Estimation of Power System Harmonics Using Hybrid RLS-Adaline and KF-Adaline Algorithms

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Abstract— **This paper presents combined RLS-Adaline (Recursive Least Square and adaptive linear neural network) and KF-Adaline (Kalman Filter Adaline) approach for the estimation of harmonic components of a power system. The neural estimator is based on the use of an adaptive perceptron comprising a linear adaptive neuron called Adaline. Kalman Filter and Recursive Least Square algorithms carry out the weight updating in Adaline. The estimators' track the signal corrupted with noise and decaying DC components very accurately. Adaptive tracking of harmonic components of a power system can easily be done using these algorithms. The proposed approaches are tested both for static and dynamic signal. Out of these two, the KF-Adaline approach of tracking the fundamental and harmonic components is better.**

Keywords-Harmonics Estimation; Adaptive Linear Neural Networks(Adaline); Discrete Fourier Transform(DFT); Fast Fourier Transform(FFT);

I. INTRODUCTION

Due to the introduction of electronically controlled loads, the harmonic distortion in power system voltage and current waveform is increased. Damped high-frequency transients are generated due to frequently switching on and off of power semiconductors at points of voltage and current waveforms. So voltage and current waveforms of a distribution or a transmission system are not pure sinusoids, but may consist of fundamental frequency, harmonics and high frequency transients. Also many of power system loads are dynamic in nature which implies time varying amplitude of the current waveform

To provide the quality of the delivered power, it is important to know the harmonics parameters such as amplitude and phase. This is essential for designing filter to eliminate or reduce the effects of harmonics in a power system [4]. So many algorithms have been proposed to evaluate the harmonics [1-2, 4-9, 11-15]. In order to get the voltage and current frequency spectrum from discrete time samples, most frequency domain harmonic analysis algorithms are based on the discrete Fourier Transform (DFT) or on the fast Fourier transform (FFT). However, these two methods suffer leakage effect [3]. Although other methods, including the proposed algorithms in this paper, suffer that problem, and this is due to existing high-frequency components in the measured signal, but truncation of the sequence of sampled data, when only a fraction of the sequence of a cycle exists in the analyzed waveform, boost leakage problem of DFT method. So the need for new algorithms that process the data, sample-by-sample, and not a window of data as in DFT and FFT, is of importance. Because these methods process data sample-by-sample, loosing one or more samples creates less leakage problems than DFT and FFT.

Kalman Filter [6, 10, 11, 14-15] is one of the robust algorithms for estimating the magnitudes of sinusoids of known frequencies embedded in an unknown measurement noise. But this algorithm cannot track abrupt or dynamic changes of signal and its harmonics. Recently, many researchers adopt Artificial Intelligence techniques [1] for harmonic estimation. Dash et al. [4] use an algorithm based on an adaptive neural network, which shows better tracking capability of dynamic amplitude as to that of classic Kalman filtering approach. In that algorithm, the weights are updated using Widrow-Hoff delta rule. As estimation of harmonic parameters is a nonlinear problem, Qidwai and Betayeb [12-13] use Genetic algorithm (GA), as a heuristic and stochastic global searching algorithm for this purpose. This method provides excellent results but main disadvantage is that is takes more time for convergence.

II. PROPOSED ALGORITHM

Let us assume the voltage or current waveforms of the known fundamental angular frequency ω as the sum of harmonics of unknown magnitudes and phases. The general form of the waveform is

$$y(t)=\sum_{n=1}^{N} A_n \sin(\omega_n t+\phi_n)+A_{dc}\exp(-\alpha_{dc}t)+\mu(t) \qquad (1)$$

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

The discrete time version of Eq. (1) can be represented as

$$y(k)=\sum_{n=1}^{N} A_n \sin(\omega_n kT_s+\phi_n)+A_{dc}\exp(-\alpha_{dc}kT_s)+\mu(k) \qquad (2)$$

Where, T_s is sampling period.

