k}{N_s} + \epsilon(k) \quad (2)$$

where N_s is the sample rate given by

$N_s = f_s / f_0$, where f_0 = nominal power system frequency and f_s = sampling frequency.

To obtain the solution for on-line estimation of the harmonics, we propose the use of an adaptive neural network comprising linear adaptive neuron called "Adaline". The block diagram of the Adaline is shown in Fig.1. The input to the Adaline is given by

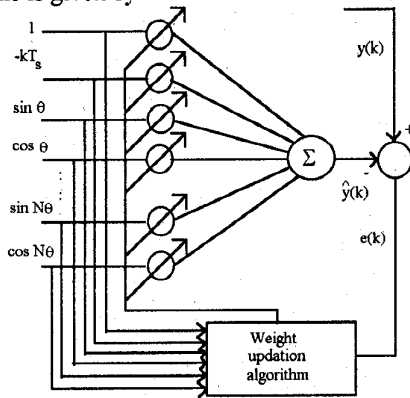


Fig.1 Block diagram for harmonic estimation using an Adaline ($\theta = 2\pi k / N_s$)

$$X(k) = \begin{bmatrix} \sin \frac{2\pi k}{N_s} & \cos \frac{2\pi k}{N_s} & \sin \frac{4\pi k}{N_s} & \cos \frac{4\pi k}{N_s} & \dots & \sin \frac{2N\pi k}{N_s} & \cos \frac{2N\pi k}{N_s} \end{bmatrix}^T \quad (3)$$

T = transpose of a quantity.

If a decaying dc quantity is added to the signal model given in equation (2), the input vector X becomes

$$X(k) = \left[\sin \frac{2\pi k}{N_s} \quad \cos \frac{2\pi k}{N_s} \quad \dots \quad \sin \frac{2N\pi k}{N_s} \quad \cos \frac{2N\pi k}{N_s} \quad 1 - kT_s \right]^T \quad (4)$$

In this equation the decaying dc component is represented as $A_{dc} - A_{dc}\beta kT_s$

where, β =decaying coefficient, $T_s = 2\pi / \omega N_s$

The weight vector of the Adaline is updated using Widrow-Hoff delta rule [13] as

$$W(k+1) = W(k) + \frac{\alpha e(k) X(k)}{X^T(k) X(k)} \quad (5)$$

where k = the time index or iteration,

$W(k) = [W_1(k) \ W_2(k) \ W_3(k) \ W_4(k) \ \dots \ W_{2N-1}(k) \ W_{2N}(k) \ W_{2N+1}(k) \ W_{2N+2}(k)]^T$

is the weight vector at time k .

$X(k)$ = input vector at time k ,

$e(k) = y(k) - \hat{y}(k)$ is the error at time k ,

α = reduction factor (a learning parameter)

$\hat{y}(k)$ = estimated signal amplitude at time k , and

$y(k)$ = actual signal amplitude at time k .

On the k th iteration, the error is

$$e(k) = y(k) - \hat{y}(k) \quad (6)$$

This error will be brought down to zero, when perfect learning is attained and the signal $y(k)$ becomes equal to

$$y(k) = W_0^T X(k) \quad (7)$$

where W_0 is the weight vector after final convergence is attained, so that the neural model exactly predicts the incoming signal.

To study the convergence of the learning rule, the following positive definite function in the way of Lyapunov is used :

$$V(k) = \|W(k) - W_0\|^2 \quad (8)$$

$$\Delta V(k) = V(k+1) - V(k)$$

By using weight adjustment algorithm (5) and with some manipulations, it can be proved that

$$\Delta V(k) \leq \left\{ -2 + \frac{\alpha X^T(k) X(k)}{\lambda + X^T(k) X(k)} \right\} \left\{ \frac{\alpha e^2(k)}{\lambda + X^T(k) X(k)} \right\} \quad (9)$$

For $0 < \alpha < 2$, and $\lambda > 0$, $\Delta V(k) \leq 0$

Therefore, if $y(k) \neq \hat{y}(k)$, the adjustment law reduces the Euclidean distance between $W(k)$ and W_0 and ensures the weight error vector ($W(k) - W_0$) going to zero as $k \rightarrow \infty$.

