A REMEDIAL MEASURE FOR DIVERGENCE PHENOMENON OF ELECTRICAL POWER SYSTEM DYNAMICS BASED ON IMPROVED KALMAN FILTER ALGORITHM

Adjei-Saforo Kwafo Edmund[1], Su Hongsheng[2]

[1]*Msc Student, Department of Electrical Engineering, School of Automation & Electrical Engineering, Lanzhou Jiaotong University, Gansu, China*

[2]*Professor, Department of Electrical Engineering, School of Automation & Electrical Engineering, Lanzhou Jiaotong University, Gansu, China*

Abstract

The presence of harmonics in electrical power system has been sole contribution of ever-growing utilization of non-linear electrical loads as well as power electronic equipment. As much as to improve operation of electrical power system by maintaining stable, controlled and quality power flow in electrical networks, there should be an appropriate method to quantify accurately, the presence of the harmonic pollution in these systems. It must be worth noting that the selected approach should be precise while being computationally effectual. Therefore, this research work seeks to propose the non-linear state estimation approach which is based on the improved Kalman Filter to measure harmonics from a distorted signal in electrical power system. The proposed technique exhibits high performance of superiority and present real estimation on face of quantities variation of the distorted source. Further, the proposed technique vis-á-vis other conventional methods is simple and robust, hence less hardware requirements and rock-bottom computational cost.

***Keywords**: Improved Kalman Filter (IKF); Kalman Filter (KF); Electrical Power System; Electrical Load; Harmonics Estimation.*

---***---

1. INTRODUCTION

1.1 Electrical Power Quality Concerns

Electrical energy is supplied at a constant magnitude of particular voltage levels and also, at constant frequency, say, 50Hz or 60 Hz. But however, these conditions are very challenging to be met in a real situation. The power quality is normally expressed in terms of a function of deviation variables from a clean-sinusoidal waveform. Harmonic distortions, flickering of voltage, variations of voltage such as surging and dipping, transient conditions, just to mention few, are various types of disturbances which affect the quality of the power system. Harmonic distortions, being a steady condition, are the most disturbing condition among all the power system disturbances. Therefore, engineers have given more attention to harmonic pollution which does not only cause disturbances but losses as well. [l - 10]

Harmonic estimation is among the challenging and critical quagmire of electrical power circuit owing to the unceasing utilization of non-linear electrical loads. These dynamic electrical loads such as regulated motor drive, arc furnaces and power electronic equipment have contributed greatly to periodical distortions in voltage and current waveforms [1]. Again, the power electronic converters which are widely proclaimed to be utilized in the distributed generation in the near future of electrical power system, also add-up to the ever growing concerns for improved estimation so as to ensure quality of supply[11],[12]. Therefore, the motive behind this work is to design a technique to mitigate to its core if cannot be eliminate completely, the unwanted-harmonic distortion in electrical power system.

1.2 Harmonics as Power Quality Problems

Harmonic is qualitatively defined as a sinusoidal waveform having frequencies that are integral multiples of the fundamental frequency. Apropos of electrical power system discipline, the term harmonic is mostly used to give a description of the distortions in both the current and voltage waveforms. That is, the steady state deviation of power frequency from a perfect sinusoidal wave. [13].

The harmonic problems are not new phenomena in electrical power systems. They were detected as early as the 11th and 12th century [14]. At that time, the main harmonic sources were instrument and power transformers and the prime problem was the inductive interferences with open-wire telephone networks. Around that same time, harmonic estimation and compensation in transmission and distribution feeders were carried-out.

Harmonic pollution, which is detrimental to distribution systems, dissipates energy as well as reduces the real capacity of electrical power systems; it can cause a malfunction of device operating on the system in a particular and the electrical distribution system as a whole.

Understanding the problems associated with harmonic distortion, which is its causes and effects, as well as the methodological approach in handling it, is of great importance in mitigating the effects and increasing the overall efficiency of the distribution system.

Apropos of state estimation of electrical power system dynamic, the established dynamic state estimation mathematical model for exploration of the improved algorithm gives way to a new school of thought. . Literature [15] uses No Trace transformation based on UKF method of dynamic power system state estimation which avoided the linearization error brought by the EKF method. That saved the calculation of Jacobian matrix which has the very good convergence and higher than that of EKF method estimation precision and stability. In order to make up for defect of EKF and UKF, literature [16] proposed hybrid Kalman particle filter. The algorithm uses No Trace Kalman filter and EKF as proposal distribution, and which was much closed to the real distribution of approximate expression. Verification of results showed that the power system after a disturbance, can be converge to the real value using MKPF as compared with EKF and UKF which has higher accuracy and stability. It can be seen that hybrid Kalman filter in dynamic state estimation in electrical power system has very good application prospects.

2. KALMAN ALGORITHM AND ESTIMATION

The Kalman Filter is applied in a dynamic state estimation system. It is a recursive technique and its estimation algorithms exhibit high performance. The two prominent Kalman filter mathematical models of signal in state space form are state variable equation and measurement equation.

2.1 Random Linear Continuous System Mathematical Models and its Discretization

Consider the following linear continuous system

$$x_{k+1} = A_{k+1,k}x_k + Q_{w,k} \quad (1)$$

$$y_k = B_k x_k + Q_{v,k} \quad (2)$$

Then, x_k is state at time k, y_k is observation at time k, $A_{k+1,k}$ is invertible transition matrix from state at time k to state at time $k+1$,B_k is the measurement matrix at time k, $Q_{w,t}$ is covariance matrix of dynamic noise w_n and $Q_{v,t}$ is covariance matrix of measurement noise v_n.