Approximating decaying term using first two terms of Taylor series as

$$y_{dc} = A_{dc} - A_{dc}\alpha_{dc}kT_s \qquad (3)$$

Now Eq. (2) becomes

$$y(k)=\sum_{n=1}^{N}A_n\sin(\omega_n kT_s+\phi_n)+A_{dc}-A_{dc}\alpha_{dc}kT_s+\mu(k) \qquad (4)$$

The nonlinearity arises in the model is due to phase of the sinusoids. Bettayeb and Qidwai used GA for estimating phases of the harmonics. Although using GA for estimating phases alleviated the mentioned problems but due to introduction of GA, the algorithm becomes slow and cannot be used as an online estimator. In this paper a fast neural network called Adaline is used. The weight of the adaline is updated using Recursive Least Square and Kalman Filter algorithm.

For estimation amplitudes and phases Eq.(4) can be rewritten as

$$y(k)=\sum_{n=1}^{N}\begin{aligned}&[A_n\sin(\omega_n kT_s)\cos\phi_n+A_n\cos(\omega_n kT_s)\sin\phi_n]\\&+A_{dc}-A_{dc}\alpha_{dc}kT_s+\mu(k)\end{aligned} \qquad (5)$$

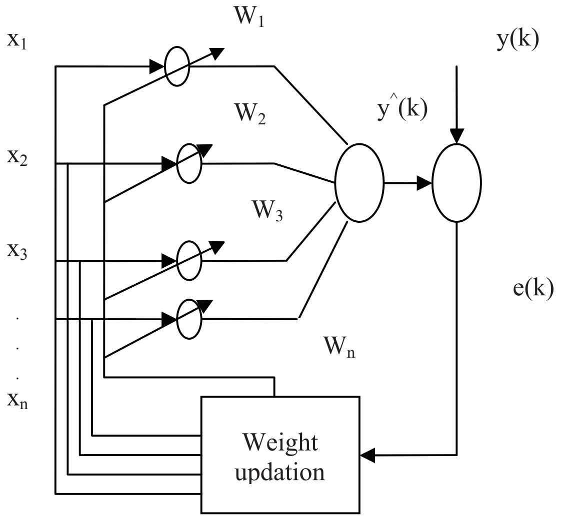

Fig.1 Block diagram of Adaline

This equation gives an idea of using an adaptive linear combiner comprising a neural network called 'Adaline' to estimate the phases of the harmonics.
The block diagram of the Adaline is shown in fig.1
The input to the Adaline is

$$x(t)=[\sin(\omega_1 t)\ \ \cos(\omega_1 t)\ \ ...\ \ \sin(\omega_N t)\ \ \cos(\omega_N t)\ \ 1\ \ -t]^T \qquad (6)$$

The weight vector of the Adaline

$$W(k)=[W_1(k)\ \ W_2(k)\ \ ...\ W_{2N-1}(k)\ \ W_{2N}(k)\ \ W_{2N+1}(k)\ \ W_{2N+2}(k)]^T \qquad (7)$$

is updated using Recursive Least Square Algorithm as

$$\hat{W}(k+1)=\hat{W}(k)+K(k+1)\varepsilon(k+1) \qquad (8)$$

Error in measurement is

$$\varepsilon(k+1)=y(k+1)-x(k+1)^T\,\hat{W}(k) \qquad (9)$$

The gain K is related with covariance of parameter vector

$$K(k+1)=P(k)x(k+1)[1+\phi(k+1)^T P(k)x(k+1)]^{-1} \qquad (10)$$

The updated covariance of parameter vector using matrix inversion lemma

$$P(k+1)=[I-K(k+1)x(k+1)^T]P(k) \qquad (11)$$

Taking some initial values for the estimate at instant t initializes these equations. As the choice of initial covariance matrix is large it is taken $P=\alpha I$ where α is a large number and I is a square identity matrix.