The practical range of α is between .1 and 1 for making the error between the computed and measured signals to converge asymptotically to zero at a rate $(1-\alpha)$. Further the value of λ is chosen very nearly zero ($\lambda = .01$) so that

$$\lambda + X^T(k) X(k) \neq 0 \quad (10)$$

After the tracking error converges to zero, the weight vector yields the Fourier coefficients as

$$W_0 = [A_1 \cos \phi_1 \ A_1 \sin \phi_1 \ \dots \ A_N \cos \phi_N \ A_N \sin \phi_N \ A_{dc} \ A_{dc} \beta]^T \quad (11)$$

The amplitude and phase of the N th harmonic is given by

$$A_N = \sqrt{W_0^2(2N-1) + W_0^2(2N)} \quad (12)$$

$$\phi_N = \tan^{-1} \{ W_0(2N-1) / W_0(2N) \}$$

After discussing the Widrow-Hoff delta rule, another adaptation algorithm is considered for this application. This algorithm for the weight adaptation of Adaline produces a fast convergence and introduces nonlinearity to the learning technique. The weight vector of the Adaline is adapted as

$$W(k+1) = W(k) + \frac{\alpha e(k) \theta_k(X)}{\lambda + X^T \theta_k(X)} \quad (13)$$

where $\theta_k(X)$ is chosen as a SGN function and is given by

$$\theta_k(X) = \left[\text{SGN} \left(\sin \frac{2\pi k}{N_s} \right) \text{SGN} \left(\cos \frac{2\pi k}{N_s} \right) \right. \quad (14)$$

$$\left. \dots \text{SGN} \left(\sin \frac{2\pi k N}{N_s} \right) \text{SGN} \left(\cos \frac{2\pi k N}{N_s} \right) 1 - 1 \right]$$

where

$$\text{SGN}(x_i) = \begin{cases} +1 & \text{if } x_i > 0 \\ -1 & \text{if } x_i < 0 \end{cases} \quad (15)$$

$i = 1, 2, \dots, 2N$

The learning parameter α can be made adaptive by using the following expression

$$\alpha = \alpha_0 / (1 + k / k_1) \quad (16)$$

where k_1 is to be chosen suitably for the best performance. This algorithm is much simpler and faster in comparison to the 3-layer ANN approach using backpropagation technique as the later takes large training time and suffers from convergence problem.

4. Numerical Experimentation

In order to evaluate the performance of the adaptive perceptron in estimating amplitude and phase of the harmonic components, numerical experiments using MATLAB software have been performed. The voltage waveform of known harmonic contents is taken for estimation

$$V(t) = 1.0 \sin(\omega t + 10^\circ) + 0.1 \sin(3\omega t + 20^\circ) + 0.08 \sin(5\omega t + 30^\circ) \\ + 0.08 \sin(9\omega t + 40^\circ) + 0.06 \sin(11\omega t + 50^\circ) \\ + 0.05 \sin(13\omega t + 60^\circ) + 0.03 \sin(19\omega t + 70^\circ)$$

The sampling frequency is chosen as 1.6kHz based on a 50 Hz voltage waveform. The estimated amplitude and phase of 3rd and 11th harmonic are shown in Fig.2.

The effect of frequency drift of the fundamental by 1.0 Hz is considered on the magnitudes of the estimates and Fig.3 shows these values for the same 3rd and 11th harmonic components of the voltage waveform.

The voltage signal is then corrupted with an exponentially decaying dc component represented by $0.1 \exp(-5t)$ and a random noise of variance .02. The results of the estimation of amplitude and phase of 3rd and 5th harmonic components (Fig.4) show excellent accuracy in the presence of noise and decaying dc component. A comparison is made with the Kalman filtering (KF) algorithm [7], which is better than the discrete fourier transform (DFT) technique and the results are presented in Fig.4. Each element of the process noise covariance matrix Q (diagonal) is chosen as .01 and the measurement noise variance, R is set equal to .001. From the figure it is observed that the Adaline produces fast and accurate tracking of harmonic components on-line in the presence of noise and other spurious signals like decaying dc components in comparison to the KF technique.