A stochastic equation for nonlinear continuous system discretization expression can be obtained by:

$$\hat{x}_{k+1} \approx A_{k+1,k}\hat{x}_{k|k} + Q_{w,k} + \xi_k \quad (3)$$

$$y_k \approx B_k x_k + Q_{v,k} \quad (4)$$

$$M_{k+1|k} = A_{k+1,k}M_{k|k}A^T_{k+1,k} + Q_{w,k} \quad (5)$$

$$M_{k|k} = M_{k|k-1} - G_k B_k M_{k|k-1} \quad (6)$$

Thus, the pair of equations (5) and (6) provides the means of updating the prediction-error covariance matrix with (6) in particular, commonly referred to as discrete form.

Where:

$$G_k = M_{k|k-1}B_k^T R_k^{-1} \quad (7)$$

$$R_k = B_k M_{k|k-1}B_k^T + Q_{v,k} \quad (8)$$

Again, $\hat{x}_{k|k}$ is filtered estimate of the state given observation $y_1, y_2, \dots, y_n; \xi_k$ is non-random vector, G_k is Kalman gain, $M_{k|k-1}$ is prediction error covariance matrix, $M_{k|k}$ is filtering error covariance matrix andinnovation process which meet the conditions as well as the discretization process [17].

Therefore, it can be seen that Kalman filter has two interactive computing circuits: update status circuit and measurement circuit, also is the process of prediction and correction.

2.2 Modelling of Time-Varying Quantity into State Variable Form

Three cases are considered to model the voltage signal into state variable. In all the cases, the signal under consideration is assumed to be static with constant quantities.

2.2.1 Case 1: Ideal Situation

Consider a time-varying signal with a frequency of $W = {}^{2\pi}/_{T}$ having T number of sample at time k, root-mean-square voltage, E_k and phase shift may be given as:

$$f_k = \sqrt{2}E_k \sin(Wk + \emptyset_k) \quad (9)$$

$$= \sqrt{2}E_k cos\emptyset_k sinWk + \sqrt{2}E_k sin\emptyset_k cosWk \quad (10)$$

Let $x_{1/k}$ and $x_{2/k}$ be the two unknown state input variables equal to $\sqrt{2}E_k cos\emptyset_k$ and $\sqrt{2}E_k sin\emptyset_k$ respectively. Therefore from equation (1), the state variable can be expressed as:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{k-1} + \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}_k \quad (11)$$

w_k permits the state variables for random walk. The measurement equation is given as:

$$y_k = [cosWk \quad sinWk] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k + v_k \quad (12)$$

In an ideal situation, $x_{1/k}$ has a maximum value and $x_{2/k}$ is zero, hence the measurement equation is modified as:

$$y_k = [\sqrt{2}cosWk \quad \sqrt{2}sinWk] \quad (13)$$

When the sampling time is changed from k to $k+1$, the new signal equation is given as:

$$f_{k+1} = \sqrt{2}E_{k+1}\sin(W(k+) + \emptyset_{k+1}) \qquad (14)$$

If the maximum value and phase shift are assumed to remain fairly constant to $k+1$from k, then the state variable and measurement equation are written as

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{k+1} = \begin{bmatrix} sinW & -cosW \\ -cosW & sinW \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k + \begin{bmatrix} w_1 \\ w_2 \end{bmatrix}_k \qquad (15)$$

$$y_k = [cosWk \quad sinWk] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k + v_k \qquad (16)$$

$$y_k = [1 \quad 0] \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k + v_k \qquad (17)$$

A constant measurement matrix B_k is obtained if static reference is considered in representation of the state variable.

2.2.2 Case 2: A Signal without Decaying Dc Component

Consider a time varying signal of m frequencies as shown below:

$$f_k = \sum_{m=1}^{M} \sqrt{2}E_{m/k} sin\left(mWk + \emptyset_{m/k}\right) \qquad (18)$$

Now from the above signal, it can been seen that each frequency has two state variable inputs, that is:

$$x_{11/k} = \sqrt{2}E_{1/k}cos\emptyset_{1/k}\; x_{21/k} = \sqrt{2}E_{1/k}sin\emptyset_{1/k}$$

$$x_{12/k} = \sqrt{2}E_{2/k}cos\emptyset_{2/k}\; x_{22/k} = \sqrt{2}E_{2/k}sin\emptyset_{2/k}$$

$$x_{13/k} = \sqrt{2}E_{3/k}cos\emptyset_{3/k}\; x_{23/k} = \sqrt{2}E_{3/k}sin\emptyset_{3/k}$$

$$\vdots \qquad \vdots$$

$$x_{2M-1/k} = \sqrt{2}E_{2M-1/k}cos\emptyset_{2M-1/k}\; x_{2M/k} = \sqrt{2}E_{2M/k}sin\emptyset_{2M/k}$$

$$x_{2M+1/k} = \sqrt{2}E_{2M+1/k}cos\emptyset_{2M+1/k}\; x_{2M+2/k} = \sqrt{2}E_{2M+2/k}sin\emptyset_{2M+2/k}$$

Note:$x_{ij/k} \neq x_{ji/k}$; $f_{k+1} = f(k+1)$

From equation (1), the state variable characteristic equation can be expressed as:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k = \begin{bmatrix} I & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & I \end{bmatrix} [x_{11/k}x_{21/k}x_{12/k}x_{22/k}x_{13/k}x_{23/k} \;\ldots\; x_{2M-1/k}x_{2M/k} \quad x_{2M+1/k}x_{2M+2/k}]^T + w_k \qquad (19)$$

The corresponding measurement equation is given by:

$$y_k = \begin{bmatrix} sinWk\; cosWk \\ sin2Wk\; cos2Wk \\ sin3Wk\; cos3Wk \\ \vdots \\ \sin(MWk)\; \cos(MWk) \end{bmatrix}^T \begin{bmatrix} x_{11/k}x_{21/k} \\ x_{12/k}x_{22/k} \\ \vdots \\ x_{2M-1/k}x_{2M/k} \\ x_{2M+1/k}x_{2M+2/k} \end{bmatrix} + v_k \qquad (20)$$