The weight vector of the Adaline is updated using Kalman Filter Algorithm as

$$G(k)=P(k/k-1)x(k)^T(x(k)P(k/k-1)x(k)^T+Q)^{-1} \qquad (12)$$

G is the Kalman gain, x is the observation vector, P is the covariance matrix, Q is the noise covariance of the signal.
So the covariance matrix is related with Kalman gain with the following equation.

$$P(k/k)=P(k/k-1)-G(k)x(k)P(k/k-1) \qquad (13)$$

So the updated estimated state is related with previous state with the following equation.

$$\hat{W}(k/k)=\hat{W}(k/k-1)+G(k)(y(k)-x(k)\hat{W}(k/k-1)) \qquad (14)$$

After the updating of weight vector using RLS or KF algorithm, amplitudes, phases of the fundamental and nth harmonic parameters and dc decaying parameters are derived as

$$A_n=\sqrt{(W_{2n}^2+W_{2n-1}^2)} \qquad (15)$$

$$\phi_n=\tan^{-1}\left(\frac{W_{2n}}{W_{2n-1}}\right) \qquad (16)$$

$$A_{dc}=W_{2n+1} \qquad (17)$$

$$\alpha_{dc}=\left(\frac{W_{2n+2}}{W_{2n+1}}\right) \qquad (18)$$

Because

$$W=[A_1\cos(\phi_1)\ \ A_1\sin(\phi_1)\ \ ...\ \ A_n\cos(\phi_n)\ \ A_n\sin(\phi_n)\ \ A_{dc}\ \ A_{dc}\alpha_{dc}]^T \qquad (19)$$

III. SIMULATION RESULTS AND DISCUSSIONS

A. Static signal corrupted with random noise and decaying DC component.

The power system signal used for the estimation, besides the fundamental frequency, contains higher harmonics of the 3rd, 5th, 7th, 11th and a slowly decaying DC component [2]. This kind of signal is typical in industrial load comprising power electronic converters and arc furnaces [2].

$$\begin{aligned}y(t)&=1.5\sin(\omega t+80^0)+0.5\sin(3\omega t+60^0)\\&+0.2\sin(5\omega t+45^0)+0.15\sin(7\omega t+36^0)\\&+0.1\sin(11\omega t+30^0)+0.5\exp(-5t)+\mu(t)\end{aligned} \qquad (20)$$

The signal is corrupted by random noise $\mu(t)=0.05rand(t)$ having normal distribution with zero mean and unity variance. Fig. 2 and 3 show actual vs.

estimated signal using rls-adaline and kf-adaline method respectively. It is seen from the fig. that actual and estimated signal almost matches with each other in both the cases. Fig. 4 shows the comparative estimation of fundamental amplitude of signal using both rls-adaline and kf-adaline method. In case of rls-adaline, estimated amplitude oscillates between 1.47 p.u. to 1.51p.u. but kf-adaline estimates fundamental amplitude as 1.5 p.u. Fig. 5 provides a comparative estimation of third harmonic component of signal using the above two methods. In the estimation using rls-adaline, during first few initial times period estimation is 0.535 p.u. after that it settles around 0.515 p.u. KF-Adaline estimates third harmonics amplitude as 0.502 p.u. Fig.6 shows the estimated result of 5^{th} harmonic amplitude using both the algorithms. RLS-adaline estimates it between 0.19 to 0.22 p.u. having more oscillations during initial time period. But the estimated value of fifth harmonic component using KF-Adaline is 0.202 p.u. Fig. 7 gives the estimated result of 7^{th} harmonic component of signal using the two algorithms. RLS-Adaline estimates it around 0.155 p.u. but oscillation varies from 0.145 to 0.16 p.u. KF-Adaline estimates 7^{th} harmonic component as 0.149 p.u. which is more accurate. Fig. 8 provides a comparative estimation of 11^{th} harmonic component of signal using both the algorithms. RLS-Adaline estimates it between 0.09 to 0.13 p.u. with it's oscillations around 0.11 p.u. but KF-Adaline estimates it as 0.101p.u.

