STATE ESTIMATION OF POWER SYSTEM USING PARTICLE FILTER

DISSERTATION-II

Submitted in partial fulfillment of the
Requirement for the award of the
Degree of

MASTER OF TECHNOLOGY
IN
ELECTRICAL ENGINEERING

By

DIPESH DOSHI

Under the Guidance of

ASSISTANT PROFESSOR

MUKUL CHANKAYA

LOVELY PROFESSIONAL UNIVERSITY

LOVELY PROFESSIONAL UNIVERSITY

PHAGWARA (DISTT. KAPURTHALA), PUNJAB

School of Electronics and Electrical Engineering
Lovely Professional University
Punjab (India)

May 2017

CERTIFICATE

This is to certify that the Thesis titled **"STATE ESTIMATION OF POWER SYSTEM BY USING PARTICLE FILTER"** that is being submitted by **DIPESH DOSHI** is in partial fulfillment of the requirements for the award of MASTER OF TECHNOLOGY DEGREE, is a record of bonafide work done under my /our guidance. The contents of this Thesis, in full or in parts, have neither been taken from any other source nor have been submitted to any other Institute or University for award of any degree or diploma and the same is certified.

Mukul Chankaya

Project Supervisor

Lovely Professional University

Objective of the Thesis is satisfactory / unsatisfactory

E x a m i n e r I **E x a m i n e r I I**

ACKNOWLEDGEMENT

First and foremost, I am deeply indebted to my mentor **"Mr. Mukul Chankaya"** whose inspiration has been unfailingly available to me at all stages of this work. This has fueled my enthusiasm even further and encouraged me to boldly step into what was a totally dark and unexplored expanse before for me. I would like to thank for my teachers for his efforts, who was always ready with a positive comment, whether it was an off-hand comment to encourage us or constructive piece of criticism. In course of present work it has been our privilege to receive help and assistance of my friends. I take great pleasure in acknowledge my debt to them. At last but not the least I want to thank my parents who appreciated me regard this work and motivate me and finally to God who made all the things possible.

Dipesh Doshi
Reg. No. 11500827

CERTIFICATE

This is to certify that **Dipesh Doshi** bearing Registration no. **11500827** has completed objective formulation of thesis titled, **"State estimation of power system using particle filter"** under my guidance and supervision. To the best of my knowledge, the present work is the result of her original investigation and study. No part of the thesis has ever been submitted for any other degree at any University.

The thesis is fit for submission and the partial fulfillment of the conditions for the award of Dissertation-I.

Mentor Name: Mr. Mukul Chankaya
Assistant Professor
School of Electronics and Electrical Engineering
Lovely Professional University
Phagwara, Punjab.

Date :

DECLARATION

I, **Dipesh Doshi**, student of **Masters of Technology** under **School of Electronics and Electrical Engineering** of Lovely Professional University, Punjab, hereby declare that all the information furnished in this thesis report is based on my own intensive research and is genuine.

This thesis does to the best of my knowledge, contain part of my work which has been submitted for the award of my degree either of this university or any other university with proper citation.

Date :

Signature and Name of the student

Registration No. : 11500827

Dipesh Doshi

ABSTRACT

State estimation of power system is important for the power system monitoring and control. It finds out the optimal estimate for the given system state. System states are the complex bus voltages in the power system, based on the network model and the measurements collected from the system. It also give best optimal state estimation for the line power flow, generator outputs, load flow, transformer taps. But, as the power system is highly non-linear in nature, so it will be difficult to state estimate of the system by the conventional methods like weighted least square method, maximum likelihood method, Kalman filters etc. These methods are useful for the linear system. With the help of extended Kalman filter, non-linearities of the system can be estimated. But it will not be reliable when non-linearity are severe in the system. So particle filter is the approach to overcome this problem. By using particle filter in the system for the state estimation non-linearity of the system can be estimated. Here in this thesis, particle filter approach has been used for the state estimation of the measurement obtained from the PMU in the six bus system. The estimated state of the system and true state of the system has been compared and found to be matching.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

LIST OF ABBREVIATIONS

PMU	Phasor Measurement Unit
SCADA	Supervisory Control And Data Acquisition System
SE	State Estimator
EHV	Extra High Voltage
HV	High Voltage
UHV	Ultra High Voltage
WAN	Wide area Network
EMS	Energy Management System
RTU	Remote Terminal Unit
GPS	Global Positioning System
A/D	Analog To Digital
KF	Kalman Filter
PF	Particle Filter
SIS	Sequential Importance Sampling
SIR	Sequential Importance Resampling
EKF	Extended Kalman Filter
WLS	Weighted Least Square
UKF	Unscented Kalman Filter
PDF	Probability Distribution Function

CHAPTER: 1 INTRODUCTION

1.1 Background

Electrical power system is used to generate, transmit and consume power in the network by using various electrical components used in the system. These components can broadly divide into main three parts. The first part is generator which generates the electricity, the second part is transmission line which is used to transmit the power from the source to load and the third component is the load which is the one who consumes the power transmitted to the load which is again distributed to consumers like home, industries, commercial load etc.

World’s first power grid was started constructing in England from the year of 1881. Now the look and protection devices, methods of generation of power and transmitting methods of the generated power all things have been changed. The new improvements in all these equipment made the system more reliable and more stable. Though, new research need to be carried out to satisfy the needs of the increasing requirement of the power system. So to control and measure the parameters of the network under certain condition is hard and it is very challenging with the growing demand of the power and after inclusion of the new equipment into the system. So the most important aspect in recent power system is: how to measure the different parameters of the power system and how to control those parameters of the power system.

This dissertation is mainly focus on this topic like how to state estimate power system. More specially, this dissertation will focus on the data of Phasor Measurement Units and state estimation of the power system based on the data available for the system. This can be understand with the simple example of the system, one operator at the system who gets the measurement from the SCADA system which lacks of the important information, then this operator will know the results of detailed analysis from the State Estimation (SE) and Energy Management System(EMS).

Obviously, this process takes several minutes to complete the process and come out with the results depends upon the size of the system. Further, if any issue found with the voltage measurement then more time needed to be spend on this extra calculations and some offline model helps needed. But with the help of the synchrophasors whole this process takes several seconds to complete and control decision can be made by sending online control signals.

1.2 SCADA

SCADA is the abbreviation for Supervision Control And Data Acquisition. In power system, SCADA system plays an important role. It is used to perform operation such as controlling of the output of the generators, switching of the generators and switching in or out the equipment from the system for the maintenance purpose remotely. It is also responsible for the measurement of the continuous measurement which is further provided for the safety procedures. SCADA systems measures the active power, reactive power, Injected power flow, system voltages [1]. A simple architecture of the SCADA system has been shown in the in the figure 1.1.

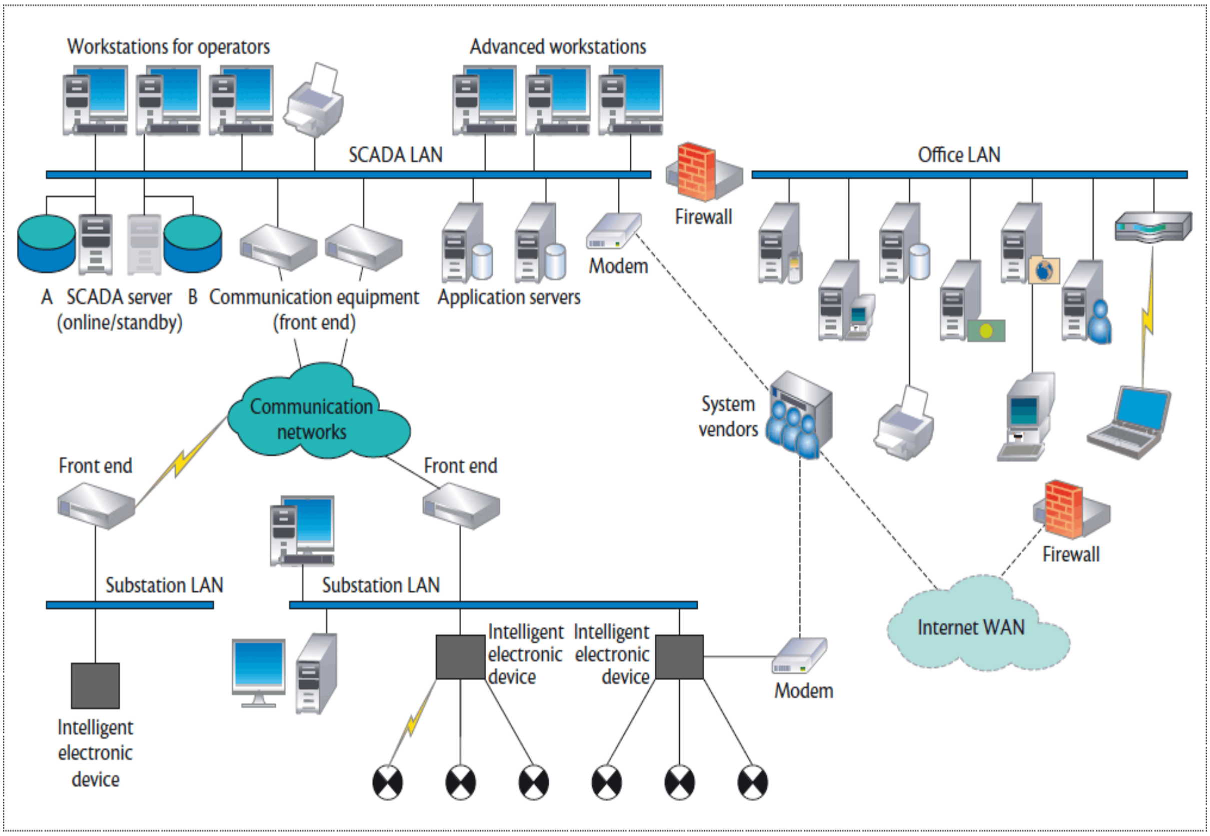

Figure: 1.1 Architecture of the SCADA system used in power system [2].

However, SCADA system has some disadvantages, such as uncoordinated and not synchronized data acquisition, low transmission rate to transfer data from work station or RTU and quasi steady state calculation. SCADA system is based on the steady stet power flow, so it may not be able to measure the parameters so it can be said that it van not monitor dynamic power flow in the system. Data updating rate of the SCADA system is nearly 0.1 to 0.25 Hz

[2]. Besides all these things, voltage phase angles cannot be measured for any instantaneous bus. Moreover, line flows for the all transmission system is not available while getting data from the SCADA. Even it is not economical to transmit all the measured data even if they are available from the measuring instruments to the RTU [3].

1.3 Phasor Measurement Unit

Phasor Measurement Unit is the alternative of the SCADA system which also overcome all the disadvantages of the SCADA system. With the invention of the PMU system, measurement of the Phase angle of the any instantaneous bus is easy to measure. A PMU is a digital device which provides the synchronized current and voltage phasors. The Phasor is a vector representation of the magnitudes and phase angle of an AC waveforms. Phase angles of different sites can be measured with the PMU as these devices are synchronized with the common time source. The common time source can be achieved with the help of the GPS system (Global Positioning System) in order of the 1 microsecond, which helps to measure very accurate voltage and current measurements of the system from different buses of the system at the same time synchronization.

The salient feature of the PMU is the synchronized Phasor calculation of the system, which makes this device as a very important measuring devices in the nearer future for the monitoring and controlling purpose of the power system. Synchronization of the sampling is achieved by the common timing signal obtained from the GPS which is available locally at the substation. Accuracy of the timing signal is 1 milliseconds which is sufficient for the synchronized relay coordinating applications. This same approach of the PMU can be used to extend its feature to the monitoring of the power system, state estimation of the power system [4]. However calculation time for the phasor is more than the 1milliseconds. Reference [5] describes the more detailed analysis of the required synchronization accuracy of PMU applications.

Figure 1.2 shows a functional block diagram of the PMU. Components of this block diagram is: Anti-aliasing Filters, A/D converters, Phasor micro-processor, modems, Phase-locked Oscillators, GPS receiver. The Anti-aliasing filter is used to filter the input waveforms which has the frequencies more than the Nyquist rate. The phase locked loop is used to convert the GPS 1 pulse per seconds into the high speed timing pulse train to use it in the sampling of the waveform.

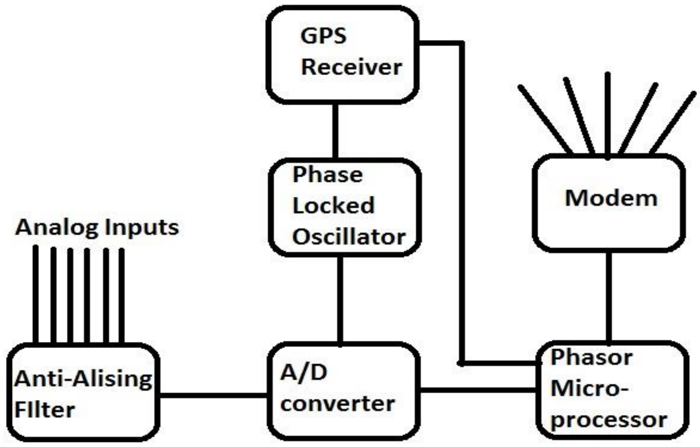

Figure: 1.2 Functional block diagram of the PMU [4].

The phasor microprocessor block is used to carry out the discrete Fourier transform for the phasor calculation. Then this calculated phasor with the time synchronized is uploaded via modem for the real time calculation to the data concentrator [6]. The advantages of the PMU in the power system includes monitoring, controlling and operation. Reference [7], from the EPRI publication has details of the thorough discussion of the current installation of the PMU in whole world. The best advantage of the PMU is that it provides the time synchronized measurement. For example, for contingency analysis and online load flow, positive sequences of the fundamental frequency voltage is used which is further directed by advanced control center applications.

Figure 1.3 shows the basic diagram of the PMUs. To transfer the data from the one substation to another substation, optic fibers are used. The measurements of the PMUs upload the measured data in the time stamped signal using mediums like telephonic lines or through the wide area network (WAN).

A for the reliable performance of the PMU, data collected by the PMU must be transferred with the fast streaming communication infrastructure. Placement of the PMU can be major topic to cover the all transmission line buses for the measurement of the system and for the proper communication of the line. Since the cost of the PMU is very high it is necessary to optimize the deployment of PMU at buses, will be major economic undertaking. In the field of protection PMU plays an important role, to determine the model of system used by the relays from which evolving swing stability can be predicted [8].

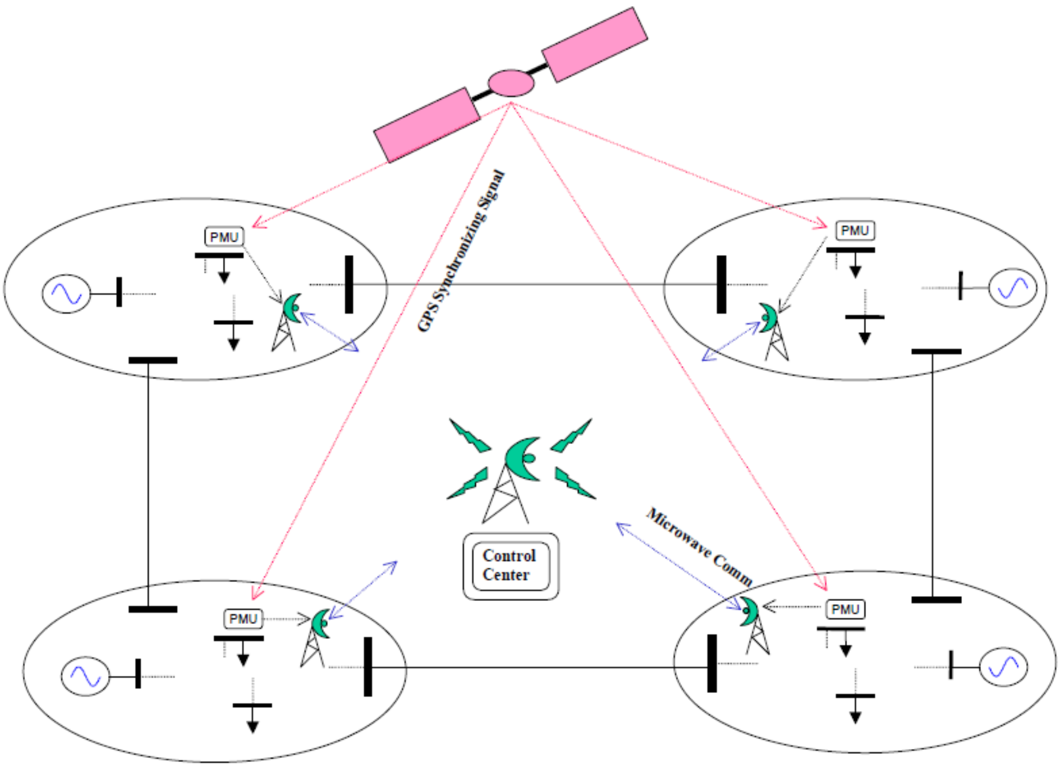

Figure: 1.3 Conceptual Diagram of Synchronized PMU system [4]

PMUs can be used to determine the accuracy of dynamic model of the system. PMU provides the detailed information of the known oscillations that's couldn't be observed by conventional measuring methods before [9]. Voltage security monitoring based on the decision tree using synchronized time stamped phasor measurements could be another desirable application [10]. State estimation of the power system based on the PMU is very important application of the PMUs, which provides a platform for the most of the advance control applications.

1.4 Applications of the PMU

There are several applications of the PMUs in order to study the interconnected grid. These applications are mentioned below [11]:

I. Dynamic state estimation
II. Wide area monitoring of the system
III. Protection of the power system
IV. Controlling of the power system
V. To monitor power system oscillations
VI. Monitor the electrical stress on the transmission system

VII. To determine the available transmission capacity of the transmission line
VIII. Control actions such as damping needed in case of discrepancies
IX. Angular stability and voltage stability studies and analysis
X. Nonlinearities of the measurements and state variables of the system
XI. Increase in reliability and robustness in bad situations
XII. Overload monitoring

1.5 State estimation

As name indicates, state estimation in power system plays an important role in the estimating the control variables of the power system while monitoring it. Control stations use estimators measurements derived from the SCADA further implemented to state estimators. These estimators are the responsible for the measurement of the phasor voltage measurement for assessment of the power system. Now a days Wide Area Measurement System is used which is based on the PMUs for advance measurement system. State estimators use the relations between the state variable to be measured and the measurements which makes the interconnected grid observable at every instance. They are able to measure current phasors, voltage phasors and voltage angle measurements. So, the nonlinearities problems of state variables and measurements can be solved easily and faster in compare to SCADA measurements. In reference [1] it is said that for the precise operation traditional state estimators can be upgraded with the PMUs. PMUs are the one who provides phase angle difference into the system. State estimators also provide phase angle difference from the system but at interval of the few minute. In contrast, PMUs provide the same at very fast rate of time such as in difference of milliseconds or microseconds. So, it can be said that PMUs provide high resolution time synchronized signals from GPS to measure the magnitude of voltages and currents, frequency, phase angle difference. They also help to monitor all high voltage, extra high voltage and ultra-high voltage lines [12].

The state estimators include the following functions [3]:

- **Topology Processor:** It arranges data of the Circuit breakers and switches and set-up a single line diagram of the system.
- **Observability analysis:** It determines the state estimation for the whole system from the available measured values of variables and recognize the unobservable and observable branches and islands if exists in the system.