If the signal level of f_k is change to f_{k+1}, the new time-varying signal will be:

$$f_{k+1} = \sum_{m=1}^{M} \sqrt{2}E_{m/k+1} sin\left(mW(k+1) + \emptyset_{m/k+1}\right) \qquad (21)$$

Then, the characteristic state variable equation can be express as:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{k+1} = \begin{bmatrix} M_m & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & M_M \end{bmatrix} [x_{11/k}x_{21/k}x_{12/k}x_{22/k}x_{13/k}x_{23/k} \;\ldots\; x_{2M-1/k}x_{2M/k} \quad x_{2M+1/k}x_{2M+2/k}]^T + w_k \qquad (22)$$

where M_m is a submatrices $\gg M_m =$

$$\begin{bmatrix} \sin(mW) & \cos(mW) \\ \cos(mW) & \sin(mW) \end{bmatrix} \qquad (23)$$

Therefore the measurement equation is given as:

$$y_k = \begin{bmatrix} sinWk\; cosWk \\ sin2Wk\; cos2Wk \\ sin3Wk\; cos3Wk \\ \vdots \\ \sin(MWk)\; \cos(MWk) \end{bmatrix}^T \begin{bmatrix} x_{11/k}x_{21/k} \\ x_{12/k}x_{22/k} \\ \vdots \\ x_{2M-1/k}x_{2M/k} \\ x_{2M+1/k}x_{2M+2/k} \end{bmatrix} + v_k \qquad (24)$$

2.2.3 Case 3: A Signal with Decaying dc Component and Artificial Noise

Consider a voltage signal which has been corrupted with decaying dc component and non-random noise vector:

$$f_k = A_{DC}e^{-\gamma k T_s} + \sum_{m=1}^{M} \sqrt{2}E_{m/k} sin\left(mWk + \emptyset_{m/k}\right) + \xi_k \qquad (25)$$

Where γ is decaying coefficient and ξ_k is non-random vector

Rewriting equation (3.25) by considering the first two terms of Taylor series for decaying dc component, we have:

$$f_k = A_{DC}(1 - \gamma k T_s) + + \sum_{m=1}^{M} \sqrt{2}E_{m/k} sin\big(mWk + \emptyset m/k + \xi k \qquad (26)$$

The state variable input characteristic equation is chosen to be:

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_k = [x_{11/k} x_{21/k} x_{12/k} x_{22/k} x_{13/k} x_{23/k} \ldots \quad x_{2M-1/k} x_{2M/k} \quad x_{2M+1/k} x_{2M+2/k}]^{\mathrm{T}} \qquad (27)$$

The measurement matrix B_k is given as:

$$B_k = [\sin(Wk)\cos(Wk)\sin(2Wk)\cos(2Wk)\cdots \sin(mWk)\cos(mWk) \quad 1 - kT_s]^T \qquad (28)$$

And;

$$x_{k-1} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}_{k-1} = [A_{1/k}\cos(\emptyset_{1/k}) A_{1/k}\sin(\emptyset_{1/k})$$

$$A_{2/k}\cos(\emptyset_{2/k}) A_{2/k}\sin(\emptyset_{2/k})$$

$$\cdots \quad A_{m/k}\cos(\emptyset_{m/k}) A_{m/k}\sin(\emptyset_{m/k}) \quad A_{DC} \; A_{DC}\gamma_{DC}]^T \qquad (29)$$

Therefore the measurement characteristic equation is given by:

$$y_k = B_k x_{k-1} \qquad (30)$$

The posterior quantities of the harmonic components are determined using:

$$E_{m/k} = \sqrt{1/2} \times \sqrt{(x_{2M/k})^2 + (x_{2M-1/k})^2} \qquad (31)$$

$$= \frac{\sqrt{2[(x_{2M/k})^2 + (x_{2M-1/k})^2]}}{2} \qquad (32)$$

$$\emptyset_{m/k} = sin^{-1}\left[\frac{2(x_{2M-1/k})}{\sqrt{2[(x_{2M/k})^2 + (x_{2M-1/k})^2]}}\right] \qquad (33)$$

Further, the decaying DC component can also be expressed as:

$$A_{DC} = x_{2M+1/k} \qquad (34)$$

$$\gamma = {x_{2M+2/k}}/{x_{2M+1/k}} \qquad (35)$$

The updated estimate is then computed as:

$$x_{k+1} = x_k + G_k(y_k - B_k x_k) \qquad (36)$$

The error covariance matrix on its posterior estimate is calculated as:

$$M_{k/k+1} = (\mathrm{I} - G_k B_k)M_{k/k} \qquad (37)$$

As it is seen from the above-mentioned cases, particularly cases 2 (section B) and 3 that when the signal is corrupted with decaying dc component and random noise, the computation of the filter becomes very complex due to the large size of the matrices under consideration. Again, it takes much longer time to evaluate some important parameters such as Kalman gain G_k which is employed in the subsequent calculation. This can be improved by adopting square root filter approach.

3. IMPROVEMENT OF KALMAN GAIN

Kalman filter is noted for its high amount of computation owing to transcendental function evaluation and matrices inversion in the real time. To eliminate the aforementioned problem as well as to make the modelling of the filter computationally plausible and mathematically elegant, discrete square root technique is proposed for Kalman filter modification. The proposed technique combined with Kalman filter make it possible to resolve the divergence problems.

