Ensemble-Kalman-Filter-Based Power System Harmonic Estimation

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***Abstract*—The growing use of power-electronics-based components and nonlinear loads is increasing the presence of harmonics in power system signals. In this scenario, proper estimation of such harmonics is intended to maintain power quality and improved operation of the system. It is also desirable that the estimation technique should be computationally efficient while being accurate. From this viewpoint, this paper proposes a nonlinear state estimation technique based on ensemble Kalman filtering for estimation of harmonics, interharmonics, and subharmonics, all using a single framework and at a time, from distorted power system signal. The proposed technique is computationally efficient compared to conventional Kalman filtering leading to less computational cost and hardware requirement. It is observed from both simulation and experimental studies that the proposed ensemble Kalman filter (KF) approach to estimation of harmonics, interharmonics, and subharmonics in a distorted power system signal exhibits superior estimation performance in terms of tracking time and accuracy as compared to performances of some of the existing techniques such as recursive least square, recursive least mean square, and KF algorithms. The proposed technique is also found to be robust and gives accurate estimates even in the presence of amplitude variations in the measured signal.**

***Index Terms*—Ensemble Kalman filter (EnKF), fast Fourier transform (FFT), harmonic estimation, KF, recursive least square (RLS).**

NOMENCLATURE

X	Ensemble matrix.
D	Data matrix.
$E(X)$	Ensemble mean.
$C(X)$	Sample covariance.
N	Number of column vectors of X.
P	State covariance.
K	Kalman gain matrix.
H	Observation matrix.
R	Error covariance matrix.
$\mu(t)$	Additive noise.
A_{dc}	Amplitude of dc component of signal.
α_{dc}	Decaying rate.
k	Discrete time (sampling) index.
T_s	Sampling period.
$y(k)$	Noisy measurement.
A_n	nth harmonic amplitude.
φ_n	nth harmonic phase.

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I. INTRODUCTION

HARMONIC estimation is one of the critical and challenging issues of power system engineers. Due to the increasing use of nonlinear loads in power systems, mostly power-electronic equipment, uninterruptible power supplies, arc furnaces, and controlled motor drives, periodical distortions in current and voltage waveforms become more. Moreover, power-electronic devices [1]. In addition, the proclaimed wide use of distributed generation in future power systems that are heavily based on power-electronic converters also contributes to the growing concern for better estimation to ensure power quality [2]–[4]. The objective of this work is to develop techniques to remove unwanted harmonic distortion in power system.

Recent literature on harmonic estimation [4], [5] shows that several techniques have been applied for the purpose. The conventional one is based on the fast Fourier transform (FFT). However, in the presence of interharmonics and variations in system fundamental frequency, FFT may lead to inaccuracies due to leakage and picket-fence effects. It is well known that Kalman filter (KF) is one of the robust algorithms for estimating the magnitudes of sinusoids of known frequencies embedded in an unknown measurement noise. However, the dynamics involved in KF raises concern since it exhibits poor performance with respect to sudden change in amplitude, phase, or frequency of signal. Moreover, it is assessed that no single method is available to estimate all the types of harmonics accurately and at a time. This suggests that superior algorithm for the purpose is intended.

On the other hand, ensemble KF (EnKF) is finding applications in hydrometeorology [6] and image processing [7]. It makes use of probability distribution function of the state of the modeled system and the data likelihood. Due to the use of stochastic information rather than of the whole available data set, it is computationally faster and performs satisfactorily for highly stochastic weather forecasting systems [8]. Since power system signals are also stochastic in nature, it would be interesting to see how it performs on the same.

In this paper, a new algorithm for the estimation of harmonics using EnKF [9], [10] is proposed. As the distorted power system signal contains higher orders of harmonics, so in the estimation process, the number of estimated parameters increases. This leads to the increase in the estimation states and the corresponding matrices involved in the estimation process. For such a case, EnKF is computationally beneficial since it uses ensembles of the measured signals rather than using the available measurement signals as a whole. Moreover, EnKF is simple to formulate and relatively easier to implement, e.g., it does not require derivation of a tangent linear operator as compared to KF estimation. On implementing the EnKF for harmonic estimation, the performance is assessed with respect to some available harmonic estimation techniques [11]–[15]. The comparison indicates that the proposed method outperforms the existing methods in terms of accuracy and robustness with respect to sudden variations in measured signal amplitudes.

This paper is organized as follows. Section II describes the proposed EnKF-algorithm-based estimation technique. Section III presents simulation studies on some existing methods such as recursive least square (RLS) [16], recursive least mean square (LMS) (RLMS), and KF [17], [18] together with the proposed EnKF approach for harmonic estimation applied to distorted power signals. Section IV describes the experimental setup developed to validate the efficacy of the proposed algorithm. Section V concludes this paper.

II. EnKF Algorithm and Estimation

A. Generalized EnKF

The EnKF is a Monte Carlo approximation of the conventional KF. Instead of evolving the covariance matrix of the probability density function of the state vector x, it uses distribution represented by a sample of x, called an ensemble, and may be expressed as

$$X = [x_1, x_2, \ldots, x_N] \tag{1}$$

where X is an $n \times N$ matrix whose columns are samples from its prior distribution.

Input data d are arranged as an $m \times N$ matrix

$$D = [d_1, d_2, \ldots, d_N] = [d_1] \tag{2}$$

$$d_i = d + \mu_i \tag{3}$$

$$\mu_i = N(0, R) \tag{4}$$

so that each column of d_i has information of the measurement data d_i and a random vector from the n-dimensional normal distribution $N(0, R)$, where R is a known error covariance matrix. The ensemble mean $[E(X)]$ and the covariance $[C(X)]$ can be written as

$$E(X) = \frac{1}{N}\sum_{k=1}^{N} X_k \tag{5}$$

$$G(X) = X - E(X) \tag{6}$$

$$C(X) = \frac{GG^{\mathrm{T}}}{N-1}. \tag{7}$$

$E(X)$ is a function of N vectors of X. N represents the number of column vectors in the unknown parameter matrix X. If columns of X represent a sample from the prior probability distribution, then the columns of

$$\hat{X} = X + K(D - HX) \tag{8}$$

will form a sample from the posterior probability distribution, where H is the observation matrix that maps true state space into observed space.