- **State estimation solution:** It finds out the optimal state estimate for the given system state, which is composed of complex bus voltages in the whole power system, based on the system network models and noted down the measured value of measurement from the system. It also give best optimal state estimation for the line power flow, generator outputs, load flow, transformer taps.
- **Bad data processing:** It finds outs the gross errors which already exist in the measured set of parameters. It find outs the bad data from the measure set of measurement and eliminates it from the measured value.
- **Parameters and structural error processing:** It estimates different network parameters from the system such as tap changing transformer parameters, transmission line model parameters, shunt rectors and capacitor.

To get the best state estimation state of the power system based on the measurement of the model of the system. The state estimator uses:

- Measurement set available from PMUs.
- Topological processors supply the system configuration
- It uses network parameters such as line impedance for the inputs of the estimators
- It executes the parameters such as it does dynamic weight adjustments

Figure 4 shows the block diagram of the state estimation process:

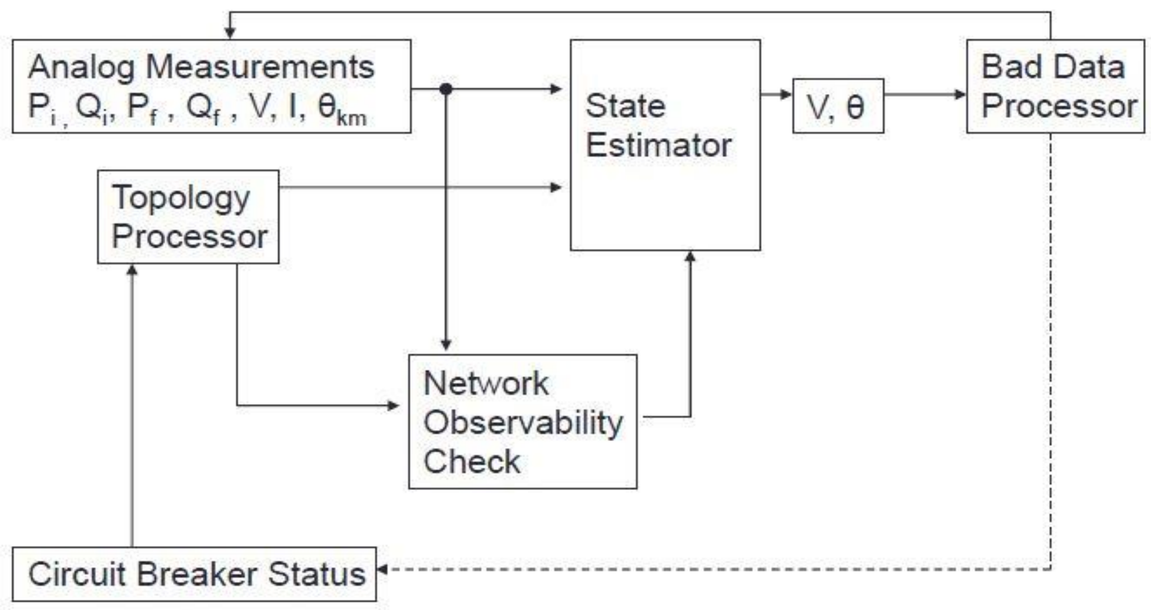

Figure: 1.4 Block diagram of the state estimation process [13]

As shown in above figure 1.4, status from the circuit breakers and switches is collected and send it to topology processors which is PMUs or SCADA system. Further collected data is given to the state estimators at the same time PMUs or SCADA system check the system observability for the whole system branches and islanded system which is observable or not and given to the state estimator. Analog measurements gathered from the transducers such as voltage, current, angle difference between voltage phasors, active power and reactive power frequencies etc. is given to the state estimators for the estimation of the state of the system. If there is any bad data in the measured values of the system then it will detect those bad data and it will eliminates those bad data from the system and use the data after the elimination.

The traditional methods used for the state estimation for the commonly encountered criteria are:

- The maximum likelihood criterion
- The weighted least square criterion

And non-traditional methods like

- Evolutionary optimization techniques like fuzzy logy, genetic algorithm, Kalman Filters, Particle Filters, differential evolution algorithms.

1.5.1 Maximum Likelihood Estimation

In this type of estimation, measurement errors are assumed to have known PDF (probability distribution function) with unknown parameters. So the joint PDF can be written for the whole system parameters in terms of the unknown parameters. This function can be mentioned as likelihood function and they will attain their maximum value when then unknown parameters are very close to their real values [3]. Here it is assumed that errors are in the form of Gaussian distribution and the problem of the maximum likelihood criterion can be solve with parameters like mean μ and variance σ. The normal probability density function for a random variable z is defined as [3]:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{\frac{-1}{2}\{\frac{x-\mu}{\sigma}\}} \quad (1.1)$$

Where σ: standard deviation of z

μ: mean of z

z: random variable

After all the new probability distribution function may become as:

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} e^{\frac{-y^2}{2}} \quad (1.2)$$

For the maximum likelihood formula can be written as

$$[G(x^k)\Delta x^{k+1} = H^T(x^k)R^{-1}[z - h(x^k)] \quad (1.3)$$

Where G(x): gain matrix, which is sparse matrix, positive definite and symmetrical provided that the system is observable.

H(x) = $\frac{\partial h(x)}{\partial x}$

R = diag {σ12, σ_2^2, …, σ_m^2}

1.5.2 Weighted Least Square Estimation Algorithm

Weighted Least Square algorithm includes iterative solution for the normal equation given by the equation 3. Iterative solution for the WLS state estimation can be outlined as shown below:

I. Set iteration index count k=0 and start the iteration.
II. Initialize the state vectors x^k, it should typically start as a flat start.
III. Gain matrix $G(x^k)$ should be calculated.
IV. Calculate $t^k = H(x^k)^T R^{-1} (z – h(x^k))$.
V. Break down $G(x^k)$ and solve for the Δx^k.
VI. Convergence testing, max $| \Delta x^k | \leq \epsilon$?
VII. If it is not so then update $x^{k+1} = x^k + \Delta x^k$, k =k + 1 , and to step number III, and if it is so then stop the program there.

Gain matrix is developed from the Jacobian measurement H and from the error covariance matrix R. Matrix R is supposed to be a diagonal matrix which has diagonal elements full of measurement variance. Gain matrix G can be written as:

$$G(x^k) = H^T R^{-1} H \quad (1.4)$$

Properties of the gain matrix can be described as follow:

I. It is numerically and structurally symmetric.
II. It is a sparse matrix, but lesser than the matrix H.

III. It is non-negative and definite matrix. It can be said that because all the value of the Eigen-values are non-negative. It is fully observable matrix.

Gain matric can be rewrite as

$$G = \sum_{i=1}^{m} H_i^T R_{ii}^{-1} H_i \tag{1.5}$$

1.5.3 Kalman Filter

Kalman filtering technique is one the most used technique for the state estimation of the linear system. It is widely used for the stet estimation of the system because it is very simple, optimal, unbiased and easy to implement. So the Kalman filter is also recognized as Best Linear Unbiased Estimator or the BLUE filter [14].

The Kalman filter is a good algorithm which is used to make the optimal use of general data and it also works on the system which is linear with Gaussian errors. It continuously update the state of the system precisely in linear system.

The state dynamic model for the Kalman filter can be defined as follow [16]:

$$x_k = Ax_{k-1} + \omega_{k-1} \tag{1.6}$$

The measurement model for the Kalman filter can be defined as follows:

$$y_k = Hx_k + v_k \tag{1.7}$$

Where,

$$p(\omega_k) \sim N(0, Q) \tag{1.8}$$

$$p(v_k) \sim N(0, R) \tag{1.9}$$

x_k is the state vector with the dimension p at time k.

A has dimension of $p \times p$ and it is state transition matrix, which associated with the state of process at times k and k - 1.

ω_k is the noise which is introduced in system due to system process and it almost supposed to be Gaussian in nature.

Q is the covariance of the process noise matrix with the dimension $p \times p$.

y_k is measurement vector with the dimension m.

H has m × p dimension.

v_k measurement noise generally in Gaussian form.

R is the covariance matrix for the measurement noise whose dimension is m × p.

1.5.3.1 Estimation Technique for the Kalman Filter

To get the current state estimation of the system through the help of the Kalman filter previous and current measurement of the system is needed. The algorithm for the Kalman filter can be very well explained by the figure 1.5 [15].

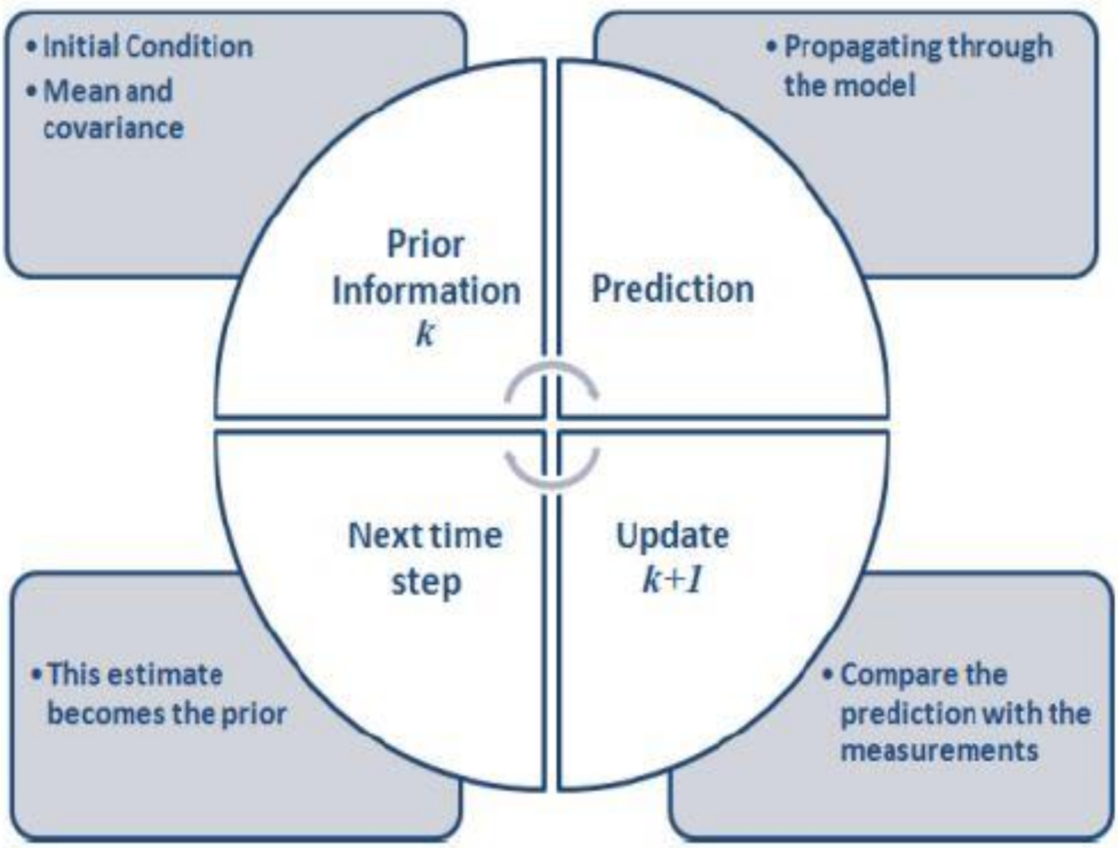

Figure: 1.5 Algorithm for the Kalman Filter [15].

Consider prior state estimation at every step k will be $\hat{x}_{k-1}$, and measurement y_k is given by the posterior estimate at step k and it can be given by $\hat{x}_k$. Priori and posteriori state estimation errors can be written as [16]:

$$e_k^- = x_k - \hat{x}_k^- \quad (1.10)$$

$$e_k = x_k - \hat{x}_k \quad (1.11)$$

Error covariance can be given as follow:

$$P_k^- = E\ [e_k^- e_k^{-T}] \tag{1.12}$$

$$P_k = E\ [e_k e_k^T] \tag{1.13}$$

P_k is the error covariance matrix which gives the measure of the accuracy of the estimation. A weighted difference between the measurement predictions $H\hat{x}_k$ and the measurements y_k.

$$\hat{x} = \hat{x}_k^- + K\ (y_k - H\hat{x}_k^-) \tag{1.14}$$

Where

$(y_k - H\hat{x}_k^-)$ is measurement innovation or the residual, which is the difference between predicted and actual measurement. Both actual and predicted measurement will be same if the residual is same.

In equation 1.14, matric K is also known as Kalman Gain or the blending factor of the system which is useful to reduce the posterior error covariance in the system. The Kalman Gain can be given by the equation [16].

$$K_k = P_k^- H^T\ (HP_k^- H^T + R)^{-1} \tag{1.15}$$

The Kalman filter get the state estimation of the system in the given time and also get the noisy measurement as a feedback. So here it can be said that it works as a feedback control. The equation used in Kalman filter can be divided in two parts, one is time update equation and another one is measurement equation.

1.5.3.2 Prediction and updation of the State in Kalman Filter

Prediction for the Kalman filter start from the guessing of the initial mean x_0 and P_0. The prediction step equation can be written as [17]:

$$\hat{x}_k = A\hat{x}_{k-1} \tag{1.16}$$

$$P_k^- = AP_{k-1}A^T + Q \tag{1.17}$$

Measurement of the output matrix y_k is obtained from the predicted measurement available. Kalman filter state updation equation can be given by 14 and 15.Improved estimate is the given by the covariance matrix and it can be written as:

$$P_k = (1 - K_k H)\, P_k^- \tag{1.18}$$

1.5.3.3 Problems with Kalman Filter [18]

- Kalman filter does not hold the assumption made in all the situations.
- In Kalman filter, most assumptions are based on the Gaussian errors only.
- Before going for Kalman filter we should know the variance and mean of the noise for all time instant.
- We should know the process noise covariance because Kalman filter works on the design parameter such as process noise, so if these parameters are unknown then it is hard to complete successful operation of the Kalman Filter.
- It is better for the linear state estimation. It will not work efficiently with the non-linearity into the system.

1.6 Scope of The Study

In this thesis, mainly the problem of the state estimation of the particle filter is solved by using particle filter. For the monitoring purpose of the power system, PMU which is a digital measurement device which is used for the measurement of the voltage and current phasors and angle difference between two buses, can be done in the observability under PMU. Bu using the measurement of the PMU, state estimation process carried out on the measurements. Here it should be noted that, power system is highly non-linear in nature. So it is hard to estimate the state of the system by using conventional methods like weighted least square method, maximum likelihood process, Kalman Filter etc. So to overcome this problem, particle filter should be implemented in the system or the state estimation purpose of the power system. By using particle filter there are some problems which might be faced during the implementation. These problems are degeneracy of the particles and impoverishment of the samples. These problem can be reduced by using the resampling. As a resampling algorithm, sequential importance resampling algorithm can be used to reduce the problem of the degeneracy and impoverishment of the samples. As the result, by using particle filter state estimation of the power system can be done easily and results of this state estimation with PF has been discussed in the chapter of results and discussion. Algorithm of the particle filters and algorithms for the resampling method sequential importance resampling has been discussed in the chapter of the research methodology.

1.7 Objectives of the Study

The main objective of this thesis is to develop algorithm for the advanced power system state estimation with the help of the PMU measurements. The topics here covered in this thesis are as follows:

1. Development of the algorithm for the particle filter for the state estimation of the power system. Power system is highly non-linear in nature. So, it is complicated when system is big and lots of buses are connected to the system. The system monitoring and control will be hard. So by using particle filter as the end of the result state estimation of the power system will be carried out.
2. Development of the algorithm for the resampling process of the particle filter. It is a part of the particle filter to reduce the degeneracy of the particle and impoverishment of the particles. As the end of the result by implementing this algorithm in the particle filter the problem of degeneracy and sample impoverishment.
3. Resampling algorithm is Sequential Importance resampling algorithm. By using this algorithm problem discussed in point two can be reduced. By choosing proper weight of the particles and by updating it at each iteration problem of the degeneracy and samples impoverishment can be reduced.
4. Comparison of two techniques Extended Kalman Filter and Particle Filter for the state estimation will be done and by comparing results which method is the best that can be concluded.

CHAPTER 2 LITERATURE SURVEY

Katsuji Uosaki, et al. [19] Now a days particle filter is broadly used for the state estimation of the highly nonlinear systems. Basically, particle filters are used to estimate posterior probability distribution function of the state variable on the basis of the previous observations. This approximation is done with the help of importance sampling method. Anyway, resampling process has been introduced to overcome the problem of degeneracy phenomena while using importance sampling which deteriorates the performance of filtering process. In this paper, the author has suggested using a new strategy on the basis of Gaussian sum filter. This Gaussian sum filter combines the idea of Gaussian mixture approximation of the posterior distribution and evolution on the basis of the particle filter. In this method selection process which is used in evolution, strategy is used into the resampling process of the particle filter. In evolution strategy, author has discussed that method generate an initial population of parent vectors randomly from the feasible outcome in each dimension and then it will modify them with the help of selection processes and perturbation such as mutation which depend on upon the fitness of the structure of any individual. Because of this type of system, it can be used with any type of system like non-Gaussian noise cases or nonlinear systems. With the help of other evolution techniques operation and with help of good choice of designing parameters will have the potential to make good filter performance.

Kianoush Emami, et al. [20] In this paper, the author has described how particle filter is powerful over Kalman filters. Author has explained that power system dynamic is nonlinear in nature and linearization is not a feasible solution of the power system. Unscented Kalman Filter (UKF) has some drawbacks which can be overcome by using particle filters. They are as listed below,

1. With the help of UKF, it is not possible to get a true approximation as a small set of sigma points in UKF.
2. UKF cannot work properly with nearly singular covariance.
3. If there is not a good estimation of covariance of noise then Cholesky factorization will not be completed because of uncorrelated received data.
4. UKF can only be applied to the systems which have Gaussian noise and unimodal distribution.

In this paper, the author has described the algorithm for the particle filter. The most important step in the particle filter is the resampling step. Systematic resampling is very good and favorable because of it is less complex and easy in computational complexity. If resampling cannot be done then the weight of the most effective particle will become one and weight of the other particles will become zero which will tend to the breakdown of the particle filter.

Yinan Cui, et al. [21] In this paper, the author has explained dynamic state estimation with the help of particle filter method in the multi-machine system. Dynamic state estimation based on Particle filter might be improved by manipulating data from the PMUs when data is available at the higher sampling frequency. In this paper, the author has used particle filter to dynamically estimate the synchronous generator state in a multi-machine with the consideration of the excitation system and prime mover control system. Author has used IEEE 14 bus system to estimate following things with the help of particle filters are

1. Sub transient dynamics model of generator
2. Turbine and governor model used for steam and hydro
3. Excitation units

Author has compared results of the particle filter and unscented Kalman filter. And it is found that with the help of particle filter the estimation is much more perfect than the unscented Kalman filter.

CHEN Huanyuan, et al. [22] In this paper, the author has described new particle filter for the dynamic state estimation of the power system. Here in this paper author has compared the state estimation results of the power system of the new particle filter with the Extended Kalman Filter (EKF) and Unscented Kalman Filter (UKF). With the help of the particle, filter authors have shown that one can obtain more nearest approximate results to the true state. As a new particle filter, the author has used a combination of Kalman filter and particle filter which is called as Mixed Kalman particle filter. The problem with the only use of EKF is, the load on the system is highly non-linear and when use EKF is in the system then EKF ignores the second and higher order equations from the system which is a big compromise with the accuracy. Even same type of problem arises when UKF is used in the system, because of the lack of linearism to non-linear state equations.