From the propagation of square root technique and application of Cholesky factorization, the filtering error covariance matrix can be written as:

$$M_{k/k} = \sqrt[2]{M_{k/k}}\sqrt[2]{M_{k/k}^T} \qquad (38)$$

Where $\sqrt[2]{M_{k/k}}$ and $\sqrt[2]{M_{k/k}^T}$ are defined as the lower triangular matrix and transposed term respectively. The most essential hint here is that the product is not likely to become indefinite. In accordance to Cholesky, the factor $\sqrt[2]{M_{k/k}}$ is better than$M_{k/k}$.

Using the idea of an orthogonal matrix is equal to its transpose and defining the Kalman filter gain matrix, we have:

$$M_{k/k} = M_{k|k-1} - M_{k|k-1}B_k^T R_k^{-1} B_k M_{k|k-1} \qquad (39)$$

Where R_k is defined in equation (8) and also bearing in mind that the equation (39) has three distinct matrix terms, hence ordering the three distinct terms in a compactible way in the K-by-K block matrix; we have:

$$y_k = \begin{bmatrix} |(R_k)| & |(B_k M_{k|k-1})| \\ |(M_{k|k-1}B_k^T)| & |(M_{k|k-1})| \end{bmatrix} \qquad (40)$$

$$= \begin{bmatrix} |(B_k M_{k|k-1}B_k^T + Q_{v,k})| & |(B_k M_{k|k-1})| \\ |(M_{k|k-1}B_k^T)| & |(M_{k|k-1})| \end{bmatrix} \qquad (41)$$

The y_k is now nonnegative define, therefore applying Cholesky technique to new block matrix, we have:

$$y_k = \begin{bmatrix} |\sqrt[2]{Q_{v,k}})| & |(B_k \sqrt[2]{M_{k/k}})| \\ |(0)| & |(\sqrt[2]{M_{k/k}})| \end{bmatrix} \begin{bmatrix} |(\sqrt[2]{Q_{v,k}})| & |(0^T)| \\ |(B_k \sqrt[2]{M_{k/k}})| & |(\sqrt[2]{M_{k/k}})| \end{bmatrix} \qquad (42)$$

Therefore, invoking the technique of matrix factorization lemma, we may have:

$$\begin{bmatrix} |\sqrt[2]{Q_{v,k}})| & |(B_k \sqrt[2]{M_{k/k}})| \\ |(0)| & |(\sqrt[2]{M_{k/k}})| \end{bmatrix} \Theta_k = \begin{bmatrix} |(Y_{11,k})| & |(0^T)| \\ |(Y_{21,k})| & |(Y_{22,k})| \end{bmatrix} \quad (43)$$

Where Θ_k is an orthogonal rotation or an orthogonal matrix. Expanding equation (43) by using property of an orthogonality of Θ_k, we may have:

$$\begin{bmatrix} |\sqrt[2]{Q_{v,k}})| & \left|\left(B_k \sqrt[2]{M_{k/k-1}}\right)\right| \\ |(0)| & \left|\left(\sqrt[2]{M_{k/k-1}}\right)\right| \end{bmatrix} \times \begin{bmatrix} |(\sqrt[2]{Q_{v,k}})| & |(0^T)| \\ \left|\left(\sqrt[2]{M_{k/k-1}} B_k^T\right)\right| & \left|\left(\sqrt[2]{M_{k/k-1}^T}\right)\right| \end{bmatrix}$$

$$= \begin{bmatrix} |(Y_{11,k})| & |(0^T)| \\ |(Y_{21,k})| & |(Y_{22,k})| \end{bmatrix} \begin{bmatrix} |Y_{11,k}^T)| & |(Y_{21,k}^T)| \\ |(0^T)| & |(Y_{22,k}^T)| \end{bmatrix} \quad (44)$$

Expanding the matrix product and equating corresponding terms, we have:

$$Q_{v,k} + B_k M_{k|k-1} B_k^T = Y_{11,k}\, Y_{11,k}^T \quad (45)$$

$$B_k M_{k|k-1} = Y_{11,k}\, Y_{21,k}^T \quad (46)$$

$$M_{k|k-1} = Y_{21,k}\, Y_{21,k}^T + Y_{22,k}\, Y_{22,k}^T \quad (47)$$

Using equation recognition, then the unknown nonzero submatrices of Y_k can be determined in equation (43). Therefore the final solution is derived as:

$$\begin{bmatrix} |\sqrt[2]{Q_{v,k}})| & \left|\left(B_k \sqrt[2]{M_{k/k}}\right)\right| \\ |(0)| & \left|\left(\sqrt[2]{M_{k/k}}\right)\right| \end{bmatrix} \Theta_k = \begin{bmatrix} |(\sqrt[2]{R_k})| & |(0^T)| \\ |(G_k \sqrt[2]{R_k})| & |(\sqrt[2]{M_{n/n}})| \end{bmatrix} \quad (48)$$

From the final solution, it can be seen that that the matrix product $G_k \sqrt[2]{R_k}$, where $\sqrt[2]{R_k}$ represents the square root of the covariance, makes it feasible to compute accurately the Kalman gain.

