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Frequency and Power Components Estimation in Power Systems using Kalman Filter

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Abstract

The state observer estimates the state variables based on signal measurement of the output and control variables. Although the theory of state variables is expanded with the incentive to be used in state feedback, the use of this theory is not limited to this application, and today it is used in many engineering applications such as frequency and power components estimation, prediction of error occurrence and its compensation, estimation of disturbances entered into the system and so on. In the observer's discussion, the system should be observable; otherwise, the design of state observer will not be possible for that. In this paper, instant estimation of power and frequency components will be presented. The Estimation is based on the use of (UKF), which is appropriate to estimate the unknown parameters of the model during strong dynamic system changes. The privilege of using UKF is its direct estimation process. This means that in its algorithm there is no requirement of linearizing the nonlinear model. The nonlinear model of state space for instantaneous power, which includes the instantaneous voltage and current components of the system, is the starting point for estimating power and frequency components. In the parametric model of instantaneous power, the system frequency is considered as an unknown parameter, which is estimated with other unknown parameters of the model (apparent power, active power, power angle).

Keywords: state observer, Kalman filter, power and frequency estimation of power systems

Introduction

Nowadays, the problem of designing observer for multi-input multi-output systems with unknown inputs such as disturbance is seriously expanding. In order to provide consumers with quality power and electrical service, it is essential to know the harmonic parameters such as magnitude and phase. This is necessary to design a filter to eliminate or reduce the effects of harmonics in a power system (1).

In this study, we will propose a new method for estimating frequency and power components of a system. The fundamental and main approach of this paper to reach the intended purpose is to utilize the Kalman Bibault UKF filter, which has the ability to estimate uncertain or unknown parameters of a modeled system, from a real system that has undergone strong dynamic changes (2).

Lots of algorithms have been proposed for harmonics evaluation. In order to find the frequency spectrum of voltage and current from the discrete time samples, most of algorithms of amplitude – frequency harmonic analysis are based on Discrete Fourier Transform (DFT) or Fast Fourier Transform (FFT). These two methods suffer from three complications: frequency interference, leakage and picket fence effect (3,4,5).

Other methods are not excluded from these three problems either and this is due to high frequency components in the measured signal (3). One method is the Kalman filter method. Using a constant gain Kalman filter, a stronger algorithm was introduced by Dash and Sharaf (6).

One of the most important advantages of the UKF is its forward-looking and direct estimator type. More generally, during the continuation of the estimation process, linearization is avoided, and it is possible to execute the estimation in the same nonlinear system or signal. Nonlinear parameters of the instantaneous power of the state space model of a nonlinear system are considered as the main components of the power, which are voltage and current (7). This methodology is in contrast with the developed Kalman filter design method, since in developed Kalman filter type, there’s a need for linearization and no need to calculate the Jacobin model. This shows the superiority of the proposed method, which is dealt with in articles 7 and 8. And then, these main components of power are considered as the starting point for estimating power and frequency. In the model of instantaneous power parameters, the frequency of the system is assumed to be an unknown parameter of the model, and is estimated by unknown parameters such as the angle of fire and active and apparent power. Finally, it can be concluded that the numerical algorithm is considered efficient, and it is capable of estimating power components even when it is very sensitive to system frequency variations.

In our case, the instantaneous power signal is known as the input signal. Frequency and power components are estimated directly by means of instantaneous power signal samples. The frequency of a system, for example, a power system, is one of its most important parameters because the basis of all calculations and economic planning is based on the same frequency, and the deviation from the steady-state value means the imbalance between load and production (6). In this method, unlike the traditional methods, voltage and current are not processed in the beginning to determine the phasor. Instead this is done in the second stage. The advantage of the proposed method, that is, the processing of the current and voltage phasor in the second stage, is to cause the system to become resistant. In this study, the above-mentioned harmonics are considered as noise, and are filtered by the estimator and exited from the system's path. One of the problems caused by voltage and current harmonics involves increased losses in the utility of the components of the power and consumer system (9). In this study, the main variables and quantities are the frequency, the Kalman filter coordinates and the input power of the system, these two factors also include the sub-parameters, the main and subsidiary components.