Piotr Kozierski, et al. [23] In this paper, the author has discussed comparison result between particle filter and Kalman filter. The particle filter is used for very high nonlinear and complex system. In this paper, the author has described the algorithm for the bootstrap filter (Particle filter). It is basically one of the Sequential Importance sampling algorithms which are very easy to implement. For the weights of particles, the author has used the weighted least square method for the weighing of the particles. Author has introduced one other method that id particle filter alone cannot give satisfactory results than multi PDF particle filter can be introduced to the system in which more than one particle filter algorithms are working parallel and after taking an average of that, it gives results which will reduce the error from the system.

Petar M. dhurrie, et al. [24] In this paper, it is explained that the man task of particle filtering is to estimate the state of x from the observation of y by sequential signal processing. The algorithms which follow the distributions very precisely those are called optimal algorithm. But, in some cases, these algorithms do not follow the same and it will be practically impossible to implement. The problem is caused because distributions updates need to be integrated which cannot be performed analytically and summation which is not possible due to large terms for the summation. The main problem, for the estimation through it, is that the random measures which are discrete in form degenerate quickly. In other words, all the generated particle expect some particles has very negligible weights. This may affect the performance of the particle filter and it will deteriorate the performance of the particle filter. To reduce the degeneracy, importance filter can be used for resampling. Resampling scheme with importance sampling will eliminate particles with small weight and replicates the particles with large weights.

Safoan M. O. Alhalali, at al. [25] In this paper, the author has used particle filter for the estimation of the distribution system. State estimation is a systematic process for the processing of pseudo and real measurement in order to estimate the bus voltage and power angles. Author has described the WLS method is not sufficient, especially when renewable source are interconnected to the grid. Dynamic state estimation is methods have been introduced to estimate severe power fluctuation caused by the large load variation and power fluctuation in power generation. In this paper, the author has used extended Kalman filter and particle filter for the state estimation of the system and compared them. Author has modeled distribution system measurement equation and which author has further used as the particle filter equations. Sequential importance sampling is performed sequentially at time t such that modifications can be done to the previously estimated states and can be updated for the further use. Author has used IEEE-34 bus system for the estimation through both of the estimation techniques which are Extended Kalman Filter and Particle Filter. At last when the author has compared the both the results then obviously results of the particle filter is better than the Extended Kalman Filter.

Haomiao Zhou, et al. [26] In this paper, the author has described different types of particle filters. Particle filter consists three important operations which are a generation of new particles, particle weights computation, and resampling of particles. There are different methods for the resampling process which includes systematic resampling process, residual resampling, multi-nominal resampling, stratified resampling and so on which helps to deal with the degeneracy problems. It has been proven that the weights can increase over a time only. After some iteration, all weights will be close to zero or zero, this is called the degeneracy problem. To eliminate this thing, the particle should be resampled regularly such that particles with the small weights will be eliminated and new particles with the higher weights will be updated.

Lisa Turner, et al. [27] In this paper, the author has explained different types of filters like Kalman Filter, Unscented Kalman Filter, and Extended Kalman Filter etc. Author has also explained the importance sampling process for the particle filter. The basic principle of the particle filter is to update particles sequentially using importance sampling techniques. Degeneracy in the particle filter can be minimized by the proper use of the importance function and by including it into the resampling step in the Sequential importance sampling algorithm. In this process, each and every particle is picked with a probability proportional to the weight associated with it.

David Salmond, et al. [28] The particle filter is viewed as a direct mechanism of the Bayesian filter. To update the samples in the measurement of any vector then a weight must be calculated for each and every particle. This weights are calculated by likelihood process and then these weights are normalized to so they some to unity. Then these particles will be resampled according to their normalized weights to produce new particle samples. The impoverishment of the particles is the result of the sampling with the discrete form rather than continuous form.

Osea Zebua, Et al. [29] In power system, voltage instability is a major issue. In some cases, voltage instability leads to the blackout of the power system. The problem discussed in this paper is how to estimate voltage stability by using particle filter. Reactive power losses in the transmission line will increase with the increase in the load connected to it. If reactive power is not inadequate amount then it will cause the voltage to start decrease until to its critical value. If the load is increased more than that value then voltage starts to become unstable. Author has used two bus system as a test system and assumed that both generators are capable of supplying any amount of reactive power with any change of the load. Author has explained particle filter algorithm step by step. In first step particles should be drawn and updated. In second step computation should be done based on likelihood process and weights should be normalized based on the value of the weights. In the third step, resampling should be done. Here the author has introduced a Gaussian error which is also called as noise into the system which is added to each parameter. Here, it has been said that if the difference between actual voltage and critical voltage is used to analyze the voltage stability. At last author has shown different results for the different value of particles like 100, 1000, 10000 particles.

Wei Cai, et al. [30] In Monte Carlo method, entire trajectory of this process will be divided into many short trajectories or paths. Most of the paths of the Monte Carlo method starts from the bottom of the base of the energy and returns from the same base. In this lecture several steps of the Monte Carlo method has been discussed. Author has also explained the flow chart of the importance sampling method.

Ning Zhou, et al. [31] When power system is moving from the traditional grid to smart grid at this time the estimation of the dynamic states will not be easier. And it will be more important where fast and system wide control is necessary. Firstly for the state estimation of the system Supervisory Control and Data Acquisition (SCADA) system was in use which helps to the system to be sampled once on every 2 to 4seconds. So it can be said that in this system sampling rate of the system is too low to expose the dynamics caused by electromagnetic interference in power system. More that thia even SCADA system is not synchronized with the grid properly so most of the controller uses local states to achieve controlling. So PMU has been invented for the state estimation of the dynamic state of the system. PMU samples the system at the rate of 30 to 60 samples per seconds.so the accuracy of the system will increase. Particle Filter is a general approach for the dynamic state estimation of the system. It is also applicable for the Gaussian and non-Gaussian nonlinear models. In this paper author has discussed the state estimation of the state of the synchronous machine with the extended particle filter which consists particle filter and Extended Kalman Filter. Author has used the simulation data generated by the fourth order model defined by the system. And the sampling rate of the simulation is taken at the 1000 samples/seconds.

N. M. Manousakis, et al. [32] Now a days, PMU is used worldwide in the field of the power system stability, monitoring, controlling, voltage security, power system protection, to protect the system from outages and many more applications are being used for the PMU. To full fill all this purposes, we install PMU at buses in the sub-stations, but the main problem encountered is the placement of the PMU in the system such that whole system becomes observable and we get the data from the various buses to monitor the system for all mentioned applications. If the placement of the PMU is not done properly then the system will not be full observable and it may cause difficulty to full fill above mentioned applications. As PMUs are very costly so optimal placement of the PMU should be done so we can reduce the number of PMUs used in the system and we can make the whole system observable in minimum number of the PMUs. There are various method to solve optimal placement problems i.e. mathematical programming, heuristic and Meta heuristic optimization methods. In this paper author has also explained four basic rules for optimal placement of any PMU in the system.

R. F. Nuqui, et al. [33] In this paper, placement of PMU based on the incomplete observability has been described. For the optimal placement of the PMU, power system should be converted into spanning tree, this is the method to check the optimal placement of the PMU into the system. Author has described that with the depth of the observability, different impacts can be seen on the placement of the PMU in the system. In this paper, authors has used simulated annealing method to solve the problem of optimal placement of the PMU based on the incomplete observability. Authors has ignored the communication constraints while transferring data from PMU to RTU and used a tree search method to determine the number of the PMUs in the system. In second method recognizes the constraints by imposing the limited.

K. Joseph. Makasa, et al. [34] In this paper, new methods for voltage stability based on the load index estimation from the optimally located PMUs have been explained. In this paper authors have carried out voltage stability load bus index by using recurrent neural network which is known is ENS (Echo State Network). Here voltage stability indexes can be got from the measurements of the PMUs which are voltage and current phasors in addition with the phase angles. The minimum numbers of the PMUs that makes the whole system observable will be placed in the system from the optimal placement of PMU method and then other remaining buses measurements can be calculated from the measurement attained from the PMU and transmission line reactance.

Pankaj Tripathi, et al. [35] PMU measures the parameters from the system and it transmit those data to RTU, control center. This transmitted data may contain the bad data, which should be eliminated before processing. To eliminate this bad data, different state estimation techniques can be used which will filter out the bad data from the useful data. In this paper, as a state estimation method weighted least square method has been introduced. When there is bad data present in the system, then the estimated error will be large because of the sum of the square. The best state estimation can be achieved by the weighted least square method, that can be seen from the results i.e. accuracy in the state estimation.

James A. Momoh, et al. [36] For planning and operational engineers, security and stability of the power system is the utmost important. Monitoring and controlling of the power system will hard when the load demand on the system increases and when interconnection of grid increases. In this paper, how to handle challenges of maintaining the stability for online application has been described. In this paper, author has used shunt and series compensators to control the violations in the system to improve the voltage stability of the system.

Allan J. Wood [37] In this book, author has explained most probably three methodsa for state estimation

I. The maximum likelihood criterion, where the objective of the system is to maximize the probability to estimate the state of the variables.
II. The weighted least square method, where objective will be minimized the sum of the square of the objective which is to be estimated from the actual measurement, z.
III. The minimum variance criterion, where the objective will be minimized the dum of the square of the derivatives of the system parameters which is to be estimated from the true state variables

M. Sanjeev Arulampalam, et al. [38] In this paper, author has described Bayesian theorem for both linear and nonlinear system. For nonlinear system in this paper they mostly concentrate on the particle filter. Here in this paper, authors have explained the generic form of the particle filter like SIR, RPF, and ASIR with the help of importance sampling process. As per authors, for linear Gaussian system no algorithm is better than the Kalman filters. The same results can be derived from the least square method but for this method, mean and covariance for the system should be known. In suboptimum Bayesian filter, three filters can be described: Extended Kalman Filter, Approximate Grid Based Methods and Particle Filter. EKF has good performance as it work with the nonlinearities of the system. As a conclusion of the paper, authors has said that particle filters approximates the density of the system state by the number of the particles available for the estimation.

Dan Simon [39] Kalman filter is most widely used in the state estimation purpose a sit is very easy to implement so it attract the engineers to use it in the linear system for the state estimation purpose. It is also used for the embedded system and control system. In order to use Kalman filter in to the system, noise from the system should be eliminated. To requirement for the

Kalman filter. First is, average value of the state estimation should be equal to the average value of the actual state value. It means filter should not be biased in any way. Seconds is, state estimate should be varied a little form its actual state. It is not as we want the average value of the state estimation should be equal to the average value of the actual state. For the perfect operation of the Kalman filter, some assumption should be made i.e. average value of process noise and system should be zero. Authors has explained the algorithm for the Kalman Filter.

Jitender Kumar, et al. [40] In this paper, author has explained the state estimation problem solved by the full weighted least square method. Authors have used IEEE 6 and IEEE 9 bus system for the comparison the results. Full weighted least square method is a nonlinear in nature and it is first order equation. Natural approaches for the calculation and state estimation of the system parameters will see PMU as a burden on the system for the measurement purpose. In conventional methods, we have different equations for the calculation of current, voltage and power flowing in the line. In this paper, author tried to correlate the conventional method and full weighted least square method with the PMU for the state estimation and as a result full weighed least method with the PMU is much more efficient than the normal conventional method for the state estimation.

Ranjana Sodhi, et al. [41] normally, state estimations programs run at every 3 to 5 minutes interval in the modern energy management program. But with the new technology state estimations program runs at every 20 to 50 milliseconds**.** PMU installed at the substations, say a few substations, from where measurement can be fetched and further it will be feed to SCADA to improve the state estimation of the measured parameters. Author has used the least square method for the state estimate the system parameters. Here author has used phasor measurement for making initial guess for the weighted least square method based state estimator. Preliminary state estimator has been used to generate initial guess. Including the phasor measurements into the system with the conventional method improved the accuracy of the state estimator.

Piotr Kozierski, et al. [42] In this paper, author has explained state estimation of the power system based on the particle filter. If there is any error in the measured value then they must be one of the following

- The measured value don't change with the time, say it stuck at some point.
- Measured value of the parameter is of opposite sign.
- Measure value of the specific parameter is biased with the constant value.

- The measurement of the parameters always shows reading as 0.

When particle filter is integrated with the anti-zero bias, then it gives good performance then the EKF. If it assumed that some errors are still in the measurement which are small and while detecting bad data from the system it stayed unnoticeable then in such type of cases particle filter has better advantages.

Thomas B. Schon [43] The main idea of the particle filter is based on the approximation of the filtering density function as a weighted set of samples. Particle filters are based on the random numbers where we need to introduce the concept of the importance sampling in the system. In this document, author has explained various sampling method such as importance sampling, perfect sampling, and systematic sampling process. All this sampling are used for the resampling process because while the first sampling degeneracy of the sampling produced in the particles which should be removed and that's the reason resampling process is done again to reduce that degeneracy effect on the particles.

Chapter: 3 Research Methodology

3.1 Background of particle filter

Particle filter started using in the early 1940s for the work with Metropolis. Norbert Wiener intimated that there is something like particle filtering in early 1940 [44]. But from 1980, particle filters started using as a computation solutions. And even now to solve many computational problems particle filters have started been using. Particle filters are known to solve those problems which can't be solved by the conventional Kalman filter. Particle filter is also known by so many other name such as Sequential Importance Sampling, Bootstrap Filter, Interacting Particle approximation, Condensation Algorithm, Sequential Monte Carlo Filter. Particle filter is based on probability. Extended Kalman Filter (EKF) is most widely used filter for the state estimation of the nonlinear system. But there is some problem with the use of this filter and that problem is that it cannot be tuned very well and it does not give the reliable estimate if the nonlinearities of the system are severe [20]. Unscented Kalman Filter (UKF) has significance improvement over the EKF. Though, UKF also gives approximation of the state estimation.

3.2 Bayesian State Estimator

Bayesian State estimator is based on the Bayes' theorem. Nonlinear system can be described by the following equation [16]:

$$x_{k+1} = f_k(x_k, w_k) \tag{3.1}$$

$$y_k = h_k(x_k, v_k) \tag{3.2}$$

Where,

x_k : State to be estimated

k : Time index

w_k: Process noise

v_k : Measurement noise induced due to measuring instruments

y_k : Measurements

At k=1, the first measurement for the state estimation will be measured, so it can be used as the initial condition of the state estimator with the PDF of x_0 and it can be given as:

$$p(x_0) = p\,(x_0|Y_0) \tag{3.3}$$

Where,

Y_0 : the set of no measurement

Consider there are two variables x and y. these variables are independent statically. $p(x, y) = p(y, x)$, is called joint commutative probability, which is based on the Bayes theorem [15].

$$p(x|y)p(y) = p(y|x)p(x) \tag{3.4}$$

$$p(x|y) = \frac{p(y|x)p(x)}{p(y)} \tag{3.5}$$

If y represents the usable measurement in the system state and x represents the current system state, then it can be said that [18]

- $p(x)$ is the PDF of the system state which is independent of the measurements. This function is called prior of x.
- $p(y)$ is the PDF of the system measurement, which is called evidence which is normally derived as the form of normalize factor.
- $p(x|y)$ is PDF of the state of the system with the given ready measurement, which is called posterior of the system.
- $p(y|x)$ is likelihood condition for the system which says the given model is right.

In Bayesian theory for the state estimation, stochastic variable named to those variables which are unknown. The equation given in 3.5 can also be written as:

$$posterior = \frac{(likelihood)(prior)}{evidence}$$

3.3 Particle Filters (PF)

Particle filter is a part of the Bayesian filter. Particle filters were discovered to implement Bayesian filter numerically. It works on the basic principle of the sequential Monte Carlo method which is used to solve the recursive Bayesian problems. In the starting of the state estimation of the system, random particles of number N generated for the initial PDF $p(x_0)$. The particles generated in time steps will be propagated to next time step by using following equation, [16]

$$x_{k,i}^{-} = f_{k-1}(x_{k-1}^{+}, w_{k-1}^{i}) \quad (i = 1, \dots, N) \tag{3.6}$$

Where,

w_{k-1}^{i} : On the base of the known PDF of randomly generated noise vector

These particles can be propagated mainly by using two techniques: Importance sampling and resampling. When the number of particles increases used in the state estimation more accurate result of the estimation can be obtained and posterior density function of the system can be more accurate. But with the increase in number of particles, more complexity will increase with the computation. So, the number of particles are limited up to certain limits [38]. The particle filter algorithm is also applicable for the state estimation where non- Gaussian errors noise is included into the measurement.

After measuring the measurements of the system, relative likelihood of the each particles $x_{k,i}^{-}$ will be computed and pdf for the system $p\left(y_k \middle| x_{k,i}^{-}\right)$ will be evaluated. Suppose for the system measurement equation can be given by the $y_k = h(x_k) + v_k$, $v_k \sim N(0, R)$ then likelihood q_i will be equal to the specific measurement y* and for given x_k is equal to the particle $x_{k,i}^{-}$ and it can be written as:

$$q_i = P\left[(y_k = y^*) | \left(x_k = x_{k,i}^{-}\right)\right]$$

$$= P\left[v_k = y^* - h(x_{k,i}^{-})\right]$$

$$\sim \frac{1}{(2\pi)^{\frac{m}{2}} |R|^{\frac{1}{2}}} \exp\left(\frac{-\left[y^* - h(x_{k,i}^{-})\right]^T R^{-1} \left[y^* - h(x_{k,i}^{-})\right]}{2}\right) \tag{3.7}$$

Normalized relative likelihood for the particle filter can be obtained by the following equation:

$$q_i = \frac{q_i}{\sum_{j=1}^{N} q_j} \tag{3.8}$$

This is to ensure that, the sum of all the likelihood should be one.

3.4 Algorithm for Particle Filter[16]

1) Equation for the system and measurement can be given as below:

$$x_{k+1} = f_k(x_k, w_k)$$

$$y_k = h_k(x_k, v_k)$$

w_k and v_k are independent process white noise with the known PDF of the system.

2) Suppose that the initial state of the system PDF $p(x_0)$ is known. N random particles will be generated on the basis of the PDF. These particles can be denoted by the $x_{0,i}^{+}$ $(i = 1, \ldots, N)$. N is chosen by the user for the accuracy for more accuracy of the state estimation, the value of N should be chosen high. But with the more value of N, complexity in computation will be increased.

3) For k=1, 2, . . . , do the following steps

   a) From the known process equation and from the known PDF of the process noise, execute time propagation step to find a priori particles $x_{k,i}^{-}$.

   $$x_{k,i}^{-} = f_{k-1}\left(x_{k-1}^{+}, w_{k-1}^{i}\right) \qquad (i = 1, \ldots, N)$$

   Where,

w_{k-1}^i is a noise vector which is randomly generated based on the known PDF.

b) Compute the likelihood q_i for the each particle $x_{k,i}^-$ for the measurement y_k.

c) Find the normalization of the likelihood obtained from the previous step, can be written as follows:

$$q_i = \frac{q_i}{\sum_{j=1}^{N} q_j}$$

It will make the sum of the all likelihood to one.

d) It's a resampling step. Here posterior particles $x_{k,i}^+$ on the basis of the likelihood q_i.