4. SIMULATION ANALYSIS

In order to determine the efficiency and reliability of the proposed estimator, an experimentation using MATLAB/Simulink is used to generate a time-varying signal to simultaneously estimate the magnitudes and phase shifts of fundamental and harmonic components. The setup is carried out to determine three cases viz; (1) Harmonic estimation in the presence of constant amplitude (static signal), (2) variable amplitude (dynamic signal) polluted with artificial noise, and (3) signal presence with artificial noise and decaying DC component. The typical signals selected are in the forms:

Case (1):

$$y_k = e_0 sin2\pi ft + 0.2e_0 \sin\left(2\pi ft + \frac{\pi}{12}\right) + 0.15e_0 \sin\left(2\pi ft + \frac{5\pi}{6}\right)$$
$$0.1e_0 sin\left(2\pi ft + \frac{2\pi}{3}\right) + 0.05e_0 sin\left(2\pi ft - \frac{\pi}{3}\right) +$$
$$0.03e_0 sin\left(2\pi ft - \tfrac{\pi}{4}\right) + 0.015e_0 \sin\left(2\pi ft - \tfrac{\pi}{6}\right) \quad (51)$$

Case (2):

$$y_k = e_0 sin2\pi ft + 0.2e_0 \sin\left(2\pi ft + \frac{\pi}{12}\right) + 0.15e_0 \sin\left(2\pi ft + \frac{5\pi}{6}\right)$$
$$0.1e_0 sin\left(2\pi ft + \frac{2\pi}{3}\right) + 0.05e_0 sin\left(2\pi ft - \frac{\pi}{3}\right) +$$
$$0.03e_0 sin\left(2\pi ft - \tfrac{\pi}{4}\right) + 0.015e_0 \sin\left(2\pi ft - \tfrac{\pi}{6}\right) + 0.02 \quad (52)$$

Case (3):

$$y_k = 0.2e^{-5t} + e_0 sin2\pi ft + 0.2e_0 \sin\left(2\pi ft + \frac{\pi}{12}\right) + 0.15e_0 \sin\left(2\pi ft + \frac{5\pi}{6}\right)$$
$$0.1e_0 sin\left(2\pi ft + \frac{2\pi}{3}\right) + 0.05e_0 sin\left(2\pi ft - \frac{\pi}{3}\right) + 0.03e_0 sin\left(2\pi ft - \frac{\pi}{4}\right)$$
$$+0.015e_0 \sin\left(2\pi ft - \tfrac{\pi}{6}\right) + 0.02 \quad (53)$$

The amplitude of the fundamental signal e_0 is taken as 1.0 expressed in per unit value. The third case resembles an industrial load made up of electrical motor controlled by power electronic circuit (rectifier-inverter controlled circuit). Figure 1 shows the waveform for the fundamental frequency for the ideal situation. Figures 2 and 3 show signal containing 3rd, 5th, 7th, 11th, 13th and 17th harmonic components polluted without and with artificial noise, ξ_k which is a non-random vector with unit variance and zero mean using algorithm of discrete Fourier transform (DFT), recursive least mean square (RLMS), Kalman filter (KF) and improved Kalman filter (IKF) whereas figures 4 and 6 display the estimation phase angle of KF and IKF which are of great important to this research. In addition, figure 5 displays the signal polluted with both artificial noise and decaying DC component.

To attempt a virtual calibration of tracking, the algorithm of DFT, RLMS, KF are properly tuned by selecting optimal noise covariance matrices to compare their monitoring performance. In the first scenario where the signal is free from artificial noise and decaying DC component, it was ascertainedthat the tracking were perfect in all the cases. Again, considering figures 3 and 5 where artificial noise and decaying DC component were used to corrupt the signal source, it was seen that unlike FFT, RLMS and KF, IKF was still stable and used a very short settling time whilst others (FFT, RLMS and KF) were still oscillating. In order to cause the correction filter in power circuit to operate efficiently and effectively without delay, then the detection time needs to be less than quarter of circle ($2ms$) which has been stipulated in IEEE standard code 1100-2005, 2006 (CBEMA curve) [18].

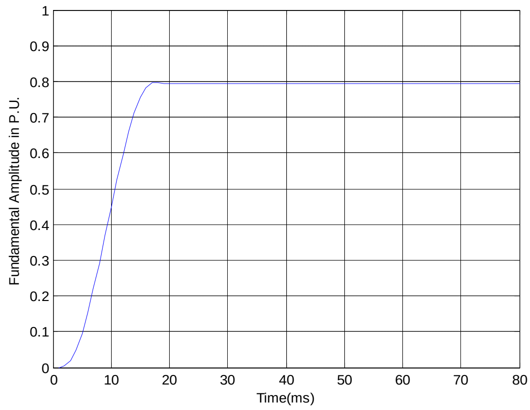
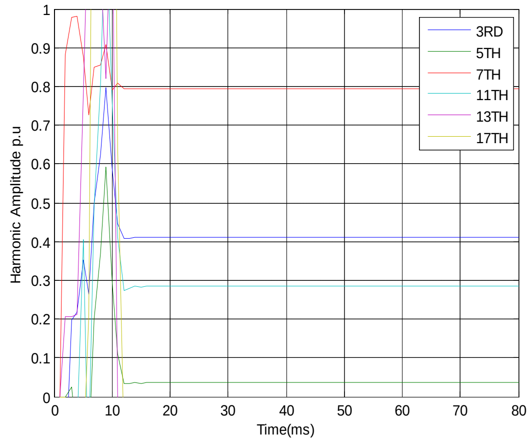
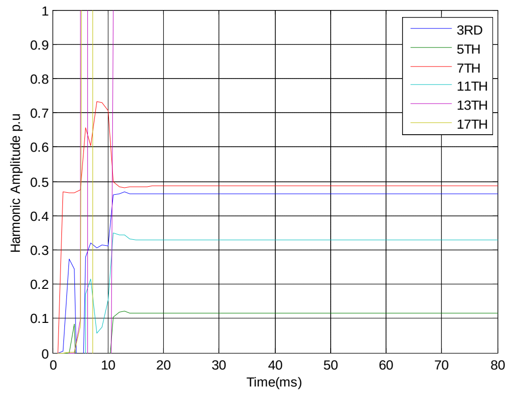


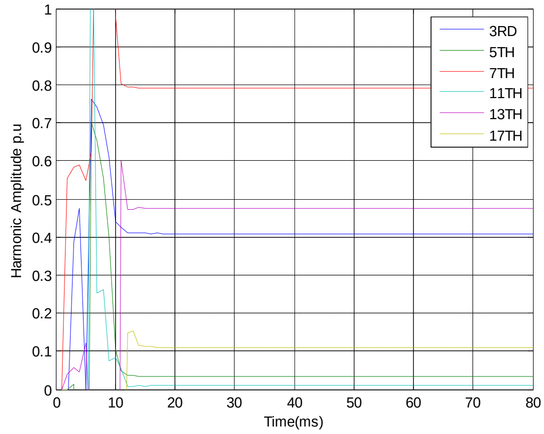
Fig. 1: Estimation of the fundamental component of the amplitude signal without harmonics.