The EnKF is now obtained by replacing the state covariance P in conventional Kalman gain matrix $K = PH^{\mathrm{T}}(HPH^{\mathrm{T}} + R)^{-1}$ by the sample covariance C computed from the ensemble members. The corresponding covariance matrix is also called ensemble covariance. When the number of unknowns to be determined becomes more, then computational feasibility of covariance matrix P in case of KF for high-dimensional system becomes uncertain and suffers from singularity problem. The huge computational time in KF is due to the huge matrix multiplication required to evaluate the covariance [14]; however, the sizes of covariance matrices in both the cases are same. To avoid this difficulty, sample covariance C is introduced in case of EnKF in gain matrix instead of state covariance matrix P. Then, updated ensemble can be written as

$$\hat{X} = X + CH^{\mathrm{T}}(HCH^{\mathrm{T}} + R)^{-1}(D - HX). \tag{9}$$

EnKF provides better estimation due to the fact that the evaluation of filter gain K in EnKF does not involve approximation of the nonlinear term unlike KF-based approach. Therefore, computational burden involving evaluation of Jacobian elements and large covariance matrix is absent. Moreover, due to less computational burden, it is faster and suitable for online estimation.

B. EnKF-Based Estimation

Let us assume the signal of the known fundamental angular frequency ω as the sum of harmonics of unknown magnitudes and phases. The general form of the waveform is given by

$$y(t) = \sum_{n=1}^{N} A_n \sin(\omega_n t + \phi_n) + A_{\mathrm{dc}} \exp(-\alpha_{\mathrm{dc}} t) + \mu(t) \tag{10}$$

where N is the number of harmonic order. In electrical power system, the magnitudes of higher order harmonics particularly higher than the 25th order are too small, but harmonic analysis may extend up to the 50th [19]. Thus, the limit of N may be 50. $\omega_n = n2\pi f_0$, f_0 is the fundamental frequency, $\mu(t)$ is the additive noise, and $A_{\mathrm{dc}} \exp(-\alpha_{\mathrm{dc}} t)$ is the probable decaying term.

The discrete time version of (10) can be represented as [7]

$$y(k) = \sum_{n=1}^{N} A_n \sin(\omega_n kT_s + \varphi_n) + A_{\mathrm{dc}} \exp(-\alpha_{\mathrm{dc}} kT_s) + \mu(k) \tag{11}$$

where T_s is sampling period.

Approximating decaying term using the first two terms of Taylor series and neglecting higher order terms

$$A_{\mathrm{dc}} \exp(-\alpha_{\mathrm{dc}} kT_s) = A_{\mathrm{dc}} - A_{\mathrm{dc}}\alpha_{\mathrm{dc}} kT_s. \tag{12}$$

Substituting (12) in (11), (11) becomes

$$y(k)=\sum_{n=1}^{N} A_n \sin(\omega_n kT_s+\varphi_n)+A_{\mathrm{dc}}-A_{\mathrm{dc}}\alpha_{\mathrm{dc}}kT_s+\mu(k). \tag{13}$$

The nonlinearity that arises in the model is due to the phase of the sinusoids. In this paper, an EnKF is used for the estimation of unknown parameters for estimation of amplitudes and phases of signal.

For estimation of amplitudes and phases, (13) can be rewritten as

$$y(k)=\sum_{n=1}^{N} \begin{matrix}[A_n \sin(\omega_n kT_s)\cos\varphi_n + A_n\cos(\omega_n kT_s)\sin\varphi_n] \\ +A_{\mathrm{dc}} - A_{\mathrm{dc}}\alpha_{\mathrm{dc}}kT_s + \mu(k)\end{matrix}. \tag{14}$$

Hence, for the purpose of estimation, the signal in the parametric form can be expressed as

$$y(k)=H(k)X \tag{15}$$

$$H(k)=\Big[\sin(\omega_1 kT_s)\cos(\omega_1 kT_s)\cdots\sin(\omega_N kT_s) \quad \cos(\omega_N kT_s)\; 1\; -kT_s\Big]^{\mathrm{T}}. \tag{16}$$

The vector of unknown parameter

$$X(k)=\Big[X_1(k)\; X_2(k)\; \cdots\; X_{2N-1}(k)\; X_{2N}(k) \quad X_{2N+1}(k)\; X_{2N+2}(k)\Big]^{\mathrm{T}} \tag{17}$$

$$X=\Big[A_1\cos(\varphi_1)\; A_1\sin(\varphi_1)\; \cdots\; A_n\cos(\varphi_n)\; A_n \quad \sin(\varphi_n)\; A_{\mathrm{dc}}\; A_{\mathrm{dc}}\alpha_{\mathrm{dc}}\Big]^{\mathrm{T}}. \tag{18}$$

The ensemble mean and covariance are computed using (5)–(7).

The updated ensemble is then given by

$$\hat{X}=X+CH^{\mathrm{T}}(HCH^{\mathrm{T}}+R)^{-1}(y-HX) \tag{19}$$

where R is error covariance matrix.