3.5 Flow chart for particle filtering

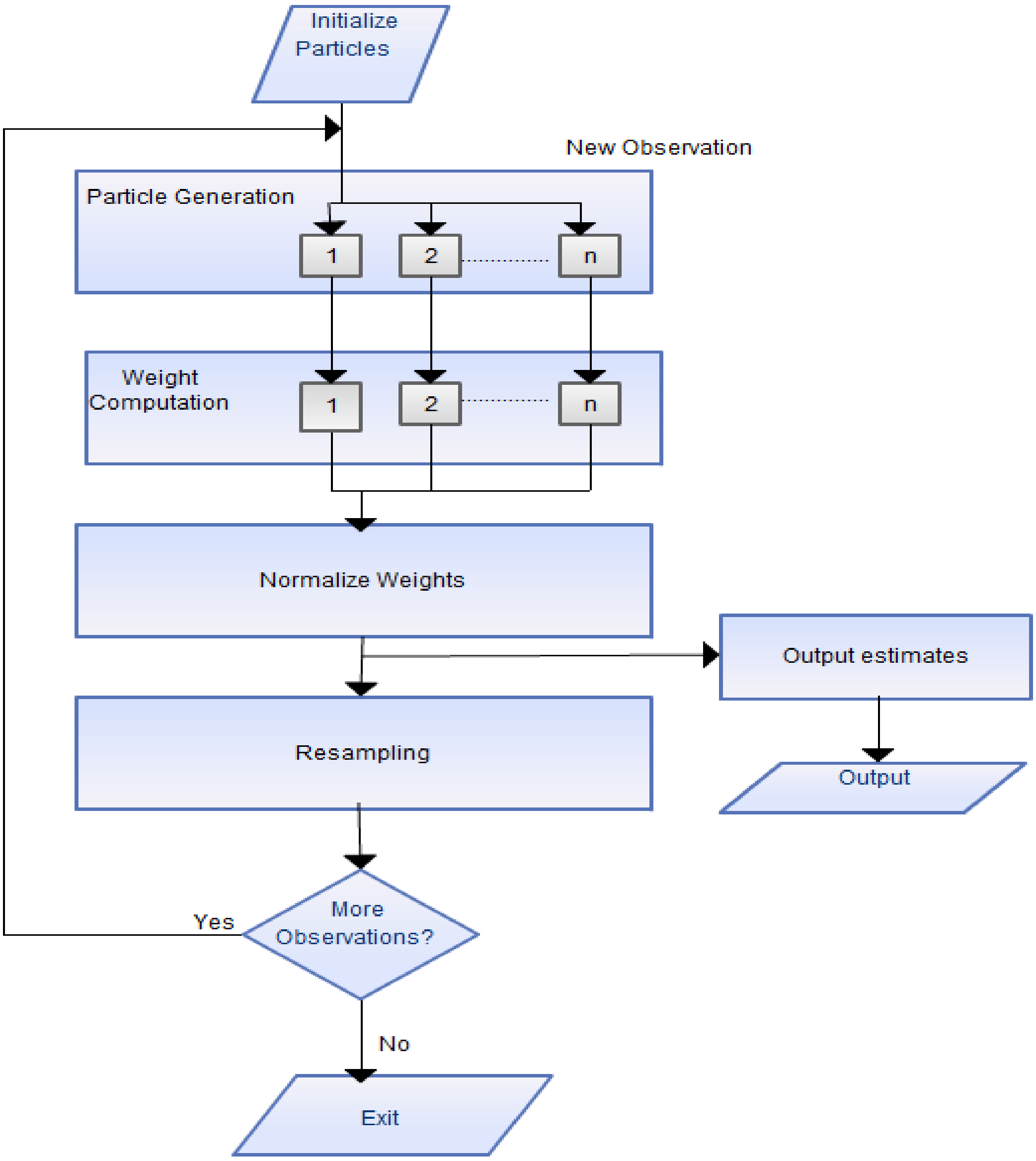

Figure: 3.1 Flow chart of Particle Filter [46]

3.6 Sequential Importance Sampling (SIS)

Property of the distribution by the generating samples from the different distribution can be estimated by using Importance Sampling. Principle of the particle filter can be described as follows: suppose a probability density function is $p(x)$ from which it is hard to draw samples. So here another density function $\pi(x)$ will be considered which is easy to evaluate, on the condition of $p(x) \propto \pi(x)$. The samples of number N are drawn based on another density function $q(x)$. This another density function $q(x)$ is called importance density. This function is used to express the weights of the function in recursive form. The weights associated with the function can be given as [48]:

$$w^i \propto \frac{p(x^i)}{q(x^i)} \tag{3.9}$$

Where,

$q\left(x^i\right)$: PDF at x^i

$$p(x) \approx \sum_{i=1}^{N} w^i \delta\left(x - x^i\right) \tag{3.10}$$

At the each iteration of the system, samples $x_{0:k}^i$ are available and in the next step it will be evaluated. The updated weights are given by,

$$w_k^i \propto \frac{p(x_{0:k}^i|y_{1:k})}{q(x_{0:k}|y_{1:k})} \tag{3.11}$$

$$q(x_{0:k}|y_{1:k}) = q(x_k|x_{0:k-1}, y_{1:k})q(x_{0:k-1}|y_{1:k-1}) \tag{3.12}$$

Posterior density can be calculated as following equation:

$$p(x_{0:k}|y_{1:k}) = \frac{p(y_k|x_{0:k}, y_{1:k-1})p(x_{0:k}|y_{1:k-1})}{p(y_k|y_{1:k-1})} \tag{3.13}$$

$$= \frac{p(y_k|x_k)p(x_k|x_{k-1})}{p(y_k|y_{1:k-1})} \times p(x_{0:k-1}|y_{1:k-1}) \tag{3.14}$$

$$\propto p(y_k|x_k)p(x_k|x_{k-1})p(x_{0:k-1}|y_{1:k-1}) \tag{3.15}$$

Weight can be updated by below equation:

$$w_k^i \propto \frac{p\left(y_k\middle|x_i^k\right)p(x_k^i|x_{k-1}^i)p(x_{0:k-1}^i|y_{1:k-1})}{q\left(x_k^i\middle|x_{0:k-1}^i, y_{1:k}\right)q(x_{0:k-1})^i|y_{1:k-1})} \tag{3.16}$$

$$= w_{k-1}^i \frac{p\left(y_k\middle|x_k^i\right)p(x_k^i|x_{k-1}^i)}{q(x_k^i|x_{0:k-1}^i, y_{1:k})} \tag{3.17}$$

One assumption to be while calculating the weights of the particles. This assumption is as below:

$$q(x_k|x_{0:k-1}, y_{1:k}) = q(x_k|x_{k-1}, y_k) \tag{3.18}$$

So the weights of the particle will be:

$$w_i \propto w_{k-1}^i \frac{p(y_k|x_k^i)p(x_k^i|x_{k-1}^i)}{q(x_k^i|x_{k-1}^i, y_k)} \tag{3.19}$$

The chosen importance density plays an important role in obtaining best results from the particle filter. The importance density should be chosen in such a way that it could minimize the noise variance. Algorithm for the sequential Importance Sampling is explained in below [14].

Table: 3.1 Algorithm for the Sequential Importance Sampling [14]

1. Initialization	Suppose there are N random samples in the system $\{\boldsymbol{x_{k-1}^i} : \boldsymbol{i-1}, \ldots, \boldsymbol{N}\}$ Here below equation can be written on the basis of the conditional probability density function: $\boldsymbol{p(x_{k-1}\|y_{1:k-1})}$
2. Prediction	Propagate N values $\{v_{k-1}^i : i = 1, \ldots, N\}$ from the process noise density function v_{k-1}, new generated sample points will be $\{x_{k\|k-1}^i : i = 1, \ldots, N\}$ using $x_{k\|k-1}^i = f(x_{k-1}^i, v_{k-1}^i)$
3. Update	With the measurement y_k allot each weight of the function $x_{k\|k-1}^i$. Equation for the weight calculation is as below: $w_k^i = \frac{p(y_k\|x_{k\|k-1}^i)}{\sum_{t=1}^N p(y_k\|x_{k\|k-1}^i)}$ The posterior density function can be given as follows: $p(x_k\|y_k) = \sum_{i=1}^N w_k^i \, \delta(x_k\|x_{k\|k-1}^i)$

Problem arises while implementing the sequential importance sampling for the state estimation which is explained in below section.

3.7 Degeneracy in Importance Sampling Process

The main problem arises while implementing sequential importance sampling in the particle filter is the degeneracy problem. Degeneracy problem is where few of the particles have significant weight and rest of the particles have very small weights. Because of this, with the time, state estimation of the probability distribution becomes very poor and updated solution of the particles becomes trivial. The degeneracy has relation with the variance and it is measured with the effective sample size N_{eff} [49].

$$N_{eff} = \frac{N}{1+V_{ar}(w_k^i)} \quad (3.20)$$

Degeneracy in the particles can be measured very well by estimating the effective sample size.

$$N_{eff} = \frac{1}{\sum_{i=1}^{N}(w_k^i)^2} \quad (3.21)$$

Where,

w_k^i : Weight of the sample

A severe degeneracy occurs when the N_{eff} will be less than N. This problem can be solved by using goof importance density and resampling process.

3.7.1 Choice of better Importance density

Importance density of the particles should be chosen in that manner where the variance of the particles are minimized, it will reduce the degeneracy problem. When importance density and transition density becomes equal at that time variance becomes zero.

$$q\left(x_k \middle| x_{0:k-1}^i, z_{0:k}\right) = p\left(x_k \middle| x_{k-1}^i, y_k\right) \quad (3.22)$$

$$w_k^i \propto w_{k-1}^i p(y_k|x_k^i) \quad (3.23)$$

3.7.2 Resampling

One of the best way to reduce the degeneracy is to resample the signal. In the process of the resampling, a new set of the particles drawn from the discrete approximation provided by the weighted particles as follows [49]:

$$p(x_k|z_{1:k}) \approx \sum_{i=1}^{N} w_k^i \delta_{x_k^i} \quad (3.24)$$

When effective sample size N_{eff} reduced then some value of the threshold then resampling process will be applicable in the system. Resampling method is carried out with the replacement of the particles. So, in this method, particles whose weights are large it will be drawn to be multiple times and particles whose weights are small, those particles will not be going to be drawn at all. Here one thing should be noted down that the weights of the all new particles will be equal to 1/ N. Thus, here it can be said that, the resampling process can easily rid of problem of degeneracy. But this process will introduce a new problem which is called as Sample Impoverishment. This problem is introduced in the system because diversity of the particles are going to be decreased after the resampling process and this is due to large weights particles are going to be drawn multiple time and particles with the small weights are not going to be drawn at all [27].

This create a negative impact on the system. Whenever sample impoverishment and degeneracy introduces in the system due to sampling process at that time this can be reduced by using resampling process. The main work area of the resampling process is to wipe out the particles whose weights are small and it will choose the particles with the higher weights. The main function of the resampling step is to generate new samples by sampling multiple time say at every iteration. There are number of methods for the resampling and one of them is explained below.

3.8 Sequential Importance Resampling Algorithm (SIR)

The Sequential Importance Resampling Algorithm (SIR) is different than the Sequential Importance Sampling Algorithm (SIS). SIR algorithm is first time introduce by the reference [47]. Resampling shows practical and theoretical benefits [50].

Sequential Importance Resampling algorithm is a one of the version of the Sequential Importance Sampling where proposal distribution $q\left(x_k \middle| x_{k-1}^i, z_k\right)$ is taken as a state transition $p(x_k|x_{k-1}^i)$ and the resampling process will be applied to each and every iteration. So, particles' update equation is reduced as follows [47]:

$$x_k^i \sim p(x_k|x_{k-1}^i) \tag{3.25}$$

$$w_k^i \propto p(z_k|x_k^i) \tag{3.26}$$

The particles will be updated at each step of the iteration of the resampling step. It should be noted that the term w_{k-1}^i will be removed in the equation 3.26 used for the weight update. It is because, after resampling at time k-1, the all weights at w_{k-1}^iwill become equal to 1/N.

Advantage of the sequential importance resampling is that it is very easy to implement. It resamples at every iterations so samples impoverishment will be reduces. Though this algorithm has some disadvantages too. It mentioned as follows: Here state of the particles will be updated directly without taking account consideration of the observation information.

3.8.1 Algorithm of the Sequential Importance Resampling (SIR)

Table: 3.2 Algorithm for the Sequential Importance Resampling [27]

Initialize:	At time t=0
1.	For i=1, . . . ,N (I) Sample $x_0^{(i)} \sim p(x_0)$ (II) Assign weights $\tilde{w}_0^{(i)} = p(y_0 \| x_0^{(i)})$
2.	For i= 1, . . . , N (I) Weight normalization $w_0^{(i)} = \frac{\tilde{w}_0^{(i)}}{\sum_{j=1}^{N} \tilde{w}_0^{(j)}}$
Iterate:	For t in 1 to T
1.	For i=1, . . ., N (I) Resample the term $\left\{x_{t-1}^{(t)}\right\}$ by the resampling from $\left\{x_{t-1}^{(t)}\right\}_{t=1}^{N}$ with probabilities $\left\{w_{t-1}^{(t)}\right\}_{t=1}^{N}$ (II) Set $\left\{x_{t-1}^{(t)}, w_{t-1}^{(i)}\right\}_{t=1}^{N} \leftarrow \left\{\tilde{x}_{t-1}^{(t)}, \frac{1}{N}\right\}_{t=1}^{N}$ (III) Weight propagation $\tilde{w}_t^{(i)} = \frac{p(y_t \| x_t^{(i)}) p(x_t^{(i)})}{\pi(x_t^{(i)} \| x_{0:t-1}^{(i)}, y_{0:t})}$
2.	For i= 1, . . ., N (I) Weight normalization $w_t^{(i)} = \frac{\tilde{w}_t^{(i)}}{\sum_{j=1}^{N} \tilde{w}_t^{(i)}}$

3.9 Expected Outcome

State estimation in the power system is the most important part of the system to control and monitor the system for the future faults, load demand, future state of the system etc. Power system id highly nonlinear in terms to estimate it. So it is impossible to estimate it with the conventional methods like weighted least square method, likelihood algorithm etc. as they are better with the linear system. After completion of the thesis, state estimation of the highly nonlinear system can be done. Future state of the system can be known by using the particle filter algorithm as it works nicely with the nonlinear system very well. Measurements taken from the PMU and it will be further send to the state estimators where particle filter algorithm will be used for the estimation of the state of the system.

CHAPTER 4: EXTENDED KALMAN FILTER

4.1 Introduction

Linear filters are used to estimate the liner system and almost all the systems are nonlinear in this world. So as the result linear filter will not work nonlinear system. So ultimately to estimate the nonlinear system, approach.h should be nonlinear state estimators. When all the parameters are propagated for probability distribution, the optimal solution of the nonlinear system can be achieved. But problem arises when system is nonlinear, finite number of parameters are not sufficient to explain the PDF. State and measurement equation can be given by below equation for nonlinear system:

$$x_k = f(x_{k-1}) + w_{k-1}(k) \tag{4.1}$$

$$y_k = h(x_k) + v_k \tag{4.2}$$

Where,

f and h: state function and measurement function

ω and v: state and measurement noise

This noises are assumed to be based on Gaussian distribution. Initial mean and covariance for the filter which is estimated would be x_0 and P_0.

4.2 Extended Kalman Filter

To estimate the nonlinear system, Extended Kalman Filter (EKF) has been used. EKF is nonlinear type of the Kalman Filter. Extended Kalman Filter is nothing but the linearization of the nonlinear system. Linearization of the nonlinear system is around the former state starting with the initial estimation. Linearization procedure is going to be done while deriving the filter equation and it can be done by using the new reference state trajectory which uses Taylor series expansion. When the measurement models and state must be different then only Jacobian can be obtained which has first order partial derivative.

Kalman filter holds the same values for the prediction and update steps. However, in the predict phase, Jacobian is evaluated at each and every iteration. These states are used to linearize the nonlinear equation of the system PDF (Probability Density Function) in the Kalman Filter.

4.2.1 Prediction

The prediction phases are measured at best estimate $\hat{x}_{k-1}$ as in the case of the Kalman Filter. Considering a linear Taylor approximation of f at the point $\hat{x}_{k-1}$ and that of h at the point $\hat{x}_k^-$ and ignoring the higher order terms before the first derivative,

$$F_{k-1} = \frac{\partial f}{\partial x}\bigg|_{\hat{x}_{k-1}} \tag{4.3}$$

$$H_k = \frac{\partial h}{\partial x}\bigg|_{\hat{x}_k} \tag{4.4}$$

Where,

F_{k-1} and H_k : Jacobian Matrix

These Jacobian matrices are useful for the Kalman Filter equation.

$$\hat{x}_k^- = f(\hat{x}_{k-1}) \tag{4.5}$$

$$P_k^- = F_{k-1}P_{k-1}F_{k-1}^T + Q_{k-1} \tag{4.6}$$

4.2.2 Update the Prediction

Updation of the state in the Extended Kalman Filter is same as the Kalman Filter Technique. Kalman gain is calculated from the predicted measurement noise covariance and covariance. The equation used for the updation of the state for the new states can be given by the following:

$$\hat{x}_k = \hat{x}_k^- + K_k(\hat{y}_k - H\hat{x}_k^-) \tag{4.7}$$

$$P_k = (I - K_kH)P_k^- \tag{4.8}$$

The gain of the Kalman Filter ca be given by,

$$K_k = P_k^-H^T(HP_k^-H^T + R)^{-1} \tag{4.11}$$

The last term $(HP_k^-H^T + R)$ is dedicated to the innovation or the covariance of the residual.

4.2.3 Algorithm of the Extended Kalman Filter [53]

Table 4.1: Algorithm of the Extended Kalman Filter

1	The equation for the system are given by below equation. This equation shows the trajectory of nominal system.

	$\dot{\boldsymbol{x}} = \boldsymbol{f}(\boldsymbol{x}, \boldsymbol{u}, \boldsymbol{w}, \boldsymbol{t})$ $\boldsymbol{y} = \boldsymbol{h}(\boldsymbol{x}, \boldsymbol{v}, \boldsymbol{t})$ $\boldsymbol{v} \sim (\boldsymbol{0}, \boldsymbol{R})$ $\boldsymbol{w} \sim (\boldsymbol{0}, \boldsymbol{Q})$ Where, $\boldsymbol{u}(\boldsymbol{t})$: process noise $\boldsymbol{v}(\boldsymbol{t})$: measurement noise This nominal trajectory is given by the following equation which is ahead of the time, $\dot{\boldsymbol{x}}_{\boldsymbol{0}} = \boldsymbol{f}(\boldsymbol{x}_{\boldsymbol{0}}, \boldsymbol{u}_{\boldsymbol{0}}, \boldsymbol{0}, \boldsymbol{t})$ $\boldsymbol{y}_{\boldsymbol{0}} = \boldsymbol{h}(\boldsymbol{x}_{\boldsymbol{0}}, \boldsymbol{0}, \boldsymbol{t})$
2	To evaluate nominal trajectory values, compute partial derivatives as following: $C = \left.\frac{\partial h}{\partial x}\right\vert_{\hat{x}}$ $L = \left.\frac{\partial f}{\partial w}\right\vert_{\hat{x}}$ $M = \left.\frac{\partial h}{\partial v}\right\vert_{\hat{x}}$ $A = \left.\frac{\partial f}{\partial x}\right\vert_{\hat{x}}$
3	Compute the following matrix, $\tilde{R} = MRM^T$ $\tilde{Q} = LQL^T$
4	Difference between the true value of the variable and nominal measurement of the variable, so need to define Δy, $\Delta y = y - y_0$
5	Following equation of the Kalman Filter should be executed $\Delta\hat{x}(0) = E[x(0)]$ $\hat{x} = f(\hat{x}, u, w_0, t) + K[y - h(\hat{x}, v_0, t)]$ $P(0) = E\left[\big(x(0) - \hat{x}(0)\big)\big(x(0) - \hat{x}(0)\big)^T\right]$ $K = PC^T\tilde{R}^{-1}$ $\dot{P} = AP + PA^T + \tilde{Q} - PC^T\tilde{R}^{-1}CP$
6	Estimation of the state can be given as follows:

$$\hat{x} = x_0 + \Delta\hat{x}$$

4.2.4 Advantages and Disadvantages

The EKF cannot be applied to the system where modelling of the system processes are not done accurately. When system processes are not modelled accurately then performance of the filter is affected, it diverges and lead to suboptimal performance of the system. When the nonlinearity of the system model is high then problem arises while calculating the posterior mean and covariance of the system. The performance related issues and more disadvantages of the EKF has been explained in the reference [52]

CHAPTER 5: RESULTS & DISCUSSION

Here for the state estimation of the system, data is used for the 5 Bus practical system. The data is taken from the [51]. This data measurement is for one hour and in this data in one second PMU has measured data from the all buses 30 times.

