An Adaptive Kalman Filter for Voltage Sag Diagnosis in power system

Hisham Alrawashdeh, Johnson Asumadu

Electrical and Computer Engineering Department, Western Michigan university, Kalamazoo, MI, USA

Abstract— **This paper proposed an adaptive kalman filter for amplitude tracking to help in diagnosing the voltage sag problem in power system, the proposed algorithm uses two kalman filter; one of them for figuring the dynamic change in the system parameters and the other for signal tracking, the kalman filter is adaptive by updating the state covariance matrix when the dynamic change occurs, exact knowledge of yhe noise covariance matrices are not needed in the proposed algorithm, where the noise covariance matrices are set to be incorrect in the kalman filter model, then the proposed algorithm is used to detect the amplitude of the fundamental component of a signal contains harmonics and noise.**

Keywords— **adaptive, kalman filter, power system harmonics, voltage sag and noise covariance matrices.**

I. Introduction

Voltage Sag is one of the major problems in power system, where the voltage is decreased slightly as the demand power has been increased, then at a certain threshold value the voltage collapses sharply to zero and this may cause severe damage in power system components. The measurement value of the voltage usually contains harmonics and noise, which make it is difficult to trust this value to detect the voltage sag problem, for that reason, the kalman filter is widely used in power system.

In the Kalman filter design, the knowledge of the noise covariance matrices (Q and R) are important to ensure the filter optimality, unfortunately, in many applications, the noise covariance matrices are unknown prior the operation of the Kalman filter. The kalman filter that estimates and adjusts the noise covariance matrices online or offline is usually called adaptive kalman filter, the importance of these matrices were discussed in several previous researches, based on [1] the incorrect values of Q and R matrices will not cause the system to diverge, but they will lead the kalman filter to converge to suboptimal solution if and only if the system is well modelled. Some adaptive kalman filters focus in estimating Q or R matrix not both of them, where in [2] only Q matrix is estimated, and they mentioned that the knowledge of Q matrix is more important than R matrix based on that, they proposed an adaptive extended kalman filter for time varying frequency estimation, while in [3,4] Q is set constant to 1 and R is calculated at each iteration. The ratio between the two matrices are discussed in [5] where, it has been concluded that the ratio between Q/R is not sufficient, when the SNR exceed certain limit and based on that they proposed an adaptive kalman filter that calculates both Q and R matrices at each iteration, while in [6] the knowledge of the ratio between the noise covariance matrices was sufficient to solve LQR problem of power system frequency estimation, also in [7] they emphasized that the ratio between Q and R is more important than the knowledge of their real values.

The importance of resetting Q and R matrix as a dynamic change occurs of the system parameters were discussed in [8-10]. In [8] The covariance matrices Q and R are reset as long as any of the system parameter is changed, where the proposed algorithm is used to measure the power system frequency. Switching between two values of Q matrix; one for transient and the other for steady state is used in [9] to improve the kalman filter performance for a step change response, the switching between the two values of the Q matrix is decided based on the student statistical model with 95 % confident. fuzzy kalman filter is proposed in [10] to track stereo visual scheme, in the proposed algorithm, there were two fuzzy models, one of them is used to adjust the covariance matrix and the other is used to reinitiate the kalman filter when it loses the tacking

Based on previous researches, the covariance matrices should be reset, when a dynamic change occurs, this leads to ask, why is it necessary to reset these matrices when the measurement noise is not changed, especially when the kalman filter shows a good response before the parameter is changed, in the proposed algorithm in this paper, the kalman filter will be adaptive by updating the state covariance matrix, the state covariance matrix P in the kalman filter approaches zero as soon the kalman filter converges to the solution and this will prevent the kalman filter from reacting well with the signal changing, the proposed adaptive kalman filter uses two kalman filters; one of them is called secondary and the other is primary kalman filter , in the secondary kalman filter the state covariance matrix P is updated periodically to let the kalman filter interact with the signal changing, then by comparing the estimated amplitude of the secondary with the primary kalman filter, a dynamic change can be diagnosis, if a dynamic changing is occurred the P matrix in the primary kalman filter will be updated otherwise it will be kept constant. The covariance matrices will be assumed to be unknown, and incorrect value of theses matrices are chosen to investigate the performance of the proposed algorithm.

II. Kalman Filter

Kalman filter is a recursive, linear, real time and optimal filter that is used to estimate a signal of noisy system, the noise sources should be independent Gaussian white additive noise [11-13]. The Kalman state vector X_k at any instant can be calculated as follows [14]:

$$\begin{aligned} X_k &= A_k X_{k-1} + B_k U_k + W_k \\ Z_k &= C_k X_k + V_k \end{aligned} \tag{1}$$

Where, X_k : is the state vector,

A_k : is the transition matrix

B_k : is the input control vector.

W_k : is the process noise, and it is assumed to be white Gaussian noise with zero mean and covariance matrix Q_k, i.e $N(0, Q_k)$.

Z_k : is observation of the state X_k.

C_k : is the observation matrix.

V_k : is the observation noise, and it is also assumed to be Gaussian white noise with zero mean and R_k covariance matrix, i.e $N(0, R_k)$.

Since the kalman filter is a recursive filter, it will be suitable for real time application, the kalman filter calculation will be based on the current and the previous instant state, the simple kalman filter is suitable for linear system, otherwise extended or unscented kalman filter can be used for nonlinear systems. The optimality of the kalman filter is subject to two conditions; that the system is accurately linear modelled and the noise source are white a dative Gaussian noise with known covariance matrices [11].