Estimated signal is given by

$$\hat{y}(k)=H(k)\hat{X}(k). \tag{20}$$

Estimation error becomes

$$e(k)=y(k)-\hat{y}(k). \tag{21}$$

After the updating of the vector of unknown parameters using the ensemble Kalman filtering algorithm, amplitudes and phases of the fundamental and nth harmonic parameters and dc decaying parameters can be computed using expressions as follows:

$$A_n=\sqrt{\left(X_{2N}^2+X_{2N-1}^{2N}\right)} \tag{22}$$

$$\varphi_n=\tan^{-1}\left(\frac{X_{2N}}{X_{2N-1}}\right) \tag{23}$$

$$A_{\mathrm{dc}}=X_{2N+1} \tag{24}$$

$$\alpha_{\mathrm{dc}}=\left(\frac{X_{2N+2}}{X_{2N+1}}\right). \tag{25}$$

Algorithm1. EnKF-algorithm-based harmonic estimation

1) Load data set, which, in present case, is one period of the voltage waveform at a sampling rate of 2.5 kHz (i.e., 500 samples/10 cycles at frequency $f=50$ Hz) conforming to 200-ms windowing in practice.
2) Initialize number of unknown parameters/ensembles (X) and specify error covariance matrix (R).
3) Model the signal in parametric form using (15).
4) Evaluate estimation error using (19)(20)(21).
5) Calculate mean and covariance of ensemble vector using (5) and (7).
6) Obtain estimate of ensemble vector using (19).
7) If final iteration (error converges to 0.001) is not reached, go to step 4.
8) Estimate amplitude and phase of fundamental and harmonic components and dc decaying components using (22)–(25) from final estimate of the ensemble vector.

III. Simulation Results

A. Static Signal Corrupted With Random Noise and Decaying DC Component

To evaluate the performance of the proposed EnKF algorithm in estimating harmonic amplitude and phase, discretized signal having fundamental frequency of 50 Hz is generated in MATLAB. The power system signal used for the estimation, besides the fundamental frequency, contains higher harmonics of the 3rd, 5th, 7th, and 11th and a slowly decaying dc component [5]. This kind of signal is typical in industrial load comprising power-electronic converters and arc furnaces [5]

$$\begin{aligned} y(t) &= 1.5\sin(\omega t+80^0)+0.5\sin(3\omega t+60^0) \\ &\quad +0.2\sin(5\omega+45^0)+0.15\sin(7\omega t+36^0) \\ &\quad +0.1\sin(11\omega t+30^0)+0.5\exp(-5t)+\mu(t). \end{aligned} \tag{26}$$

The aforementioned signal is corrupted by random noise $\mu(t)=0.05$ randn having normal distribution with zero mean and unity variance. All the amplitudes given are in per unit (p.u.) values.

Fig. 1 shows actual versus estimated values of signal using five different algorithms. Actual versus estimated signals

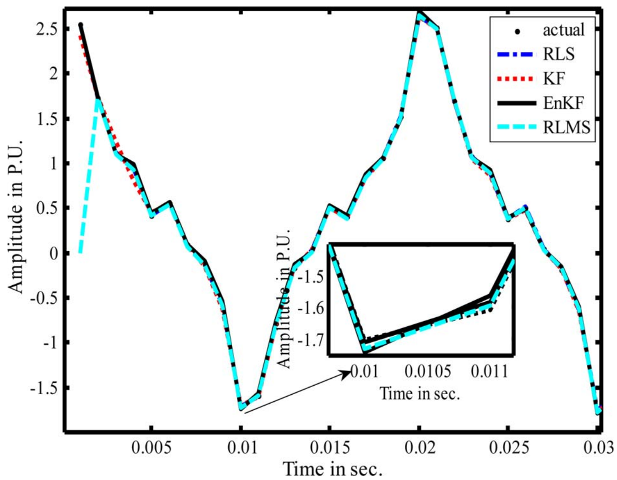

Fig. 1. Actual and estimated signals using RLS, KF, EnKF, and RLMS.

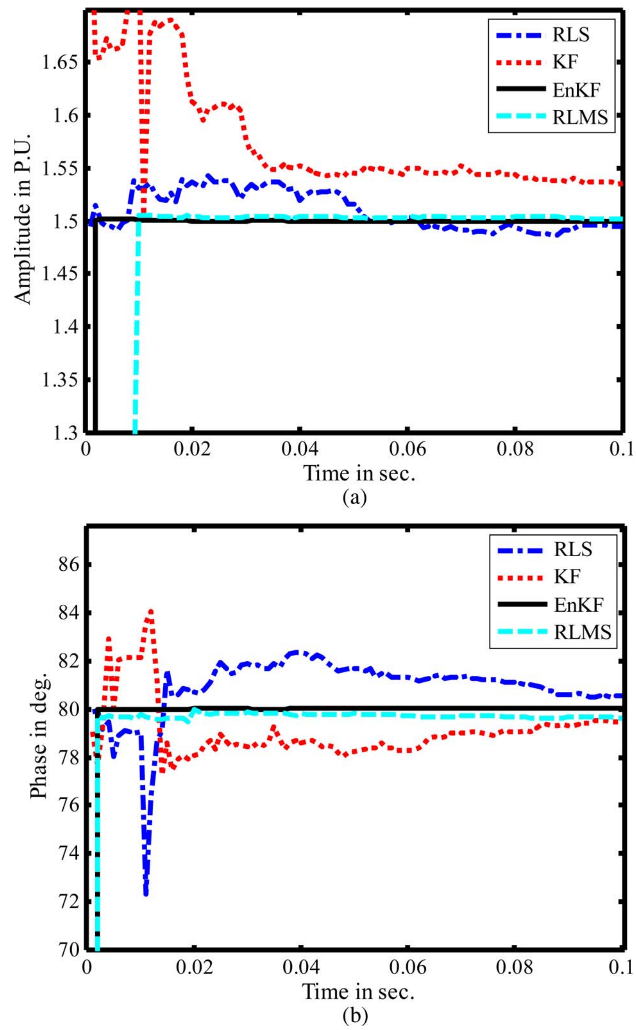

Fig. 2. (a) Estimation of amplitude of fundamental component of signal. (b) Estimation of phase of fundamental component of signal.