4.1 Tracking of time varying amplitude and phase of harmonics

The proposed neural estimator is used to track the time varying harmonic currents during no-fault and fault conditions in a parallel AC-DC power system. The parallel AC-DC system is simulated using EMTDC software package, which provides realistic representation of various subsystem models of the AC-DC system. The inverter ac system is made weak and the fault occurs on the inverter ac-bus. The amplitudes of 3rd, 7th, 11th and 13th harmonic components are shown in Fig.5 without noise and Fig.6 shows the 3rd and 7th harmonic components when a random noise of variance .02 is added to the current waveform of A-phase ac system. On comparison with Fig.5, it is found that the performance of the neural estimation algorithm is excellent when the noise level is lower than the estimated magnitude of the harmonic component. The performance deteriorates with time, as the magnitude of the harmonic component decreases and the noise predominates.

The Adaline has been also tested in real-time using the data from a SCR fed drive system through a PC-based

data acquisition interface and processing system. The test results will be reported in a future paper.

5. Conclusions

The paper presents a new approach for estimation of amplitude and phase angles of harmonics in power systems. The approach is based on the weight vector estimation of an Adaline using Least Mean squares and a nonlinear weight adjustment algorithm. Several computer simulation tests have been conducted to estimate harmonics of power system signals corrupted with random noise and decaying dc components to assess the speed of convergence and tracking accuracy of the new approach using an adaptive linear combiner. The results presented in this paper indicate the excellent accuracy and convergence speed of the new algorithm in comparison with the DFT based algorithm. Further the adaptive nature of the algorithm is suitable for tracking harmonics with time varying amplitude and phase angles. An adaptive learning parameter α is used in this paper in bringing a faster convergence and noise rejection in tracking the harmonic components.

6. References

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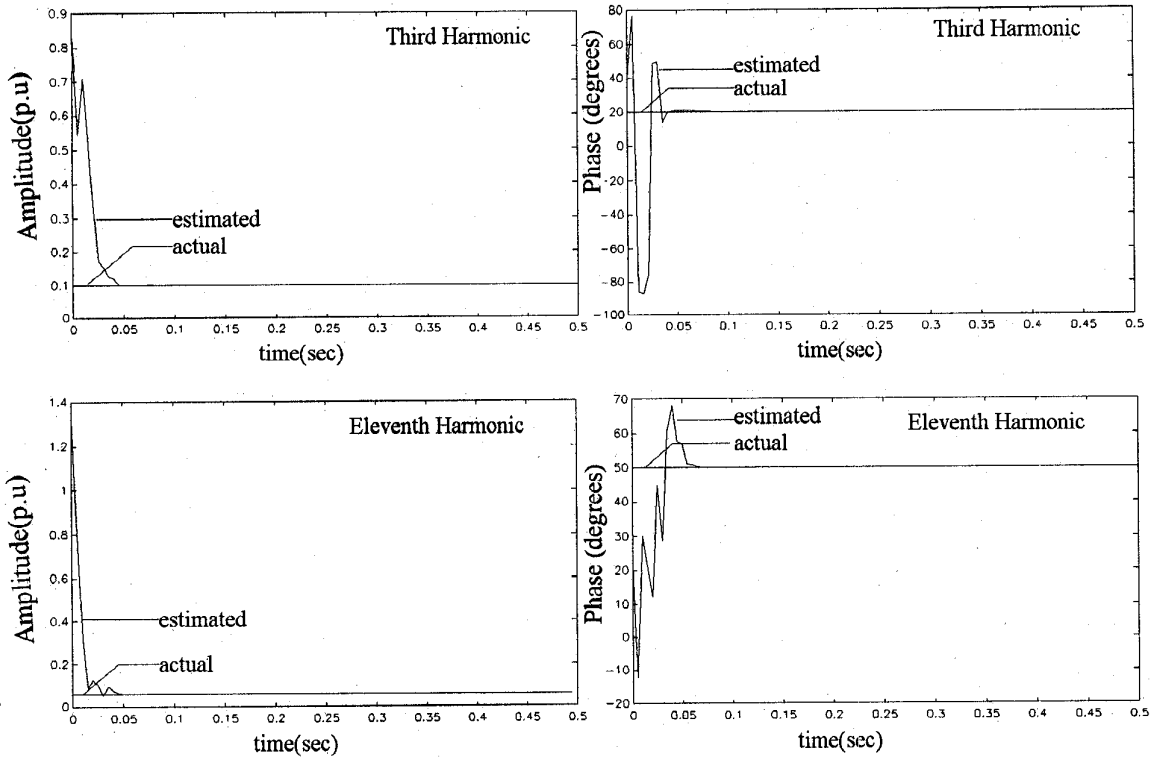