Here, state estimation using particle filter has been done using the MATLAB. And data from the reference [51] has been load to the MATLAB. Here we have used only bus 1 voltage data for the state estimation of the system.

In next step, we assumed if measured data is linear so we have added some Gaussian error into it and after adding Gaussian error into the measured data from the PMU we get some voltage waveforms which has error in measurement. The graph obtained by using the MATLAB coding is shown in below figure 5.1.

From the below figure, it can be said that after adding the Gaussian errors into the measurement the waveforms of the voltage for the bus 1 is totally different than the voltage of bus 1 before adding the Gaussian error.

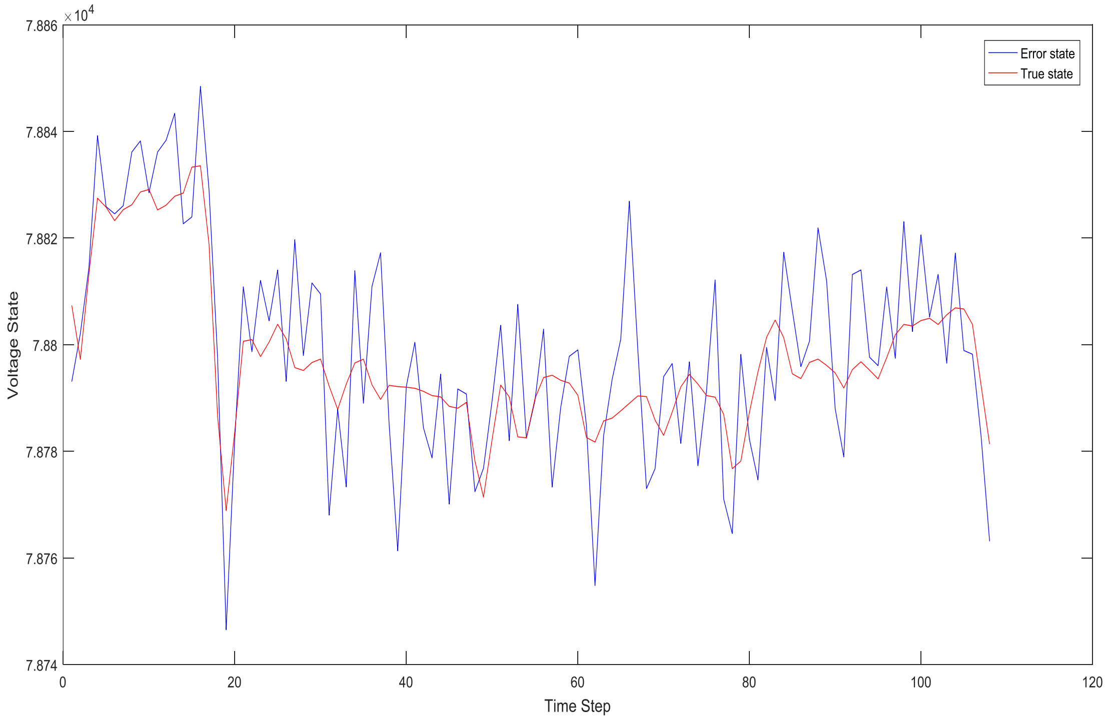

Figure: 5.1 Voltage waveforms for Bus-1, before and after adding Gaussian Errors.

Here we have tried to compare particle filter state estimation technique with the Extended Kalman Filter Technique. As we have discussed in the chapter 4, Extended Kalman Filter is also used for the non-liner system. But when the non-linearity of the system is too high it starts deviating from its true estimation state and gives more error. This can be identified by the plotting between True state of the voltage at bus 1 and estimated state of the voltage at bus 1 by using extended Kalman filter. This is shown in figure 5.2.

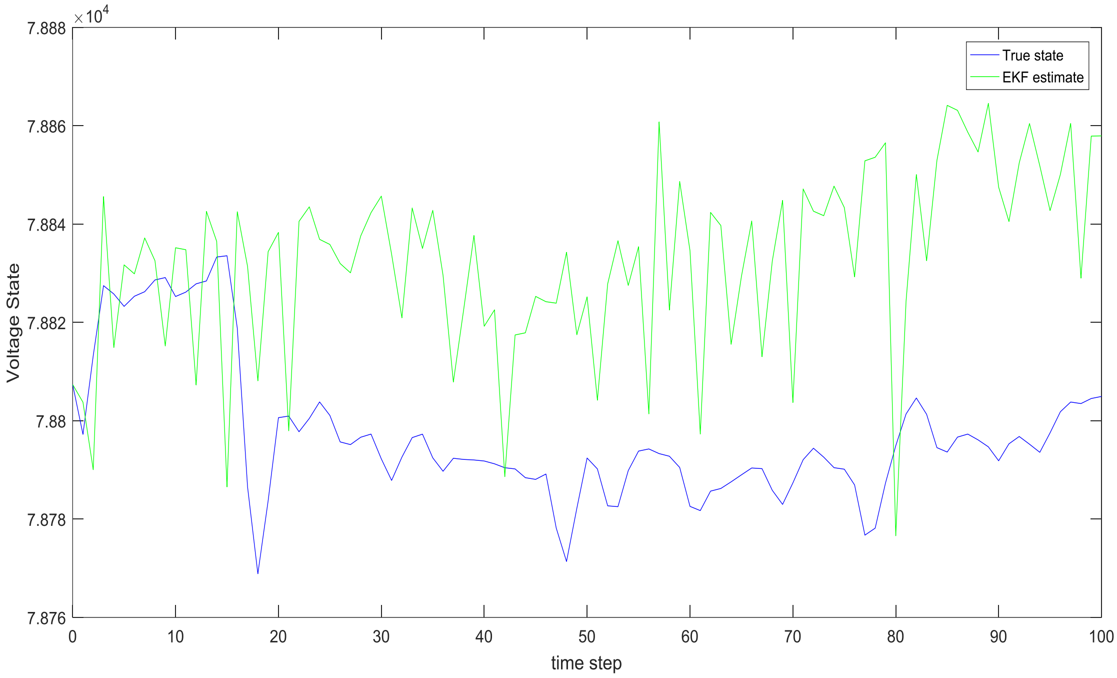

Figure 5.2: Voltage estimation at bus 1, plotting between True State and Extended Kalman State

In the next step, particle filters are initialized and then perform the sampling process. But as discussed earlier in the previous chapter, because of the degeneracy and impoverishment of the samples, resampling of the particles must be done. Here, Sequential Importance Resampling process has been used for the resampling of the particles. Here, 200 random particles has been generated for the state estimation purpose of the system. After the whole process of the particle filter, when plots of the voltage estimation has been done, the graphs obtained is as shown in the Figure 5.2. Here for the plotting purpose, we have used first hundred measured value and we have estimated it. Because in reference [51] is hourly data and there are more than one lac measured value for the voltage. For the plotting purpose, it will be hard to check whether, proper and exact results are obtained for the state estimation of the system from the particles filter or not. So for the simplification and better understanding only hundred measured and estimated value has been plotted.

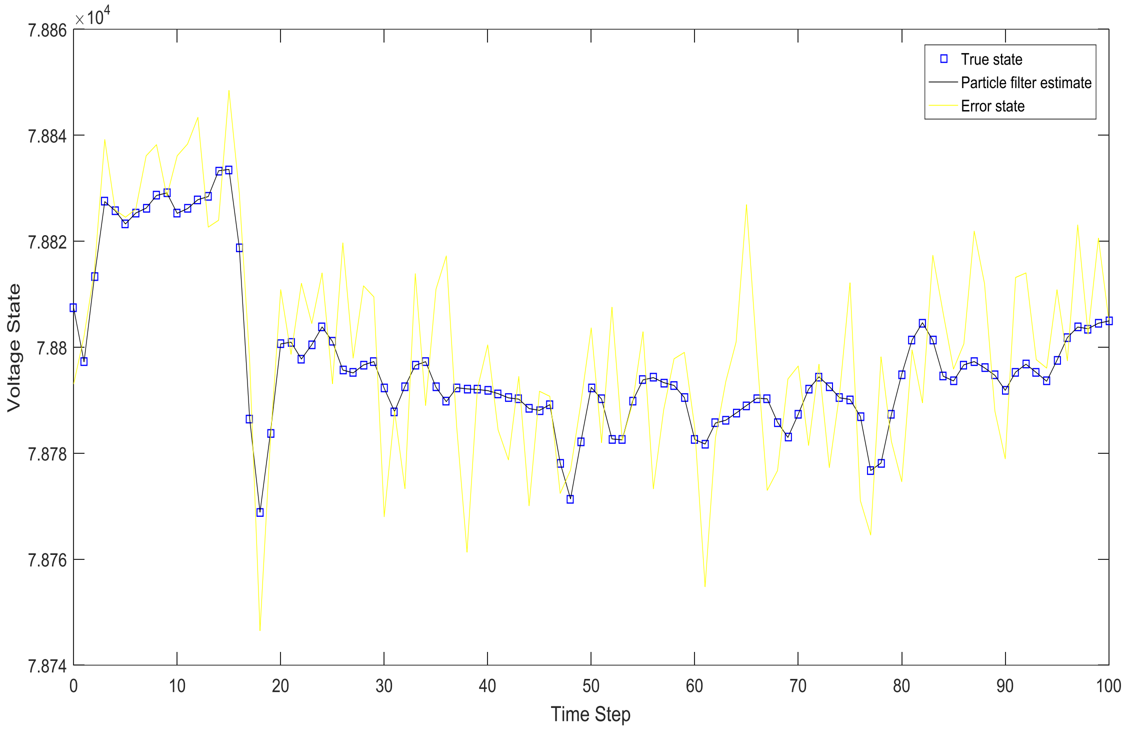

Figure: 5.3 Estimated voltage graphs with using particle filter for Bus-1

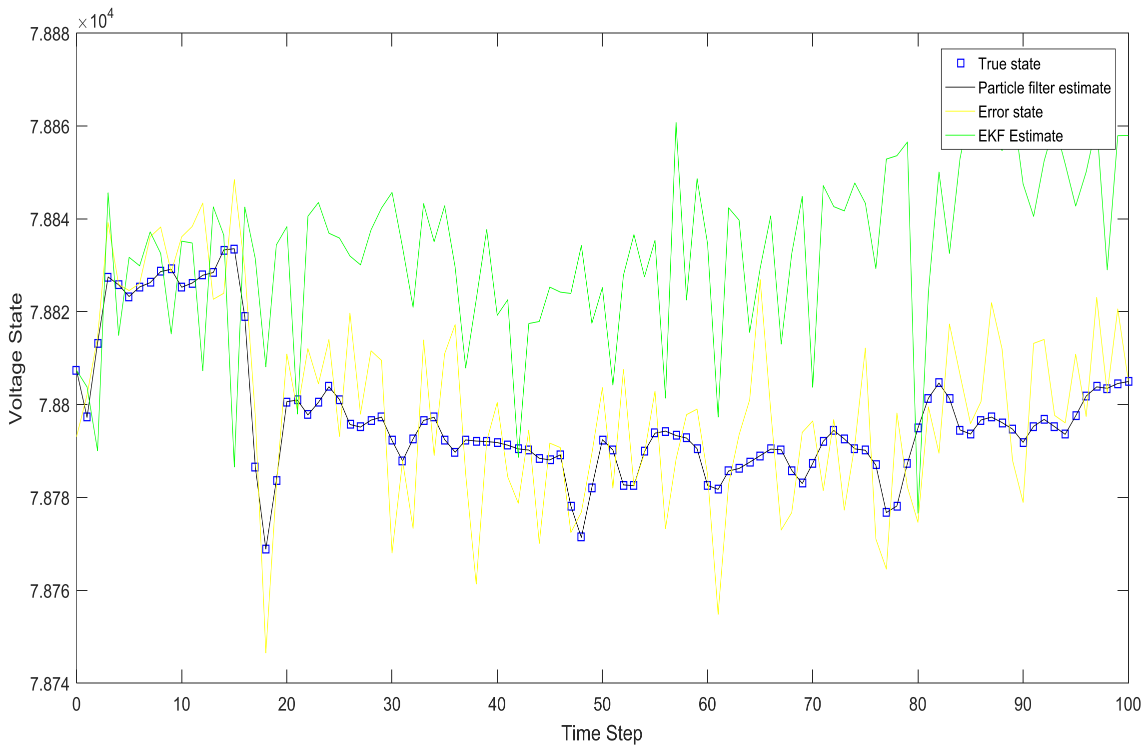

Figure 5.4: Comparative plotting of the voltage at bus 1, Plotting among true state, error state, EKF state and Particle filter state

In figure 5.4, we have compared the estimated data with the error state, true state, EKF estimation state and particle filter state. As we know that extended Kalman Filter is not that much effective when non-linearity of the system is much high. So we have moved to the particle filter for the much exact state estimation of the variables and to reduce the error between estimated state and true state.

From the figure 5.5, it can be conclude that by using particle filter and Extended Kalman Filter for the state estimation, the estimated and true value are plotted. Form the figure we can say that, estimated values are almost similar to the true values even after adding Gaussian errors for particle filter but for the Extended Kalman Filter difference for the true state and estimated state is more. It looks like the estimated values are exact to true state value for the particle filtering estimation technique. But we are getting some RMS error at the end of the estimation which shows there is mismatch somewhere with the true value and estimated value. But by using particle filter, we almost got same estimated and true values, which shows it gives better results for the state estimation for the nonlinear system. But in case of the Extended Kalman Filter has not enough tendency to overcome high non-linearity and give more improved version of the estimation which has least error between true state and estimated state.

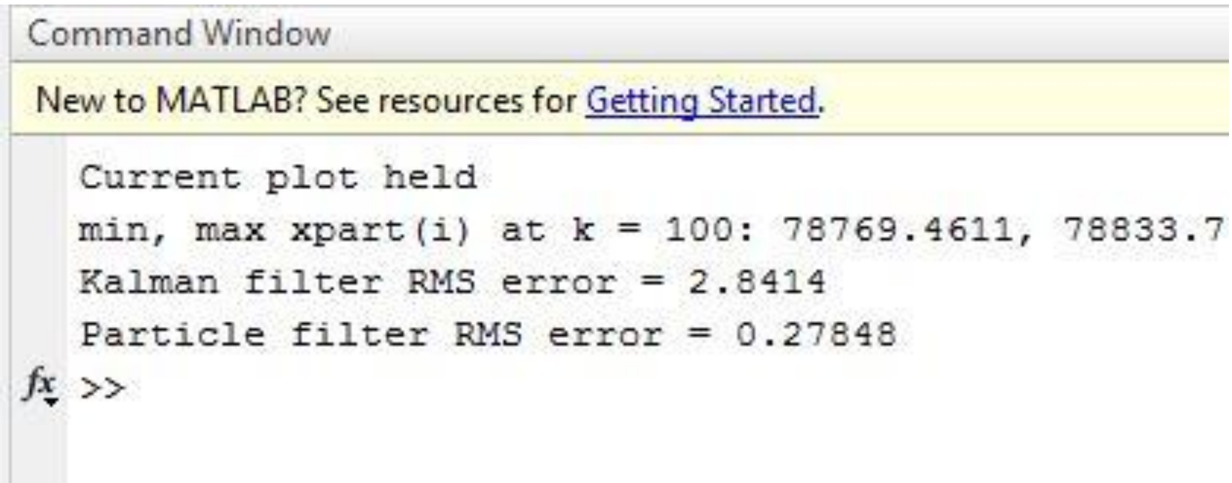

Figure: 5.5 RMS error between true state and estimated state for Bus-1

From the figure 5.5, it can be said that RMS error for the particle filter is 0.27848 and for Extended Kalman Filter RMS error is 2.8414. This error is completely based on the random number. Because by using the random numbers particles are generated. So these error may have some minor variation every time when we run programme.