Research Methodology

1- Instantaneous power model

In order to expand the numerical relations of the algorithm of estimating power and frequency components, we consider an RLC series circuit as a parametric model. The power supply voltage and current in the circuit can be written as follows:

$$v(t) = V_m \cos(\omega t) \qquad (11)$$

$$i(t) = I_m \cos(\omega t - \varphi) \qquad (2)$$

V_m and I_m are the maximum range of voltage and current respectively and φ is the power angel. The power angle is the phase difference between voltage and current. according to the equations (1) and (2), the instantaneous power is:

$$p(t) = v(t)\,i(t) = P + S\cos(2\omega t - \varphi) \qquad (3)$$

$$P = VI\cos(\varphi) \qquad (4)$$

$$S = VI \qquad (5)$$

In the recent equations, P and S are active power and apparent power respectively. V and I are RMS values of voltage and current. According to (4) and (5), reactive power is obtained as follows:

$$Q = \sqrt{S^2 - P^2} \qquad (6)$$

Equation (3), which describes the parametric instantaneous power equation, is the starting point for the expansion of the estimator equations. The instantaneous power is only calculated taking into account the effect of the base frequency (50Hz or 60Hz).

The effect of higher harmonics is eliminated. Considering the frequency of the system as an unknown parameter leads to non-linearization of the estimation problem.

2- UKF Kalman filter

Consider the nonlinear discrete model below:

$$x_k = f(x_{k-1}) + q_k \quad ; \quad y_k = h(x_k) + r_k$$

That the $x_k \epsilon R^n$ is state vector and $y \epsilon R^m$ is measuring vector. Which includes samples processed from the input signal. q_k and r_k are the process noise and noise measurements with normal distribution respectively, with the average value of zero and the covariance matrix of Q and R respectively. The time-update equations will be as follows.

$$x_{k-1} = \left[\bar{x}_{k-1}, \bar{x}_{k-1} \pm \sqrt{(n+\lambda) P_{k-1}} \right] \tag{7}$$

$$x^*_{k|k-1} = f\left(x_{k-1}\right) \tag{8}$$

$$\bar{x}_{k|k-1} = \sum_{i=0}^{2n} W_i^{(m)} x^*_{i,k|k-1} \tag{9}$$

$$P_{k|k-1} = \sum_{i=0}^{2n} W_i^{(c)} \left[\left(x^*_{i,k|k-1} - \bar{x}_{k|k-1}\right) \times \left(x^*_{i,k|k-1} - \bar{x}_{k|k-1}\right)^T \right] + Q \tag{10}$$

$$x_{k|k-1} = \left[\bar{x}_{k|k-1}, \bar{x}_{k|k-1} \pm \sqrt{(n+\lambda) P_{k|k-1}} \right] \tag{11}$$

$$\gamma_{k|k-1} = h\left(x_{k|k-1}\right) \tag{12}$$

$$\bar{y}_{k|k-1} = \sum_{i=0}^{2n} W_i^{(m)} \gamma_{i,k|k-1} \tag{13}$$

The coefficients λ and $W_i^{(m)}$ and $W_i^{(c)}$ are defined according to the previous section.

$$P_{yy} = \sum_{i=0}^{2n} W_i^{(c)} \left[\left(\gamma_{i,k|k-1} - \bar{y}_{k|k-1}\right) \times \left(\gamma_{i,k|k-1} - \bar{y}_{k|k-1}\right)^T \right] + R \tag{14}$$

$$P_{xy} = \sum_{i=0}^{2n} W_i^{(c)} \left[\left(x_{i,k|k-1} - x_{k|k-1}\right) \times \left(\gamma_{i,k|k-1} - \bar{y}_{k|k-1}\right)^T \right] \tag{15}$$

$$K_k = P_{xy} P_{yy}^{-1} \tag{16}$$

$$P_k = P_{k|k-1} - K_k P_{yy} K_k^T \tag{17}$$

$$\bar{x}_k = \bar{x}_{k|k-1} + K_k \left(y_k - \bar{y}_{k|k-1} \right) \tag{18}$$

P_{yy} is measuring covariance matrix andis $y(k)$is gain Kalman matrix and K_k measurement at the moment k.