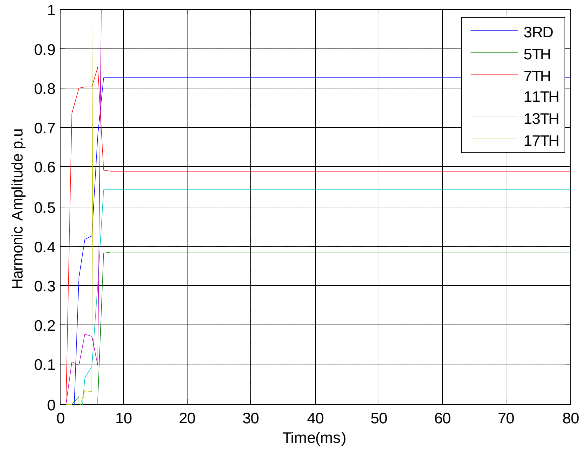
(a)



(b)

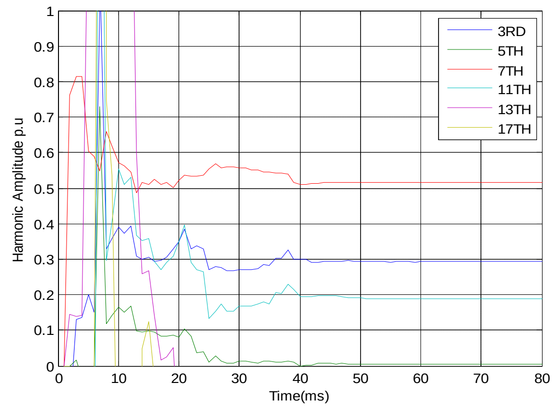


(c)

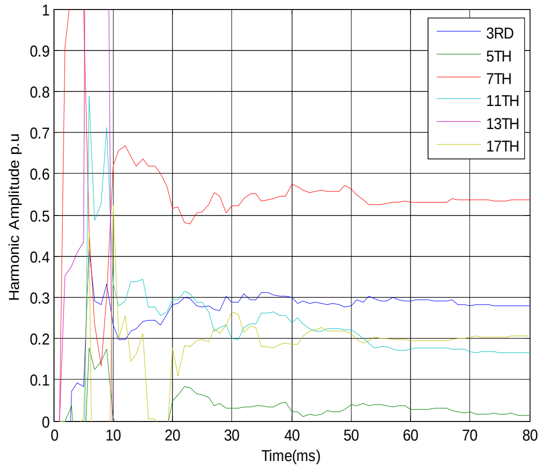


(d)

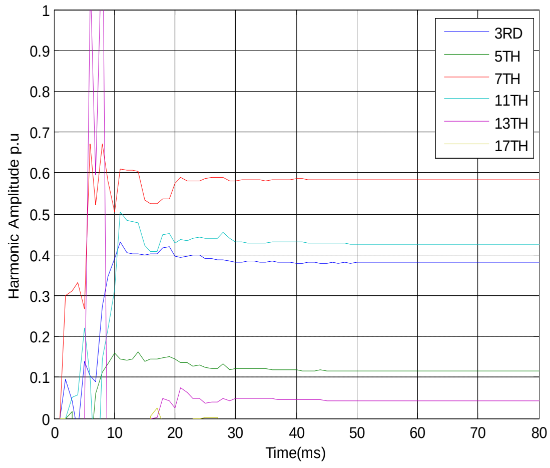
Fig. 2: Estimation of static magnitude of the harmonic components without artificial noise and decaying DC component using (a) FFT (b) RLMS (c) KF and (d) IKF



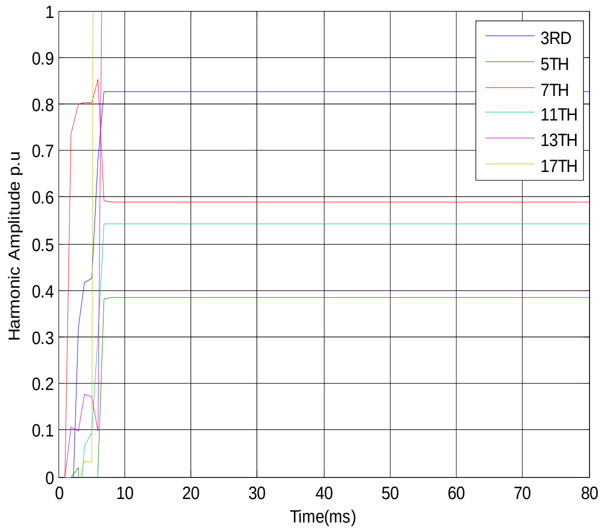
(a)



(b)