Based on the kalman filter model matrices, the output will be predicted through the predicted stage calculation, then the measured data will interact with the predicted state to have optimal estimation of the output without the measurement noise, the kalman filter calculations are [11-13]:

Predicted stage

$$\begin{aligned} X_{k/k-1} &= A_k X_{k-1/k-1} + B_{k-1} U_{k-1} \\ P_{k/k-1} &= A_k P_{k-1/k-1} + A_k^T + Q_k \end{aligned} \tag{2}$$

Updating stage

$$\begin{aligned} Y_k &= Z_k - C_k X_{k/\ k-1} \\ K_k &= P_{k/k-1} C_k^T [C_k P_{k/k-1} C_k^T + R_k]^{-1} \\ X_{k/k} &= X_{k/k-1} + K_k Y_k \\ P_{k/k} &= [I - K_k C_k] P_{k/k-1} \end{aligned} \tag{3}$$

Where, P is the state covariance matrix

III. HARMONICS IN POWER SYSTEM AND VOLTAGE SAG PROBLEM

The power system signals usually have harmonic components due to the nonlinearity of the power system components such as convertor, transformer, rotating machines, power electronics devices ... etc, the harmonic components have multiple frequency of the fundamental signal frequency, which is normally 50 or 60 Hz [15-17], the order of the harmonic will be defined as the ratio between the harmonic frequency and the fundamental frequency which is an integer number, the magnitude of the harmonic signals is inverse proportional with the harmonic order, and for the single phase power system the orders of harmonic are odd. The most severe harmonic components are the component with low order harmonics since they have higher amplitude comparing with the low order harmonics.

The harmonics cause a distortion in the electrical signal, losses , voltage stress, interference between the power system and the communication system and increasing in the dielectrically stress in protection devices [17].

As it is mentioned earlier that the harmonics distorted the electrical signal and leads to inaccurate amplitude measurement, which may cause to incorrect decision of the protection device, especially in voltage sag problem, where in normal operation of the power system the voltage decreases slightly for load demand increasing until a certain threshold value, the voltage collapse sharply to zero and causes severe damage in the power system, for that reason an accurate measurement of the voltage amplitude is needed to avoid the voltage sag problem and to allow the protection device to operates before the threshold value of the voltage. The measurement noise will be also one of the problem in the protection device operation, which causes an error in the measured amplitude of the voltage, based on that, the kalman filter will be used to detect the fundamental signal amplitude of a signal contains harmonics and noise. By assuming a constant fundamental frequency and including only the fundamental component in the kalman filter model, this will lead to a linear model as follows:

$$X(k) = [x_1(k) \quad x_2(k)]^T \tag{4}$$

$$\begin{aligned} x_1(k) &= A\cos(wkT + \theta_1) \\ x_2(k) &= A\sin(wkT + \theta_1) \end{aligned} \tag{5}$$

The state equations will be as follows:

$$\begin{aligned} X(k+1) &= AX(k) + B\ U(k) + w_k \\ Y(k+1) &= C\ \ X(k) + D\ U(k) + v_k \end{aligned} \tag{6}$$

$$A = \begin{bmatrix} \cos(jwT) & -\sin(jwT) \\ \sin(jwT) & \cos(wjT) \end{bmatrix} \tag{7}$$

$$B = [0 \quad 0]^T \tag{8}$$

$$C = [1 \quad 0] \tag{9}$$

$$D = 0 \tag{10}$$

And the amplitude of the fundamental signal is given as follows:

$$Amp(k) = \sqrt{x_1^2(k) + x_2^2(k)} \tag{11}$$

IV. PROPOSED ADAPTIVE KALMAN FILTER

The state covariance matrix P approaches to zero when the kalman filter converges to a solution, and for a dynamic change in the measured signal, the value of P prevents the kalman filter to interact with the signal variation, since its value is measured the kalman filter convergence, updating the P matrix to a higher value as soon as the dynamic change occurs will help the kalman filter to track the signal, the problem arises here is to determine the transient time t_r where the dynamic change occurs . in the proposed algorithm two kalman filter will be used primary and secondary kalman filters; the primary kalman filter will be used to track the signal to diagnosis the voltage sag problem and the secondary kalman filter will be used to figure the necessary time for updating the P matrix in the primary kalman filter.

In the secondary kalman filter, the P matrix will be updated periodically in a very short time which causes a variation in the output of the kalman filter but this variation is bounded within a narrow limits, by comparing the estimated output of the primary and the secondary kalman filter in the normal operation the difference between them will be within this narrow limit, if a dynamic change in the signal occurs, the secondary output will interact with the signal more than the primary kalman filter due to P matrix updating in the secondary one, which causes the amplitude difference between the secondary and primary kalman filter to exceed this narrow limit, and this will be used as an indication for a dynamical changing in the signal, at this instant the *P* matrix in the primary filter must be updated to track the signal variation.

