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Several variants of Kalman Filter algorithm for power system harmonic estimation

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ABSTRACT

This paper presents the maiden application of a variant of Kalman Filter algorithm known as Local Ensemble Transform based Kalman Filter (LET-KF) for power system harmonic estimation. The proposed algorithm is applied for estimating the harmonic parameters of a power signal containing harmonics, sub-harmonics, inter-harmonics in presence of white Gaussian noise. These algorithms are applied and tested for both stationary as well as dynamic signals containing harmonics. The LET-KF algorithm reported in this paper is compared with the earlier reported Kalman Filter based algorithms like Kalman Filter (KF) and Ensemble Kalman Filter (EnKF) algorithms for harmonic estimation. The proposed algorithm is found superior than the reported algorithm for its improved efficiency and accuracy in terms of simplicity and computational features, since there are less multiplicative operations, which reduces the rounding errors. It is also less expensive as it reduces the requirement of storing large matrices, such as the Kalman gain matrix used in other KF based methods. Practical validation is carried out with experimentation of the algorithms with the real time data obtained from a large paper industry. Comparison of the results obtained with KF, EnKF and LET-KF algorithms reveals that the proposed LET-KF algorithm is the best in terms of accuracy and computational efficiency for harmonic estimation.

Introduction

For the development of effective Power Quality (PQ) monitoring techniques, greater efforts are made by the researchers towards the development of less-complex and more efficient techniques for detection, classification, identification of power quality disturbances. Another key and challenging problem reported recently by the researchers related to power quality is the estimation of harmonic parameters for fundamental, harmonics, inter-harmonics and sub-harmonics components of voltage and currents signals. Accurate and efficient estimation of harmonics from the distorted voltage signals is an important issue for monitoring and analysis of power quality problems [1,2].

Harmonics are components of a distorted periodic waveform, whose frequencies are integer multiples of the fundamental frequency. In electrical power networks, the increasing use of nonlinear loads and power electronic based load devices has caused much more harmonic pollution, which significantly deteriorates the power quality [1]. In order to reduce the harmonic pollution, it is necessary to estimate the parameters of the harmonics. With the estimated parameters, such as amplitudes and phases, appropriate compensation system can be designed for improving the poor power quality performances [1,2].

For past few decades, various approaches have been proposed to estimate the parameters of these harmonics [1]. The Fast Fourier Transform (FFT) is a suitable approach for stationary signal, but it loses accuracy under time varying frequency conditions and also posses picket and fence problems [3–5]. The International Electro-Technical Commission (IEC) standard drafts have specified signal processing recommendations and definitions for harmonic, sub-harmonic and inter-harmonic measurement [4]. These standards recommend using Discrete Fourier Transform (DFT) for harmonic estimation with some windowing based issues but the DFT-based algorithms do not perform stably for systems with time varying frequency [5–7].

Many recursive algorithms are also proposed to solve harmonic estimation problem but each of them have several limitations in terms of accuracy, convergence and computational time. The Least Mean Square (LMS) based algorithms have the drawbacks for their poor convergence in addition to being failure in case of signal drifting and changing conditions. However, Recursive Least Square (RLS) group is the successful algorithms to some extent but the initialization for these algorithm parameters still remains a challenge in case of time varying dynamic signals. The accuracy is also limited for this class of algorithms [5–7].

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Nomenclature

$\hat{y}^f$	forecast observation ensemble perturbation matrix	$\bar{y}^f$	mean of ensemble perturbation matrix
R	error covariance	$\tilde{x}$	update of state estimate
y'^f	forecast observation ensemble	$\bar{x}^f$	ensemble mean
C	$N \times N$ Eigen vector matrix	X'^f	$n \times N$ ensemble perturbation matrix
$\wedge$	diagonal matrix of corresponding Eigen values	H	observation matrix
V	$M \times M$ orthogonal matrix	μ_t	additive noise
Σ	$N \times M$ matrix	k	discrete time (sampling) index
k_e	Kalman gain matrix	Ts	sampling period
I	identity matrix	ξ	performance index
d	product vector		

Another extensively used algorithm is the Kalman filter, which is known for its simplicity, linearity and robustness. This algorithm is capable enough to estimate harmonic parameters in presence of noise and other non-linearities present in the harmonic signal [7–9]. However, the main limitation is that it requires prior information of the statistics of the harmonic signal and the initialization of the state matrix in an accurate and faster way is the main challenge. The dynamic variations present in the harmonic signals calls for some suitable and enhanced methods for accurate estimation of these harmonic components present in the signal [10–19].