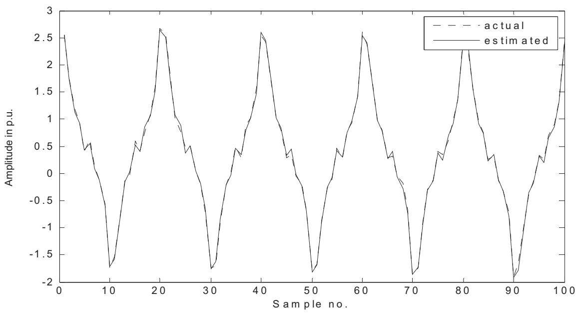

Fig.2 Actual and Estimated value of signal using rls-adaline

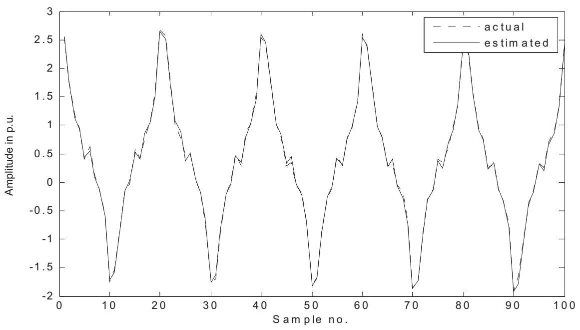

Fig.3 Actual and Estimated value of signal using kf-adaline

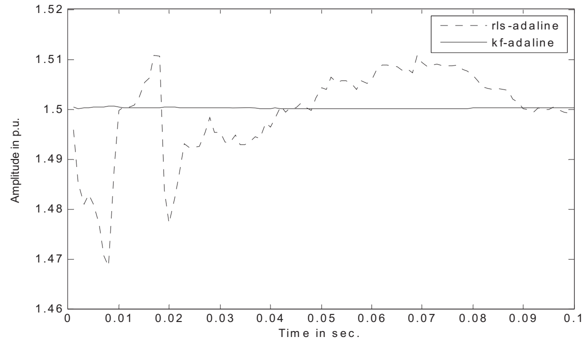

Fig.4 Estimation of amplitude of fundamental component of signal

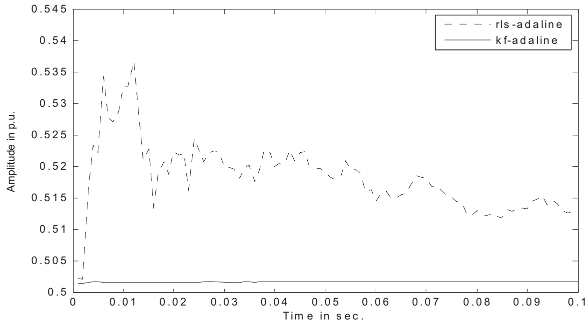

Fig. 5 Estimation of amplitude of third harmonic component of signal

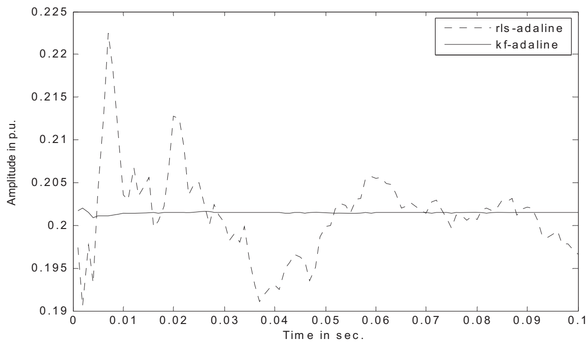

Fig. 6 Estimation of amplitude of fifth harmonic component of signal

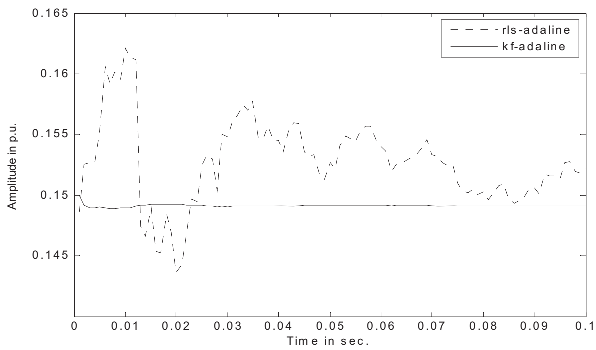

Fig. 7 Estimation of amplitude of seventh harmonic component of signal

