Smart Power Grid Synchronization with Nonlinear Estimation

by Hossein Darvish, Bachelor of Science

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ABSTRACT

SMART POWER GRID SYNCHRONIZATION WITH NONLINEAR ESTIMATION

by

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Chairperson: Professor Xin Wang

Grid synchronization is a critical concern for proper control of energy transfer between the Distributed Power Generation Systems (DPGS) and the utility power grid. Nonlinear estimation techniques are proposed to track the voltage magnitude, phase angle, and frequency of the utility grid. Instead of directly analyzing in *abc* coordinate frame, the symmetrical component is employed to separate the positive, negative, and zero sequences in the transformed $\alpha\beta$ stationary coordinate frame. By using the Fortescue's Transformations and Clarke's Transformation, the number of system state variables is reduced to five. The results show that our proposed nonlinear estimation technique is efficient in smart power system synchronization. The MATLAB simulation studies have been conducted to compare the performance of the Extended Kalman Filter (EKF), the Particle Filter (PF), and the Unscented Kalman Filter (UKF). Computer simulations have shown that the efficacy of our proposed nonlinear estimation methods. It also shows that the Unscented Kalman Filter, and the Particle Filter are better estimators, because voltage synchronization problem is nonlinear, and linearization process which the Extended Kalman Filter is based on is not very accurate. The number of particles in Particle Filter can be increased to improve the accuracy, but there exists a trade off between computational effort and estimation accuracy. In our research, considering the same amount of computational complexity, we calculate the Mean Square Error (MSE) to examine the performances of different nonlinear estimation approaches. By comparing the MSE of different estimators, we prove that the Unscented Kalman Filter shows the most accurate performance in voltage synchronization for three phase unbalanced voltage. Our results have shown the potential applications of the nonlinear estimation techniques in the future smart power grid synchronization.

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CHAPTER 1

INTRODUCTION

The number of Distributed Power Generation Systems (DPGS) which is connected to the smart power grid is increasing rapidly, due to the necessity of producing more renewable and sustainable energy [1][2]. There are also many micro-grids which use distributed generation resources to manage their load optimally [3]. The voltage synchronization is a critical concern because DPGS can not be properly controlled without accurate and efficient grid synchronization [4]. The utility network may face instability or even black out, when several Distributed Generations (DGs) are connected to our utility grid but they are not synchronized [5]. Our purpose in this work for grid synchronization is to compute the phase angle, voltage magnitude, and frequency. The phase angle and magnitude can be used to turn on/off the distributed sources, and therefore to control the active and reactive power flowing between DGs and the utility grid [6].

1.1 Background and History

The Kalman Filter was initialized by Rudolf Kalman in 1960s [20]. Kalman is the proven optimal solution for linear time invariant system, but it fails to provide reliable estimated value for nonlinear systems. The Extended Kalman Filter uses a linearization process, and have a better performance over the Kalman Filter in nonlinear system estimations [21].

The Particle Filter is based on the Monte Carlo method which was proposed in 1954 by Hamely and Morton. However, due to the computational effort and complexity, this method was not applicable in industry until 1993 [10]. After that, this method becomes very popular in different areas including target tracking robotics, signal processing, and etc[41].

The Unscented Kalman Filter was first proposed by the Julier, and Uhlman [11][43].

The Unscented Kalman Filter is developed based on the Unscented Transformation. It shows the similar computational complexity as the Extended Kalman Filter, but provide much better estimation for the highly nonlinear applications.

Other types of nonlinear estimation schemes have also been developed for special systems applications as shown in [28][29]. D. Simon propose the Kalman Filter estimation with state constraints. He extended his research to develop innovative filtering techniques for nonlinear systems, including Smoothy Kalman Filter, modified Extended Kalman Filter, modified Unscented Kalman Filter, and modified Particle Filter [30].

In [6], Sun uses an Extended Kalman Filter to synchronize the voltages, and phases of three phase unbalanced voltage. In order to calculate the state equation, the Fortescue's transformation, and Clarke's transformation are used to reduce the number of the state variables. The paper in [6] relies on the Extended Kalman Filter only.

1.2 Literature Review

There are different algorithms proposed for grid synchronization of DPGS [7]. A variety of nonlinear state estimation was proposed in literature based on the frequency domain and time domain approaches. The frequency domain is mostly based on the Fourier analysis. The time domain methods show much better accuracies and computational effort [8][9].

The most commonly used method in voltage synchronization are the Phase-Locked Loop (PLL) techniques [12]. In the conventional PLL, by using the Park's transformation, the three phase voltage from *abc* coordinate frame can be translated to the *dq* rotating reference frame [16]. A feedback loop is used to synchronize the DG voltage with a reference signal. The *d*-axis component regulates the voltage magnitude. The phase angle can be regulated by the output of the feedback loop in the *q*-axis [17][18][13]. Although this method can provide synchronization performance, it is also very sensitive to the system noises and unbalanced voltages, and therefore, it is not reliable for grid synchronization

[19][22]. A few improved methods have also been proposed. The Decoupled Double Synchronous Reference Frame Phase Locked Loop (DDSRF-PLL) which uses two sets of opposite dq-frame to cancel out the negative component. The Delayed Signal Cancellation Phase Locked Loop (DSC-PLL), which is based on the delayed signal cancellation, can eliminate the oscillatory error, and specific harmonic error from unbalance three phase voltage [14][23]. However, all of the phase locked loop based techniques suffer from external disturbances and noises.

Zero-crossing method has also been developed for synchronization. This method is based on the time domain approach [24], which is relatively easy to be implemented, but it very sensitive to the disturbances [15]. Therefore, the dynamic performance of this technique is not very practical in industry applications [7][25].

There are a variety of Kalman Filter based methods, which are used for estimation in power synchronization applications [26]. The Kalman Filter has been used widely in the industries, and it is the optimal method for estimation, when the state equations, and measurement equations are linear. For nonlinear dynamic systems, Kalman Filter can not provide reliable solutions. Many advanced filtering methods based on the Kalman are proposed to cope with the nonlinearities [27].

The Extended Kalman Filter is an improved solution for nonlinear cases [30][31]. The Extended Kalman Filter is based on first order linearization algorithm, and it shows good performances for nonlinear systems. However if the system is highly nonlinear, the linearization process can lead to huge errors [31] [32] [33].

In this paper, we present new methods of using the Particle Filter (PF), and the Unscented Kalman Filter (UKF) for power system synchronization applications, and compare the results with the Extended Kalman Filter (EKF). Our results shows that in all of our proposed methods the estimated values converge to the real values. Based on the Mean Square Error (MSE), given the same amount of computational effort, it is concluded that the Unscented Kalman Filter works best among our proposed methods. In order to deal with the unbalanced voltages, we use the symmetrical component transformation to separate the positive, negative, and zero sequence. Then, the Clarke's transformation is applied to transform *abc* coordinate frame to the $\alpha\beta$ stationary coordinate frame. By applying these methods, we obtained the state space model of smart grid synchronization. Then the nonlinear estimators EKF, PF, and UKF are applied to estimate the voltage magnitudes, phase angles, and frequency. Computer simulations confirm better performance of the Unscented Kalman Filter estimator in the presence of unbalanced three phase voltages and external disturbances, considering the same computation effort.

1.3 Contribution

Among different synchronization techniques, Kalman Filtering based methods show superior performance, and reliability. This work presents that Kalman Filter nonlinear based estimators including the Extended Kalman Filter, the Particle Filter, and the Unscented Kalman Filter can be used to estimate the phase angles, voltage magnitudes, and frequency of three phase unbalanced voltage.

First, a novel three phase power system model is reached by applying the Fortescue's and the Clarke's transformation. A set of system state space equations consisting of five state variables can exactly characterize the feature of arbitrary unbalanced three phase voltage. Then, the Extended Kalman Filter, the Particle Filter and the Unscented Klaman Filter are revisited and developed for the voltage synchronization applications. Our simulation results and MSE studies have shown the superior performance of UKF, comparing with other estimation techniques given the similar computational effort. Therefore, our proposed nonlinear estimations techniques can be powerful alternatives for the future smart grid synchronization applications.

This thesis is organized as follows: Chapter II presents the problem formulation. We discussed about the three phase unbalanced system,and a general model of three phase unbalanced voltage. We use the Fortescue's Transformation, and Clarke's Transformation to obtain a novel five state-variables system model. After that, we start the discretization process, and the discrete time system and measurement models are obtained. Chapter III presents the Extended Kalman Filter. We start from explaining the basic theory behind the Kalman Filter, which is the basic of the other nonlinear filtering methods. The inaccuracy of Kalman Filter for the nonlinear case is argued, and the Extended Kalman Filter, which use the linearization process is investigated. The results and simulations are provided at the end of the chapter to show the efficacy of EKF. In Chapter IV, the Particle Filter is proposed. First, the Bayesian filtering method is introduced. After that, the PF is implemented with the MATLAB software. The Unscented Kalman Filter is developed based on the Unscented Transformation, and is summarized in Chapter V. Then, the simulations are used to prove the accuracy of the Unscented Kalman Filter. Chapter VI summarize all the simulation results. The MSE of the different estimator is compared and then concluded that Unscented Kalman Filter is the best method in voltage synchronization. The last chapter, both of the conclusion and future work are presented.

CHAPTER 2

PROBLEM FORMULATION

Chapter 2 presents the system model formulation. The utility grid in the presence of unbalanced voltages can be expressed as:

$$\begin{aligned}\bar{v}_a &= v_a \cos(\omega t + \phi_a)\\ \bar{v}_b &= v_b \cos(\omega t + \phi_b)\\ \bar{v}_c &= v_c \cos(\omega t + \phi_c)\end{aligned} \tag{2.1}$$

where t is the time, ω is angular frequency and $\bar{v}_i$ and ϕ_i for $i = a, b, c$ are the voltage amplitudes and phase angles of the phase i. It is worthwhile mentioning that the three system voltages is not necessarily balanced, so they may not have the same magnitude, nor the phase angle of 120^o. The grid frequency and the sampling frequency are considered to be 60Hz, 2400Hz respectively. We also neglect the system noise.

As shown in Eqn.(2.1), there are seven different variables. In order to simplify the system, the following two transformations are used: symmetrical component transformation and Clarke's transformation. Based on symmetrical component transformation (Fortescue's Transformation) the three-phase voltage signal can be separated to positive, negative, and zero sequence according to Fortescue's Theorem [34] [35].

$$\bar{v}(t) = \bar{v}_0(t) + \bar{v}_p(t) + \bar{v}_n(t) \tag{2.2}$$

where $\bar{v}(n)$ is the representative of 3 phase voltage in the natural coordinate frame and $\bar{v}_i$ for $i = \mathit{0}, p, n$ is the zero, positive, and negative consequences which can be defined by

$$\bar{v}_p(t) = v_p(cos(\theta_p(t)), cos(\theta_p(t) - \frac{2\pi}{3})), cos(\theta_p(t) + \frac{2\pi}{3}))^T$$

$$\bar{v}_n(t) = v_n(cos(\theta_n(t)), cos(\theta_n(t) + \frac{2\pi}{3})), cos(\theta_n(t) - \frac{2\pi}{3}))^T \tag{2.3}$$

$$\bar{v}_0(t) = v_0(cos(\theta_0(t)), cos(\theta_0(t))), cos(\theta_0(t))^T$$

where θ_i for $i = (p, n, 0)$ are the phase angle of positive, negative and zero sequences. Calculating the θ_p or positive phase angle is the base of controlling of connecting the DGs to the unit network. Based on symmetrical component transformation, the signals can be separated to positive, negative, and zero sequence.