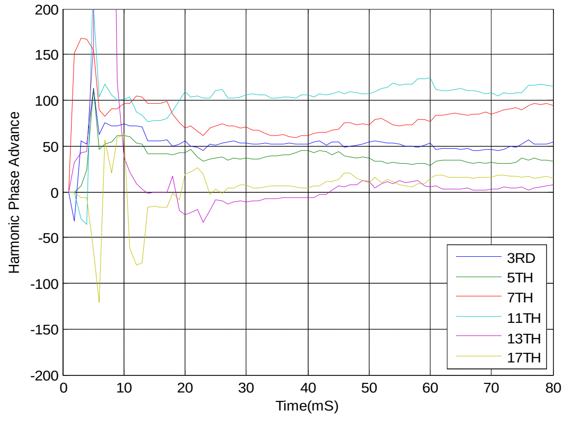


(c)

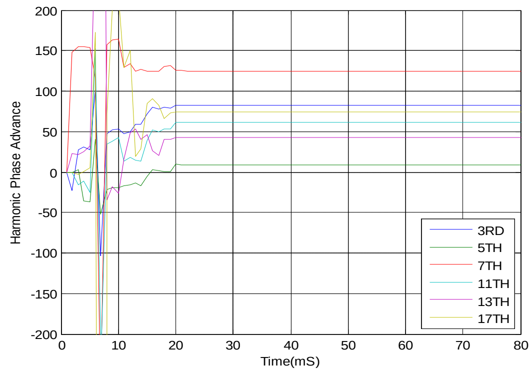


(d)

Fig. 3: Estimation of magnitude of the harmonic components polluted with artificial noise using (a) FFT (b) RLMS (c) KF and (d) IKF

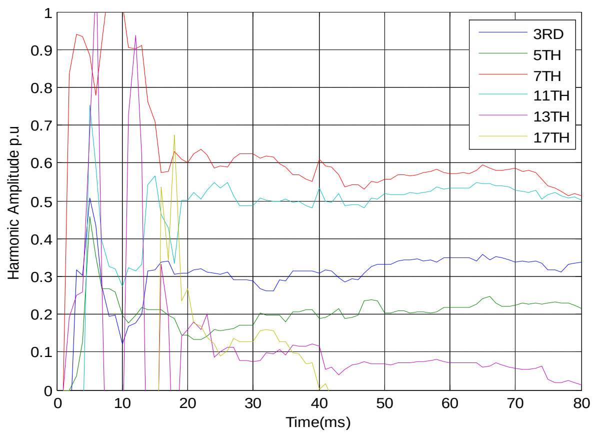


(a)

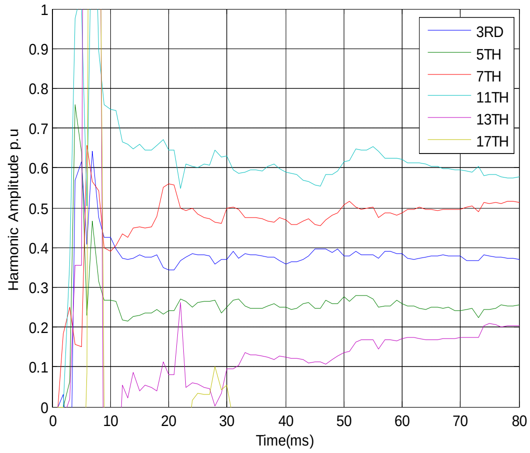


(b)

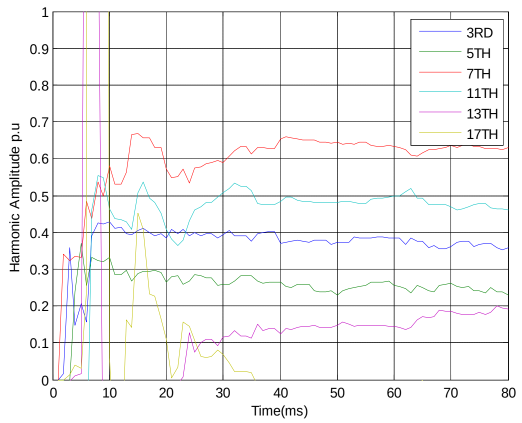
Fig. 4: Estimation of phase shift of the harmonic components corrupted with only artificial noise using (a) KF and (b) IKF



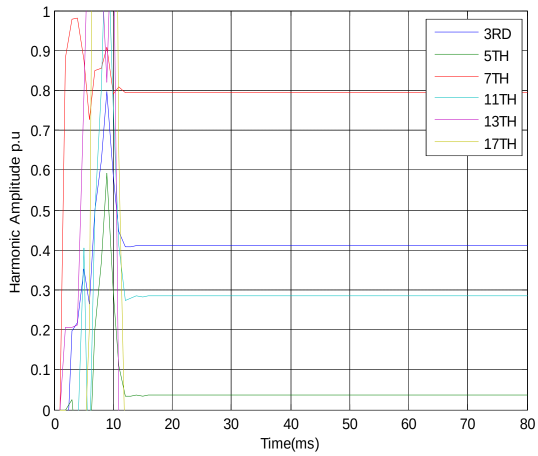
(a)



(b)

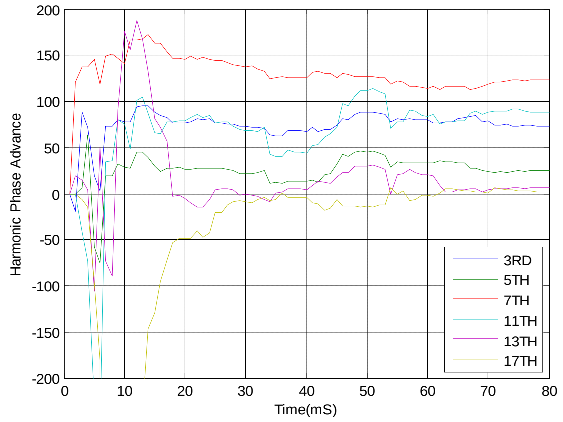


(c)