almost match with each other with little deviation in case of KF algorithm. Fig. 2(a) and (b) show the tracking of fundamental component of signal in the presence of random noise and decaying dc components using RLS, RLMS, KF, and EnKF algorithms. Fig. 3(a) and (b) show the estimation of fundamental amplitude and phase of signal in the presence of more random noises ($\mu(t) = 0.3162$ randn, i.e., 10-dB SNR) and dc decaying components. Fig. 4 shows a comparison of estimation of third harmonic phase of signal with 20- and 30-dB noises. Fig. 5(a) and (b) show the estimation of 11th harmonic amplitude and phase, respectively, using RLS, RLMS, KF, and EnKF algorithms. In the aforementioned estimation process, proper choice of covariance and noise covariance matrices optimally tune KF, RLS, and RLMS algorithms. In EnKF, the covariance matrix is replaced by sample covariance computed from ensemble as per (7). The KF exhibits oscillations in the estimated amplitude of fundamental and harmonic components in the presence of a distorted signal and noise as per (26). These results are quite significant in tracking steady-state fundamental and harmonic components of a power system over a period of 24 h for the assessment of power quality and harmonic distortions. Fig. 6 compares mean squared errors (MSEs) in the estimation of signal using five different algorithms such as RLS, RLMS, KF, and EnKF. It is found from Fig. 4 that MSE is in the order of 10^{-3}. Fig. 7 shows the estimation of fundamental frequency of signal. Fig. 8 shows the robustness of the proposed algorithm by estimating the signal when there is sudden jump in frequency from 50 to 50.2 Hz at 0.04 s. Figs. 7 and 8 show that estimation performance of EnKF in estimating fundamental frequency is comparatively better than the other three algorithms. Fig. 9 shows a sensitivity analysis of estimation of power system harmonics using EnKF algorithm. It gives an idea regarding variation of estimation error in signal with respect to variation of sampling frequency in estimation. It is found that estimation error in signal is very much reduced with increase in sampling frequency and the minimum estimation error is 0.0011 at a sampling frequency of 5 kHz. From Figs. 1–8, it is seen that estimation accuracy using EnKF is more as compared to that using the other three such as RLS, RLMS, and KF.

Table I shows the amplitude and phase estimates of all harmonic components using EnKF in the presence of noise and dc decaying components. In comparing the actual values of parameters, it is found that EnKF is a good estimator as far as estimation accuracy of harmonic components is concerned.

B. *Estimation of Harmonics in Presence of Amplitude Drift*

Fig. 10 shows the estimation of third harmonic amplitude using the aforementioned four algorithms. It is observed that all algorithms track the change in amplitude from 0.5 to 2.0 p.u. in third harmonic case with oscillations in estimation using KF. The proposed algorithm takes 1 ms to reach steady state during transition that can be marked in a zoomed figure.

C. *Harmonic Estimation of Signal in Presence of Inter- and Subharmonics*

To evaluate the performance of the proposed algorithm in the estimation of a signal in the presence of subharmonics and interharmonics, a subharmonic and two interharmonics components are added to the original signal. The frequency of subharmonic is 20 Hz, the amplitude is set to be 0.2 p.u.,

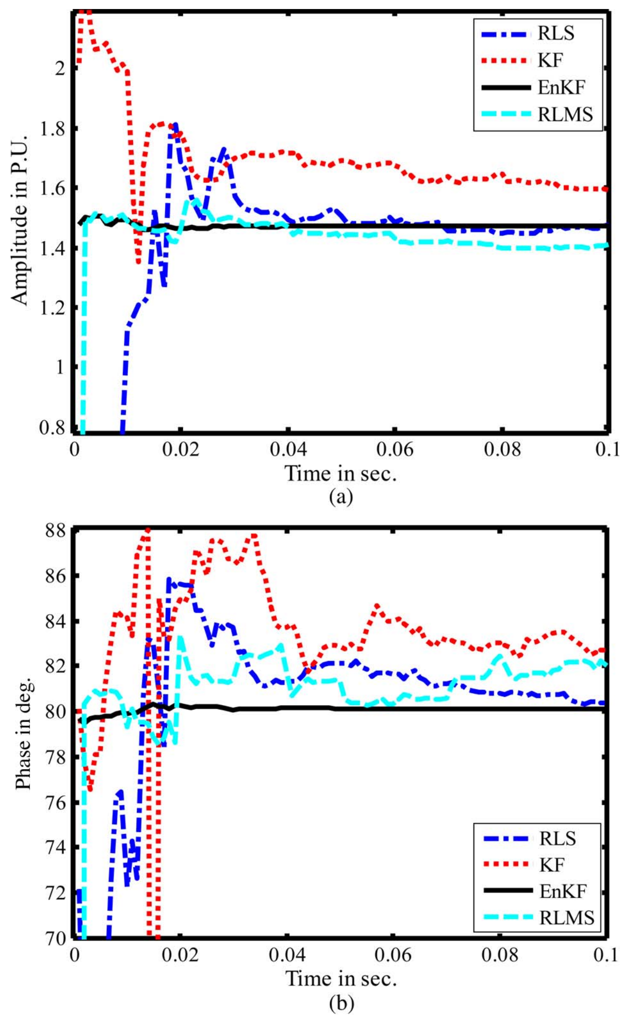

Fig. 3. (a) Estimation of amplitude of fundamental component of signal (SNR of 10 dB). (b) Estimation of phase of fundamental component of signal (SNR of 10 dB).