There are several factors restricted the quality of the proposed algorithm; the first one is the periodically time that is used to update the *P* matrix in the secondary kalman filter, in this paper , the *P* matrix is updated every 1/2 cycle , based on the application and the behaviour of the measured signal, the value of this time can be changed, if the signal is changed rapidly, the period time could be decreased and if it is changed slowly a larger periodic time can be selected, a very small periodic time can be selected regardless of the signal feature. Other factor could be affected the proposed algorithm is the updating value of the *P* matrix, if the *P* matrix is largely increased this will caused a large variation in the amplitude and less time to settle down to the solution, and if it is increased slightly the variation in the amplitude will be small and it will take more time to settle down.

For the secondary kalman filter the *P* matrix is slightly increased to limit the variation in normal condition to a narrow limits and to differ this variation from the variation that is created by the dynamic changing in the signal, while the *P* matrix is largely increased in the primary kalman filter to have faster response in signal tracking. These two factors and the performance of the proposed filter will be discussed in details in the simulation results section.

V. SIMULATION RESULTS

The primary kalman filter will be used to estimate the amplitude of the fundamental signal of the voltage to avoid the voltage collapse problem. Suppose the voltage signal has first and third order of harmonics as follows:

$$y(t) = 1.414\cos(100\pi t + \pi/6) + 0.3\cos(300\pi t + \pi/5) + \ldots \\ 0.1\cos(500\pi t + \pi/8) \qquad (12)$$

The kalman filter model matrices will includes only the fundamental components as follows:

$$A = \begin{bmatrix} \cos(wT) & -\sin(wT) \\ \sin(wT) & \cos(wT) \end{bmatrix}, B = \begin{bmatrix} 0 \\ 0 \end{bmatrix}$$

$$C = [1 \quad 0],, D = [0]$$

The real value of the measurement noise covariance is 0.1 and it is assumed to be unknown in the proposed model so the *R* value in the kalman filter model is assumed to be 0.01 (small value are suggested to let the kalman filter to interact more with the measured signal). Before illustrate the proposed adaptive kalman filter, it is worth to show the effective of updating *P* matrix in kalman filter performance, Fig.1 shows the estimated amplitude of the fundamental component using kalman filter when the *P* matrix is updated, *R* is 0.01(the real value of R in this experiment is 0.1) , updating *P* at the instance of signal changing improve the kalman filter performance, even though that *R* in the kalman filter is not equal to the real value of the noise covariance, *P* matrix is updated to several values, as the value of *P* is increased the response of the kalman filter is improved but this will increases the amplitude transient.

Updating *P* matrix at the instant of the amplitude changing helps the kalman filter to detect the changing in the measured signal but usually the transient time of the signal changing is unknown.

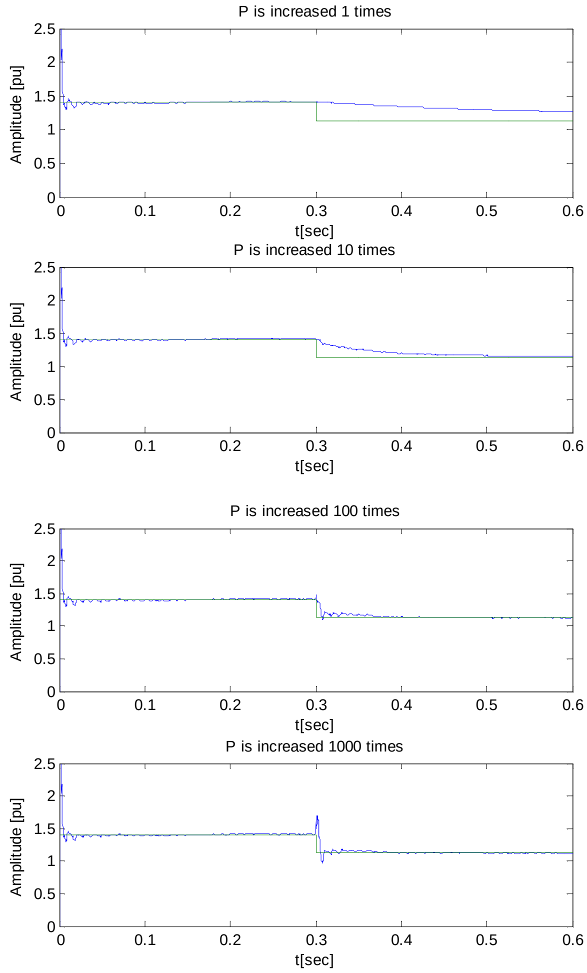

Fig. 1 Amplitude of the fundamental signal estimated by kalman filter for different values of *P* matrix updated at t =0.3

Fig. 2 and Fig. 3 show the estimated amplitude by the kalman filter, when the *P* matrix is updated periodically, in Fig.2 the *P* is increased 100 times each time the *P* matrix is updated for several period time, if the periodic time is increased, this will lead the kalman filter to settle down and get better results, but the problem in this case, that if the periodic time is large this may lead to update *P* matrix in un appropriate time as it happen when the periodic time is 0.04 and 0.07 in Fig.2.