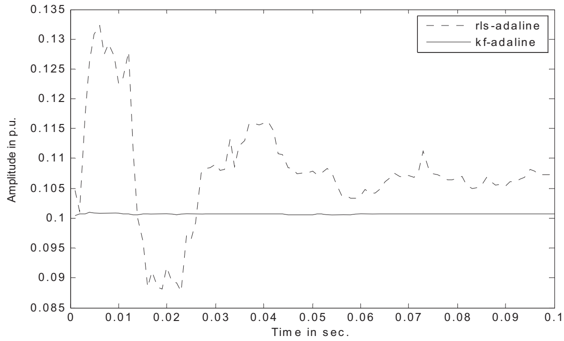

Fig. 8 Estimation of amplitude of eleventh harmonic component of signal

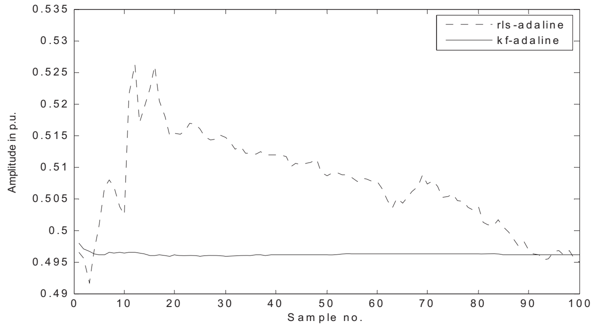

Fig. 9 Estimation of amplitude of dc component of signal

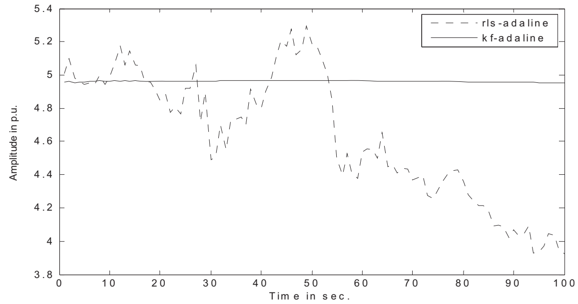

Fig. 10 Estimation of amplitude of alphadc of signal

Fig. 9 shows the comparative estimation of dc component of signal using both the algorithms. Estimated value of signal using KF-Adaline is 0.496 p.u. but it's value using RLS-Adaline varies from 0.492 to 0.525 p.u. and it settles at 0.495 p.u. Fig.10 gives the estimated result of alphadc using both the algorithms and it shows that estimation using KF-Adaline is more accurate.