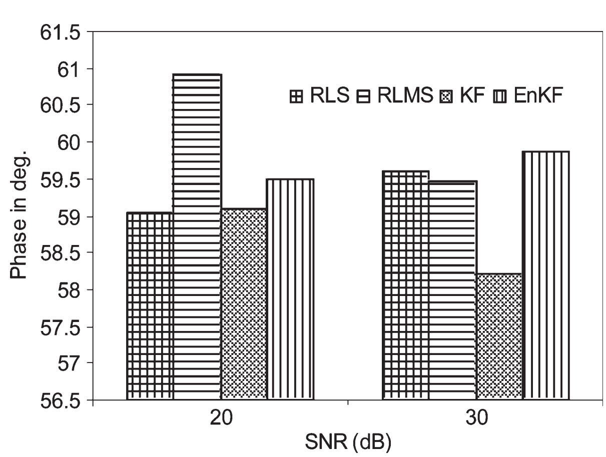

Fig. 4. Comparison of estimation of third harmonic phase of signal.

and the phase is equal to 75°. The frequency, amplitude, and phase of one of the interharmonics are 130 Hz, 0.1 p.u., and 65°, respectively. The frequency, amplitude, and phase of the other interharmonic are 180 Hz, 0.15 p.u., and 10°, respectively. Fig. 11 shows the estimation of amplitude of sub-harmonic component.

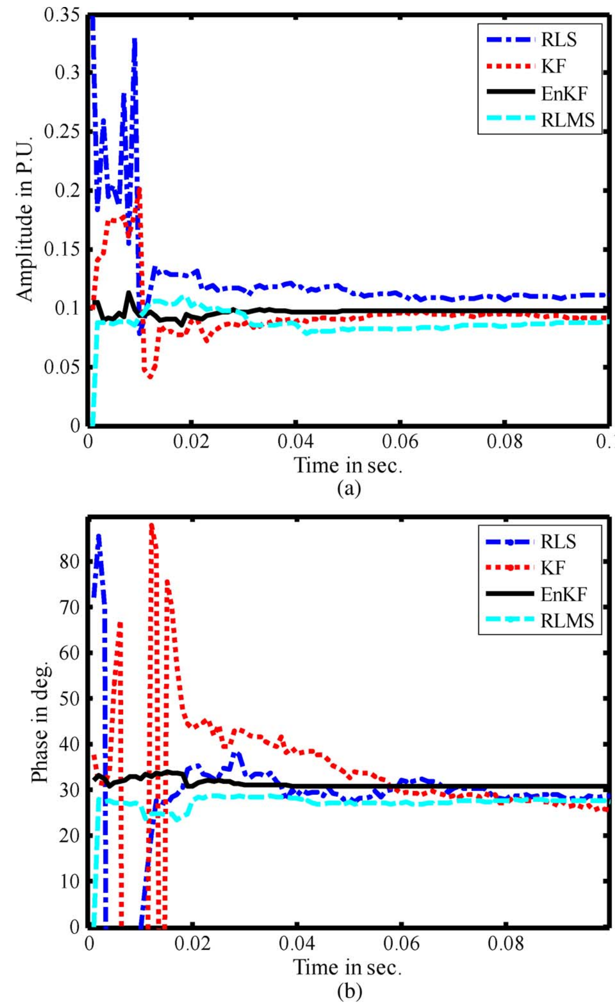

Fig. 5. (a) Estimation of amplitude of 11th harmonic component of signal. (b) Estimation of phase of 11th harmonic component of signal.

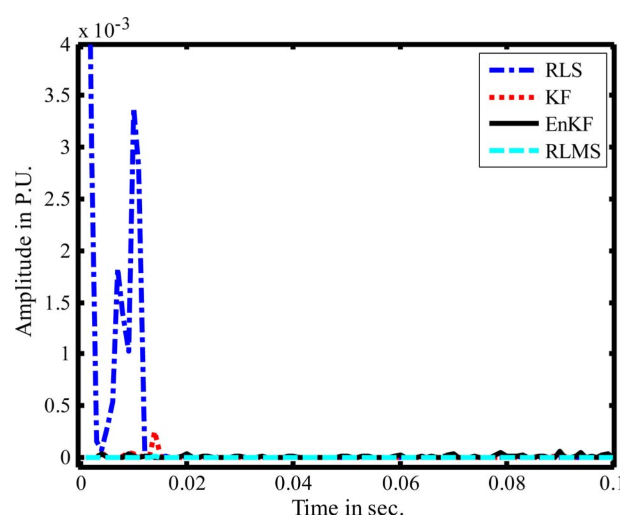

Fig. 6. Comparison of MSE in estimation of signal.

Table II gives the simulation results of the signal having two interharmonics and one subharmonic component using RLS, RLMS, KF, and EnKF algorithms. From this table, it is observed that, as a whole, the performance of estimation using EnKF is the best as compared to that using the other three

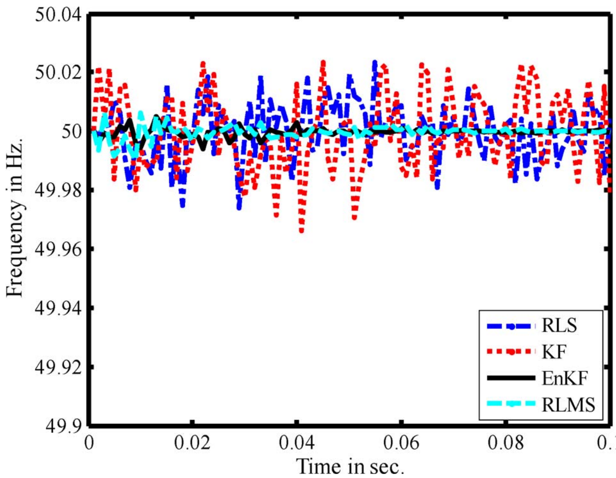

Fig. 7. Estimation of fundamental frequency of signal.