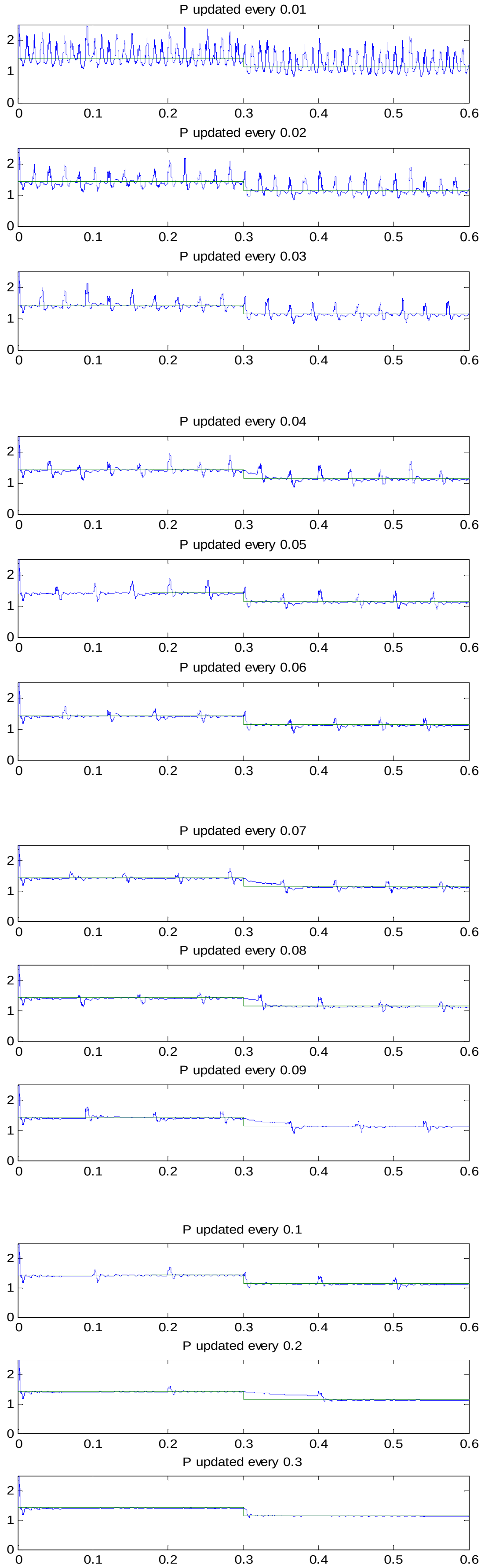

Fig. 2 Estimated amplitude by kalman filter for different periodic updating time, *P* is increased to a fixed value.

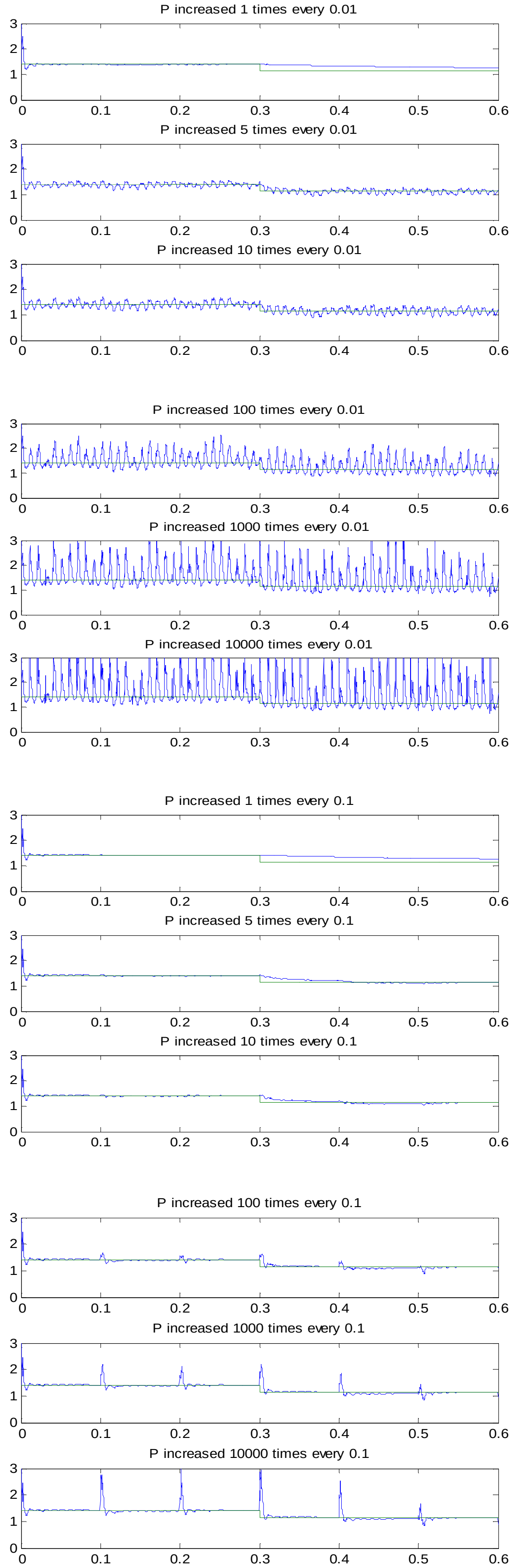

Fig. 3 Amplitude estimated by kalman filter for different periodic updating time and different updating values

if the periodic time is small the delay time of detecting the amplitude changing will be reduced, but the transient in the estimated amplitude will be increased and especially when the updating value is large, as it is seen in Fig.3, where two periodic time are chosen 0.01 and 0.1 sec with different updating values of the *P* matrix.