First we use the symmetrical component transformation to separated the positive, negative, and zero sequence through the following formula:

$$\begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} = \begin{bmatrix} 1 & 1 & 1 \\ 1 & a^2 & a \\ 1 & a & a^2 \end{bmatrix} \begin{bmatrix} v_0 \\ v_p \\ v_n \end{bmatrix} \tag{2.4}$$

where v_i for i=0, p, n are zero, positive, and negative consequence, and the $a = 1\angle 120$. It is difficult to estimate phase angle directly because of various number of variables, and the nonlinearity of the system, so we use the Clarke's Transformation to translate to $\alpha\beta$ stationary coordinate frame.

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = \frac{2}{3} \begin{bmatrix} 1 & -\frac{1}{2} & -\frac{1}{2} \\ 0 & \frac{\sqrt{3}}{2} & -\frac{\sqrt{3}}{2} \end{bmatrix} \begin{bmatrix} v_a \\ v_b \\ v_c \end{bmatrix} \tag{2.5}$$

Based on equation (2.4), and(2.5), we have:

$$\begin{bmatrix} v_\alpha \\ v_\beta \end{bmatrix} = \begin{bmatrix} 1 & 1 \\ -j & -j \end{bmatrix} \begin{bmatrix} v_p \\ v_n \end{bmatrix} \tag{2.6}$$

Converting the phasor expression in (6) to instantaneous voltage, we obtain $v_\alpha(t)$ and $v_\beta(t)$ as follows:

$$\begin{aligned}\bar{v}_\alpha(t) &= v_p \cos(\omega t + \theta_p) + v_n \cos(\omega t + \theta_n) \\ &= (v_p \cos\theta_p + v_n \cos\theta_n)\cos\omega t - (v_p \sin\omega_t + v_n \sin\theta_n)\sin\omega t \\ &= v_\alpha \cos(\omega t + \phi_\alpha)\end{aligned} \tag{2.7}$$

$$\begin{aligned}\bar{v}_\beta(t) &= v_p \sin(\omega t + \theta_p) - v_n \sin(\omega t + \theta_n) \\ &= (v_p \cos\theta_p - v_n \cos\theta_n)\sin\omega t + (v_p \sin\theta_p - v_n \sin\theta_n)\cos\omega t \\ &= v_\beta \cos(\omega t + \phi_\alpha)\end{aligned} \tag{2.8}$$

The zero sequence quantities are zeros after using the Clarke's transformation.

2.1 State Space System Dynamics

Based on Equation equation (2.7) and (2.8), and after discretization process, the dynamic model of three phase unbalanced voltage system can be obtained as follows

$$\begin{aligned}x_1(k) &= v_\alpha \cos(k\omega T + \phi_\alpha) \\ x_2(k) &= v_\alpha \sin(k\omega T + \phi_\alpha) \\ x_3(k) &= v_\beta \cos(k\omega T + \phi_\beta) \\ x_4(k) &= v_\beta \sin(k\omega T + \phi_\beta) \\ x_5(k) &= \omega\end{aligned} \tag{2.9}$$

Denote $t = kT$ and $T = 1/f_s$, where T is sampling time and f_s is sampling frequency. By substituting k with $k+1$ in equation (2.9), we have:

$$
\begin{aligned}
x_1(k+1) &= x_1(k)\cos(x_5(k)) - x_2(k)\sin(x_5(k)) \\
x_2(k+1) &= x_1(k)\sin(x_5(k)) + x_2(k)\cos(x_5(k)) \\
x_3(k+1) &= x_3(k)\cos(x_5(k)) - x_4(k)\sin(x_5(k)) \\
x_4(k+1) &= x_3(k)\sin(x_5(k)) + x_4(k)\cos(x_5(k)) \\
x_5(k+1) &= x_5(k)
\end{aligned}
\tag{2.10}
$$

The process noise is assumed to be zero. The measurement equation can be defined as follows:

$$
\begin{aligned}
y_1(k) &= x_1(k) + e_1(k) \\
y_2(k) &= x_3(k) + e_2(k)
\end{aligned}
\tag{2.11}
$$

where $e_1(k)$, and $e_2(k)$ are considered to be the Additive White Gaussian Noise (AWGN).

CHAPTER 3

EXTENDED KALMAN FILTER

3.1 Kalman Filter

In this section, the Kalman Filter (KF) is introduced, which serves as the foundation for other nonlinear filters deviations. The Kalman Filter (KF) is the most commonly used linear estimation, because of its accuracy and simplicity [36]. The Kalman filter is used in a different application including navigation, military system, robotics, and etc [37]. In Kalman Filter uses the process equation and measurement data with noise, and apply recursively operation on data to estimate the desired state. In the Section 3.1, we discussed the theory of Kalman Filter.

3.1.1 Formulation

The Kalman Filter uses the mean of the state variable in order to estimate the desired value, and use the measurement to update the mean, and covariance. In order to implement a Kalman Filter, we need state equation, and measurement equations to be linear. The state equation and measurement equation for our system can be formulate as follows:

$$x_{k+1} = Ax_k + Bu_k + w_k \tag{3.1}$$

where x_k is state variable at the time k, A and B are matrices with appropriate dimensions, and are often called system matrix and input matrix. w_k is the process noise that most of the time assumed to be normal.

The measurement process can be formulate with following formula

$$y_k = Hx_k + v_k \tag{3.2}$$

where y_k is measurement at the time K . H is marices with appropriate dimension, and are called often output matrix. v_k is the process noise that assumed to be white Gaussian noise. The noise process and measurement process is considered to have a known covariance matrices as defined below

$$w_k \sim (0, Q_k) \tag{3.3}$$

$$v_k \sim (0, R_k) \tag{3.4}$$

where the Q_k and R_k are covariance matrices. The process noise and measurement noise are independent from each other, it can be written mathematically as follows:

$$E[v_k w_j^T] = 0 \tag{3.5}$$

After defining our system model, we can apply Kalman Filter through recursive iterations. The Kalman Filter operates in two steps: 1. priori state estimate 2. posteriori estimate [38]. In order to have a better understanding of posteriori and priori we briefly define them here. The priori estimate is the estimate of state variable before we run the measurement process at that time. The posteriori estimate is the estimate after we process the measurement at desired time. The priori and posteriori estimate can be denoted as $\hat{x}^-$, $\hat{x}^+$

$$\hat{x}^- = E[x_k|y_1, y_2, ...y_{K-1}] \tag{3.6}$$

$$\hat{x}^+ = E[x_k|y_1, y_2, ...y_K] \tag{3.7}$$

where the $\hat{x}^-$, $\hat{x}^+$ are the estimation of state variable, before and after we apply our measurement. In order to develop the Kalman Filter, an initialization process with a initial estimates for the state variable are given, and after that the initial value for the covariance can be calculated as follows:

$$P_0^+ = E[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T] \tag{3.8}$$

After making the initial guess for state and calculating the initial covariance, we can start the time step. The time update process can be achieved through following formula:

$$\hat{x}_{k+1}^{-} = A_K \hat{x}_k^{+} + B_k u_k \tag{3.9}$$

$$P_{k+1}^{-} = A_k P_k^{+} A_k^T + Q_k \tag{3.10}$$

where $\hat{x}^{-}$ is predicted or priori state estimate and P_k^{-} is priori estimated covariance matrix. One can calculate A_k matrix can be obtained directly from State Equation.

After finding the priori, we use the measurement equation, to find posteriori estimate, and correct our estimation. These procedures are called measurement update, and can be formalized as follows:

$$K_k = P_k^{-} H_k^T (H_k P_k^{-} H_k^T + R_k)^{-1} \tag{3.11}$$

$$\hat{x}_k^{+} = \hat{x}_k^{-} + K_k[y_k - H_k(\hat{x}^{-}, 0)] \tag{3.12}$$

$$P_k^{+} = (I - K_k H_k) P_k^{-} \tag{3.13}$$

where $\hat{x}_k^{+}$ is updated or posteriori state estimate and P_k^{+} is updated or posteriori estimate covariance.

3.2 Extended Kalman Filter

The Kalman Filter is the best optimal estimation for linear system, but most of the system in the nature are nonlinear, or they will ultimately show nonlinear behaviors. The Kalman Filter provides poor results for nonlinear estimator [39]. One proposed method is based on the linearization of the nonlinear system, which is called Extended Kalman Filter (EKF). The EKF is the most widely used estimator in the nonlinear dynamic system.

3.2.1 EKF formulation

The Extended Kalman Filter is derived based on the linearization process. The system is nonlinear, so the state variable and measurement process is defined as a function of state variable, input and noise. The process and measurement noise are with known covariance and zero mean. Our nonlinear system can be summerized as follows:

$$\begin{aligned} x_{k+1} &= f_k(x_k, u_k, w_k) \\ y_k &= h_k(x_k, v_k) \\ w_k &\sim (O, Q_k) \\ v_k &\sim (O, R_k) \end{aligned} \tag{3.14}$$

where x_k is state variable at the time k, and w_k is the process noise. Y_k is measurement at the time K. v_k is the process noise. f_k is function of state variable, input, and process noise. After defining the state variable, before starting the time update, and measurement update, we need to initialize the state variables, and Covariance matrix.

$$P_0^+ = E[(x_0 - \hat{x}_0^+)(x_0 - \hat{x}_0^+)^T] \tag{3.15}$$

The Extende Kalman Filter is applied to estimate the voltage phase, amplitude and frequency of three phase voltages. EKF estimator consists of two steps: 1. time update 2. measurement update [40][44].

For time update, we need to calculate the priori covariance and priori estimate

$$P_{k+1}^- = A_k P_k^+ A_k^T + L_k Q_{k-1} L_k^T \tag{3.16}$$

$$\hat{x}_{k+1}^- = f_k(\hat{x}_k^+, u_k, 0) \tag{3.17}$$

where $\hat{x}^-$ is predicted or priori state estimate and P_k^- is priori estimated covariance matrix. A can be calculated with the following formula

$$\begin{aligned} A_k &= \frac{\partial f}{\partial x} \\ L_K &= \frac{\partial f}{\partial w} \end{aligned} \tag{3.18}$$

In our system A is a 5×5 matrix. A can be calculated as follows

$$A = \begin{pmatrix} \cos x_5 & -\sin x_5 & 0 & 0 & A_{15} \\ \sin x_5 & \cos x_5 & 0 & 0 & A_{25} \\ 0 & 0 & \cos x_5 & -\sin x_5 & A_{35} \\ 0 & 0 & \sin x_5 & \cos x_5 & A_{45} \\ 0 & 0 & 0 & 0 & 1 \end{pmatrix} \tag{3.19}$$

where

$$A_{15} = sinx_5 - x_2 \cos x_5$$

$$A_{25} = x_1 \cos x_5 - x_2 \sin x_5$$

$$A_{35} = -x_3 \sin x_5 - x_4 \cos x_5$$

$$A_{45} = x_3 \cos x_5 - x_4 \sin x_5$$

Q is the covariance matrix of process noise. We neglect the process noise, so the second term will in equation (3.16) will be zero. The next step is to update priori estimate and calculate the posteriori estimate. The measurement update can be modeled as:

$$K_k = P_k^- H_k^T (H_k P_k^- H_k^T + M_k R_k M_k^T)^{-1} \tag{3.20}$$

$$\hat{x}_k^+ = \hat{x}_k^- + K_k[y_k - h_k(\hat{x}^-, 0)] \tag{3.21}$$

$$P_k^+ = (I - K_k H_k) P_k^- \tag{3.22}$$

where $\hat{x}_k^+$ is updated or posteriori state estimate, and P_k^+ is updated or posteriori estimate covariance. M_k is $\partial h / \partial v$, and v is measurement noise. h_k is the measurement function, so Jacobian matrix H_k can be defined as follows:

$$H_k = \frac{\partial h_k}{\partial x}$$
$$M_K = \frac{\partial h}{\partial v} \tag{3.23}$$