STATE ESTIMATION FOR BUS 2

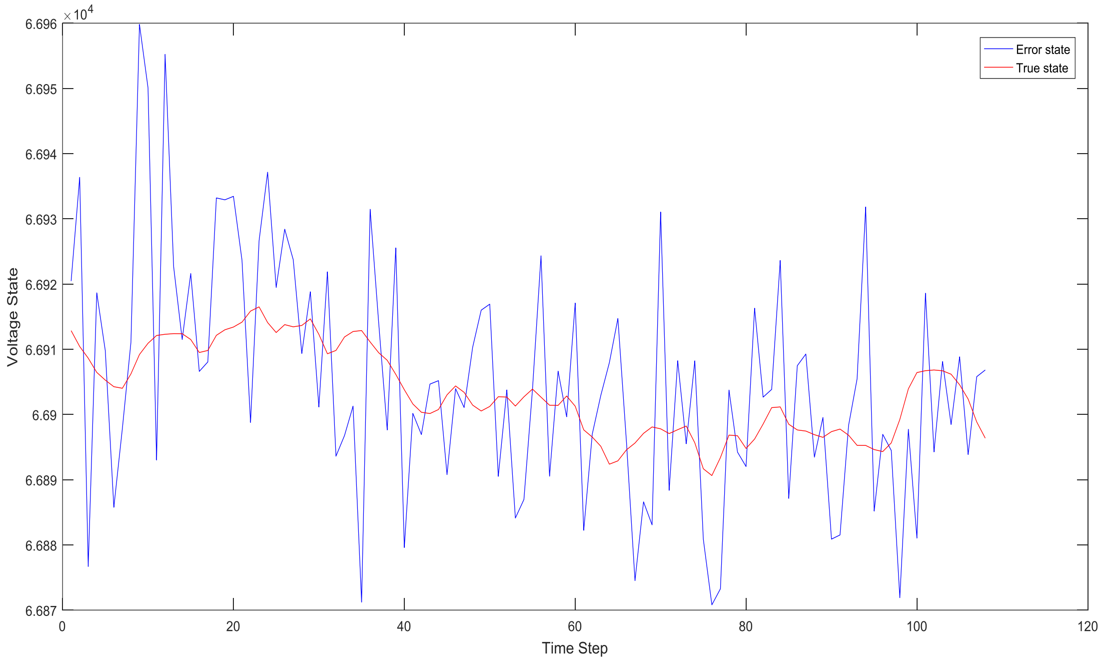

Figure 5.6: Voltage waveforms for Bus 2, before and after adding Gaussian Errors

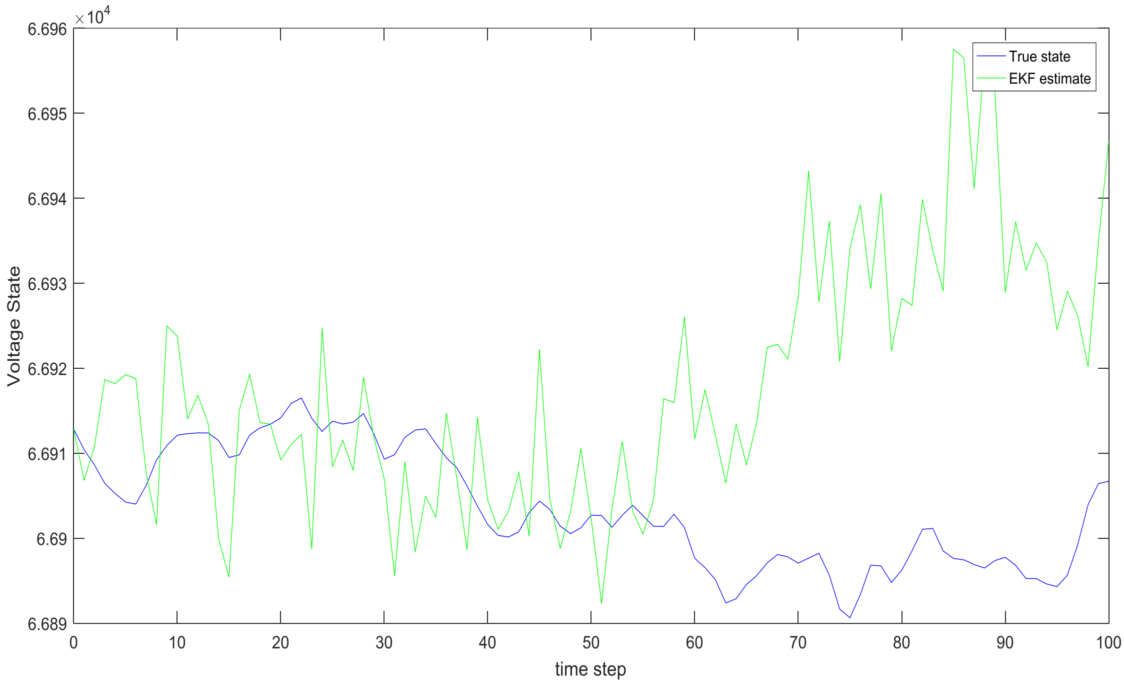

Figure 5.7: Voltage estimation at bus 2, plotting between True State and Extended Kalman State

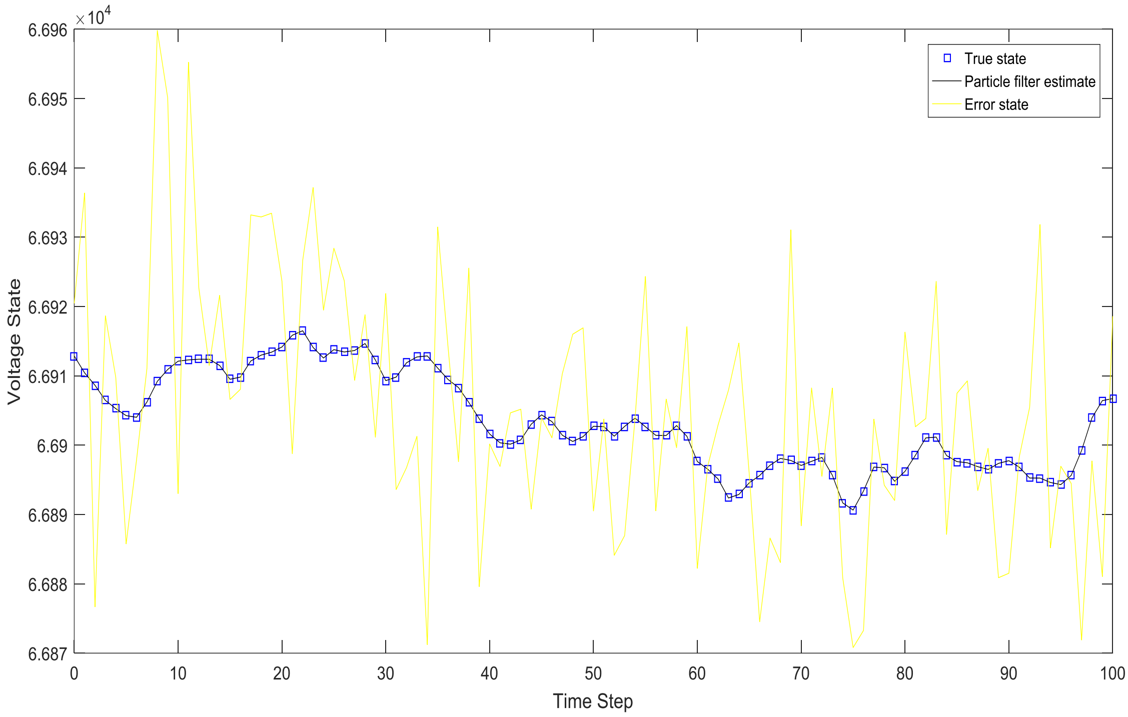

Figure: 5.8 Estimated voltage graphs with using particle filter for Bus-2

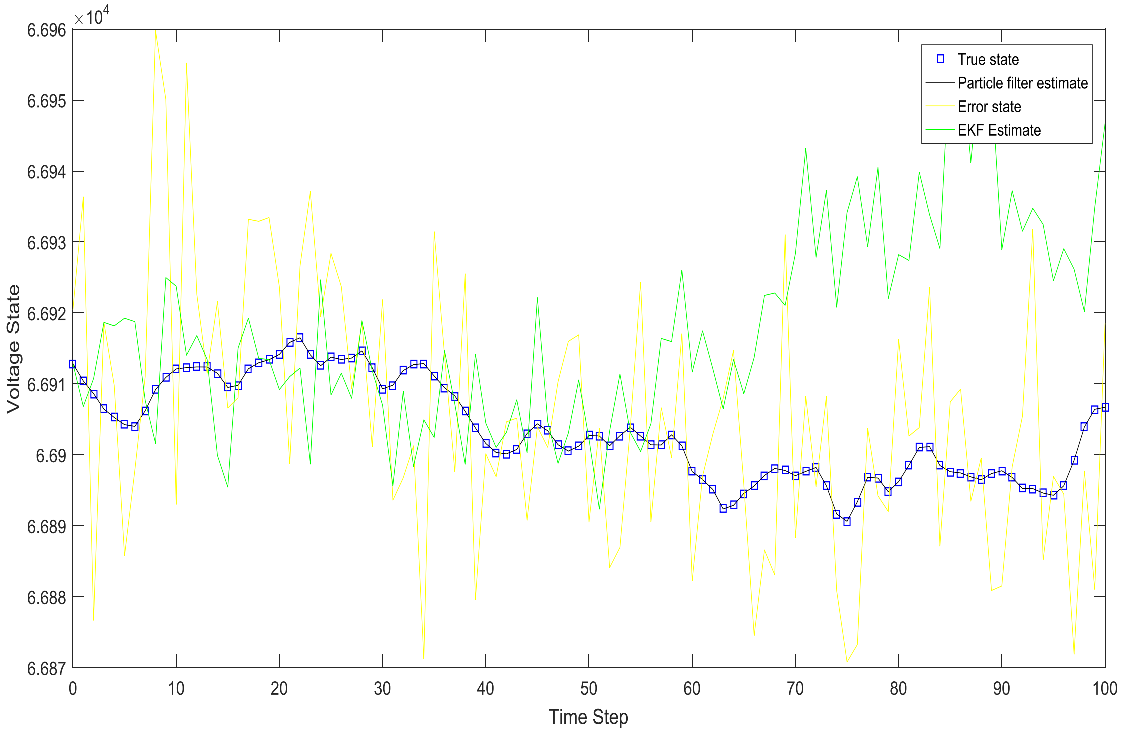

Figure 5.9: Comparative plotting of the voltage at bus 2, Plotting among true state, error state, EKF state and Particle filter state

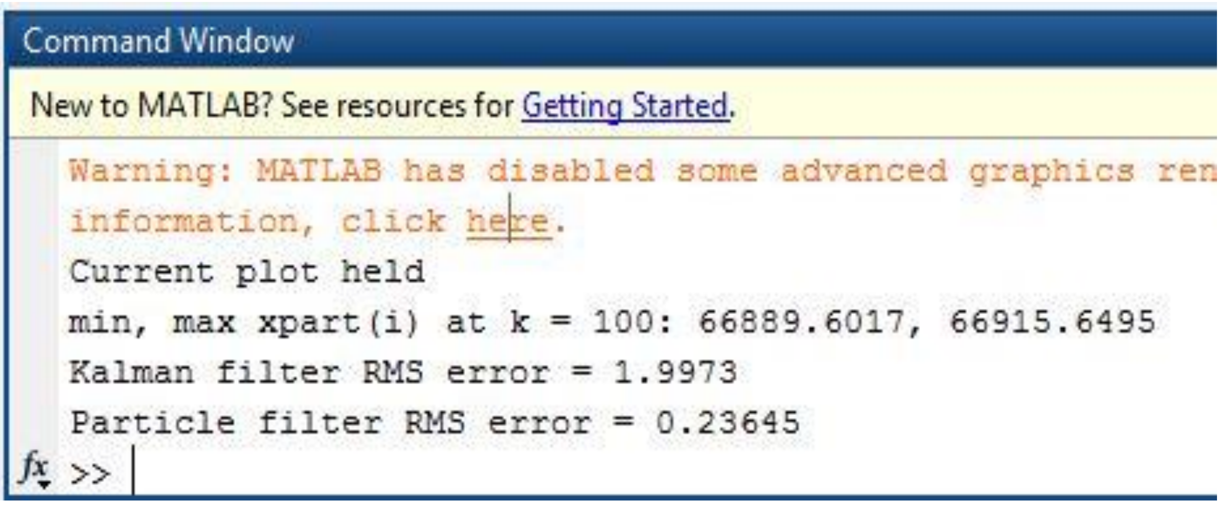

Figure: 5.10 RMS error between true state and estimated state for Bus-2

STATE ESTIMATION OF THE BUS-3

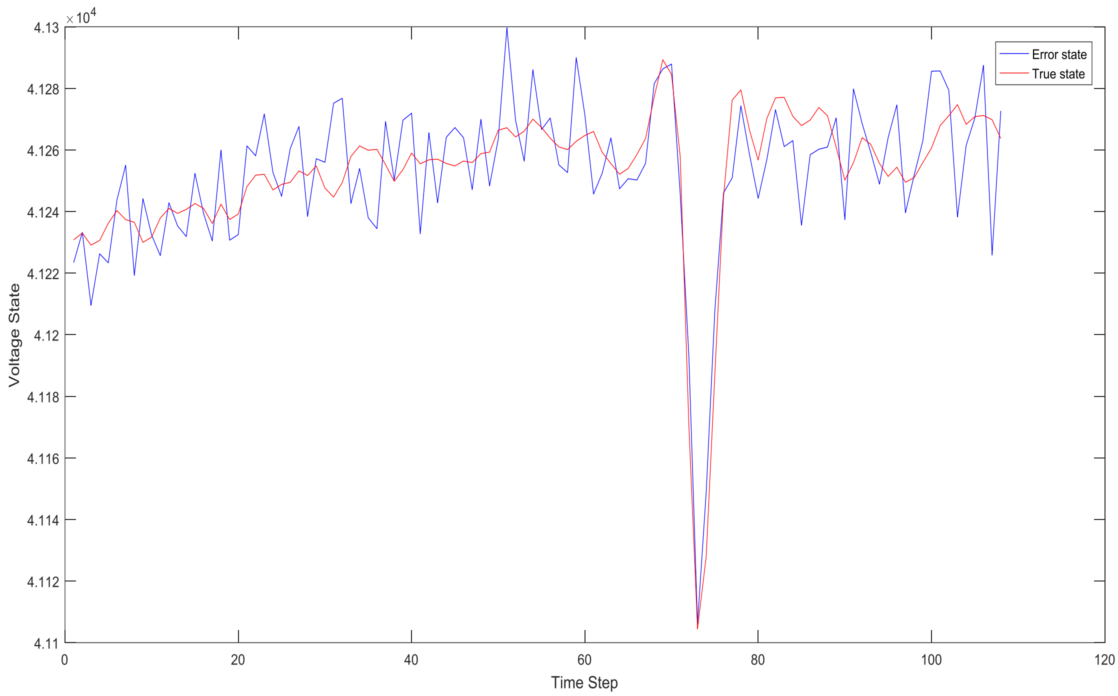

Figure 5.11: Voltage waveforms for Bus 3, before and after adding Gaussian Errors

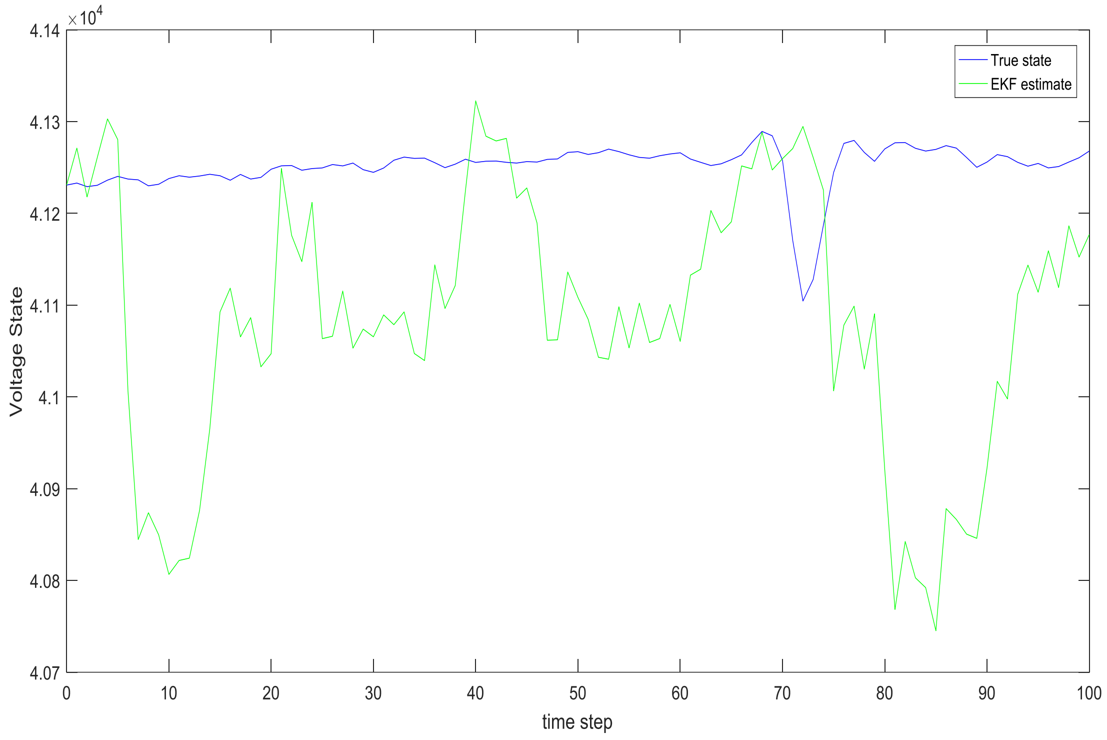

Figure 5.12: Voltage estimation at bus 3, plotting between True State and Extended Kalman State

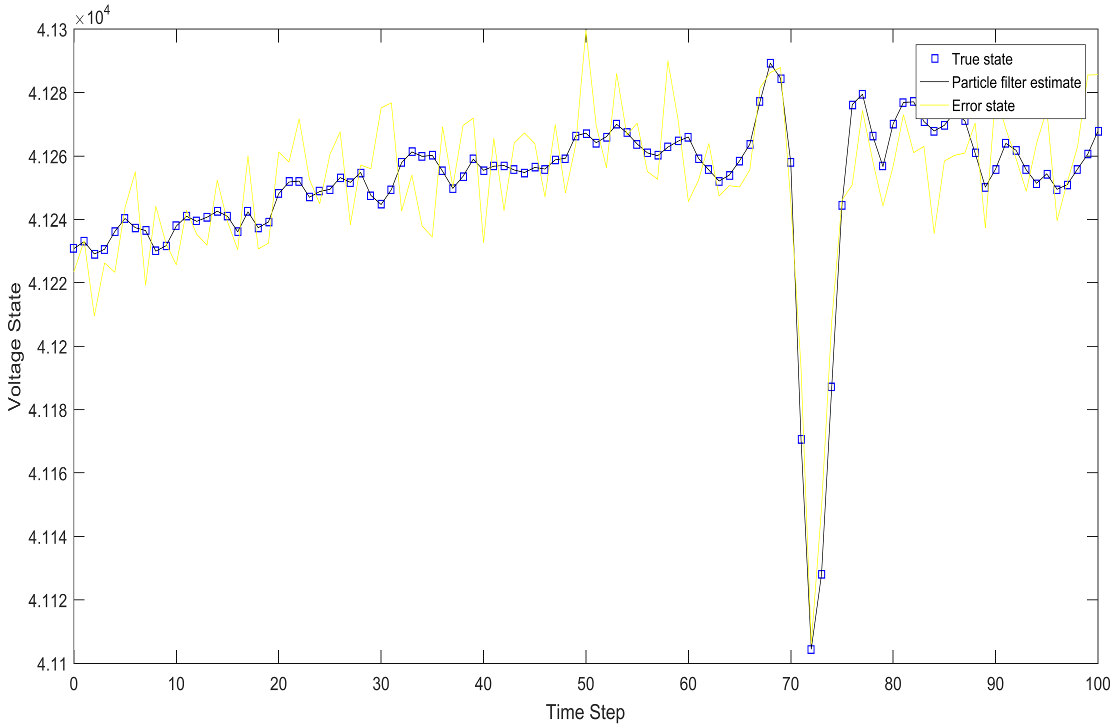

Figure 5.13: Comparative plotting of the voltage at bus 3, Plotting among true state, error state and Particle filter state

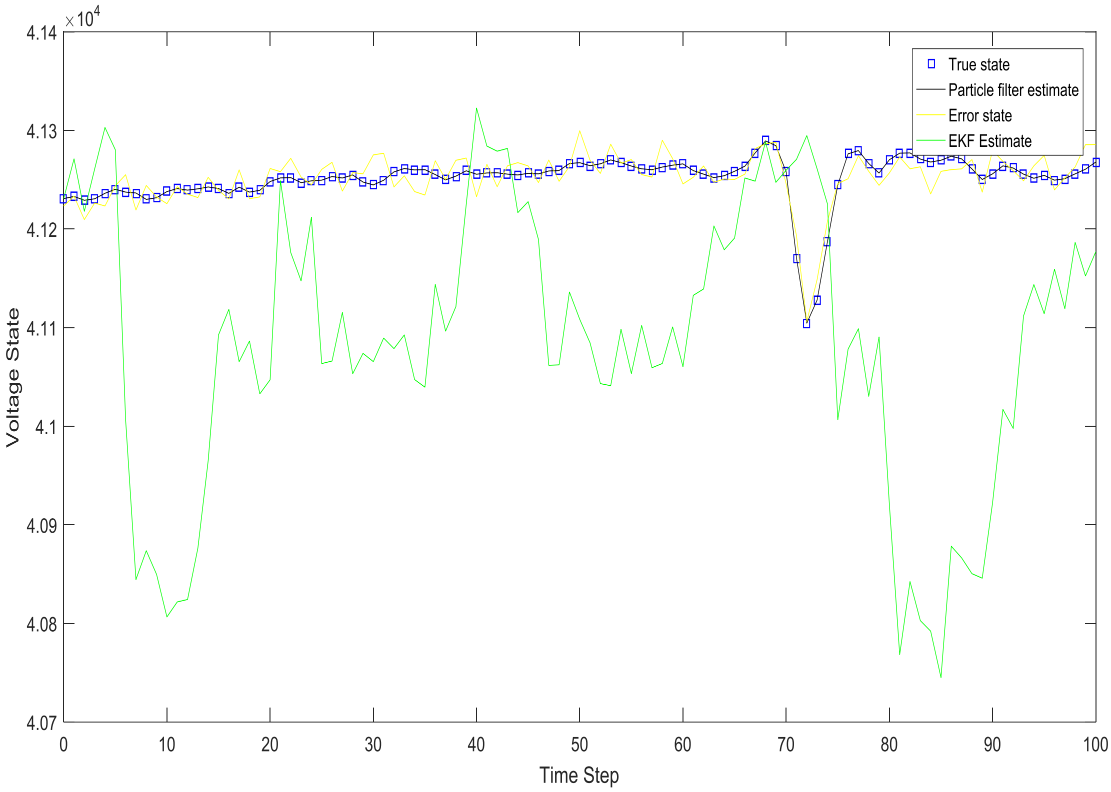

Figure 5.14: Comparative plotting of the voltage at bus 3, Plotting among true state, error state, EKF state and Particle filter state