It will better if the kalman filter updates the *P* matrix as soon as a dynamic change occurs, to achieve this goal a secondary kalman filter will be used. The secondary kalman filter will update the *P* matrix periodically with small period time to avoid the time delay problem, the updating value is chosen to be very small based on the results shown in Fig.4 and Fig.5. in Fig.4 the amplitude of the measured signal is kept constant and *P* matrix is updated every 0.01 sec with several updating values, the variation in the amplitude is increased when the updating value is increased, the variation due to updating matrix may exceed the amplitude changing and this will lead to a problem in detecting the time of the signal changing, Fig. 5 shows the absolute value of the amplitude variation between the primary and the secondary kalman filters, in this figure the signal amplitude is kept constant and *P* matrix in the secondary kalman filter is updated every 0.01sec for several updating values, the results show that in case of small updating value the variation is very small and bounded in a narrow band.

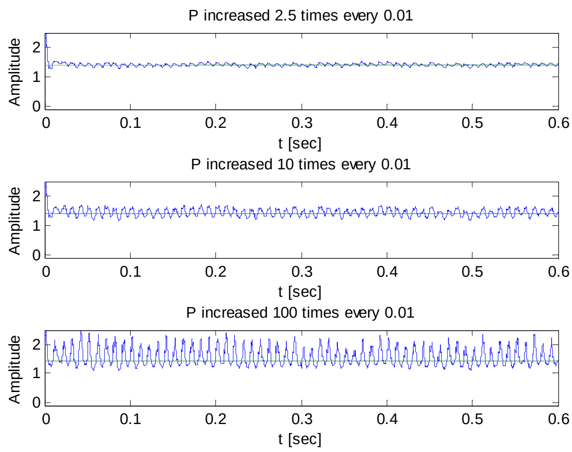

Fig. 4 Estimated amplitude by kalman filter for fix periodic time and different updating values

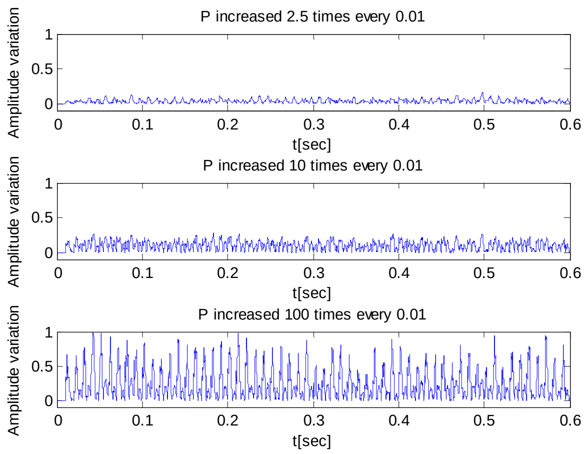

Fig. 5 absolute value of the amplitude variation between the amplitude estimated by kalman filter without updating *P* matrix and with one updates the *P* matrix every o.01 sec to different updating values.

Fig.6 shows the amplitude variation between the primary and the secondary kalman filters, the *P* matrix in the secondary kalman filter is updated every 0.01 sec to 1.05 from the previous value of the *P* matrix, the amplitude of the signal is changed at t = 0.3 sec to several values in this figure, when the amplitude is constant the amplitude variation is bounded within 0.09 limit, then when a dynamic change occurs in the signal amplitude at t = 0.3 sec, the variation between the two kalman filters increases and exceeds the normal limit (0.09), this will be used to detect the dynamic change in the signal to update the *P* matrix in the primary kalman filter when the dynamic change occurs.

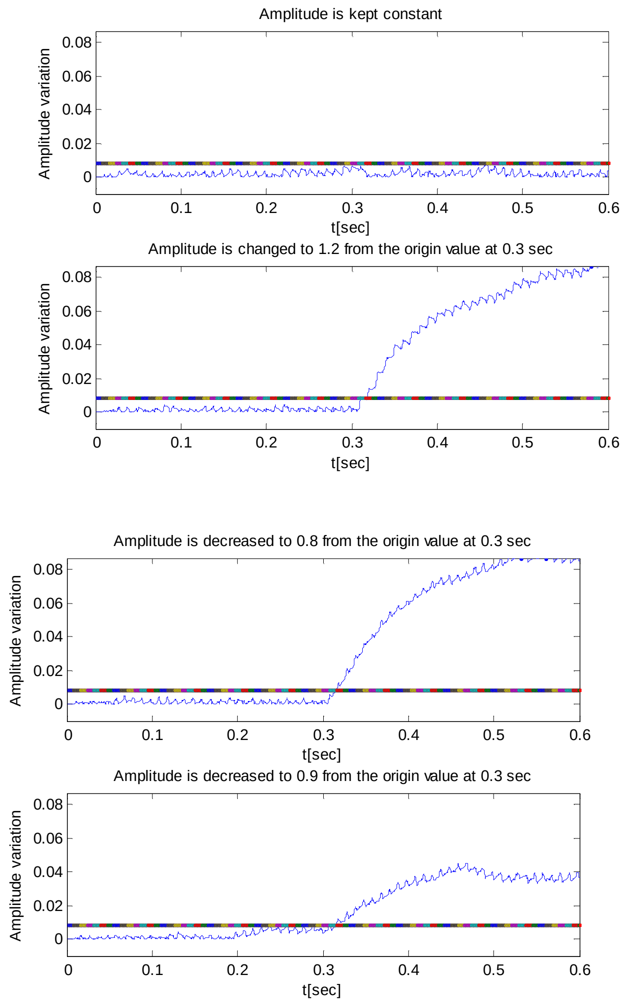

Fig. 6 Amplitude variation between the primary and the secondary kalman filter for different signal amplitude changing, *P* is increased 1.05 every 0.01 sec

In the proposed algorithm, as soon as the amplitude difference variation between the secondary and the primary kalman filters exceeds the normal limit, then the primary kalman filter will update the *P* matrix to higher value to interact fast with the dynamic change, so the main two differences between the secondary and the primary kalman filters are that, the *P* matrix is updated periodically in the secondary kalman filter, while it is updated only when the amplitude difference exceeds the limit in the primary kalman filter, the second difference is that the updating value of the *P* matrix in the secondary kalman filter is small and the updating value in the primary kalman filter is high to achieve faster response in amplitude tracking.