In our system H is 5×2 matrix. H can be calculated by the following matrix

$$H = \begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \end{pmatrix} \tag{3.24}$$

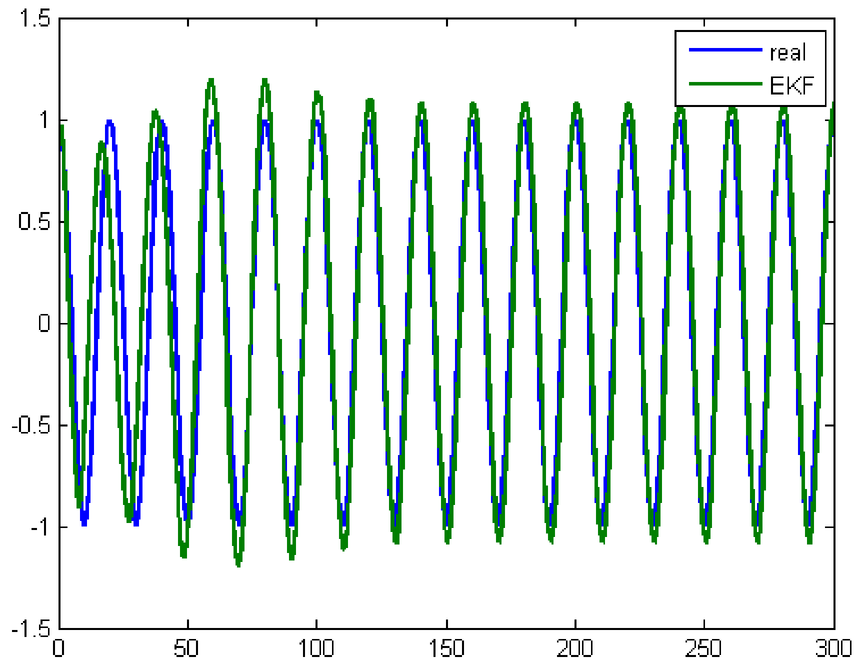

Figure 3.1: The First State Variable Comparison

3.2.2 EKF for highly nonlinear system

For extreme nonlinear case, the first order Extended Kalman Filter may lead into an error. If the case is extreme nonlinear, the linearizion process is not so accurate. This section will show that the EKF is not capable of estimating all nonlinear cases. The first order linearizion is used in the Extended Kalman Filter, and it might have some error when applying this method to nonlinear case. The measurement y can be expanded as a

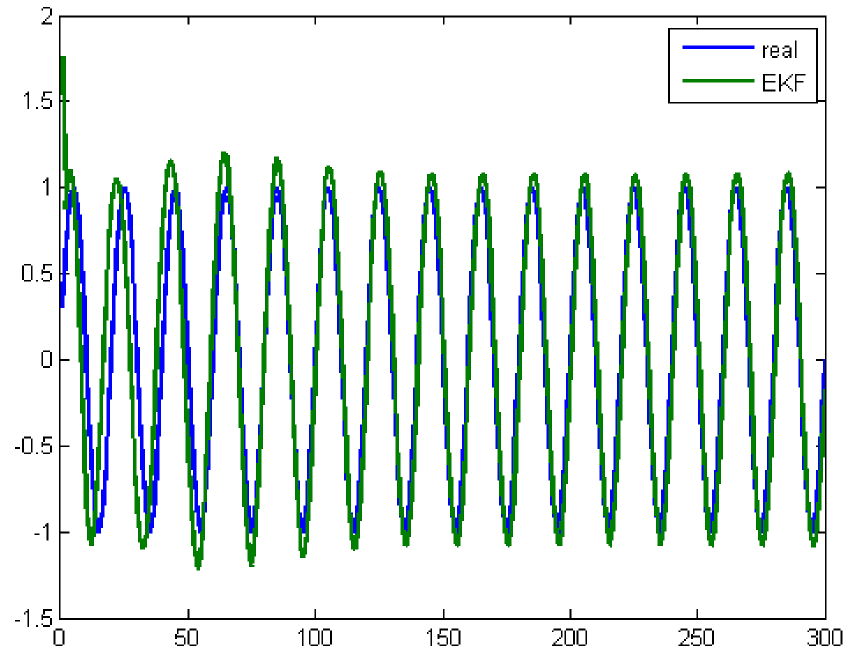

Figure 3.2: The Second State Variable Comparison

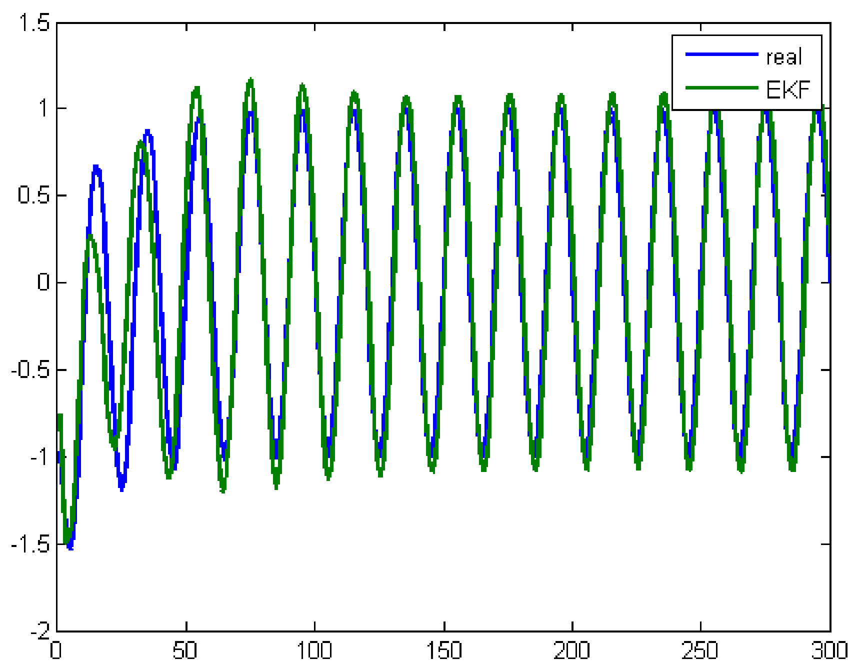

Figure 3.3: The Third State Variable Comparison

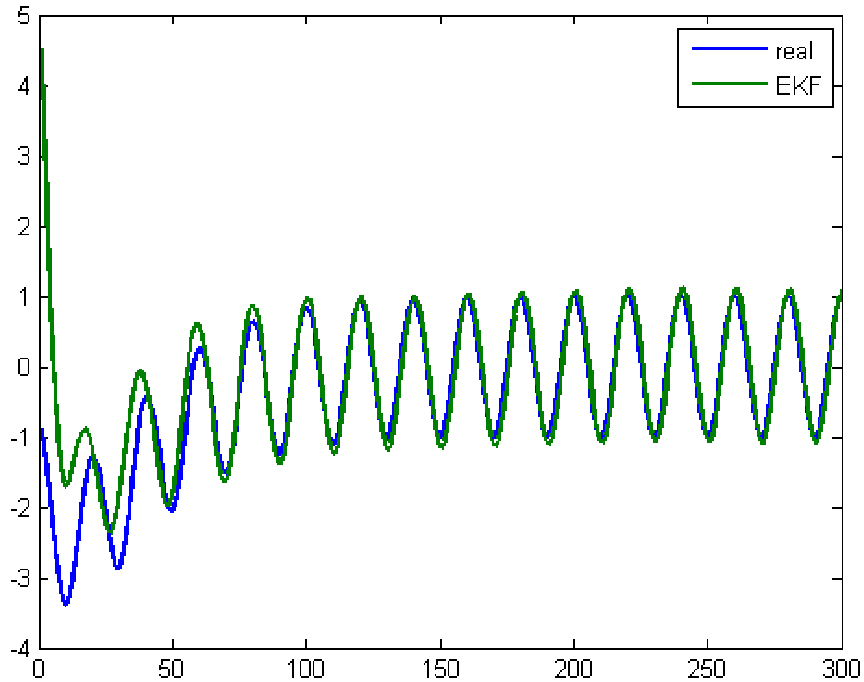

Figure 3.4: The Fourth State Variable Comparison

Taylor series around the mean value of x,

$$\begin{aligned} y &= h(x) \\ &= h(\bar{x}) + D_{\hat{x}}h + \frac{1}{2!}D_{\hat{x}}^2 h + \frac{1}{3!}D_{\hat{x}}^3 h + ... \end{aligned} \tag{3.25}$$

so that the expected value of measurement can be calculated as follows:

$$\bar{y} = E[h(\bar{x}) + D_{\hat{x}}h + \frac{1}{2!}D_{\hat{x}}^2 h + \frac{1}{3!}D_{\hat{x}}^3 h + ...] \tag{3.26}$$

It can be shown that all odd term will be zero, so we will have

$$\bar{y} = h(\bar{x}) + \frac{1}{2!}D_{\hat{x}}^2 h + \frac{1}{4!}D_{\hat{x}}^3 h + ... \tag{3.27}$$

Truncating Eqn. (3.27) to the first order term and neglecting the higher order term will lead to severe inaccuracy. The covariance can be calculated as follows:

$$P_y = E[(y - \bar{y})(y - \bar{y})^T] \tag{3.28}$$

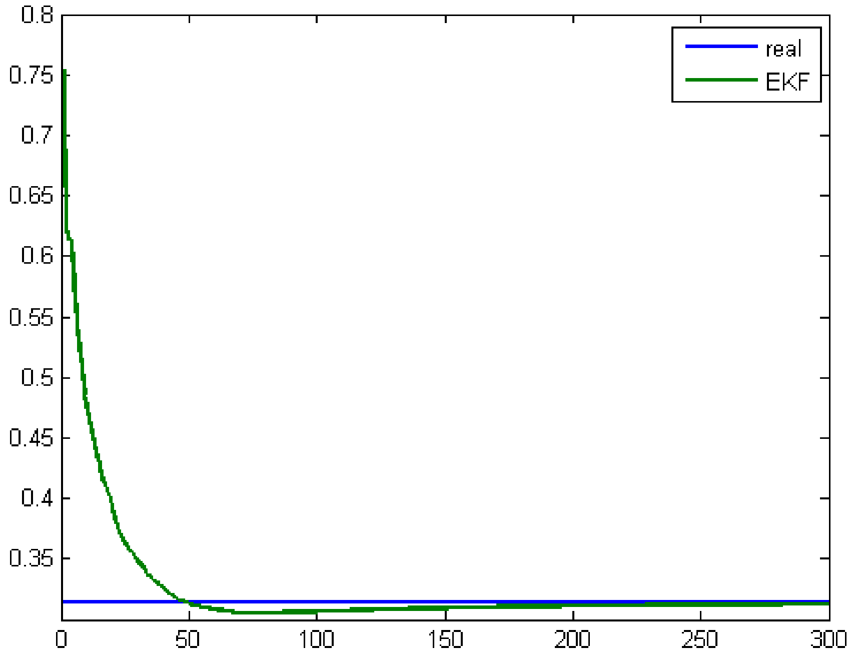

Figure 3.5: The Fifth State Variable Comparison

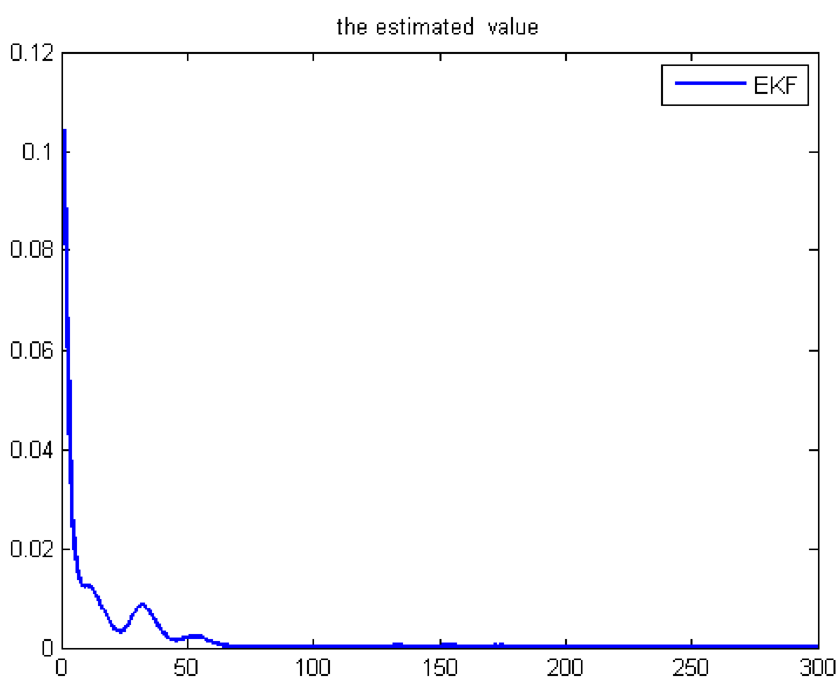

Figure 3.6: MSE Comparison

After expanding Taylor series around the expected value

$$P_y = HPH^T + E[\frac{D_{\hat{x}}h(D_{\hat{x}}^3h)^T}{3!} + \frac{D_{\hat{x}}^2h(D_{\hat{x}}^2h)^T}{2!2!} + \frac{D_{\hat{x}}^3h(D_{\hat{x}}h)^T}{3!}] + E(\frac{D_{\hat{x}}^2}{2!})(\frac{D_{\hat{x}}^2}{2!})^T + ... \tag{3.29}$$