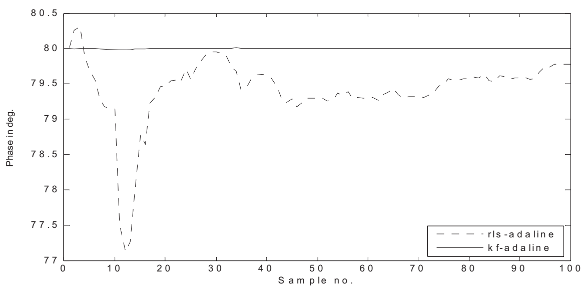

Fig.11 Estimation of phase of fundamental component of signal

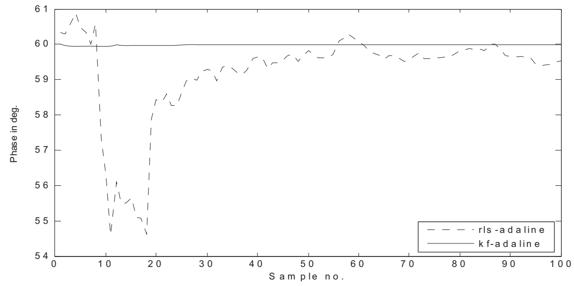

Fig.12 Estimation of phase of third harmonic component of signal

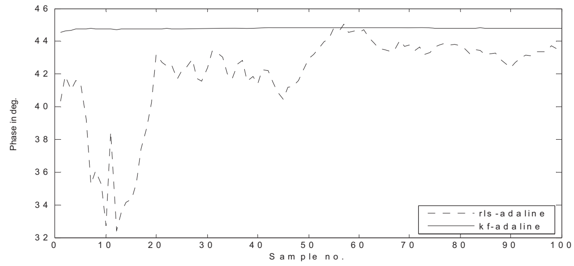

Fig.13 Estimation of phase of fifth harmonic component of signal

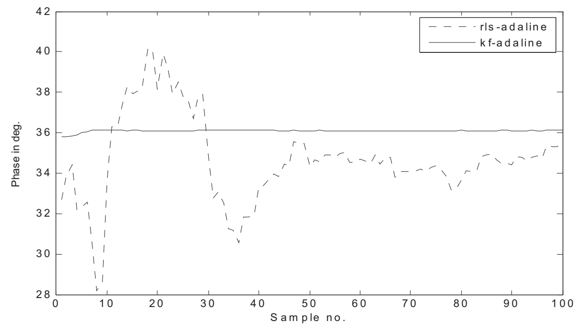

Fig.14 Estimation of phase of seventh harmonic component of signal

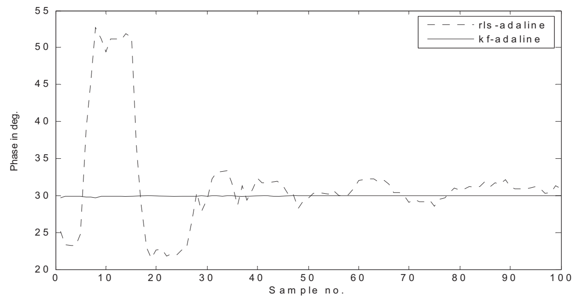

Fig.15 Estimation of phase of eleventh harmonic component of signal

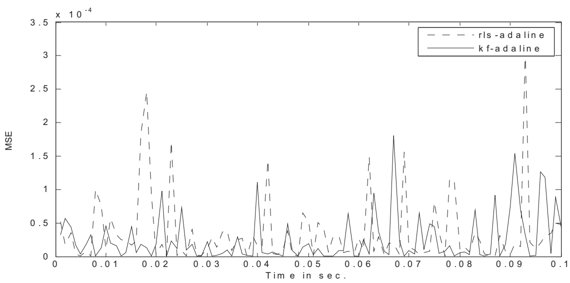

Fig.16 Estimation of MSE of static signal

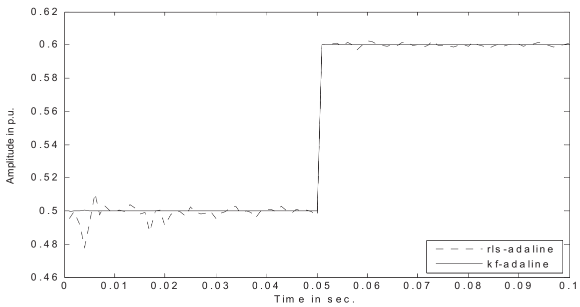

Fig. 17 Estimation of 3rd harmonic component of signal during amplitude change

Fig. 11-15 show the tracking of the fundamental, 3rd, 5th, 7th and 11th harmonic component of signal in presence of random noise and decaying DC component using RLS-Adaline and KF-Adaline methods. In the above estimation process, KF-Adaline is tuned optimally by properly choosing the covariance and noise covariance matrices. The time required for trapping the fundamental and harmonic is approximately 0.02 sec. (20 samples) for RLS-Adaline method but KF-Adaline traps the fundamental and harmonic components initially with more correct estimation.

Fig.16 shows the comparative estimation of Mean Square Error (MSE) of signal using the two algorithms. From the figure, it is found that, MSE performance in case of KF-Adaline is comparatively better than RLS-Adaline method. Fig.17 shows the tracking of 3rd harmonic component of signal, when it's amplitude suddenly changes from 0.5 p.u. to 0.6 p.u. at 0.05 sec. From the fig., it is seen that both the methods track the 3rd harmonic component but tracking by KF-Adaline is comparatively better.