-

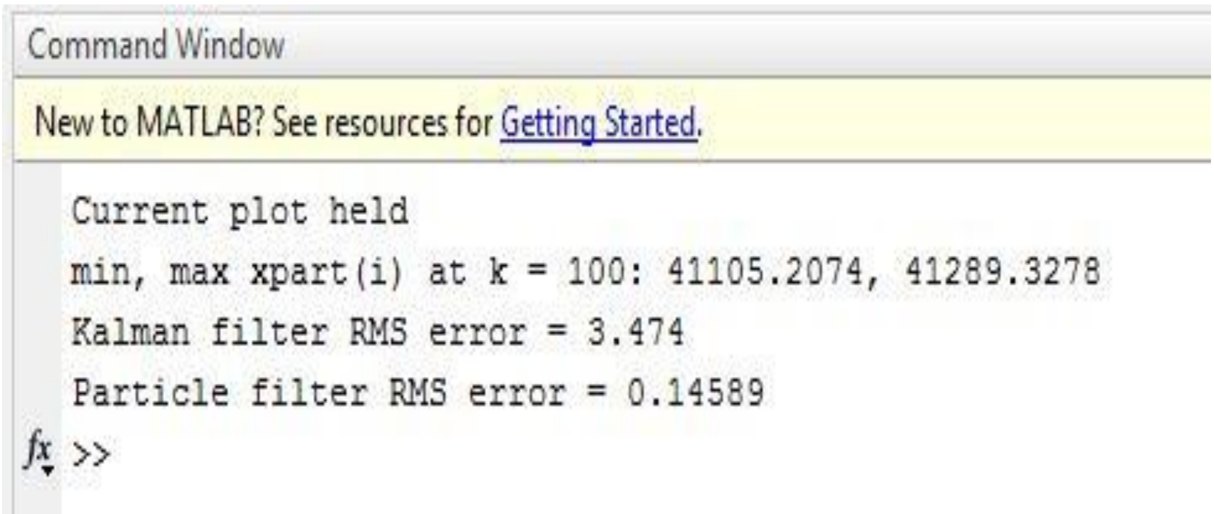

Figure 5.15: RMS error between true state and estimated state for Bus-3

STATE ESTIMATION FOR THE BUS 4

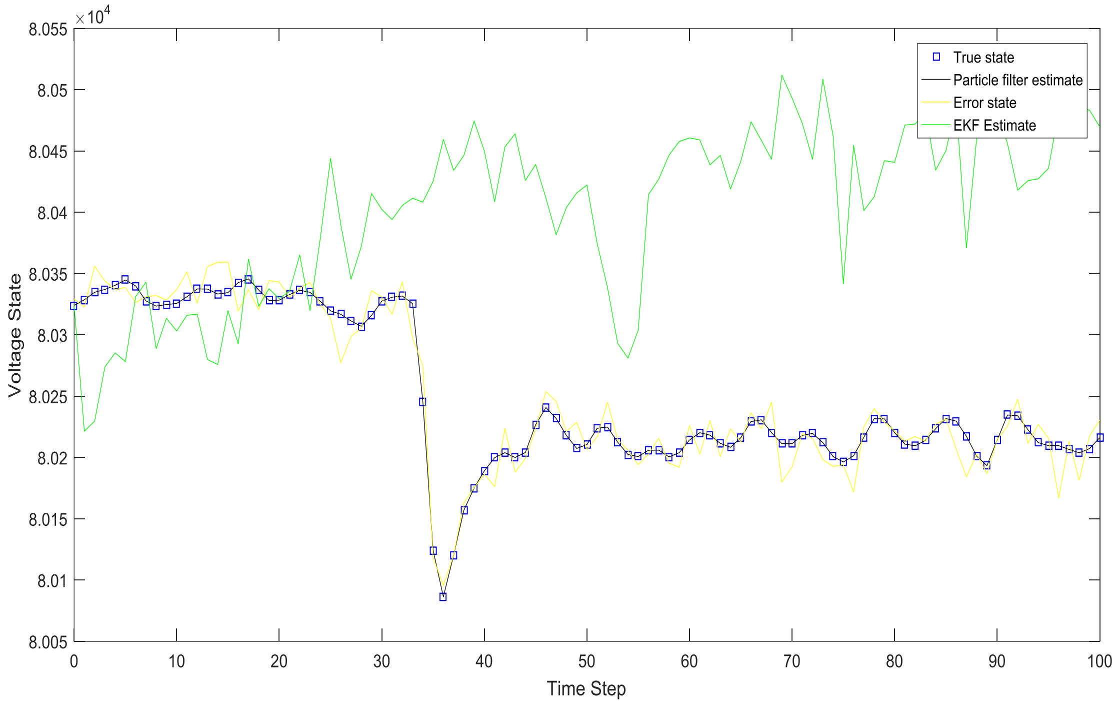

Figure 5.16: Voltage waveforms for Bus 4, before and after adding Gaussian Errors

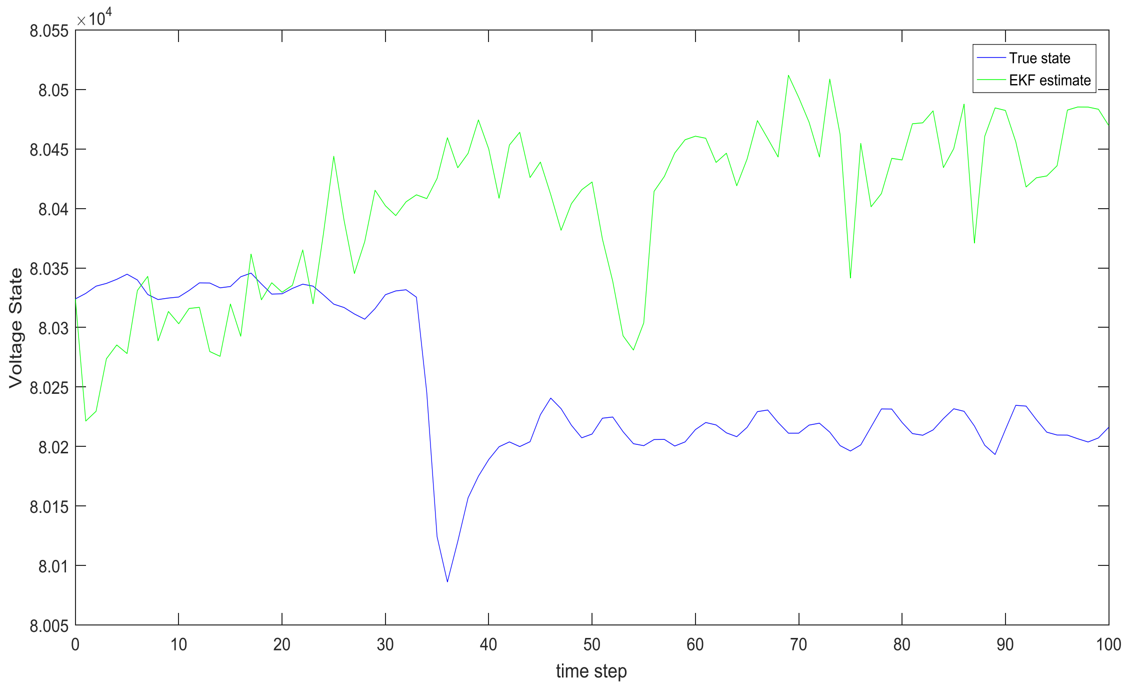

Figure 5.17: Voltage estimation at bus 4, plotting between True State and Extended Kalman State

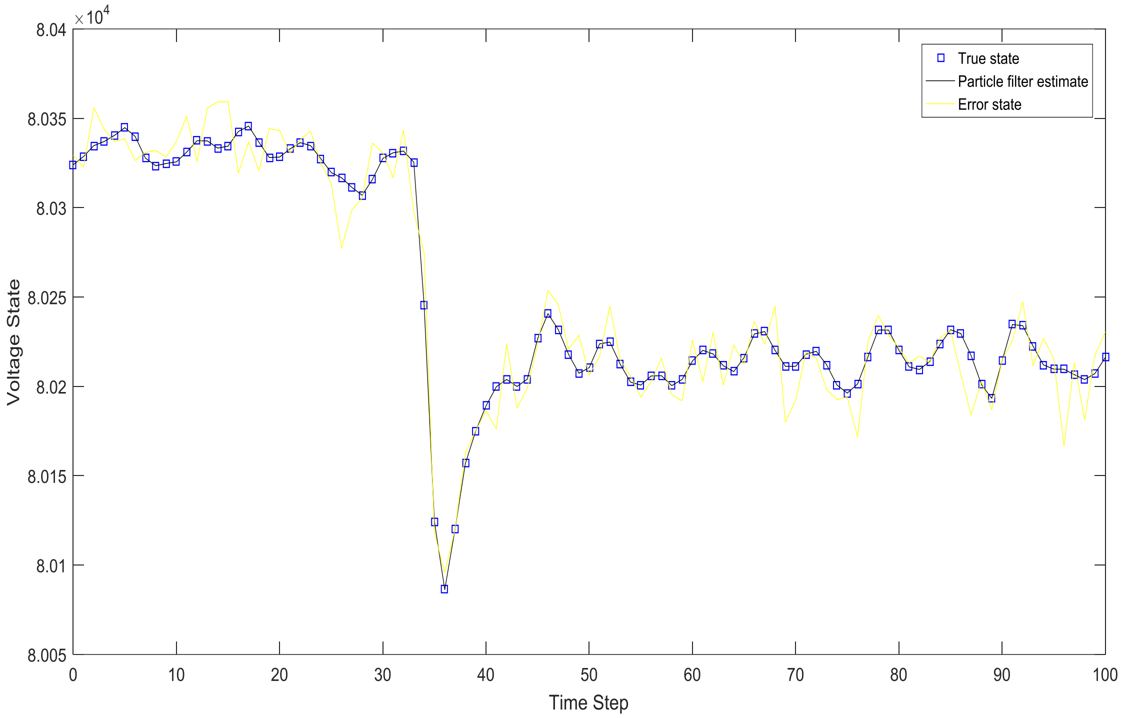

Figure: 5.18 Estimated voltage graphs with using particle filter for Bus-4

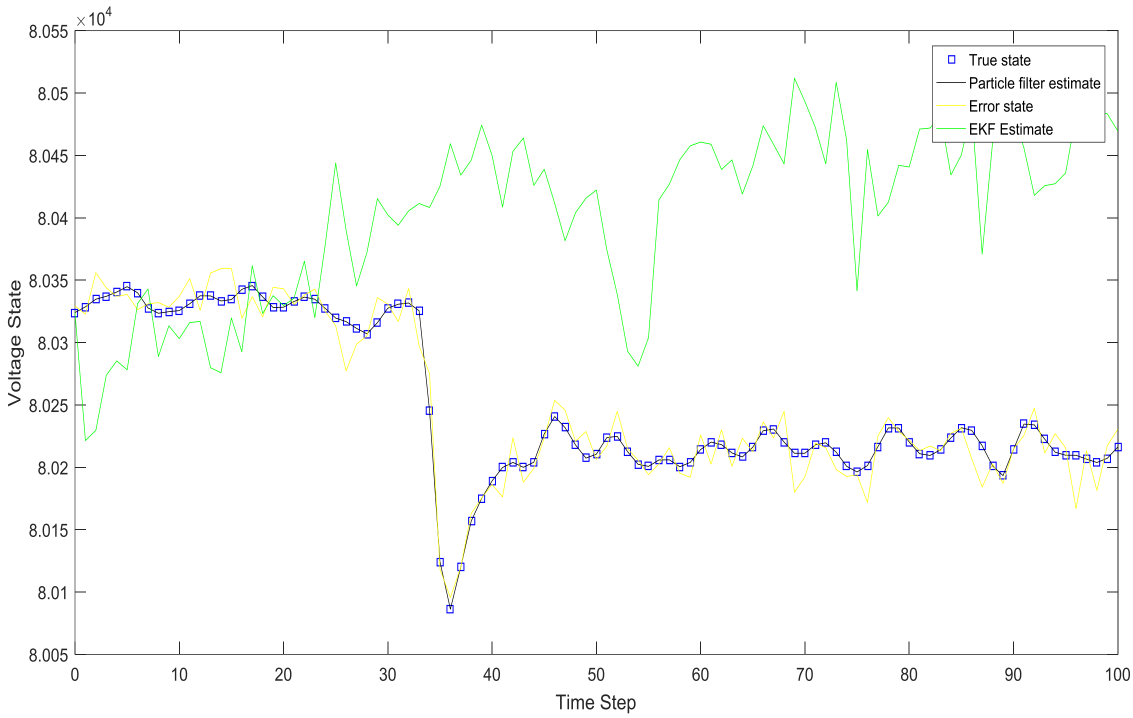

Figure 5.19: Comparative plotting of the voltage at bus 4, Plotting among true state, error state, EKF state and Particle filter state

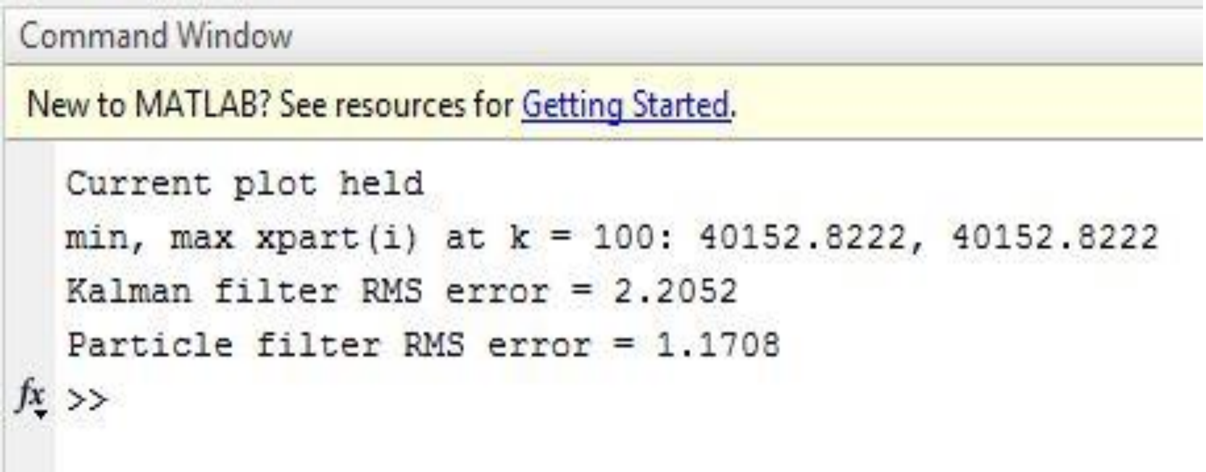

Figure 5.20: RMS error between true state and estimated state for Bus-4

STATE ESTIMATION OF THE BUS-5

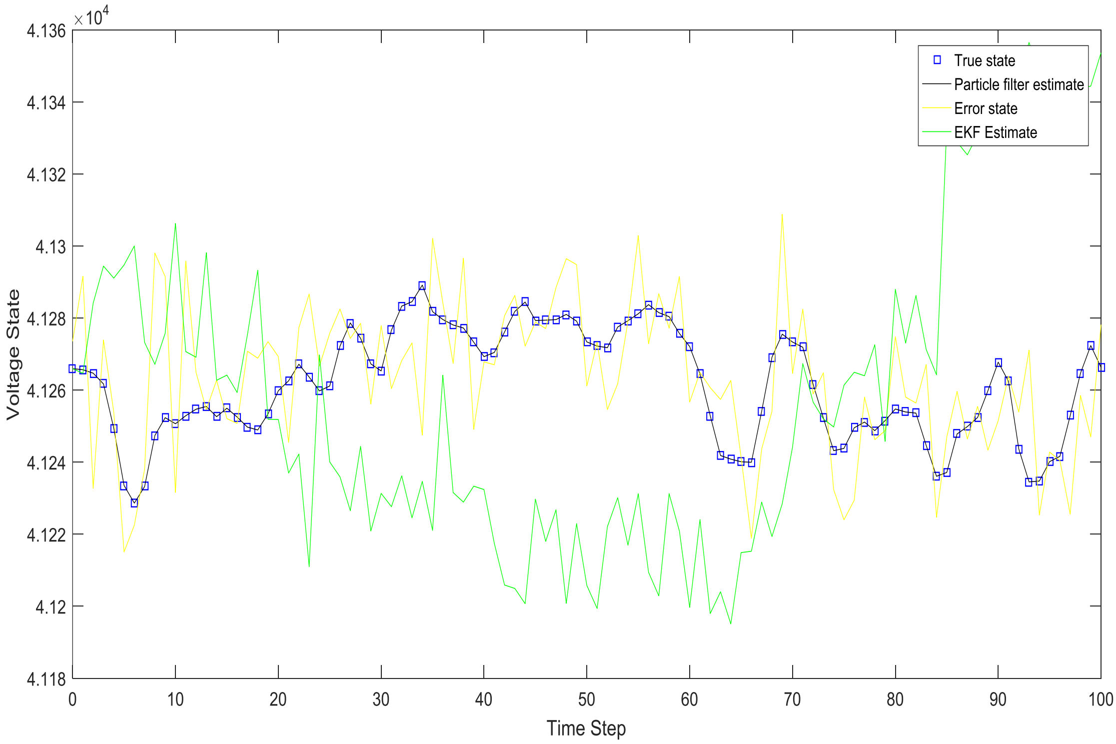

Figure 5.21: Voltage waveforms for Bus 5, before and after adding Gaussian Errors