Truncating Eqn. (3.29) to the first order term and neglecting the higher order term will lead to severe inaccuracy in Covariance calculation. The smart power grid system dynamics is nonlinear, and it's applications need an accurate estimation. In the following chapter, two other nonlinear estimators are proposed, which show better performance in estimation.

CHAPTER 4

PARTICLE FILTER

As previously discussed, the Extended Kalma Filter is based on linearization process. EKF shows inaccuracy if the system is severely nonlinear. To adress this issue, we introduce the Particle Filter. Particle Filter (PF) is also known as a Sequential Monte Carlo Estimation using different set of particle, rather than linearization. It does not use linearization method, but it requires a lot of computation, so we need to trade off between the computational time and accuracy.

4.1 Bayesian Filtering

When the state variables are nonlinear, the Particle Transformation can provide a good solution. One advantage of the Bayesian Filter over the Extended Kalman Filter is that it does not need the linearizion technique [41]. Although particle filter needs a great number of computation, it is been widely used in a variety of the field from robotic, computer vision to financial economic and chemical engineering [42]. Particle Filter works based on the the Bayesian algorithm [45]. Bayesian Filter uses probabilistic and stochastic process for estimating the desired states.

4.1.1 The Bayesian state estimation

The system is nonlinear, so the state variable and measurement variable can be defined as follows:

$$\begin{aligned} x_{k+1} &= f_k(x_k, w_k) \\ y_k &= h_k(x_k, v_k) \end{aligned} \tag{4.1}$$

where w_k and v_k is considered to be with known pdf. For staring the process we need an initial guess. The Bayesian Filter approximates the conditional pdf of state variable based on the measurement. For the initial guess, we do not have any measurement, so it can be denoted as below:

$$p(x_0) = p(x_0 \mid Y_0) \tag{4.2}$$

Y_0 is the defined as a set whit no measurement. After the initial guess we start the process to find the priori estimate.

Then priori pdf can be defined as follows:

$$\begin{aligned} P(x_k \mid Y_{k-1}) &= \int p[(x_k, x_{k-1}) \mid Y_{k-1})]dx_{k-1} \\ &= \int p[x_k \mid (x_{k-1}, Y_{k-1})]p(x_{k-1} \mid Y_{k-1})dx_{k-1} \\ &= \int p(x_k \mid x_{k-1})p(x_{k-1} \mid Y_{k-1})dx_{k-1} \end{aligned} \tag{4.3}$$

After the time update procedure, similar to the other Kalman Filter based methods the measurement update should be implemented to find the posteriori state variable. Then a posteriori pdf can be obtained by following formula

$$\begin{aligned} P(x_k \mid Y_k) &= \frac{p(Y_k \mid x_k)}{p(Y_k)} p(x_k) \\ &= \frac{p(x_k, y_k, Y_{k-1})p(x_k, Y_{k-1})p(Y_{k-1})p(x_k, Y_k)}{p(x_k)p(y_k, Y_{k-1})p(y_{k-1})p(Y_{k-1} \mid x_k)p(x_k, y_k)} && (4.4) \\ &= \frac{p[Y_{k-1} \mid (x_k, y_k)]p(y_k \mid x_k)p(x_k \mid Y_{k-1})}{p(y_k, Y_{k-1})p(Y_{k-1} \mid x_k)} && (4.5) \end{aligned}$$

$$P(x_k \mid Y_k) = \frac{p(y_k \mid x_k)p(x_k \mid Y_{k-1})}{p(y_k \mid Y_{k-1})} \tag{4.6}$$

After that we need to calculate the denominator of the above equation. it can be equated as follows:

$$\begin{aligned} P(y_k \mid Y_{k-1}) &= \int p[(y_k, x_k) \mid Y_{k-1})]dx_k \\ &= \int p[y_k \mid (x_k, Y_{k-1})]p(x_k \mid Y_{k-1})dx_k \\ &= \int p(y_k \mid x_k)p(x_k \mid Y_{k-1})dx_k \end{aligned} \tag{4.7}$$

After substituting Eqn. (4.6)(4.7) we will have:

$$P(x_k \mid Y_k) = \frac{p(y_k \mid x_k)p(x_k \mid Y_{k-1})}{\int p(y_k \mid x_k)p(x_k \mid Y_{k-1})dx_k} \tag{4.8}$$

4.2 Particle Filter

In this section, the particle filter is implemented to estimate the voltage amplitude, phase angle and frequency. The Partical Filter is based on five steps [33]: The first step is particle generation. N random number is generated on the basis of the initial pdf $p(x_0)$(which is assumed to be known) [33]. All of these N particle will be transfered to the priori and posteriori step. The second step is obtain a priori particle from known process equation:

$$x^-_{k,i} = f_{k-1}(x^+_{k-1,i}, \omega^i_{k-1}) \tag{4.9}$$

where the particles are denoted as $x^-_{k,i}$, N is the number of particle, ω^i_{k-1} is the process noise vector. The third step is to calculate the likelihood of each particle $x^-_{k,i}$, conditioned on the measurement. The likelihood (q_i) can be defined as the following formula:

$$\begin{aligned} q_i &= P[(y_k = y^*) \mid (x_k = x^-_{k,i})] \\ &= P[(v_k = y^* - h(x^-_{k,i}))] \\ &\propto \frac{1}{(2\pi)^{m/2}\left|R\right|^{1/2}} \exp(\frac{-[y^* - h(x^-_{k,i})]^T R^{-1}[y^* - h(x^-_{k,i})]}{2}) \end{aligned} \tag{4.10}$$

Then we normalize the relative likelihood of (4.10). The final step is re-sampling steps, which is to generating the posteriori particle based on the calculated normalized q_i. For implementing the re-sampling procedure , a random number uniformly distributed in [0,1] is generated. Then the if loop will be conducted:

$$If: \qquad \sum_{m=1}^{j-1} q_m < r \; and \; \sum_{m=1}^{j} q_m \geq r,$$

$$then: \quad the\ posteriori\ state\ will\ be\ updated\ as\ x_{k,i}^{+} = x_{k,j}^{-}.$$