Fig.2 Estimation of harmonic components

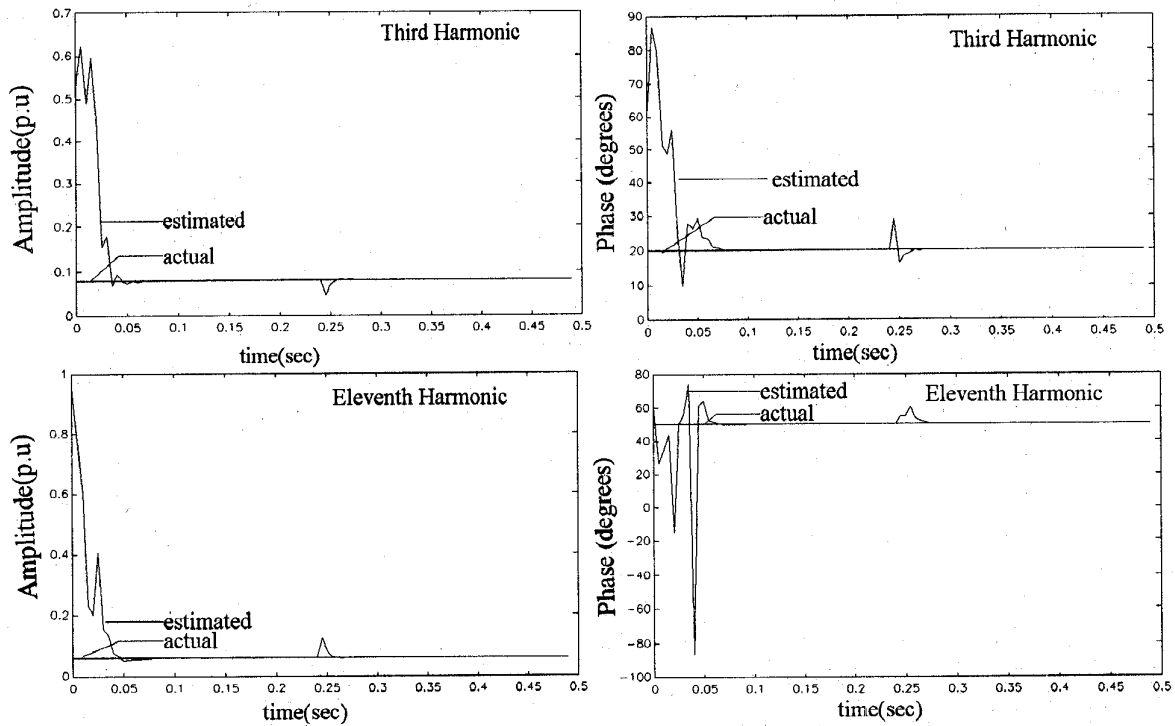


Fig.3 Estimation of harmonic components for a frequency change of 1Hz of the fundamental frequency