B. Harmonic Estimation of a Dynamic Signal

To examine the performance of RLS-Adaline algorithm in tracking harmonics and its robustness in rejecting noise, a time-varying signal of the form

$$y(t) = \{1.5 + a_1(t)\}\sin(\omega_0 t + 80^0)$$
$$+ \{0.5 + a_3(t)\}\sin(3\omega_0 t + 60^0) \qquad (21)$$
$$+ \{0.2 + a_5(t)\}\sin(5\omega_0 t + 45^0) + \mu(t)$$

is used where:

$$a_1 = 0.15\sin 2\pi f_1 t + 0.05\sin 2\pi f_5 t \qquad (22)$$
$$a_3 = 0.05\sin 2\pi f_3 t + 0.02\sin 2\pi f_5 t \qquad (23)$$
$$a_5 = 0.025\sin 2\pi f_1 t + 0.005\sin 2\pi f_5 t \qquad (24)$$

$f_1 = 1.0$ Hz $f_3 = 3.0$ Hz. $f_5 = 6.0$ Hz.

and random noise $\mu(t)$ is same as in the case of static signal.Fig.18 and 19 show the actual vs. estimated value of signal using RLS-Adaline and KF-Adaline respectively. In both the cases actual and estimated value closely matches with each other. Fig. 20-22 show the tracking of fundamental, 3rd and 5th harmonic component of amplitude of a dynamic signal using both RLS-Adaline and KF-Adaline methods. In all the three cases RLS-Adaline provides oscillatory estimation but KF-Adaline provides more accurate and consistent performance. Fig 23 and 24 show the tracking of fundamental and 3rd harmonic component of phases of a dynamic signal using both the methods. Both the methods estimates correctly but KF-Adaline performance is better having negligible oscillations. Fig.25 provides a comparative performance of Mean Square Error (MSE) of signal. KF-Adaline performance is slightly better in MSE analysis.