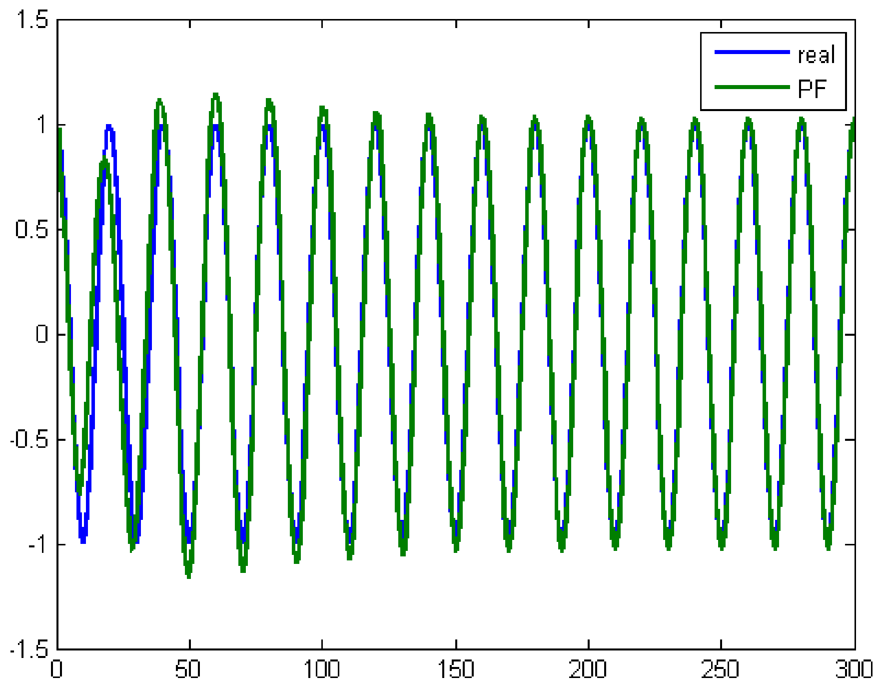

Figure 4.1: The First State Variable Comparison

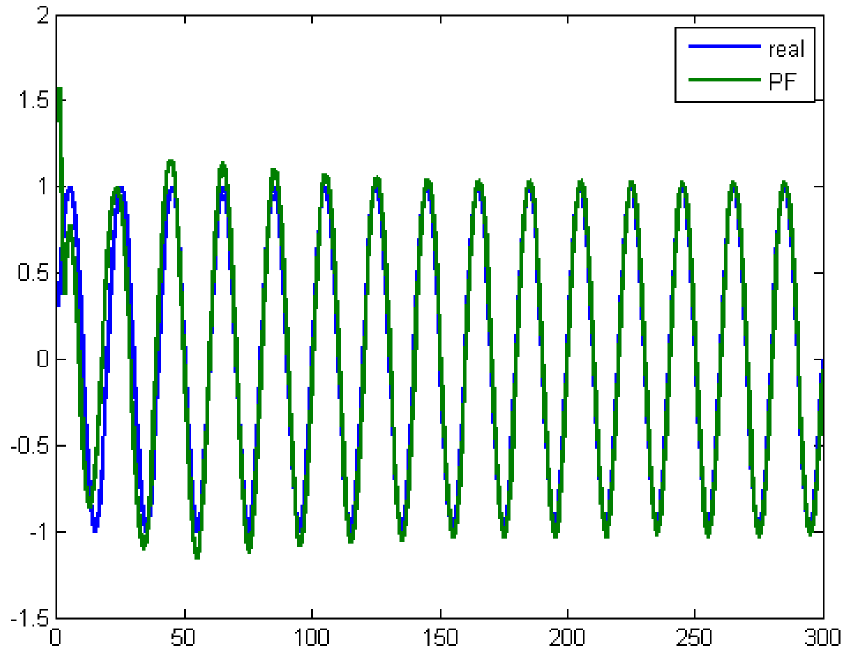

Figure 4.2: The Second State Variable Comparison

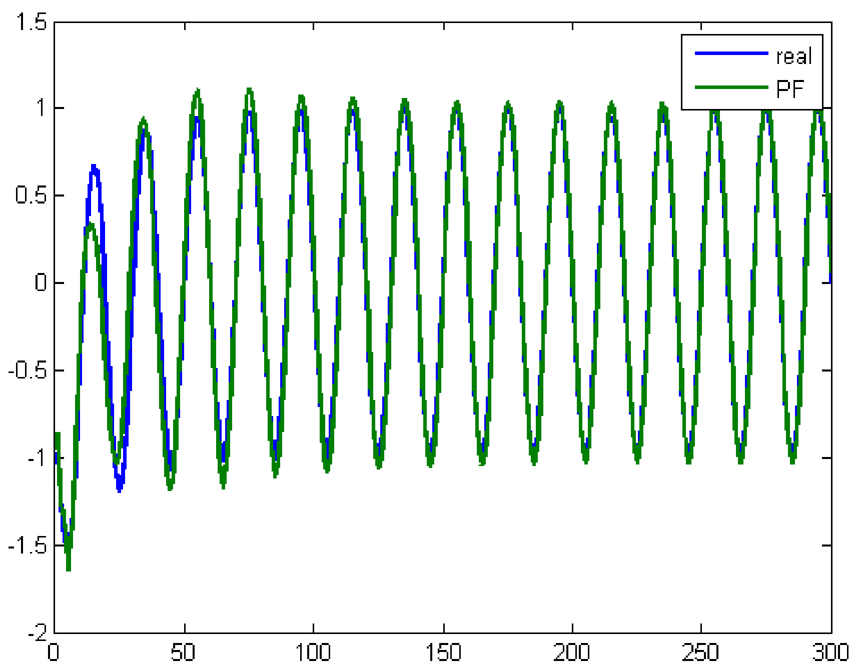

Figure 4.3: The Third State Variable Comparison

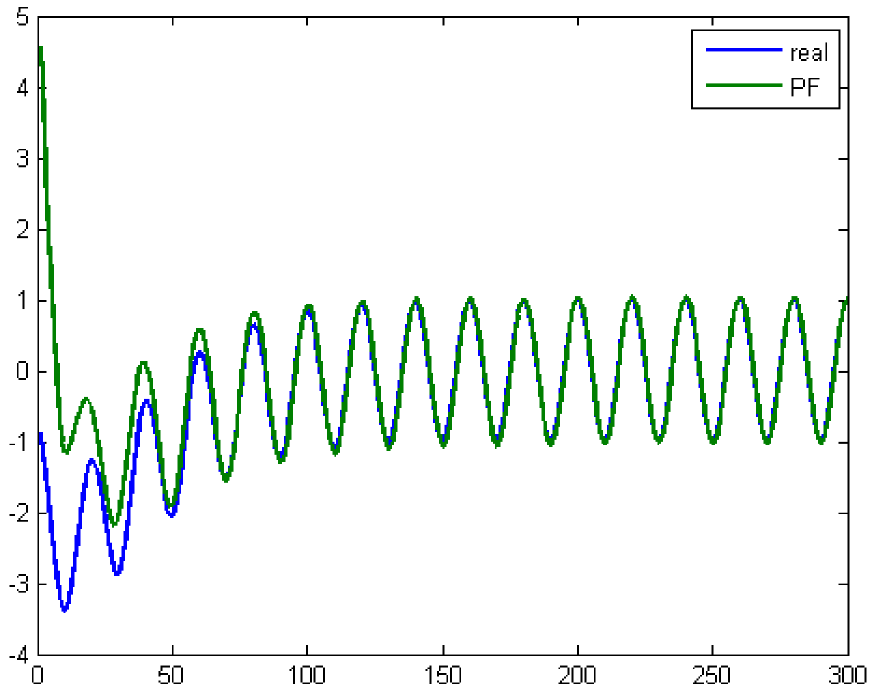

Figure 4.4: The Fourth State Variable Comparison

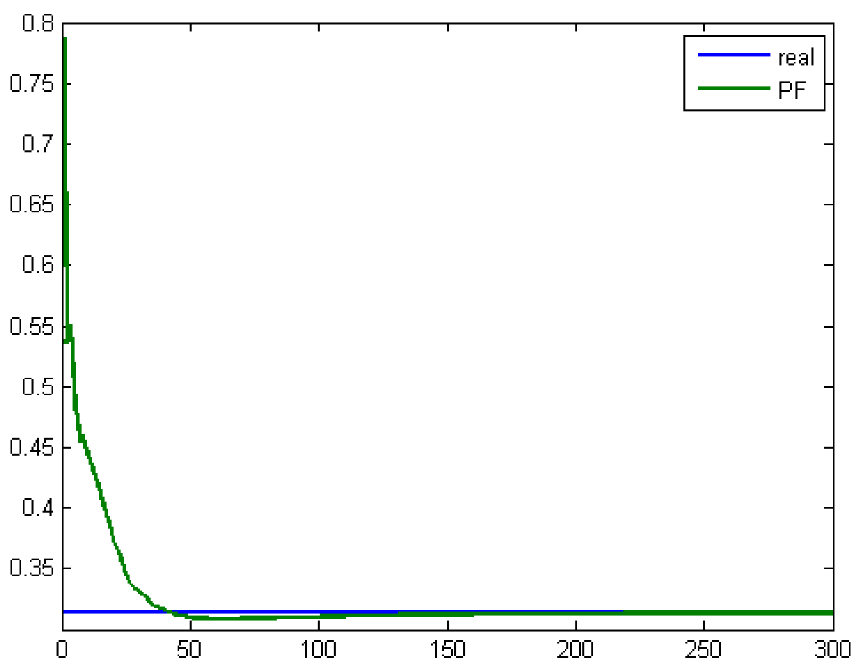

Figure 4.5: The Fifth State Variable Comparison

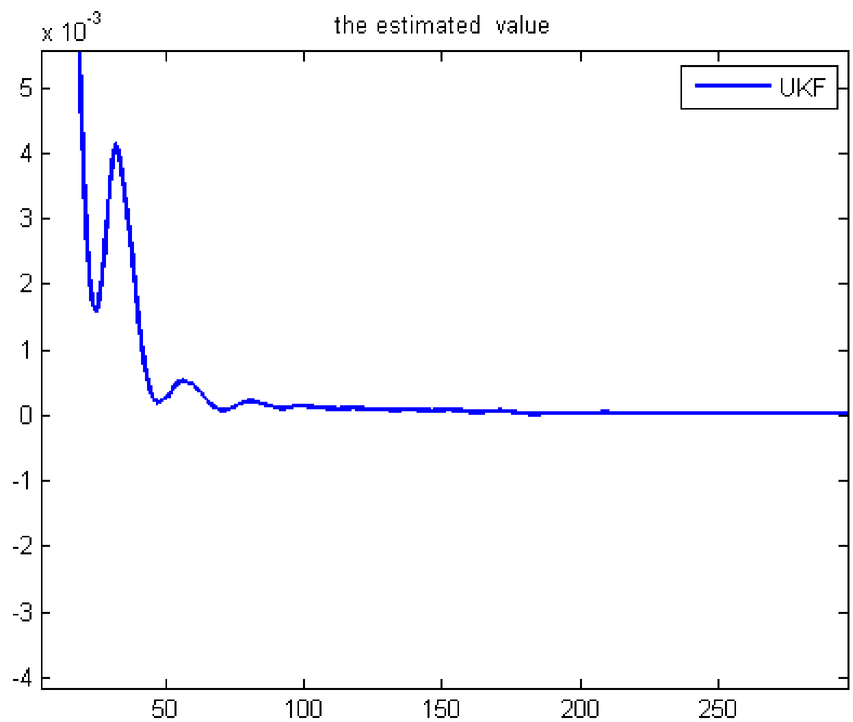

Figure 4.6: MSE Comparison

CHAPTER 5

UNSCENTED KALMAN FILTER

The third method is to implement the estimation using the Unscented Kalman Filter. The Unscented Kalman Filter was used as a solution when the system is extremely nonlinear, and can provide superior performance in nonlinear estimations [43]. The advantage of Unscented Kalman Filter over the Extended Kalman Filter is that it is not based on linearization. The Unscented Kalman Filter is based on Unscented Transformation in which sigma points are used. Particle Filter is very complicated, since it uses numerous points to characterize the pdf of the state variable. UKF is more computationally effective, since the $2n$ number of sigma points can be used to obtain the pdf, which is very closed to the real pdf. Three steps are needed to be implemented for the UKF estimation: 1. calculating the sigma points 2. time update 3. measurement update[46].

5.1 Unscented transformation

Unscented Transformation is a mathematical procedure used in mean approximation, and covariance approximation. It uses set of vectors which it's mean and covariance are equal to real mean and covariance. In order to start the unscented transformation we need to make sigma points. The sigma point for an n-element vector can be formulate as following:

$$\hat{x}_{k-1}^{(i)} = \hat{x}_{k-1}^{(+)} + \tilde{x}^{(i)} \tag{5.1}$$

$$\tilde{x}^{(i)} = (\sqrt{nP_{K-1}^{+}})^{T} \tag{5.2}$$

$$\tilde{x}^{(n+i)} = -(\sqrt{nP_{K-1}^{+}})^{T} \tag{5.3}$$

where the $\sqrt{np}$ is the matrix square root of np. After the sigma point is made, we need to transform the sigma points

$$y^{(i)} = h(X^{(i)}) \tag{5.4}$$

Then we can start the mean and covariance approximation as follows:

$$\hat{y}_u = \frac{1}{2n}\sum_{i=1}^{2n} \hat{y}^{(i)} \tag{5.5}$$

$$P_u = \frac{1}{2n}\sum_{i=1}^{2n} (\hat{y}^{(i)} - \hat{y}_u)(\hat{y}^{(i)} - \hat{y}_k)^T \tag{5.6}$$

where P_y is the covariance of the predicted measurement.

Unscented Kalman Filter estimates the state variables through Unscented Transformation. We can showed that Unscented Kalman Filter is more accurate because it is not based on the linearizion process. Here we discuss an example to verify that linearizaton process is unable to estimate the mean and the covariance of our highly nonlinear case. In order to show the difference between te real mean and covariance, and estimated mean and covariance the following system is studied:

$$y_1 = r\cos\theta$$

$$y_2 = r\sin\theta \tag{5.7}$$

$$\tag{5.8}$$

where r is a random variable with mean of 1 and standard deviation of δr. 300 randomly generated points with $\hat{r}$ uniformly distributed between .01 and $\hat{\theta}$ uniformly distributed between.3. The H can be calculated as follows:

$$H_k = \frac{\partial h_k}{\partial x} \tag{5.9}$$

$$\tag{5.10}$$

In this system H is 2×2 matrix. H can be calculated by the following matrix

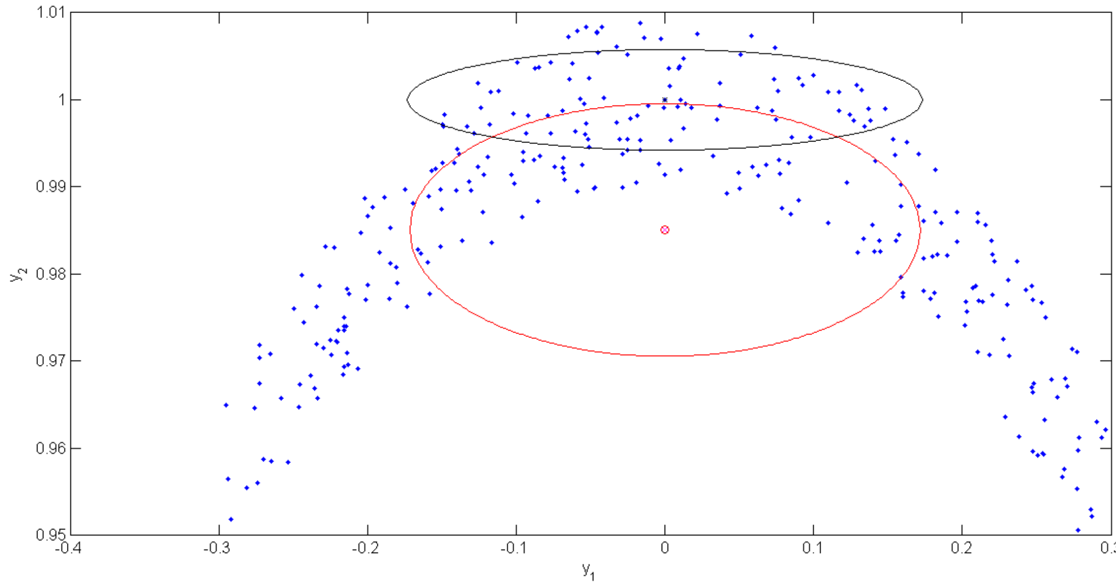

Figure 5.1: Linearized and Nonlinearized Mean and Covariance of 300 Random Variables

$$H = \begin{pmatrix} \cos\theta & -r\sin\theta \\ \sin\theta & r\cos\theta \end{pmatrix} = \begin{pmatrix} 0 & -1 \\ 1 & 0 \end{pmatrix} \tag{5.11}$$

This figure shows that the mean and covariance for this example is not a good approximation of the mean and covariance of the system. Therefore, we need an alternative solution instead of the linearization process. The Unscented Kalman Filter is proposed in this Chapter that deal much better with the nonlinear systems. According to simulation results in the following figure, Unscented Kalman Filter is capable of tracking both mean and covariance for the highly nonlinear example.