Fig. 7 shows the amplitude estimated by the proposed adaptive kalman filter for a single dynamic change in the signal amplitude at t = 0.5sec to different values, as it is shown in this figure, the proposed kalman filter is capable to track the signal, multi signal changing is investigated in Fig.7, the proposed adaptive kalman filter shows a good response in signal tracking especially when extreme changing occurs, the proposed algorithm is still used incorrect value of *R*.

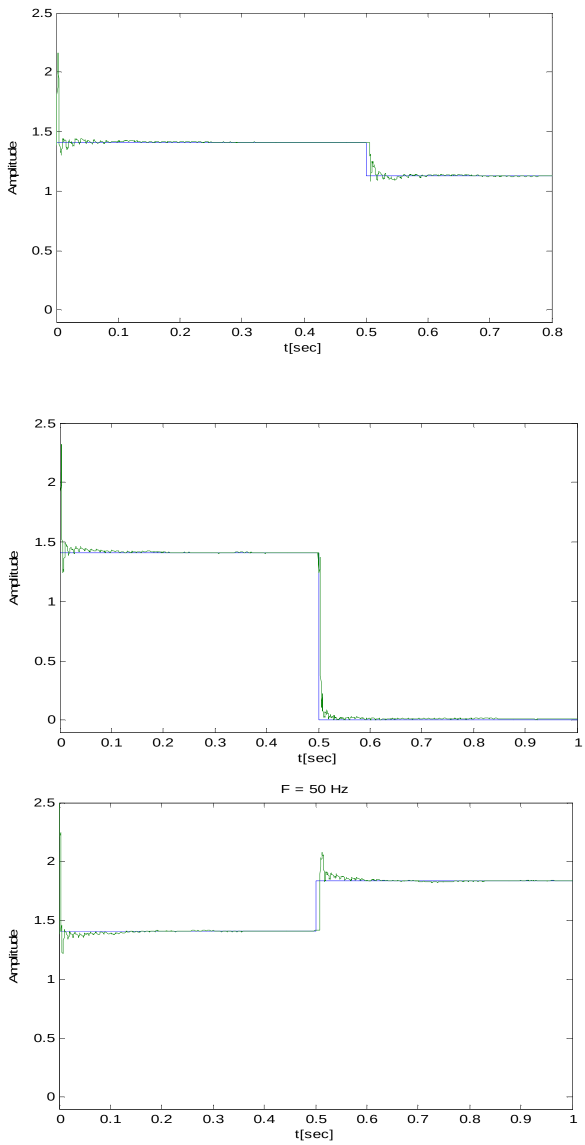

Fig.7 Estimated amplitude by the proposed adaptive kalman filter for different amplitude changing at t = 0.5 sec

The signal frequency is kept constant (50 Hz) for all the previous results, while in the normal operation of the power system the signal frequency could be varied slightly, usually the variation must be less than 0.5 Hz to consider it as a normal operation, the simple kalman filter is used to estimate the amplitude under a constant frequency condition to have a linear model, otherwise the system becomes nonlinear and an extended or unscented kalman filter must be used. the signal frequency is included in the kalman filter matrices, and the kalman filter predicts the output based on these matrices, in this case the predicted value of the kalman filter will be not accurate and will cause a major error in the estimated output of the simple kalman filter, Fig.9 shows the estimated amplitude by the proposed adaptive kalman filter for signal amplitude changing at t = 0.5 for different signal frequency, for small frequency variations the proposed filter shows a good response, when the frequency is equal to 49.5 Hz , the estimated amplitude start to decrease than the real value due to the frequency changing before the amplitude changing occurs, this cause the amplitude difference between the primary and the secondary kalman filter exceeds the limit since updating *P* matrix in the secondary kalman filter allows the secondary kalman filter to interact more with the signal, this leads to update the *P* matrix in the primary kalman filter to correct the estimated amplitude, then when a dynamic change occurs in the amplitude, the *P* matrix is also updated to keep signal tracking, when the frequency is decreased to 49 Hz the estimated amplitude by the primary kalman filter is less than the real value and this causes several triggering from the secondary kalman filter to update the *P* matrix in the primary kalman filter to keep signal tracking, based on the results shown in Fig.9 the proposed filter shows a good response for normal operation of the power system, where the frequency within 0.5 Hz range, otherwise the proposed algorithm should be modify to use extended kalman filter.