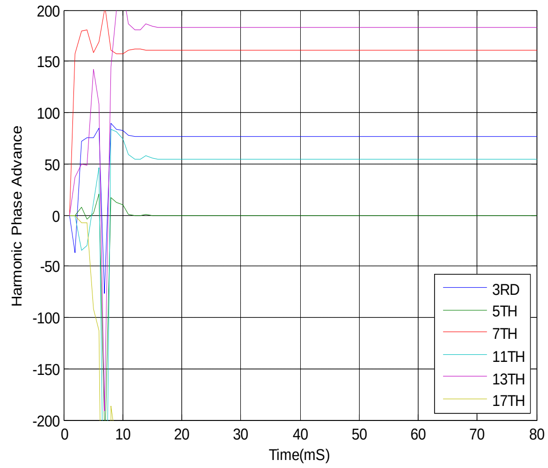


(d)

Fig. 5: Estimation of magnitude of the harmonic components corrupted with both artificial noise and decaying DC component using (a) FFT (b) RLMS (c) KF and (d) IKF



(a)



(b)

Fig. 6: Estimation of phase shift of the harmonic components polluted with both artificial noise and decaying DC component using (a) KF and (b) IKF

5. CONCLUSION

The Kalman filter application is known for its speed and accuracy in terms of estimating the magnitude, phase shift and frequency of fundamental and harmonic components of a polluted electrical power signal by combining with or without other intelligent algorithms. Its computational difficulty arises when the signal under consideration is nonlinear resulting in handling of enormous data which may involve large matrices inversion. Not all but also the estimator can exhibit poor performance when the signal is corrupted with artificial noise and decaying quantity. Therefore to come out of these quagmires, this research paper has shown that the performance can be improved by properly tuning of the Kalman filter parameters by selecting appropriate covariance matrices for each of the sampling frequency. Further, the Kalman Gain can be reduced to power of half by the implementation of square root filter which improves the subsequent computation. The proposedtechnique has proved to be paramount among other techniques which have been compared in the simulation analysis even in the presence of artificially generated noise and decaying quantity. It has also been shown that that the proposed design uses minimum rise time, less than quarter of a cycle and minimum settling time to prevent oscillation as compared with the traditional Kalman filter.

REFERENCES

[1] A. S. Yilmatz, A. Alkan, and M. H. Asyali, “Application of parametric spectral estimation methods on detection of power system harmonics, “Elect. Power Syst. Res., vol. 78, no. 4, pp. 683–693, Apr. 2008.

[2] J. Barros and E. Pérez, “Automatic detection and analysis of voltage events in power systems,” IEEE Trans. Instrum. Meas., vol. 55, no. 5, pp. 1487–1493, Oct. 2006

[3] R. C. Dugan, M. F. McGranaghan and H. W. Beaty, Electrical Power Systems Quality, McGraw-Hill, 1996

[4] A. E. Emanuel, “Summary of IEEE standard 1459: Definitions for the measurement of electric power quantities under sinusoidal, non-sinusoidal, balanced, or unbalanced conditions,” IEEE Trans. Ind. Appl., vol. 40, no. 3, pp. 869-876, May/Jun. 2004

[5] S. N. Govindarajanet. al., “Survey of Harmonic Levels on the Southwestern Electric power Company System," IEEE trans. On Power Delivery, Vol. 6, No. 4, pp. 1869-1873, Oct. 1991.

[6] Greenwood, Electrical Transients in Power Systems, John Wiley & Sons, Inc. New York, 1991.

[7] G. Manchur and CC. Erven, "Development of a Mode1 for Predicting Flicker from Electric Arc Furnaces,” IEEE Tran. On Power Delivery, Vo1.7, No. 1, pp. 41-6426, January 1992.

[8] G.P. Christoforidis and A. P. Meliopoulos, “Effects of Modeling the Accuracy of Harmonic Analysis," IEEE Tran. On Power Delivery, Vo1.5, No. 3, pp. 1598-1607, July 1990.

[9] Douglas, J.: "Solving problems of power quality", EPRI Journal, pp. 6-15, Dec 1993.

[10] Heydt, G. H, Electrical Power Quality, Stars in a Circle Publication, 1991.

[11] J. B. V. Reddy, P. K. Dash, R. Samantaray, and A. K. Moharana, “Fast tracking of power quality disturbance signals using an optimized un-scented filter,” IEEE Trans. Instrum. Meas., vol. 58, no. 12, pp. 3943–3952, Dec. 2009.

[12] P. K. Ray and B. Subudhi, “BFO optimized RLS algorithm for power system harmonics estimation,” Appl. Soft Computer,” Vol. 12, no. 8, pp. 1965–1977, Aug. 2012.

[13] B. L. Theraja and A. K. Theraja, “A Textbook of Electrical Technology” The Twenty-Third Revised Edition by Armagetter, ISBN Code 81-219-2441-3, eBook Code 10 291 D.

[14] IEEE Working Group on Power System Harmonic, “Power System Harmonics: An Overview,” IEEE Trans. on Power App. Syst., PAS-102 (8), pp. 2455-2460, Aug. 1983.

[15] LI Da-lu, LI Rui, SUN Yuan-zhang. Power system dynamic state estimation with mixed measurements based on UKF [J]. Automation of Electric Power Systems, 2010, 34(17): 17-21.

[16] CHEN Huan-yuan, LIU Xin-dong, SHE Cai-qi. Study on power system dynamic state estimation algorithm [J]. Science Technology and Engineering, 2011, 25(11): 6071-6074.

[17] ZHAO Lin. Nonlinear system filtering theory [M]. Beijing: National Defense Industry Press, 2012: 1-8.

[18] IEEE Emerald Book, Recommended Practice for Powering and Grounding Electronic Equipment, IEEE std. 1100-2005 (2006), IEEE inc., ISBN 0-7381-4979-9, New York, USA