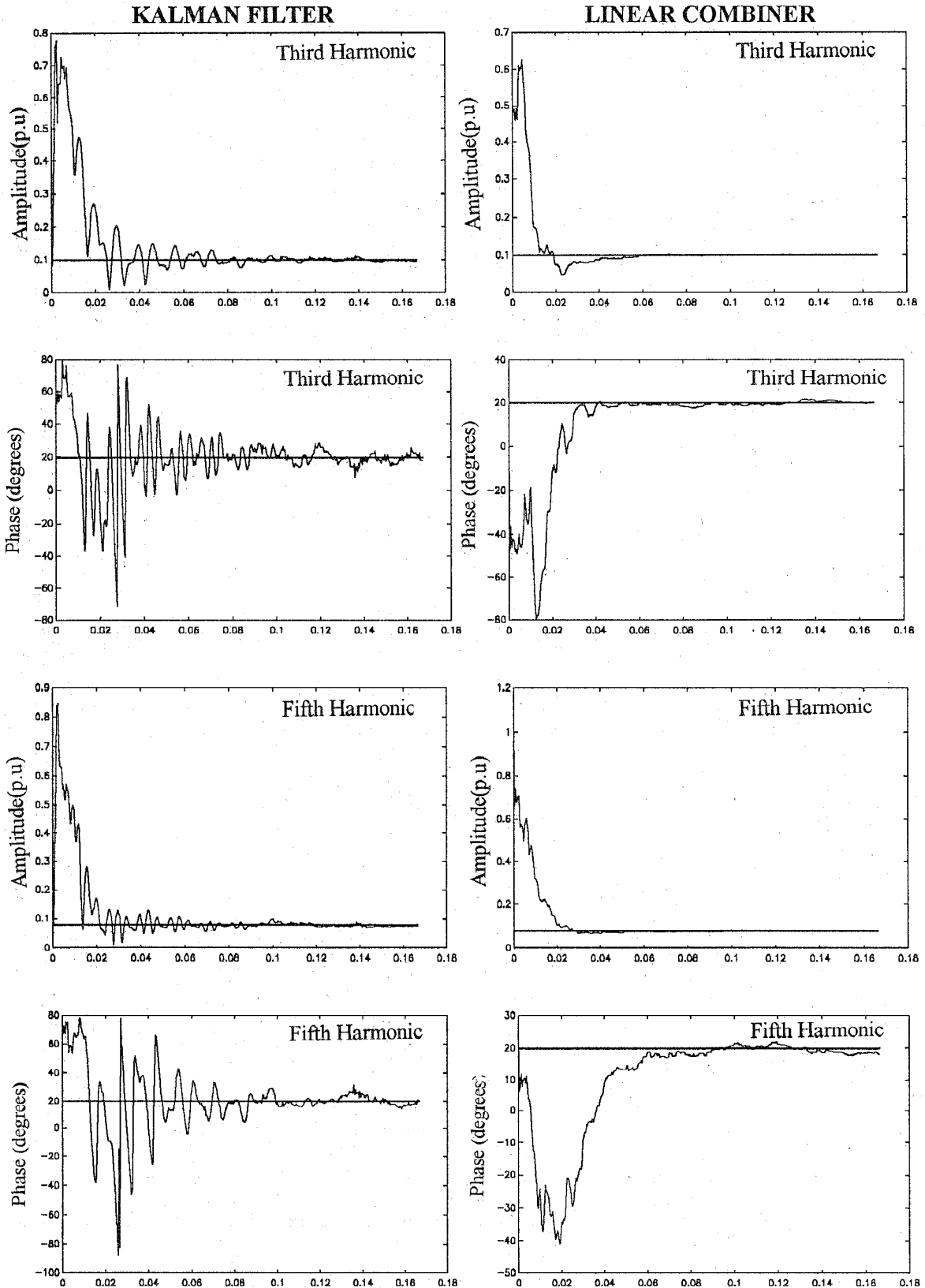


Fig 4: Estimation of harmonic components in presence of d.c. components and random noise