VI. CONCLUSIONS AND FUTURE WORKS

An adaptive kalman filter is proposed in this paper to detect the changing of the signal amplitude, two kalman filters are used; primary and secondary kalman filters, the main aim of the primary kalman filter is to figure the signal changing and trigger the primary kalman filter to update the *P* matrix to keep the signal tracking , the proposed adaptive kalman filter shows a good performance even though that the noise covariance matrices are not correct in the kalman filter model (less than the real value by 10 times) for several amplitude changing under a constant frequency condition, it is also a good response for a normal range of the power system frequency, where the results show that the secondary kalman filter will trigger the primary kalman filter to update the *P* matrix not only in the case of signal amplitude changing but also for frequency variation.

Future works will include more studies of the sensitivity of the proposed filter for the updating value and the updating period and also will include a replacement of the simple kalman filter with extended or unscented kalman filter to avoid the frequency variation problem.

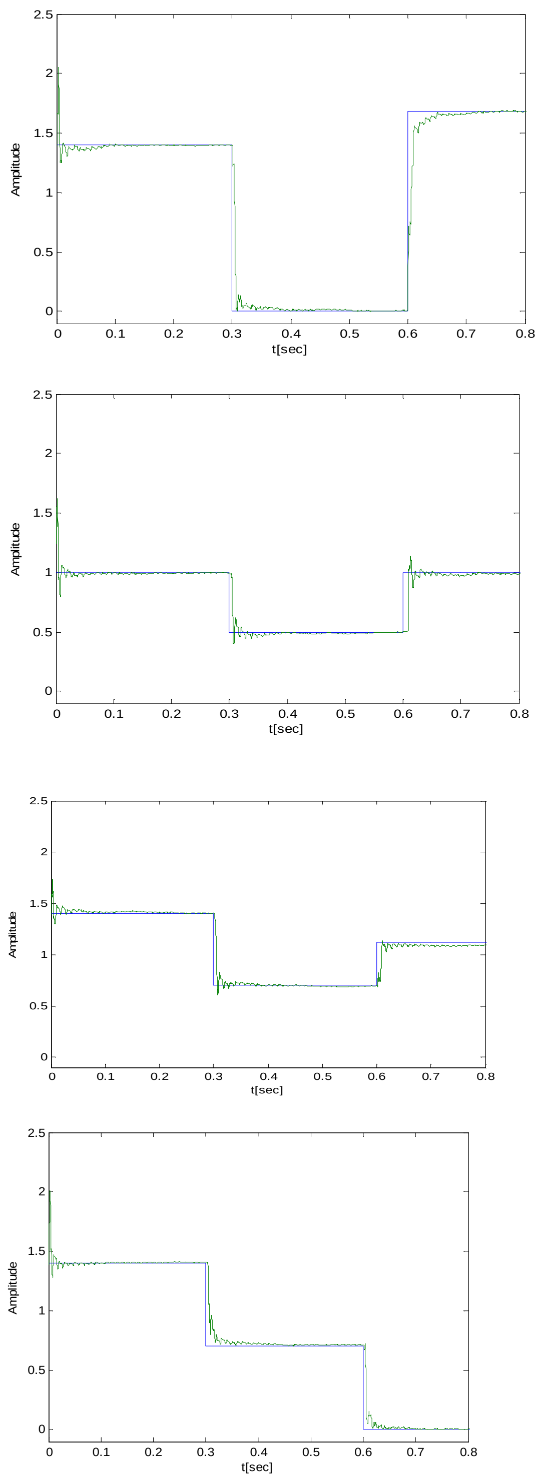

Fig. 8 Amplitude estimated by the proposed adaptive kalman filter for dynamic changing in the signal amplitude

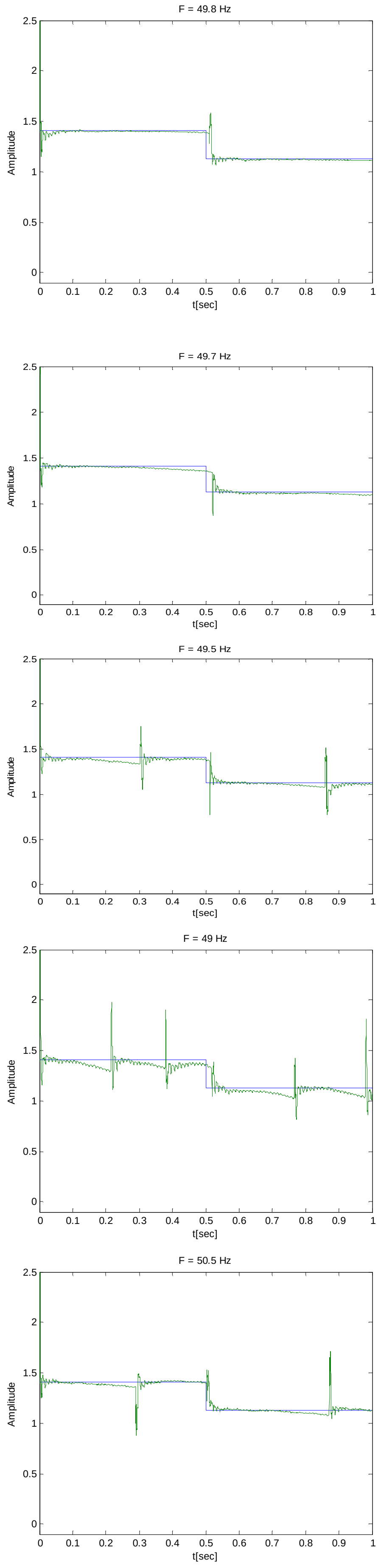

Fig.9 the estimated amplitude by the proposed adaptive kalman filter for amplitude changing at t = 0.5sec and different signal frequency values

REFERENCES

[1] G, Noriega and S. Pasupathy, "Adaptive estimation of noise covariance matrices in real-time preprocessing of geophysical data," Geoscience and Remote Sensing, IEEE Transactions on , vol.35, no.5, pp.1146-1159, Sep 1997.