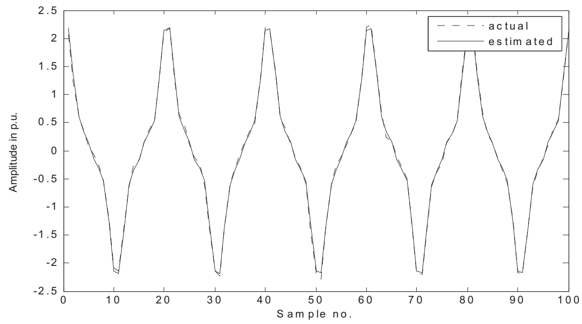

Fig.18 Actual and Estimated waveforms of dynamic signal using rls-adaline

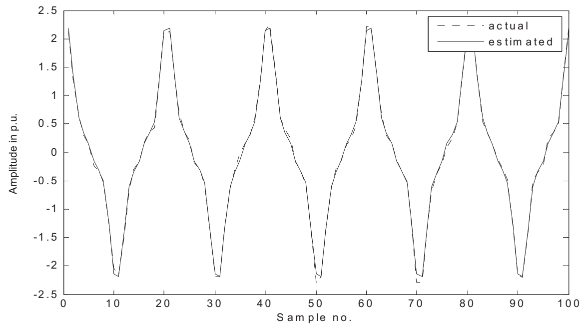

Fig.19 Actual and Estimated waveforms of dynamic signal using kf-adaline

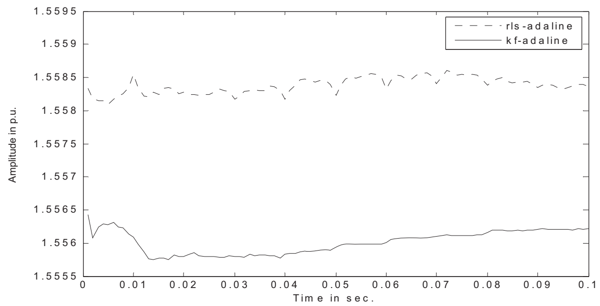

Fig.20 Estimation of amplitude of fundamental component of dynamic signal

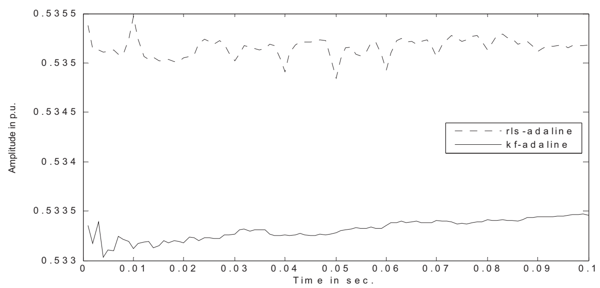

Fig.21 Estimation of amplitude of third harmonic component of dynamic signal

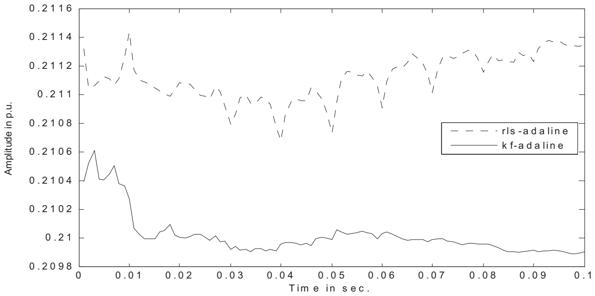

Fig.22 Estimation of amplitude of fifth harmonic component of dynamic signal

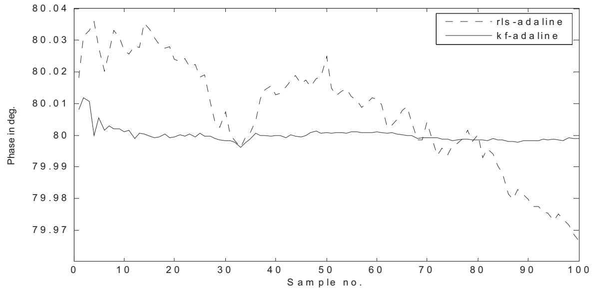

Fig.23 Estimation of phase of fundamental component of dynamic signal

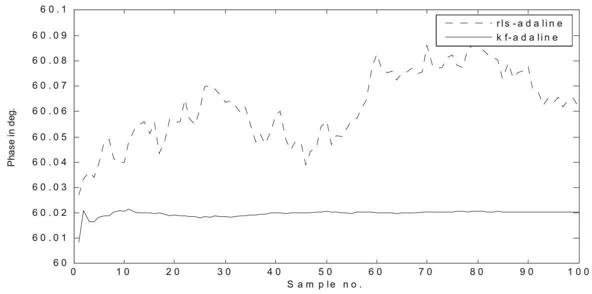

Fig.24 Estimation of phase of third harmonic component of dynamic signal

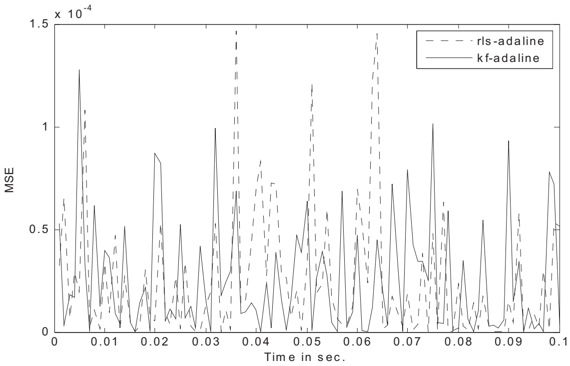

Fig.25 Estimation of MSE of dynamic signal

The performances of the proposed hybrid algorithms are very dependent on the initial choice of weight vector W and Covariance matrix P . By using an optimal choice of weight vector, faster convergence to the true value of signal parameter can be achieved. After the optimization of the weight vector, online tracking of the changes in amplitudes and phases of the fundamental and harmonic components in presence of noise and decaying dc components can be carried out. Both the algorithms track the fundamental and harmonic signals very well for both static and dynamic signal but the performance of tracking using KF-Adaline is better than RLS-Adaline. Both the static and dynamic signals are generated in MATLAB platform. The used PC had a 1.46 GHz CPU and 1GB RAM. The same algorithms can be applied to other areas such as communication channels, telephones and other encrypted signals.

IV. CONCLUSIONS

This paper presents two new approaches for adaptive estimation of amplitudes and phase angles of harmonics in a power system. The approaches are based on weight vector estimation of an Adaline using Recursive Least Square and Kalman Filter algorithms. Comparing with RLS-Adaline, simulation results reveal improvement in the performance of proposed KF-Adaline in tracking harmonic parameters even in presence of white noise and decaying dc components.

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