A variant Kalman filter, called Ensemble Kalman Filter (EnKF) [20] is proposed for accurate estimation of amplitude and phase of the harmonic components of distorted power system signal. The proposed method used sample covariance in Kalman gain instead of state covariance to avoid the singularity problem and computational feasibility for high-dimensional system [20]. But the prominent limitation of the most EnKF-based systems is perhaps the resource limited ensemble size [21–23]. This is true even for medium-size systems, with the model state vector size of the order of just tens of thousands, not to mention the large-scale applications [22,23]. This limitation calls for the use of the method, known as localization, which artificially reduces the influence of observations of spatial domain during the update [21]. The localization makes it possible to dramatically reduce the necessary ensemble size and create operational systems with as small as a hundred ensemble members or less [22]. Local Ensemble Transform Kalman Filter (LET-KF) as proposed by Szunyogh [23] has three features, (i) assimilation of all observations that may affect the analysis at a given local domain simultaneously, (ii) obtaining the analysis independently for each domain and (iii) introduction of changes when non-local observations are assimilated that improve the computational efficiency and add flexibility [21,23]. The authors have used the method for assimilation of large number of observational data for weather prediction and demonstrated its better performance in terms of accuracy and computational time [23]. However, there has been no attempt made to investigate its performance for harmonic estimation in power system.

In the view of the above following are the main objectives of the present work.

(a) To study several variants of Kalman Filter algorithms for harmonic estimation.
(b) Maiden application of Local Ensemble Transform based Kalman Filter (LET-KF) algorithm for estimating amplitudes and phases of the fundamental, harmonics, inter and sub harmonics in presence of Gaussian noises in power system signal.
(c) To evaluate the comparative performances of KF [9,18], EnKF [20] and the proposed LET-KF algorithms to find the best harmonic estimator.
(d) To check the accuracy and time of convergence for harmonic signal estimation with the proposed LET-KF algorithm.
(e) To evaluate the performance of the proposed LET-KF algorithm for accurately estimating harmonic signal parameters on real time data obtained from a real time industrial data setup for harmonic estimation.

Several variants of Kalman Filtering (KF) algorithms applied for harmonic parameter estimation

In this section, several variants of KF algorithms, which are applied for harmonic estimation problems, are discussed. The details of KF and EnKF algorithms may be referred from [9,18,20]. The detail procedure of the LET-KF algorithm for harmonic estimation is also reported in this section.

Kalman Filter (KF)

The vector of unknown parameters X is taken and then KF algorithm is applied to update the weights as in Eq. (1). The KF discussed in this section is referred from [9,18].

$$G(k) = P(k/k-1)H(k)^T\left(H(k)P(k/k-1)H(k)^T + Q\right)^{-1} \quad (1)$$

where, G is the Kalman gain, H is the observation vector, P is the covariance matrix, and Q is the noise covariance of the signal. The covariance matrix is related with Kalman gain as given in the following equation.

$$P(k/k) = P(k/k-1) - G(k)H(k)P(k/k-1) \quad (2)$$

The updated estimated state vector is related with previous state vector as follows.

$$\widehat{X}(k/k) = \widehat{X}(k/k-1) + G(k)\left(y(k) - H(k)\widehat{X}(k/k-1)\right) \quad (3)$$

After updating the weight vector, amplitudes, phases of the fundamental and nth harmonic parameters and dc decaying parameters are found out using Eqs. (38)–(41).

Ensemble Kalman Filter (EnKF)

The EnKF discussed in this section is referred from [20]. This method is based on Monte Carlo approximation method of the Kalman filter, which avoids evolving the covariance matrix of the probability density function (pdf) of the state vector, x [20]. In this case, the distribution is represented by a sample, which is called an ensemble [20].

$$X = [x_1, x_2, \ldots, x_N] \quad (4)$$

X is a $n \times N$ matrix, whose columns are the ensemble members, and it is called the prior ensemble. Ensemble members form a sample of the prior distribution [20]. As every EnKF step ties ensemble