5.2 Unscented Kalman Filter

In this section, we apply the Unscented Kalman Filter to our system. As the other method our system is a five-state variable which is given by:

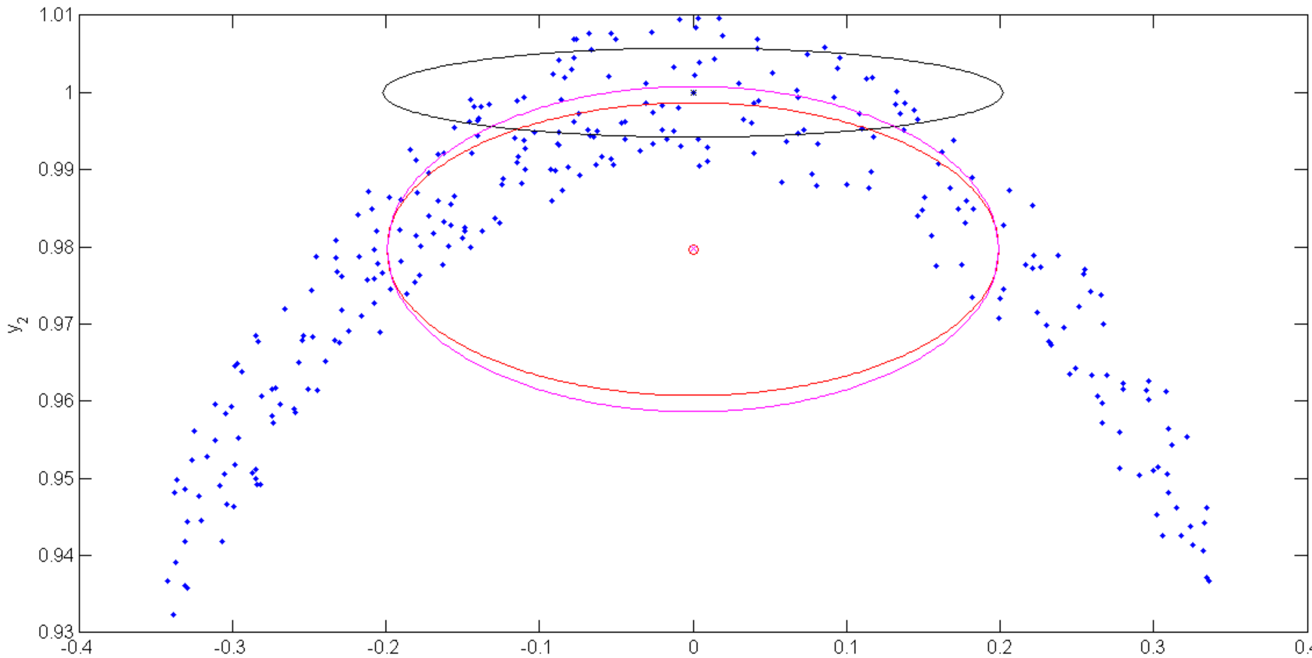

Figure 5.2: Comparison of the Unscented Transformation Technique and Linearization Technique for Mean and Covariance of 300 Random Variables

$$\begin{aligned} x_{k+1} &= f_k(x_k, u_k, w_k) \\ Y_k &= h_k(x_k, v_k) \\ w_k &\sim (0, Q_k) \\ v_k &\sim (0, R_k) \end{aligned} \tag{5.12}$$

After that for starting the estimate process, we need the initialization process.

$$\begin{aligned} X_0^+ &= E(X_0) \\ P_0^+ &= E[(X_0 - \hat{X}_0^+)(X_0 - \hat{X}_0^+)^T] \end{aligned} \tag{5.13}$$

After making an initial guess we can start the process measurement and find the priori state. To run UKF application we need to make the sigma points. Sigma Points are set of vectors, whose covariance and mean are equal to real mean and covariance. For this purpose the following formulas are used:

$$\hat{x}_{k-1}^{(i)} = \hat{x}_{k-1}^{(+)} + \tilde{x}^{(i)} \tag{5.14}$$

$$\tilde{x}^{(i)} = (\sqrt{nP_{K-1}^{+}})^T \tag{5.15}$$

$$\tilde{x}^{(n+i)} = -(\sqrt{nP_{K-1}^{+}})^T \tag{5.16}$$

where $\tilde{x}$ are our sigma points. Since we have 5 state equations in our model, we will need to produce 10 sigma points based on (5.15)and (5.22). The next step is time update. We use these 10 sigma points to calculate priori covariance matrix and priori state estimate. First we transsorm these sigma points into $\hat{x}_k^{(i)}$

$$\hat{x}_k^{(i)} = f(\hat{x}_{k-1}^{(i)}, u_k, t_k) \tag{5.17}$$

After that we combine $\hat{x}_k^{(i)}$ vector to find priori estimate

$$\hat{x}_k^- = \frac{1}{2n}\sum_{i=1}^{2n} x_k^{(i)} \tag{5.18}$$

$$P_k^- = \frac{1}{2n}\sum_{i=1}^{2n}(x_k^{(i)} - \hat{x}_k^-)(x_k^{(i)} - \hat{x}_k^-)^T \tag{5.19}$$

where $\hat{x}^-$ is predicted or priori state estimate and P_k^- is predicted or priori estimate covariance. $\tilde{x}^i$ is weighted sigma points. The next step is to start the measurement update. Again for this process, we need to choose sigma points

$$\hat{x}_k^{(i)} = \hat{x}_k^{(+)} + \tilde{x}^{(i)} \tag{5.20}$$

$$\tilde{x}^{(i)} = (\sqrt{nP_{K-1}^{+}})^T \tag{5.21}$$

$$\tilde{x}^{(n+i)} = -(\sqrt{nP_{K}^{+}})^T \tag{5.22}$$

It is not necessary to make new sigma points if the fast calculation is desired. We can also use the previous sigma points that were generated at the time update. This will decrease the calculation amount, and of course, it will decrease the accuracy. After making the new sigma points we need to transform them by measurement equations.

$$\hat{y}_k^{(i)} = h(\hat{x}_k^{(i)}, t_k) \tag{5.23}$$

After that, we combine the predicted sigma point measurement vector $\hat{y}_k^{(i)}$ to obtain predicted measurement.

$$\hat{y}_k = \frac{1}{2n}\sum_{i=1}^{2n}\hat{y}_k^{(i)} \tag{5.24}$$

Then we need to estimate the covariance of the predicted measurement

$$P_y = \frac{1}{2n}\sum_{i=1}^{2n}(\hat{y}_k^{(i)} - \hat{y}_k)(\hat{y}_k^{(i)} - \hat{y}_k)^T \tag{5.25}$$

The cross covariance between $\hat{x}_k^-$ and$\hat{Y}_k$ is defined as below:

$$P_{xy} = \frac{1}{2n}\sum_{i=1}^{2n}(\hat{x}_k^{(i)} - \hat{x}_k^-)(\hat{y}_k^{(i)} - \hat{y}_k^-)^T \tag{5.26}$$

The measurement Update can be performed using Kalman Filter algorithm.

$$K_k = P_{xy}P_y^{-1} \tag{5.27}$$

$$\hat{x}^+ = \hat{x}^- + K_k(y_k - \hat{y}_k) \tag{5.28}$$

$$P_k^+ = P_k^- - K_k P_y K_k^T \tag{5.29}$$

where P_y is the covariance of the predicted measurement, P_{xy} is the cross covariance between $\hat{x}_k^{(i)}$ and $\hat{y}_k^T$.