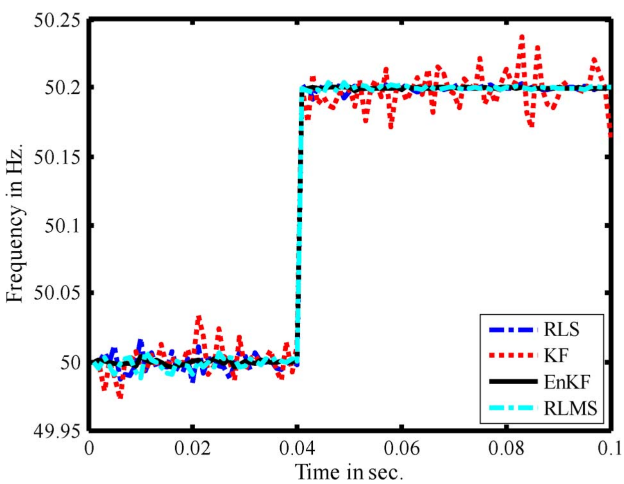

Fig. 8. Estimation of frequency during frequency jump.

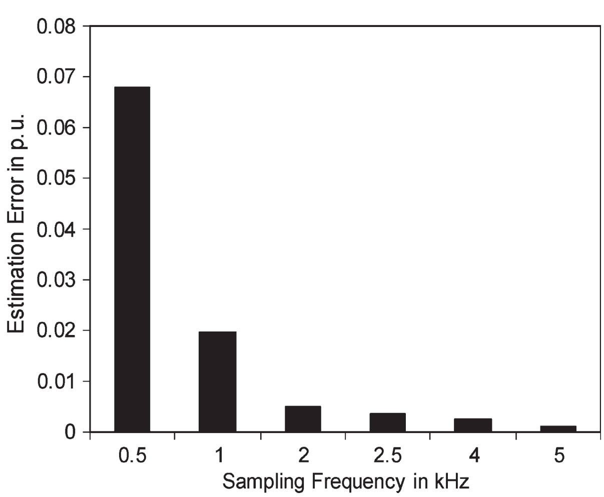

Fig. 9. Variation of estimation error with sampling frequency.

methods. The largest amplitude deviation is 0.7% that occurred at interharmonic 1 estimation, and the largest phase angle deviation is 0.4321° which occurred at the seventh harmonic estimation. The computational time taken for estimation is also minimum in the case of EnKF algorithm.

TABLE I
HARMONIC PARAMETERS ESTIMATION USING ENKF

Parameters	3rd	5th	7th	11th
Amplitude	0.501	0.2	0.151	0.0989
Phase	59.964	44.613	35.854	29.948

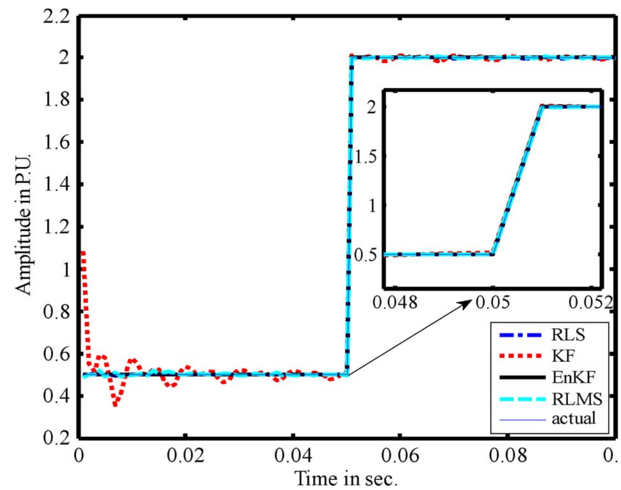

Fig. 10. Estimation of third harmonic amplitude during amplitude drift.

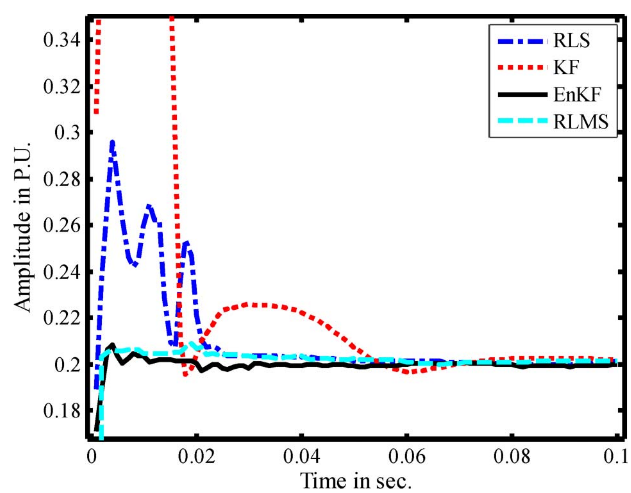

Fig. 11. Estimation of subharmonics having an amplitude of 0.2 p.u.

The RLMS algorithm is also robust in estimating harmonic parameters, but the complexity that arises in this algorithm is more due to the combination of both LMS and RLS algorithms. In RLMS, we have to initialize different parameters of LMS and RLS in particular proper initialization of covariance matrix in RLS. On the other hand, EnKF is a simple one with replacement of covariance matrix by the sample covariance matrix.