1. Simulation and review of results

We consider the voltage and current as:

$$u(t) = 1.\cos(\omega t) \quad p.u. \tag{19}$$

$$i(t) = 0.9.\cos\left(\omega t - \frac{\pi}{6}\right) \quad p.u. \tag{20}$$

$$\omega = 2\pi.50 \quad rad/s \tag{21}$$

$$f = 50Hz$$

$$P = 0.3897$$

$$S = 0.45$$

$$Q = 0.225$$

$$\cos(\varphi) = \cos\left(\frac{\pi}{6}\right) = 0.866$$

We have used the following program to generate the measurement data used in the Fienner algorithm. In fact this program is designed to apply the effect of process noise and noise measurement on the system and output measurement so $y(k)$ data are valid in the UKF algorithm. R and Q matrices are as follows:

- For the case that we have considered the noises:

$$\mathrm{Q} = 0.000001 \times I_{4\times4}, R = 0.00001$$

- In the case we considered noises very low:

$$\mathrm{Q} = 10^{-8} \times I_{4\times4}, \mathrm{R} = 10^{-14}$$

1-3-Estimation using UKF for small noise

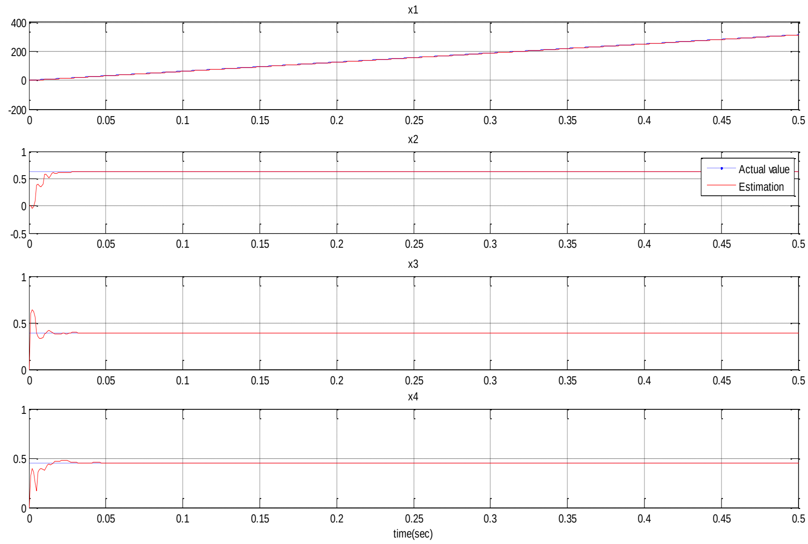

Figure 1: Estimation of system states along with actual values (low noise)