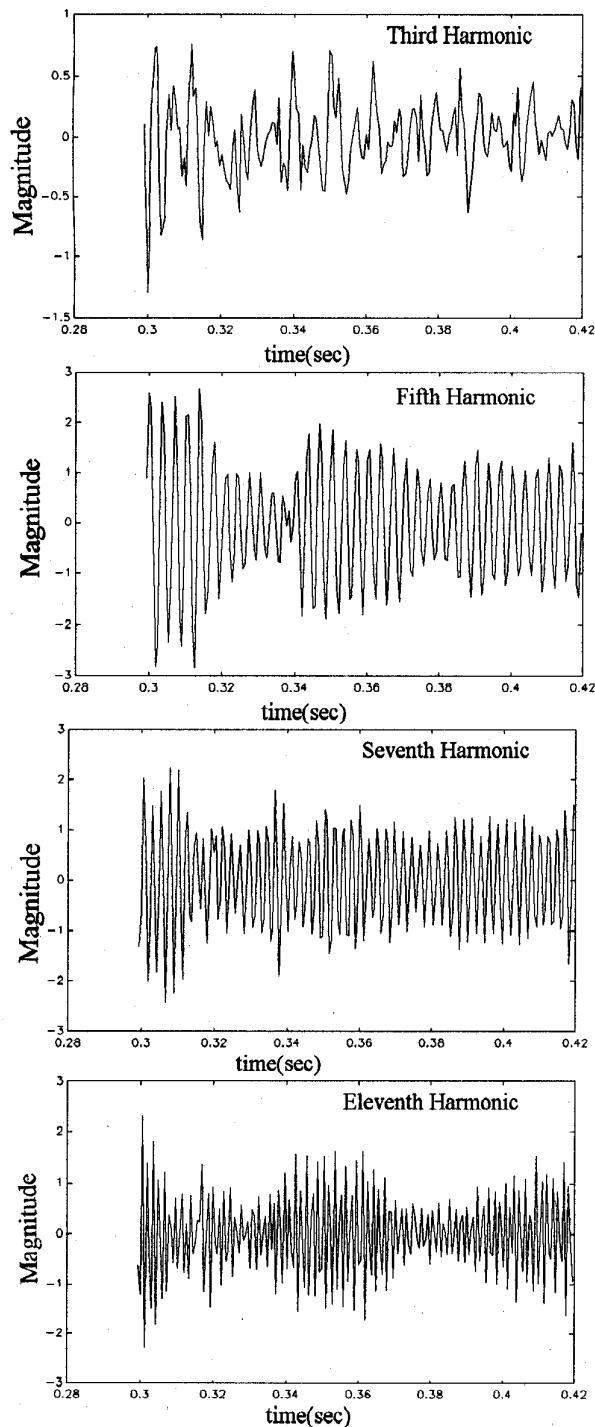


Fig.5 Estimating the harmonic components of a AC-DC system

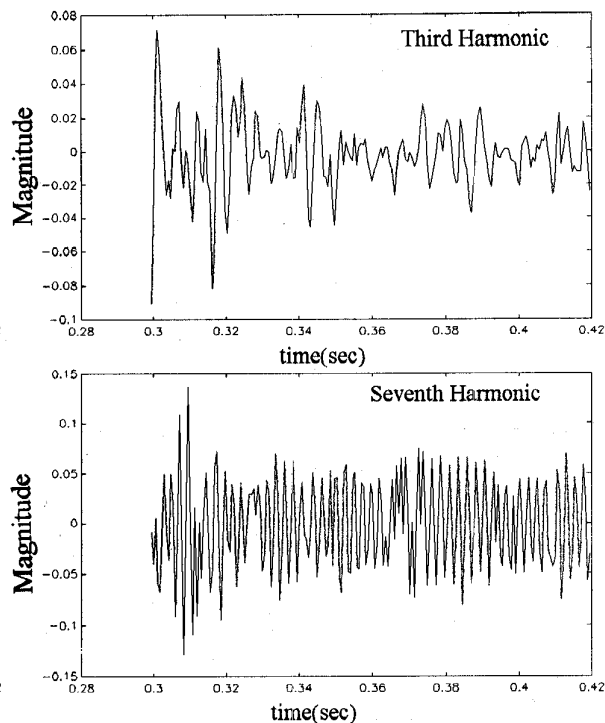


Fig.6 Estimation of Harmonic components of AC-DC System with random noise.

P.K.Dash was educated at the Utkal University and I.I.Sc., Bangalore. He was a post-doctoral fellow at the University of Calgary, Canada and held several visiting appointments with North-American Universities, BBC Brown Boveri, Switzerland, and Bristol Aerospace, Canada. His recent collaborations are with Virginia Polytechnic Institute and State University, U.S.A. and the National University of Singapore.

Ah.Choy Liew received the B.E. and Ph.D. Degree from the University of Queensland, Australia in 1969 and 1972 respectively. From 1972 to 1979, he was with the Electrical Engineering Department of the university of Malaya. He is presently with the National University of Singapore where he is associate professor and head of department. His man areas of interest are lightning and lightning protection, high voltage and power systems engineering.

Debi P Swain received B.E. degree in 1993 and Continuing M.E. degree in Regional Engineering College, Rourkela, India. Presently he is working as Research Associate in the Centre for Intelligent Systems, Electrical Engineering Department, Regional Engineering College, Rourkela, India.

Saifur Rahman graduated from the Bangladesh University of Engineering and Technology in 1973 with a B.Sc degree in Electrical Engineering. He obtained M.S. degree in Electrical Sciences from SUNY at stony brook in 1975 and Ph.D. from VPSU, Blacksburg in 1978. He has taught at Bangladesh University of Engineering and Technology, the Texas A&M University, VPSU, Blacksburg.