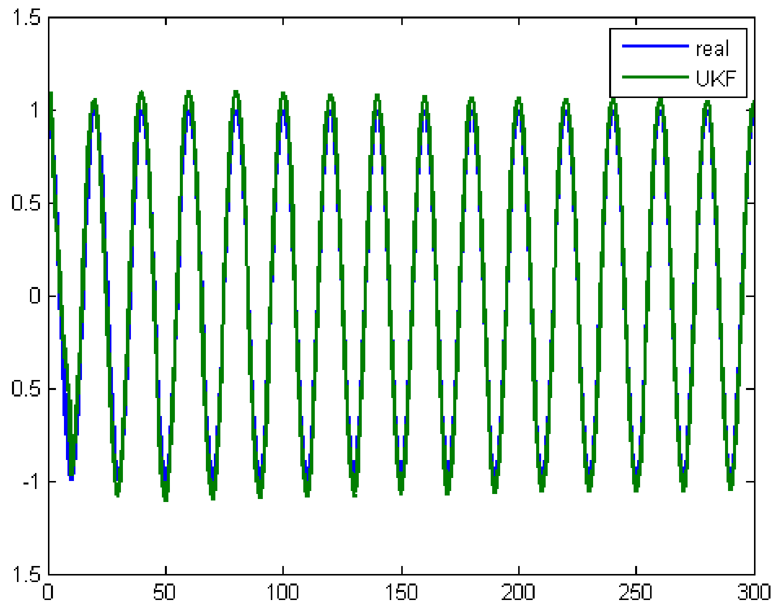

Figure 5.3: The First State Variable Comparison

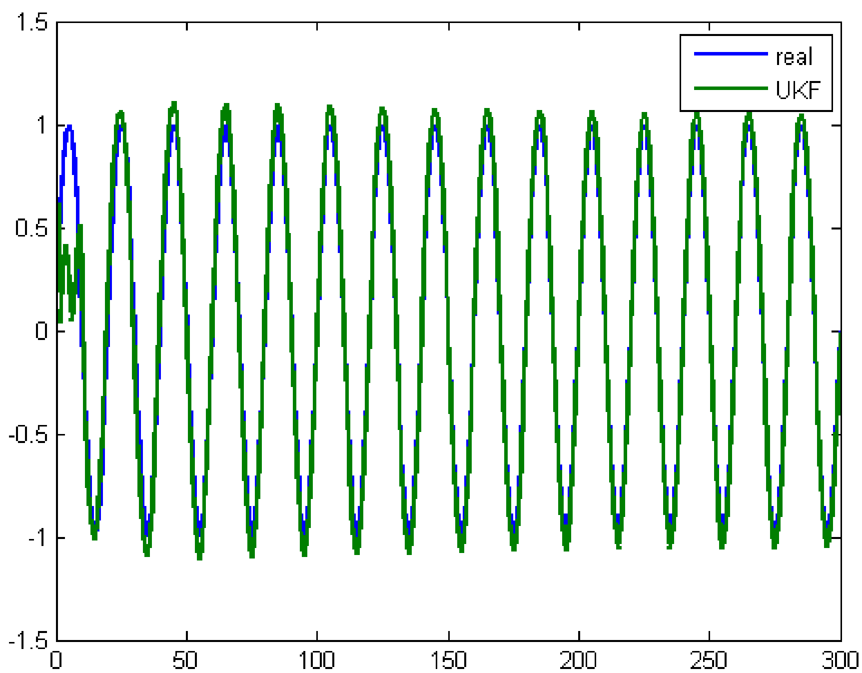

Figure 5.4: The Second State Variable Comparison

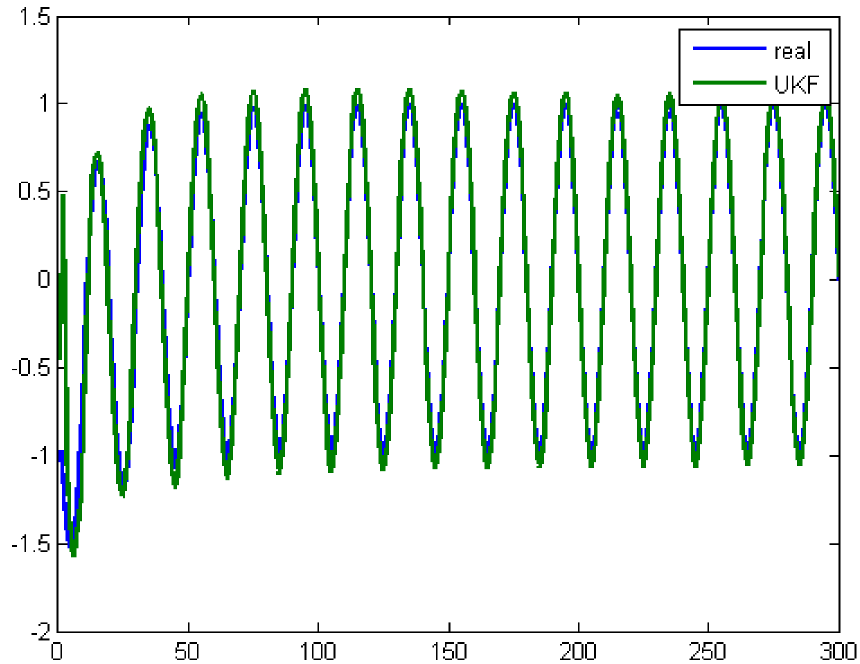

Figure 5.5: The Third State Variable Comparison

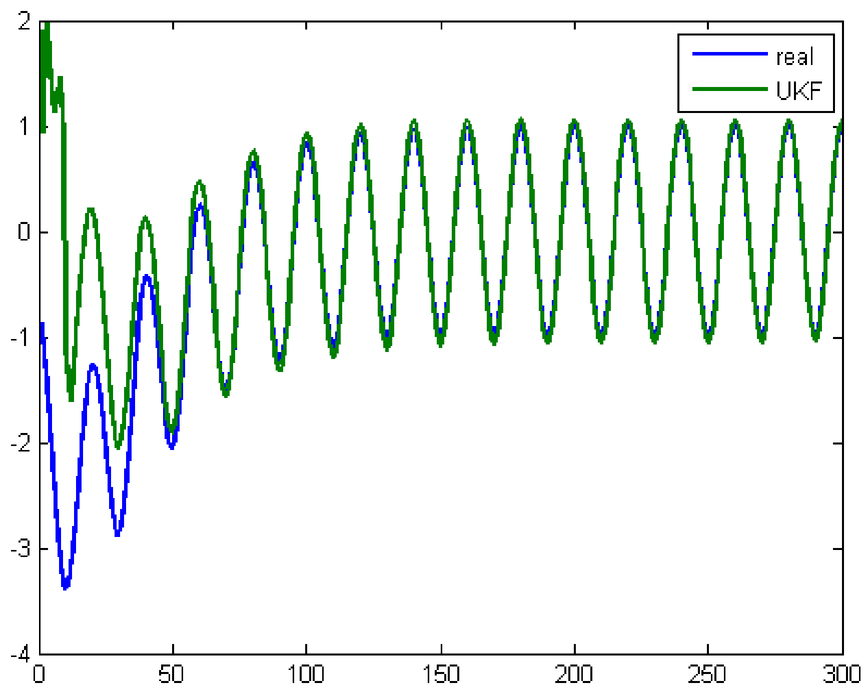

Figure 5.6: The Fourth State Variable Comparison

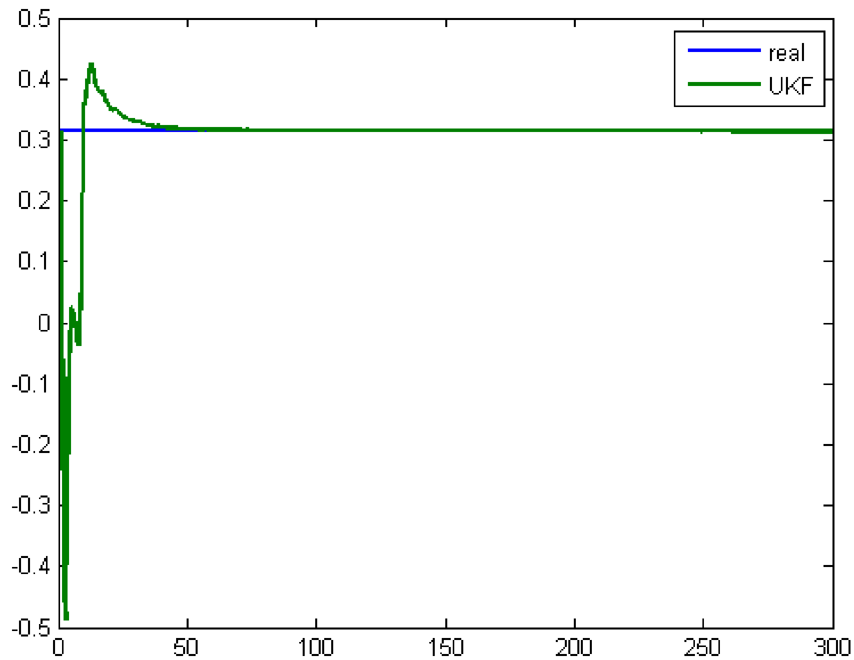

Figure 5.7: The Fifth State Variable Comparison

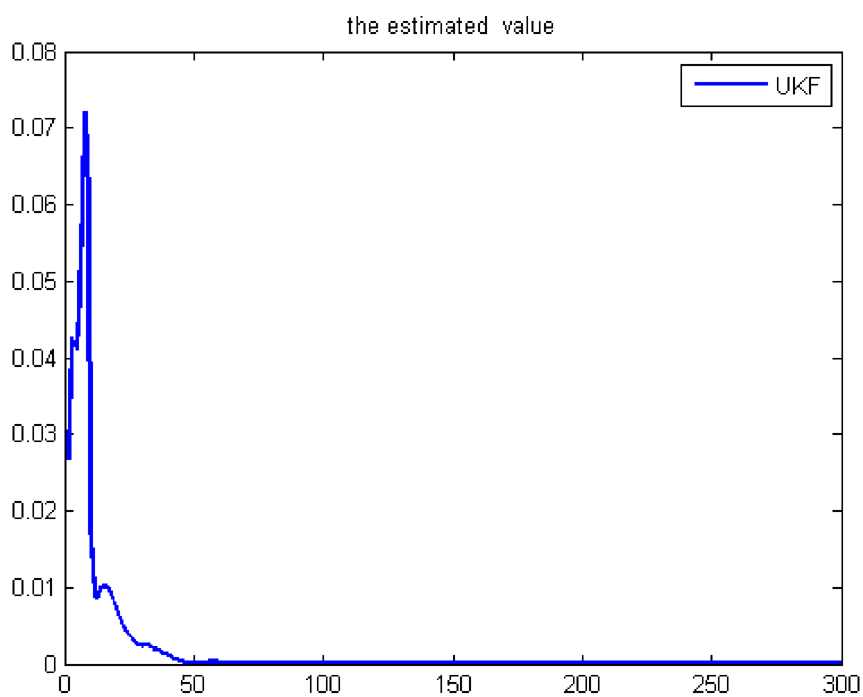

Figure 5.8: MSE Comparison

CHAPTER 6

SIMULATION STUDIES

In Chapter 6, we compare the performances of the Extended Kalman Filter, the Particle Filter, and the Unscented Kalman Filter. The state estimation for 5 state variable is provided, and the MSE of all of these five states are added, and a single MSE is used for better comparison of different nonlinear state estimation.

The result of Mean Square Error (MSE) comparison is provided. 300 iterations of MATLAB simulation are conducted for each nonlinear estimation technique. The sampling frequency is chosen as 1200Hz, and the initial value of the state variables are chosen as $[1, 1.2, .8]$, and $[0, \pi/3, -2\pi/3]$ as the initial amplitudes, and initial phase angles of the unbalanced three phase voltages respectively. We consider the Additive Gaussian Noise with zero mean and Identity covariance for measurement noise and neglect the process noise.

Fig. 6.1-6.5 show that all of the proposed nonlinear estimators successfully track the state variables with good accuracy. For better comparison the mean square error is defined and calculated:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2 \tag{6.1}$$

Fig. 6.6 shows the MSE of 300 samples. As can be seen the MSE is relatively small for all of our proposed method. UKF is the most accurate method among the proposed nonlinear estimator given the same amount of computational effort. Particle Filter is also accurate as can be seen in Fig. 6.6. The accuracy of Particle Filter can be improved by increasing the number of particles, but we find a trade off between the accuracy and computation results. For the Particle filter simulation , we choose 500 particles in order to make a trade off between the calculation accuracy, and computation time. The particle filter MSE can be improved by adding more particle points. Although the Extended

Kalman Filter shows the largest MSE, it is the fastest method compared with the other two methods.