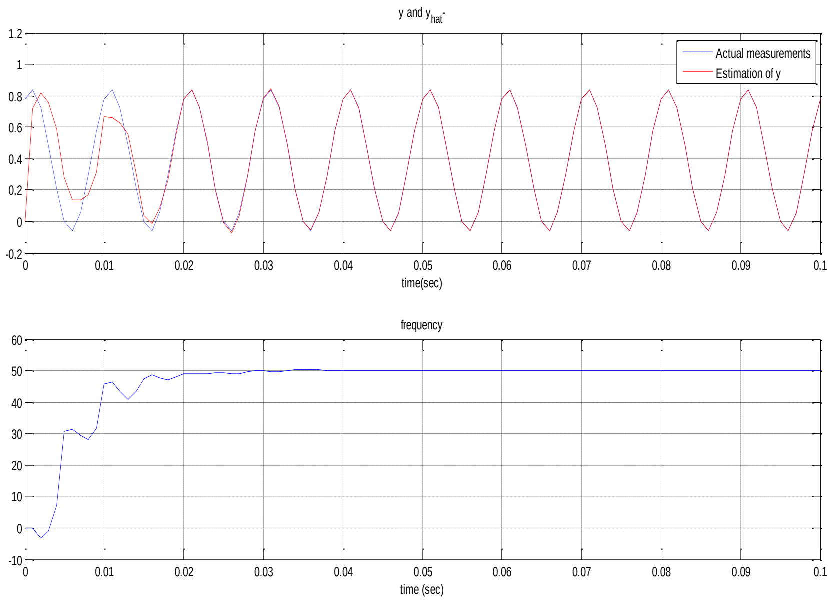

Figure 2: Measurement estimation along with its actual values and frequency estimation

As seen in Fig. 2, The estimation of the actual values has been made in a fraction of a second (less than 0.02 seconds). Frequency changes are also seen in this figure.

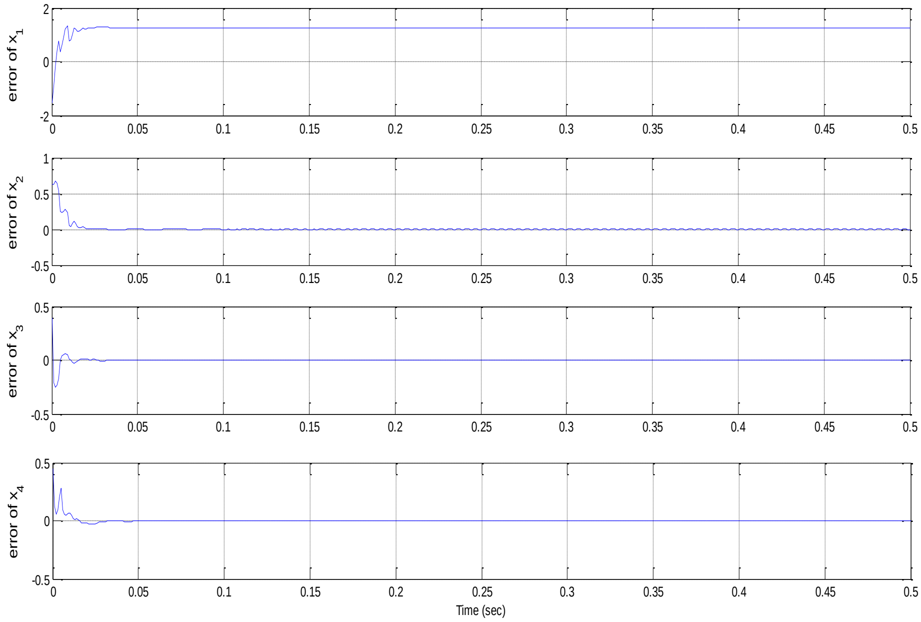

Figure 3: Estimation error

According to Figs. (1) and (2), it was observed that the estimation of actual values was carried out rapidly and with great accuracy. Figure (3) shows the error graph from the estimation. As you can see, it takes about 0.02 seconds for error to reach zero and make an accurate estimate.