The performance index (a measure of accuracy in estimation) ε is estimated by

$$\varepsilon = \frac{\sum_{k=1}^{N} (y(k) - \hat{y}(k))^2}{\sum_{k=1}^{N} y^2(k)} \times 100 \tag{27}$$

where $y(k)$ and $\hat{y}(k)$ are actual and estimated signals, respectively. In this case, the significance of the performance index

TABLE II
COMPARISON OF METHODS WITH INTER- AND SUBHARMONICS

Methods	Param-	Sub	Fund-	3rd	Inter1	Inter2	5th	7th	11th	Computational time (seconds)
Actual	f (Hz)	20	50	150	130	180	250	350	550	
	A (V)	0. 2	1.5	0.5	0.1	0.15	0.2	0.15	0.1	
	φ (°)	75	80	60	65	10	45	36	30	
RLS	A (V)	0.2185	1.483	0.494	0.112	0.169	0.228	0.155	0.0995	0.114
	Deviation (%)	9.25	1.085	1.072	12	12.66	14.273	3.946	0.5361	
	φ (°)	73.351	78.111	58.086	61.894	11.49	46.793	34.858	34.541	
	Deviation (°)	1.648	1.888	1.913	3.105	1.49	1.797	1.1419	4.541	
KF	A (V)	0.2116	1.496	0.503	0.11	0.162	0.205	0.161	0.117	0.360
	Deviation (%)	5.821	0.240	0.657	10	8	2.957	7.918	17.222	
	φ (°)	75.353	80.244	59.613	64.218	8.680	42.204	37.109	35.316	
	Deviation (°)	0.353	0.244	0.386	0.782	1.319	2.792	1.109	5.316	
RLMS	A (V)	0.203	1.4925	0.4975	0.105	0.154	0.201	0.146	0.1010	1.418
	Deviation (%)	1.5	0.5015	0.5021	5	2.6	0.5	3.141	1.0081	
	φ (°)	74.432	79.548	59.677	64.559	10.405	43.454	35.566	32.446	
	Deviation (°)	0.5678	0.451	0.322	0.440	0.405	1.54	0.433	2.446	
EnKF	A (V)	0.2005	1.497	0.501	0.1007	0.1506	0.1997	0.1499	0.1003	**0.097**
	Deviation (%)	**0.25**	**0.167**	**0. 313**	**0.7**	**0.4**	**0.15**	**0.0917**	**0.349**	
	φ (°)	75.311	79.888	59.853	64.7822	10.219	44.952	35.5679	29.8834	
	Deviation (°)	**0.311**	**0.111**	**0.1462**	**0.2178**	**0.219**	**0.048**	**0.4321**	**0.1164**	

TABLE III
COMPARISON OF PERFORMANCE INDICES

SNR	No noise	40 dB	20 dB
RLS	0.0583	0.0636	0.8921
KF	0.0197	0.04	0.6477
RLMS	4.5163	4.5550	5.2386
EnKF	7.6×10^{-4}	0.0041	0.4272

ε is that it provides the accuracy of the estimation algorithm. Small value of ε corresponds to more accurate estimation and *vice versa*.

The performance indices of all the four algorithms are given in Table III. From which, it can be seen that EnKF achieves significant improvements in terms of reducing error for harmonic estimation in comparison to the other three algorithms. EnKF exhibits superior estimation performance and is more robust as compared to RLMS and KF owing to the fact that, unlike in RLMS and KF, the performance of the EnKF is not influenced by the initial choice of covariance matrix used in the RLS of RLMS and KF.

D. Harmonic Estimation of a Dynamic Signal

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

$$\begin{aligned} y(t) = &\{1.5 + a_1(t)\} \sin\left(\omega_0 t + 80^0\right) \\ &+ \{0.5 + a_3(t)\} \sin\left(3\omega_0 t + 60^0\right) \\ &+ \{0.2 + a_5(t)\} \sin\left(5\omega_0 t + 45^0\right) + \mu(t) \end{aligned} \tag{28}$$

is used, where the amplitude modulating parameters $a_1(t)$, $a_3(t)$, and $a_5(t)$ are given by

$$a_1 = 0.15 \sin 2\pi f_1 t + 0.05 \sin 2\pi f_5 t \tag{29}$$

$$a_3 = 0.05 \sin 2\pi f_3 t + 0.02 \sin 2\pi f_5 t \tag{30}$$

$$\begin{aligned} a_5 &= 0.025 \sin 2\pi f_1 t + 0.005 \sin 2\pi f_5 t \\ f_1 &= 1.0 \text{ Hz} \quad f_3 = 3.0 \text{ Hz} \quad f_5 = 6.0 \text{ Hz}. \end{aligned} \tag{31}$$

In the case of static signal, which is discussed in Section III-A, signal parameters such as amplitude, phase, and frequency do not change with respect to time, but in the case of a dynamic signal, in the aforementioned example, $a_1(t)$, $a_3(t)$, and $a_5(t)$ change with respect to time. Here, the random noise $\mu(t)$ has a normal distribution of zero mean, unity variance, and amplitude of 0.05 randn.

The estimation of time-varying third harmonic signal in the presence of random noise is shown in Fig. 12. It is observed that there is more oscillation in estimation using KF, but using other four algorithms such as RLS, RLMS, and KF, the estimated

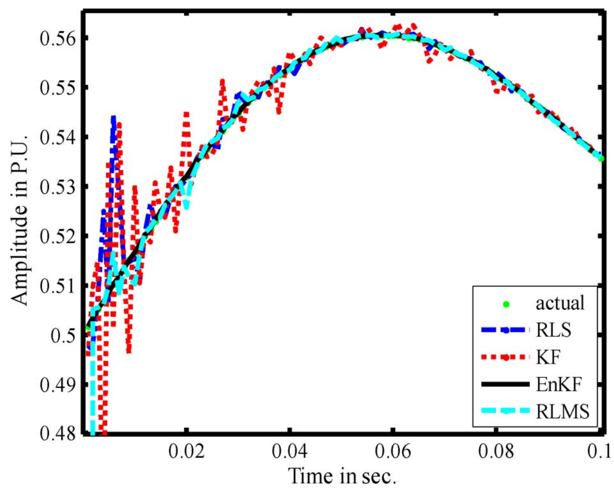

Fig. 12. Estimation of third harmonic amplitude of dynamic signal.