[2] B.F. La Scala and R.R. Bitmead, "Design of an extended Kalman filter frequency tracker," Signal Processing, IEEE Transactions on , vol.44, no.3, pp.739-742, Mar 1996.

[3] A. A. Abdelsalam, A.A.. Eldesouky and A.A. Sallam, "Characterization of power quality disturbances using hybrid technique of linear Kalman filter and fuzzy-expert system", Electric Power Systems Research, Volume 83, Issue 1, pp. 41-50, February 2012

[4] A. A. Abdelsalam1, A. A. Eldesouky and A. A. Sallam, "Wavelet, Kalman Filter and Fuzzy-Expert Combined System for Classifying Power System Disturbances" ,Proceedings of the 14th International Middle East Power Systems Conference (MEPCON'10), Cairo University, Egypt, pp. 398-403, December 19-21, 2010.

[5] K. Kennedy, G. Lightbody and R, Yacamini, "Power system harmonic analysis using the Kalman filter," Power Engineering Society General Meeting, 2003, IEEE , vol.2, no., pp. 4 vol. 2666, 13-17 July 2003.

[6] A. Griffo, G. Carpinelli, D. Lauria and A. Russo, An optimal control strategy for power quality enhancement in a competitive environment, International Journal of Electrical Power & Energy Systems, Volume 29, Issue 7,pp. 514-525, September 2007.

[7] S. Bittanti and S.M. Savaresi, "On the parameterization and design of an extended Kalman filter frequency tracker," Automatic Control, IEEE Transactions on , vol.45, no.9, pp.1718-1724, Sep 2000.

[8] A. Routray, A.K. Pradhan andK.P Rao, "A novel Kalman filter for frequency estimation of distorted signals in power systems", Instrumentation and Measurement, IEEE Transactions on , vol.51, no.3, pp.469-479, Jun 2002.

[9] Kent K.C. Yu, N.R. Watson and J, Arrillaga, "An adaptive Kalman filter for dynamic harmonic state estimation and hamonic injection tracking," Power Delivery, IEEE Transactions on , vol.20, no.2, pp. 1577- 1584, April 2005.

[10] S. Aja-Fernández, C. Alberola-López and J. Ruiz-Alzola, "A fuzzy-controlled Kalman filter applied to stereo-visual tracking schemes", Signal Processing, Volume 83, Issue 1, pp. 101-120, January 2003.

[11] G.Chen, *Approximate Kalman Filtering*, Word Scientific, 1993.

[12] H.M. Beides and G.T. Heydt, "Dynamic state estimation of power system harmonics using Kalman filter methodology", Power Delivery, IEEE Transactions on , vol.6, no.4, pp.1663-1670, Oct 1991.

[13] M. Haili and A.A. Girgis, "Identification and tracking of harmonic sources in a power system using a Kalman filter," Power Delivery, IEEE Transactions on , vol.11, no.3, pp.1659-1665, Jul 1996.

[14] H. Alrawashdeh, J. Asumadu, and J. Alshawawreh. "Effect of Noise Covariance Matrices in Kalman Filter Performance of Power System Harmonics Detection." IJEECS, Volume: 13, Issue: 1, pp.707-717, March 2013.

[15] K.W. Louie, P. Wilson, R. Mazur, K. Kent, H.W. Dommel and J.R. Marti, "Power System Harmonic Analysis in the Frequency Domain", Electrical and Computer Engineering CCECE 2007. Canadian Conference on , vol., no.,pp.1421-1424,22-26April2007.

[16] K,W. Louie, P. Wilson, R.A. Rivas, A. Wang, and P. Buchanan, "Discussion on Power System Harmonic Analysis in the Frequency Domain," Transmission & Distribution Conference and Exposition: Latin America, 2006. TDC '06. IEEE/PES , vol., no., pp.1-6, 15-18 Aug. 2006.

[17] W.M, Grady and S. Santoso, “Understanding power system harmonics”, Power Engineering Review, IEEE vol. 21, no. 11, pp. 8-11, Nov. 2001.

Hisham O. Alrawashdeh received her M.SC in communication Engineering from Mutah university, Jordan 2007, and he is now pursing his Ph.D. degrees in Electrical and Computer Engineering, WMU, USA. Eng. Alrawashdeh is specialized in electronics and communication engineering His areas of research include power system harmonics, adaptive filters, fiber optics, modern control.

Johnson A. Asumadu (S’82, M’94, SM’00) received his B.S. from the University of Science Technology, Ghana, in 1975, his M.S. from Aston University, England, in 1978, his MEE from the Rensselaer Polytechnic Institute, USA, in 1983, and his Ph.D. from the University of Missouri-Columbia, USA, in 1987. He is now a faculty member at Western Michigan University, Michigan. He has published several technical papers and books, has a number of patents and has been involved in numerous government and industrial-sponsored projects. His current research interests include power electronics and control engineering including fuzzy logic applications, and microprocessor / microcontroller embedded applications**.**