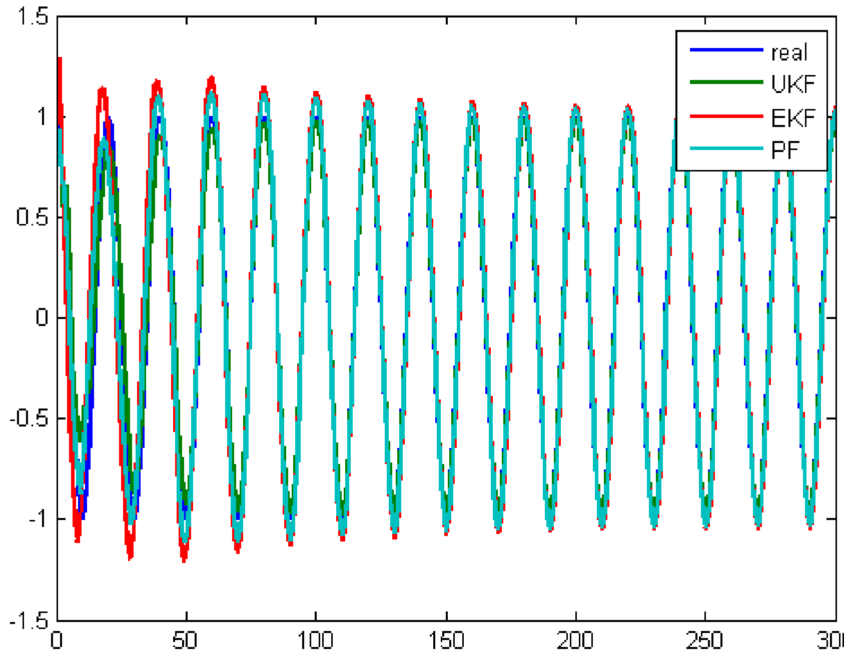

Figure 6.1: The First State Variable Comparison

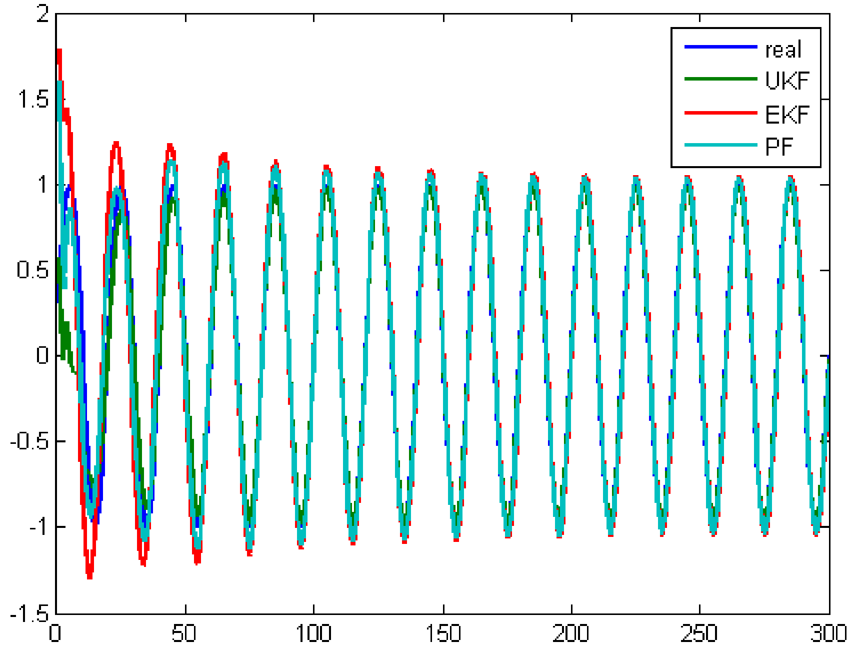

Figure 6.2: The Second State Variable Comparison

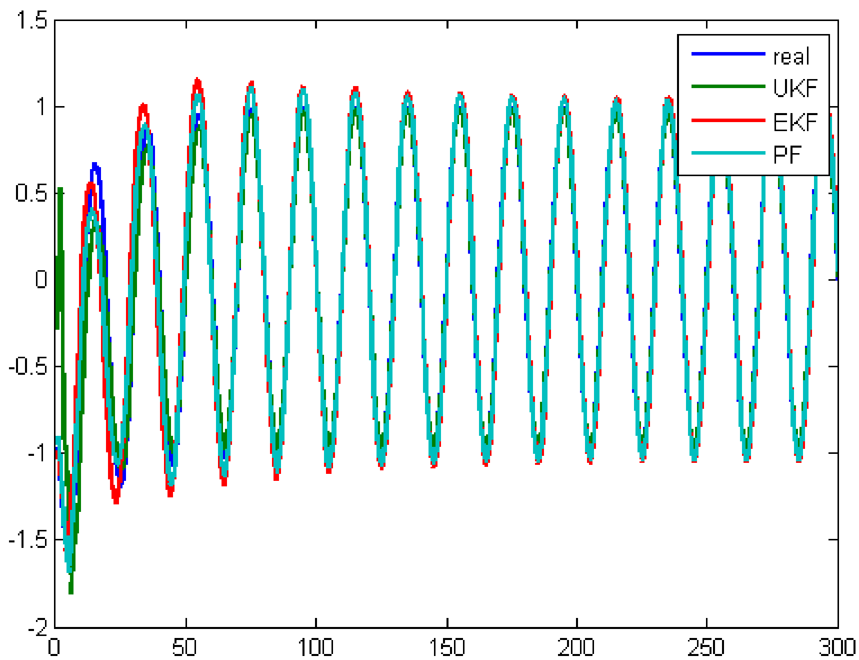

Figure 6.3: The Third State Variable Comparison

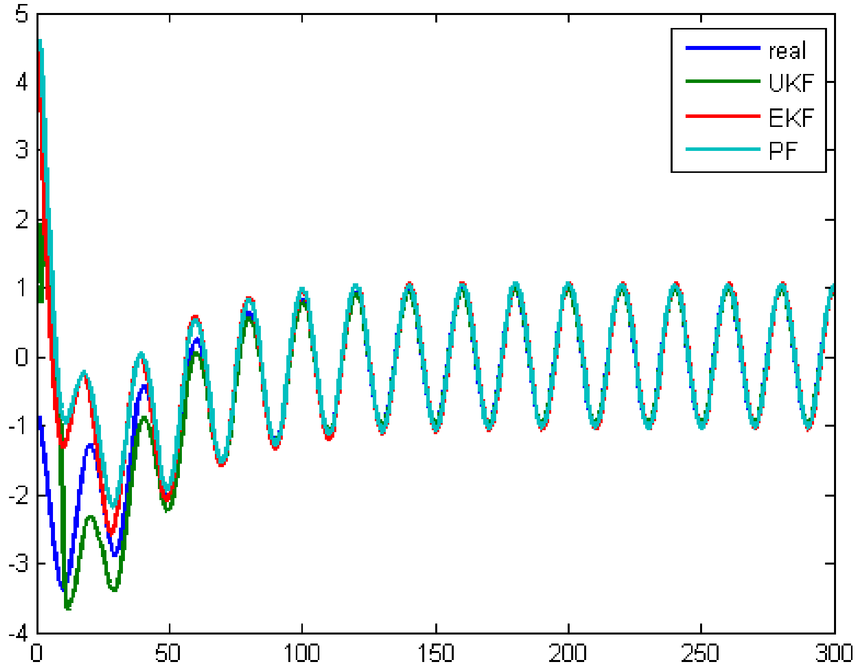

Figure 6.4: The Fourth State Variable Comparison

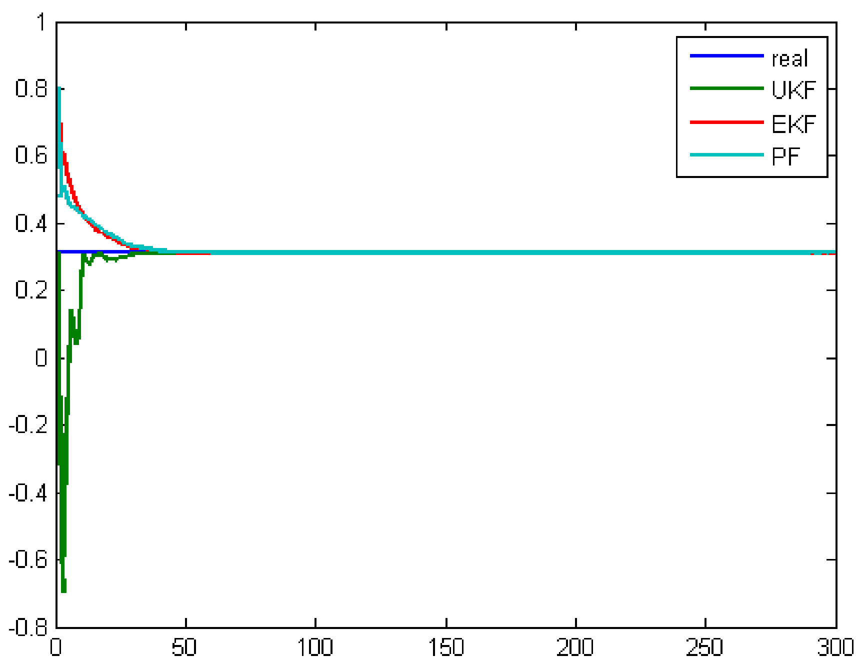

Figure 6.5: The Fifth State Variable Comparison

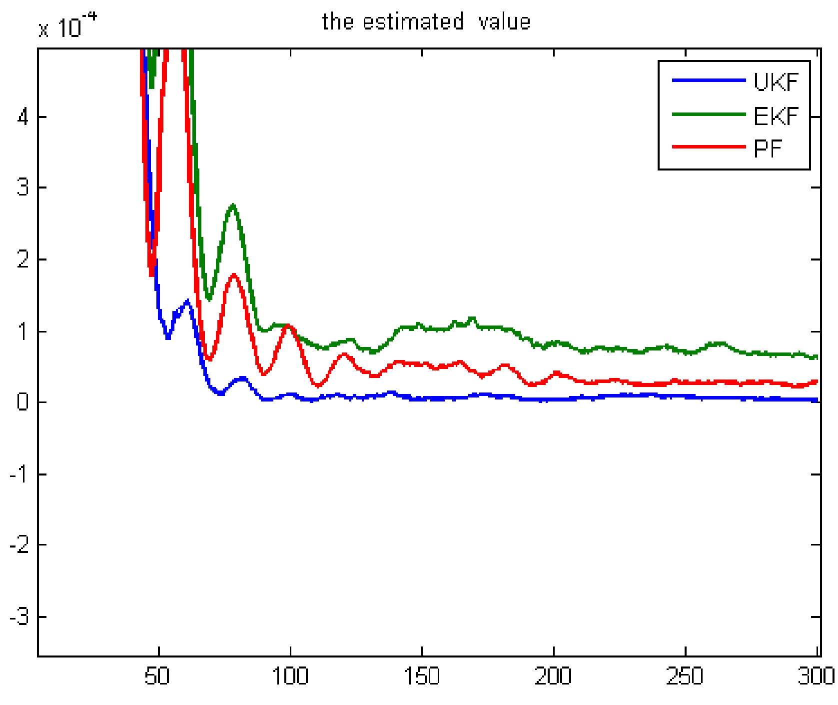

Figure 6.6: MSE Comparison

CHAPTER 7

CONCLUSION AND FUTURE WORK

7.1 Conclusion

This paper presents novel nonlinear estimation techniques with the applications to smart power grid synchronization. With the Clarke's transformation and symmetrical component transformation, the state space dynamical equations are derived. The Extended Kalman Filter, the Particle Filter, and the Unscented Kalman Filter are employed to track the three phase voltage amplitudes, phase angles and frequency, with unbalance voltage and noisy measurements. The comparison results show that all of the proposed method convergence with good accuracy. The Unscented Kalman Filter gives the smallest MSE and reasonable computational complexity, therefore, is the preferred technique for smart grid power system synchronization.

7.2 Future Work

In this thesis, we discuss the innovative method for estimating the state variable for voltage synchronization in three phase unbalanced voltage. We start with the Kalman Filter. Then, we extended it to the Extended Kalman Filter which is the most widely used method for nonlinear systems. After that, we introduce the Particle filter, and the Unscented Kalman Filter. For future work, other methods can be implemented and the results will be compared with our proposed methods such as H_∞ Filter [47]

The Extended Kalman Filter can be improved in a variety of ways: higher order Extended Kalman Filter, including iterated Extended Kalman Filter, the second order Extended Kalman Filter, and Adaptive Extended Kalman Filter,etc [48][33] [49].

The Unscented Kalman Filter can be modified with the Simplex Unscented Transformation, the Spherical Transformation to compare the performances [50]. Meanwhile, Rao-Blackwellised additive unscented Kalman filter (RBAUKF) and the Adaptive Unscented Kalman filter also provides us powerful alternatives design which will also be studied in the future [51] [52].

The Particle Filter performance can also be improved by increasing the number of particles, but the computational efforts limit the number of particle we can increase. The Adaptive Particle Filter change the likelihood distribution according to statistic characteristic of the system, and therefore, will be studied in the future work [53].

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