2-3-Estimation of using UKF for high noise

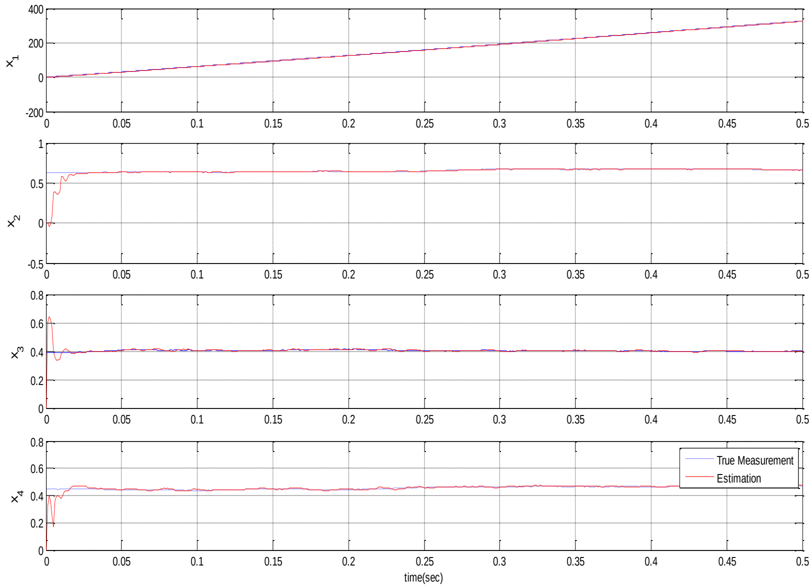

Figure 4: Estimation of system states along with actual values (high noise)

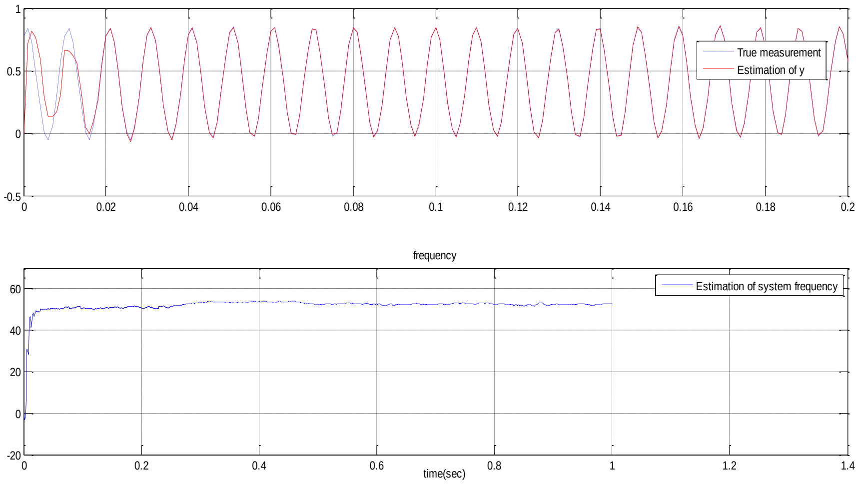

Figure 5: Measurement estimation along with their actual values and frequency estimation

As it can be seen from Fig. 5, the estimation of the real values is calculated in a fraction of a second (less than 0.02 seconds). Frequency changes are also seen in this figure.