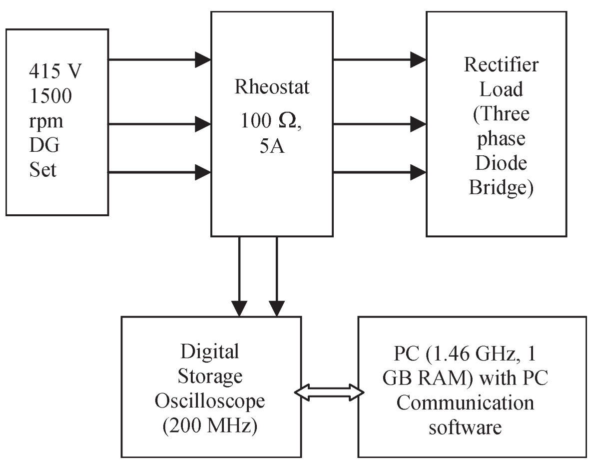

Fig. 13. Experimental setup for online data generation.

values of amplitudes and phases of signal closely match with the actual with more accurate estimation using EnKF algorithm.

IV. Experimental Studies and Results

In view of real-time application of the algorithm for estimating harmonics in a power system, voltage data generation was accomplished in the laboratory on running a diesel generator (DG) set using the experimental setup as shown in Fig. 13.

Specifications of the instruments used are as follows:

1) DG set:
   a) alternator—three phase, 50 Hz, Y connected, 415 V, 1500 r/min, 55.8 A, and 40 kVA
   b) diesel engine—$Bore \times stroke = 110 \times 116$, 37.2 KW, and 1500 r/min
2) rheostats: 100 Ω and 5 A (three in number);
3) nonlinear load: three-phase diode bridge rectifier with a 5-Ω resistor in series with a 100-mH inductor at the dc side;
4) digital storage oscilloscope: bandwidth—200 MHz, sample rate—2 GS/s, channels—two, record length—2500 data points, personal computer (PC) connectivity—universal serial bus port, and Open Choice PC Communication software, Probe-P2220;
5) PC: 1.46-GHz CPU and 1-GB RAM notebook PC.

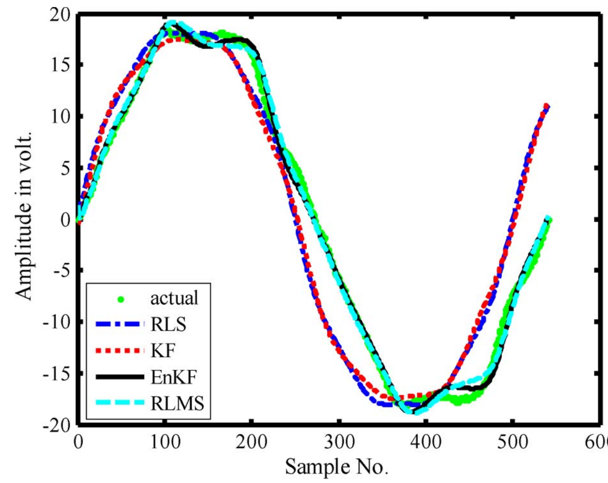

Fig. 14. Estimation of signal from real data.

TABLE IV
Comparison of Performance Indices of Real Data

Parameter	RLS	KF	RLMS	EnKF
ε	2.4985	7.4718	0.1328	0.1026

The input voltage waveform is stored in a digital storage oscilloscope (Tektronix Ltd.) across almost 10-Ω resistance (measured using multimeter), and then, through Open Choice PC Communication software, data are acquired to the PC.

As per International Electro-technical Commission 61000-4-30 [20], for computing the power quality parameters, 10 cycles in a 50-Hz system which is 200-ms windowing at a sampling time of 0.4 ms has been used [21]. Laboratory measurement is deliberately made crude by inserting multiple loops in connecting wire to catch extraneous noise. Measurement uncertainties, such as errors introduced due to transducer frequency response and errors in the presence of noise and harmonic and initial estimates of covariance matrix, can be attributed to model error.

Fig. 14 shows the estimation of voltage signal using RLS, RLMS, KF, and EnKF algorithms from the real data obtained from the experiment. In Fig. 14, the estimated waveform approaches the actual waveform over the cycle.

The performance index of estimation as per (27) is calculated for the four algorithms, and the results are given in Table IV. EnKF obtains the most accurate estimation result since it has the smallest performance index (around 0.10%), which is acceptable. From Fig. 14, the estimated waveform is very close to the actual one over the cycle for the case of RLMS and EnKF estimations, and deviations are there for the case of RLS and KF estimations. The overall performance of EnKF is better as compared to the other three algorithms. Hence, the obtained results are satisfactory for the application with real data.

V. Conclusion

This paper has presented an ensemble Kalman filtering algorithm, for accurate estimation of amplitude and phase of the harmonic components of distorted power system signal. The proposed method is based on applying a sample covariance C in Kalman gain instead of state covariance P to avoid the singularity problem and computational feasibility of P for high-dimensional system. Improved harmonic estimation performance has been achieved by using the EnKF compared to the four existing methods such as RLS, RLMS, and KF. Several computer simulation tests have been conducted to estimate harmonics in a power system signal corrupted with random noise and decaying dc offsets. The performance index of estimation of EnKF in case of signal containing harmonics, inter-, and subharmonics at 20-dB noise has been found as 0.42%. The aforementioned value is 0.11% for the case of experimental data. These are the minimum values compared to other estimation methods. The simulation results in various cases of power system signal at SNR of 20 dB and experimental results show the robustness of the proposed EnKF for effective harmonic estimation.

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