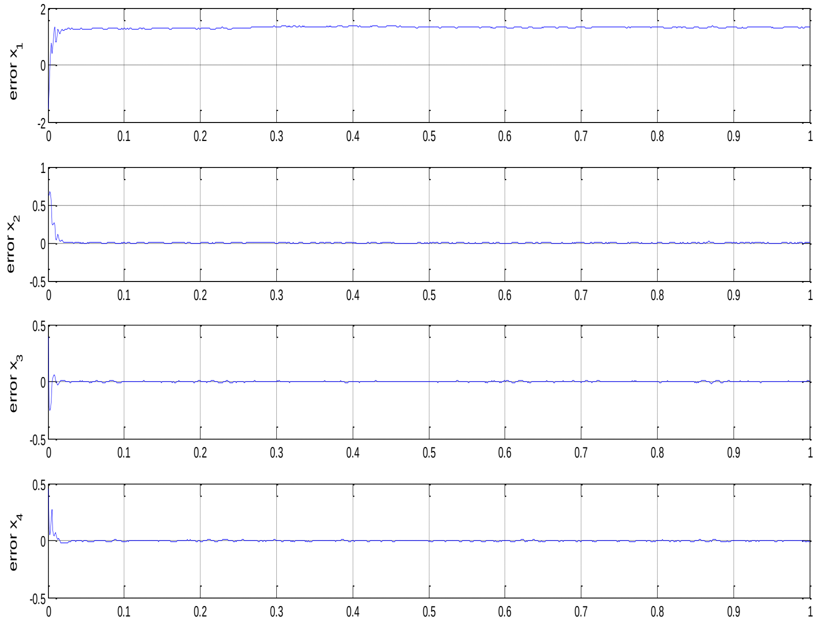

Figure 6: state estimation Error

According to Figs (4) and (5), it was observed that the actual values were quickly and accurately estimated. Figure (6) shows the error chart from the estimation. As you can see, it takes about 0.02 seconds for the error to reach near zero and exact estimation is made. In the estimation mode with a large noise, a small oscillation is observed in the error signal of the estimator. But since the incident noise is large and the oscillations are small and negligible, it can be concluded that the state predictor can be able to estimate the power and frequency components in the system with strong dynamic variations.

Conclusion

In this paper, the instantaneous estimation of power and frequency components were presented. The estimation was based on the use of the Kalman Filter (UKF), which is appropriate for estimating uncertain parameters of the model during strong dynamic system changes. Superiority of UKF is the direct estimation process. This means that in the algorithm it is not necessary to linearize the nonlinear model. A nonlinear model of state space for instantaneous power, which includes voltage and current components of the system, is the starting point for estimating power and frequency components. In the parametric model of instantaneous power, the frequency of the system is considered as an unknown parameter which is instantaneously estimated with other unknown parameters (apparent power, active power, power angle). Reviews and simulations were investigated in both small and large noise situations. In low noise mode, estimating system states was done in a fraction of a second and the estimation error reached zero.

In high noise mode, the estimation of system states was carried out with high speed and precision and the estimation error reached near zero. According to the results and reviews obtained, we conclude that the estimation of the power and frequency components is performed well and with high precision using the Kalman UKF filter, which indicates the excellent performance of the method as well as its applicability.

Resources

1. Girgis, Adly A., W. Bin Chang, and Elham B. Makram. "A digital recursive measurement scheme for online tracking of power system harmonics." IEEE transactions on Power Delivery 6, no. 3 (2016): 1153-1160.
2. Wan, Eric A., and Rudolph Van Der Merwe. "The unscented Kalman filter for nonlinear estimation." In Adaptive Systems for Signal Processing, Communications, and Control Symposium 2015. AS-SPCC. The IEEE 2015, pp. 153-158. Ieee, 2015.
3. Chang, Y. N., Y. C. Hsieh, and C. S. Moo. "Truncation effects of FFT on estimation of dynamic harmonics in power system." In Power System Technology, 2015. Proceedings. PowerCon 2015. International Conference on, vol. 3, pp. 1155-1160. IEEE, 2015.
4. Girgis, Adly A., and Fredric M. Ham. "A quantitative study of pitfalls in the FFT." IEEE Transactions on Aerospace and Electronic Systems 4 (2015): 434-439.
5. Dash, P. K., A. C. Liew, D. P. Swain, and B. Mishra. "Fast tracking of transient power system signals using fuzzy LMS algorithm." International Journal of Electrical Power & Energy Systems 20, no. 8 (2015): 555-561.
6. Grewal, Mohinder S., and Angus P. Andrews. "Applications of Kalman filtering in aerospace 1960 to the present [historical perspectives]." IEEE Control Systems 30, no. 3 (2010): 69-78.
7. Pigazo, Alberto, and Víctor M. Moreno. "Estimation of electrical power quantities by means of Kalman filtering." In Kalman Filter Recent Advances and Applications. InTech, 2013.

8. Karimi-Ghartemani, M., and M. R. Iravani. "Wide-range, fast and robust estimation of power system frequency." Electric Power Systems Research 65, no. 2 (2003): 109-117.
9. Isermann, Rolf. Fault-diagnosis applications: model-based condition monitoring: actuators, drives, machinery, plants, sensors, and fault-tolerant systems. Springer Science & Business Media, 2011.