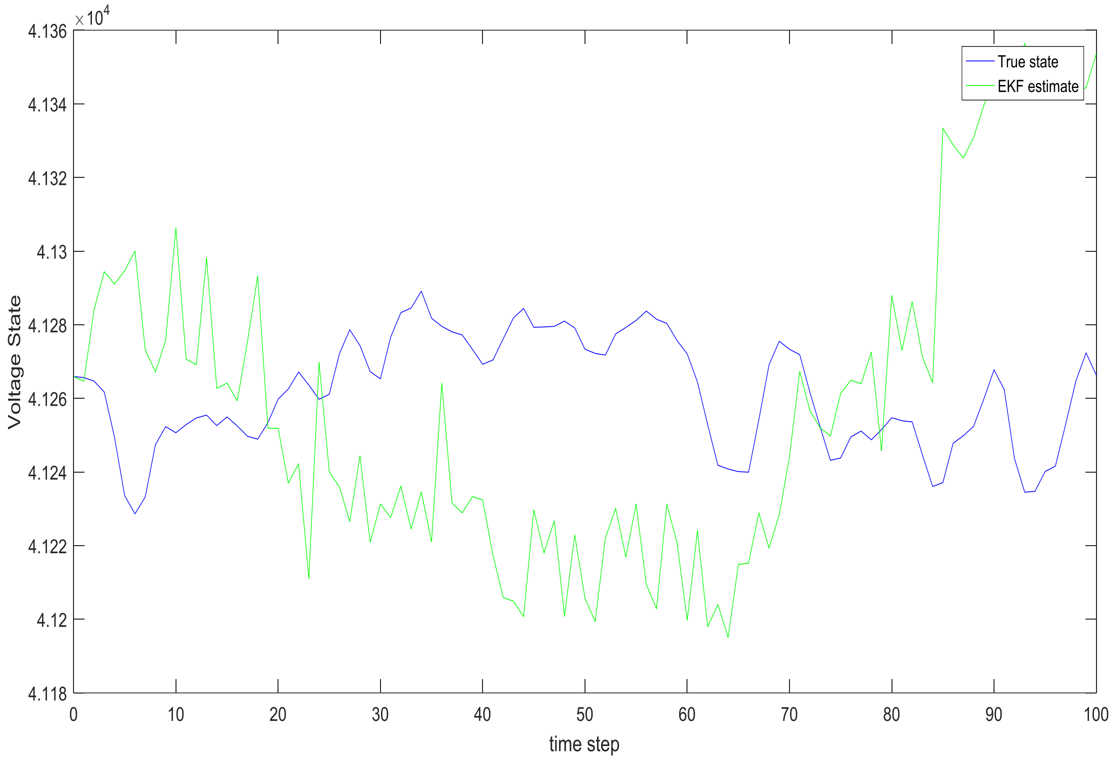

Figure 5.22: Voltage estimation at bus 5, plotting between True State and Extended Kalman State

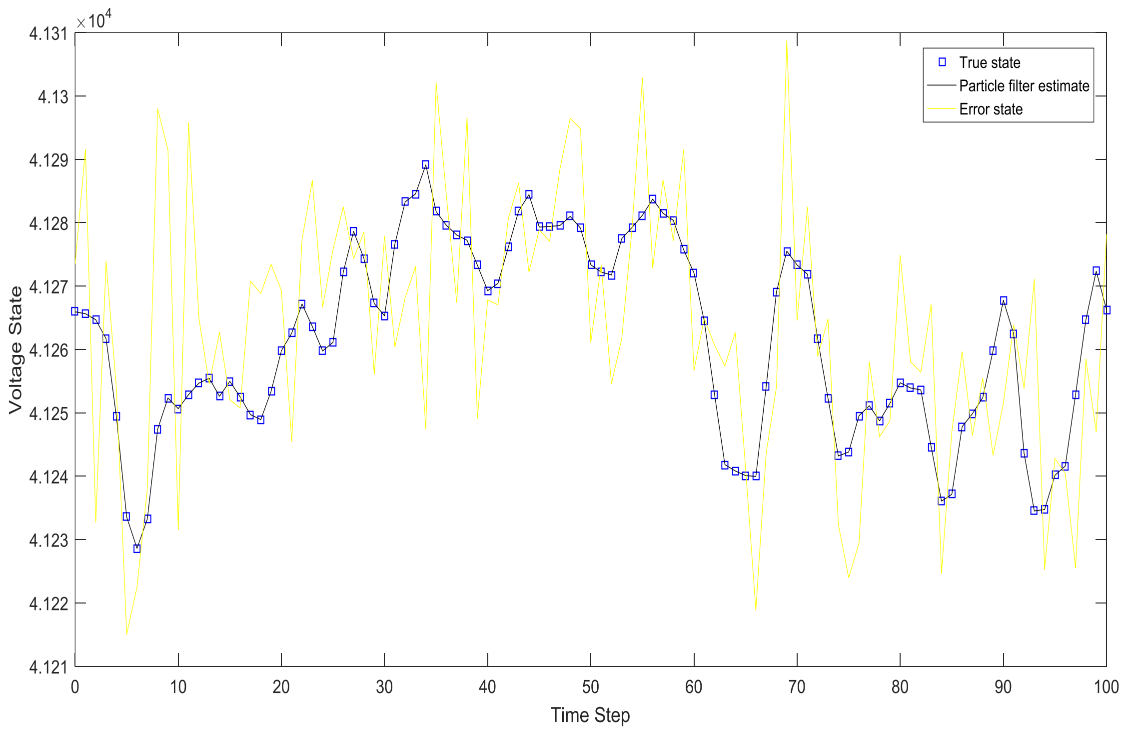

Figure: 5.23 Estimated voltage graphs with using particle filter for Bus-5

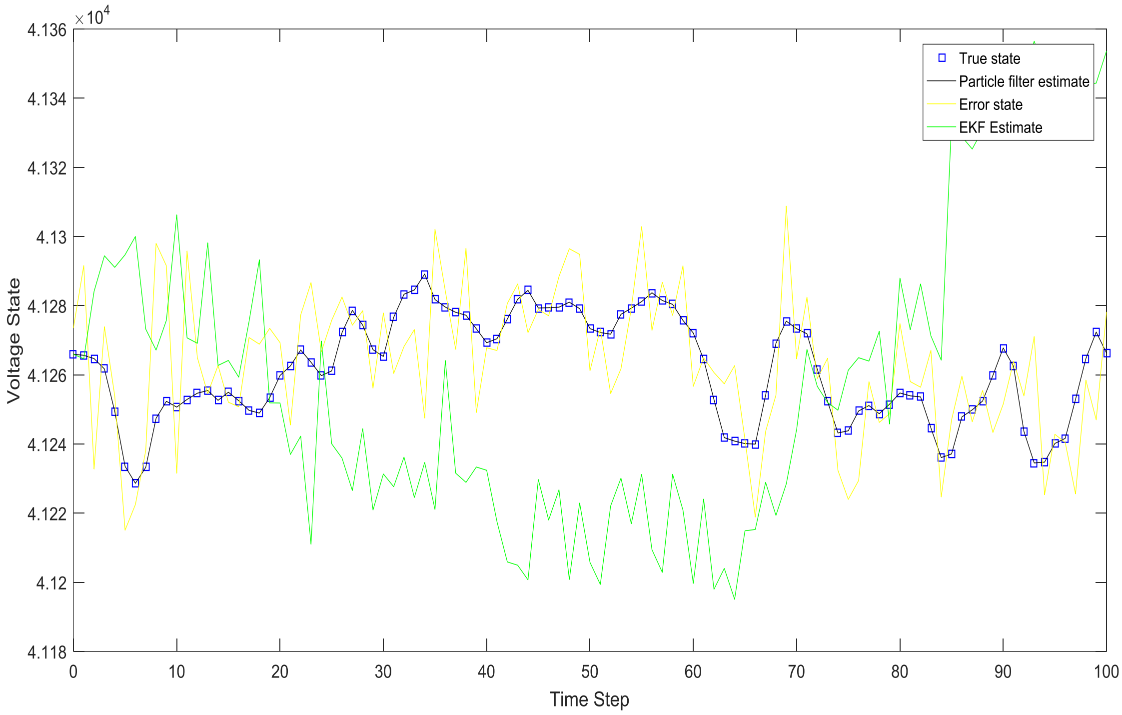

Figure 5.24: Comparative plotting of the voltage at bus 5, Plotting among true state, error state, EKF state and Particle filter state

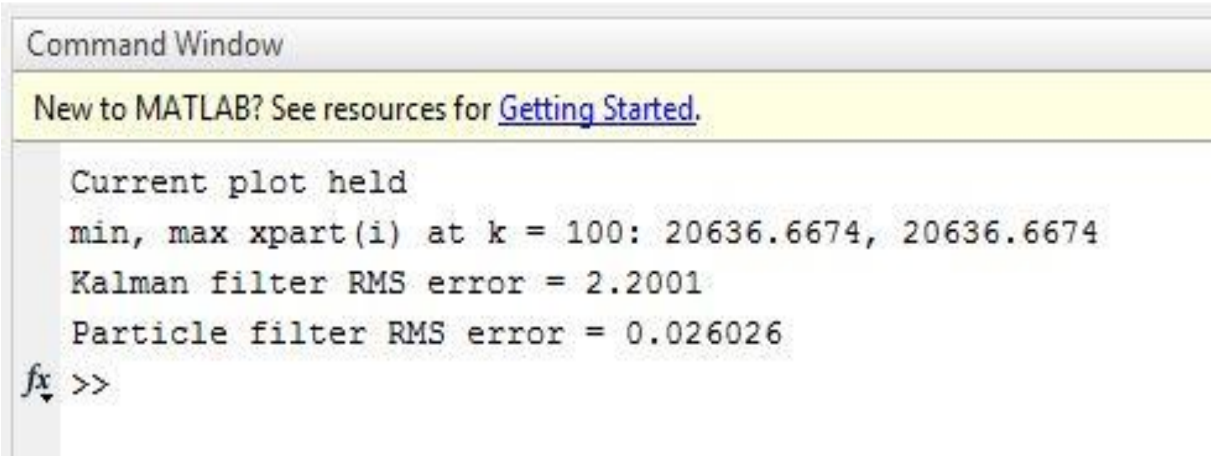

Figure 5.25: RMS error between true state and estimated state for Bus-5

CHAPTER: 6 CONCLUSION & FUTURE WORK

6.1 Conclusion

Extended Kalman Filter is used for the state estimation of the non-linear system. But the problem of the Extended Kalman Filter is that, it cannot handle high non-linearity of the system and because of that the estimated output of the system variables are not that much precise and the error between true state and estimated state is higher than the particle filter. By using particle filter, as the state estimator algorithm, it will be easy to state estimate the state of the power system very precisely. As particle filters handles with the nonlinearities of the system very well, the estimation of the finale estimation will be more precise. From the results we can conclude that by using particle filter RMS error between estimated and true state is very low, which shows that estimated value is close to true value. If estimated values are near to true values then based on the state estimation, controlling and monitoring of the power system can be done effectively. Result shows the ability of the particle filter for the state estimation of the non-linear system.

6.2 Future Work

This work can be extended in the following area:

- Bad data can be eliminated before doing the state estimation of the gathered data from the PMUs.
- Hybrid type filters can be used for the state estimation purpose e.g. Nested particle filter, extended Kalman particle filter etc.

REFERENCES

[1] M. Hurtgen, J-C. Maun, “Applications of PMU Measurements in The Belgian Electrical Grid”, *Technical Report*, May 2012.

[2] Henrik Sandberg, Gyorgy Dan, Mathias Ekstedt, Gunnar Bjorkman, "Challenges in Power System Information Security", *IEEE Security & Privacy*, vol. 10, no. , pp. 62-70, July-Aug. 2012, doi:10.1109/MSP.2011.151

[3] Ali Abur, “Power system State Estimation theory and implementation”, marcel Dekker Inc, edition 2004.

[4] A.G. Phadke, “Synchronized Phasor Measurements in Power Systems", *IEEE Computer Applications in Power*, April 1993.

[5] IEEE Working Group H-7, “Synchronized Sampling and Phasor Measurements for Relaying and Control”, *IEEE Transactions on Power Delivery*, Vol. 9, No.1, January 1994, pp. 442-452.

[6] IEEE Working Group H-8, “IEEE Standard for Synchrophasors for Power Systems”, *IEEE Transactions on Power Delivery*, Vol. 13, No. 1, January 1998

[7] GE Power Systems Engineering, "Assessment of Applications and Benefits of Phasor Measurement Technology in Power Systems", *EPRI Final Report*, April 1997.

[8] V. Centeno, J. De la Ree, A.G. Phadke, G. Michel, J. Murphy, R. Burnett, “Adaptive Out-of-Step Relaying Using Phasor Measurement Techniques,” *IEEE Computer Applications in Power Magazine*, October 1993.

[9] H.K. Clark, R.K. Gupta, C. Loutan, D.R. Sutphin, “Experience with Dynamic System Monitors to Enhance System Stability Analysis”, *IEEE Transactions on Power Systems*, Vol. 7, No. 2, May 1992.

[10] R. F. Nuqui, A.G. Phadke, R.P. Schulz, N.B. Bhatt, “Fast On-Line Voltage Security Monitoring Using Synchronized Phasor Measurements and Decision Trees”, Paper presented at the *IEEE PES 2001 Winter Power Meeting*, 01 WM 287-2-PWRS.

[11] Power System Operation Corporation Limited, “synchrophasors Initiative in india”, June 2012.

[12] Smart Grid Communications and Networking, Yi Deng, Hua Lin, Arun G. Phadke, Sandeep Shukla, James S. Thorp, *Cambridge University Press*, 2012, Print ISBN: 9781107014138.

[13] www.iitmandi.ac.in/ciare/files/9_Ashwani_Power_System_State_Estimation.pdf *(as time on 11/11/2016, 3:09PM)*

[14] Arulampalam, M., Maskell, S., Gordon, N., Clapp, T., A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking, *IEEE Trans. on Signal Processing*., vol. 50, no. 2,174-188, Feb. 2002.

[15] Gordon, N. J., Salmond, D. J., Smith, A. F. M., Novel approach to nonlinear/ non-Gaussian Bayesian state estimation, *IEE Proceedings*, vol. 140, no. 2, 107-113, Apr. 1993

[16] Dan Simon, "Optimal State Estimation Kalman, H_∞ and Nonlinear Approaches", Cleveland State University, *A John Wiley & Sons Publication.*

[17] Julier, S. J., Uhlmann, J. K., New extension of the Kalman filter to nonlinear systems, *Proc. SPIE*, vol. 3068, no. 182, 1997.

[18] Dan Simon, " Kalman Filter", *Embedded system programming,* June 2001.

[19] Katsuji Uosak and Toshiharu Hatanaka, "State estimation of nonlinear stochastic systems by evolution strategies based Gaussian sum particle filter," *Control, Automation and Systems, 2007. ICCAS '07. International Conference on,* Seoul, pp. 2633-2638, Dec 2007.

[20] K. Emami, T. Fernando, H. H. C. Iu, H. Trinh and K. P. Wong, "Particle Filter Approach to Dynamic State Estimation of Generators in Power Systems," in *IEEE Transactions on Power Systems*, vol. 30, no. 5, pp. 2665-2675, Sept. 2015.

[21] Y. Cui and R. Kavasseri, "A Particle Filter for Dynamic State Estimation in Multi-Machine Systems With Detailed Models," in *IEEE Transactions on Power Systems*, vol. 30, no. 6, pp. 3377-3385, Nov. 2015.

[22] CHEN Huanyuan, LIU Xindong, SHE Caiqi, Yao Cheng, "Power System Dynamic State Estimation Based On a New Particle Filter", *Intelligent Information Technology Application Research Association*", Pp. 655-661, 2011.

[23] Kozierski, Piotr, Marcin Lis, and Joanna Ziętkiewicz. "Particle Filter in State Vector Estimation Problem for Power System.", *Pomiary Automatyka Robotyka*, pp. 71-77, Jan 2014.

[24] Peter M. Dhuric, Jayesh H. Kotecha, Jianqui Zhang, Yufei huang, Tadesse Ghirmai, Monica F. Bugallo, Joaquin Miguez, "Particle filtering: A Review of the theory and how it can be used for solving problems in wireless communication", *IEEE signal Processing,* Sept. 2003.

[25] S. M. O. Alhalali and R. A. Elshatshat, "State estimator for electrical distribution systems based on a particle filter," *2015 IEEE Power & Energy Society General Meeting*, Denver, CO, pp. 1-5, Oct 2015.

[26] Haomiao Zhou, Zhihong Deng, Yuanqing Xia, Mengyin Fu, “A new sampling method in particle filter based on pearson correlation coefficient” *Neurocomputing,* http://dx.doi.org/10.1016/j.neucom.2016.07.036.

[27] Turner, Lisa, and Christopher Sherlock. "An Introduction to Particle Filtering.", www.lancs.ac.uk/~turnerl/PartileFiltering.pdf, 14 Nov, 2016, 5:28 PM.

[28] Salmond, David, and Neil Gordon. "An introduction to particle filters.", *dip.sun.ac.za/~herbst/MachineLearning/ExtraNotes/ParticleFilters.pdf, 2005, 14 Nov 2016,* 5.54 PM.

[29] Osea Zebua, Norikazu Ikoma, Hiroshi Maeda, “Dynamic Voltage Stability Estimation using Particle Filter”, *International Journal of Electrical, Computer, Energetic, Electronic and Communication Engineering,* Vol:6, No:5, 2012.

[30] W. Cai, “Importance Sampling in Monte Carlo Simulation of Rare Transition Events 2005”, *Stanford Summer Lecture.*

[31] Ning Zhou, Da Meng, Zhenyu Huang and G. Welch, "Dynamic state estimation of a synchronous machine using PMU data: A comparative study," *2015 IEEE Power & Energy Society General Meeting*, 2015.

[32] N. M. Manousakis, G. N. Korres and P. S. Georgilakis, "Optimal placement of phasor measurement units: A literature review," *Intelligent System Application to Power Systems (ISAP), 2011 16th International Conference on*, pp. 1-6, Sept 2011.

[33] R. F. Nuqui and and A. G. Phadke , “Phasor Measurement Unit Placement Based on Incomplete Observability”, *Power Engineering Society Summer Meeting, 2002 IEEE* , vol. 2, pp. 888-893, July 2002.

[34] K. Joseph. Makasa and Ganesh K. Venayagamoorthy, “On-line Voltage Stability Load Index Estimation Based on PMU Measurements”, *IEEE Power and Energy Society General Meeting,* pp. 1-6, July 2011.

[35] Pankaj Tripathi and Nim Anurag Radhamohan, “Analysis of State Estimation for Power System using Weighted Least Square Method”, *Computational Intelligence and Computing Research (ICCIC), IEEE International Conference*, pp 1-5, Dec. 2014.

[36] Momoh, J.A.; Yan Xia; Boswell, G.; "Voltage stability enhancement using Phasor Measurement Unit (PMU) technology," *Power Symposium, 2008. NAPS '08. 40th North American,* vol., no., pp.1-6, 28-30 Sept. 2008.

[37] Allan J. Wood, “Power Generation, operation and control”, *Wiley Publication*, pp. 453-507.

[38] Arulampalam, M., Maskell, S., Gordon, N., Clapp, T., “A Tutorial on Particle Filters for Online Nonlinear/Non-Gaussian Bayesian Tracking”, *IEEE Trans. on Signal Processing.*, vol. 50, no. 2,174-188, Feb. 2002.

[39] Dan Simon, “Kalman Filtering” *Embedded System Programming*, pp. 72-79, June 2001. *academic.csuohio.edu/simond/courses/eec644/kalman.pdf (date: 25 /11 /2016, time: 10.26 AM)*

[40] J. Kumar; J. N. Rai; N. Hasan, “Use of Phasor Measurement Unit (PMU) for Large Scale Power System State Estimation”, *Power Electronics (IICPE), 2012 IEEE 5th India International Conference*, Dec. 2012.

[41] Ranjana Sodhi; S. C. Srivastava; S. N. Singh, “An Improved Phasor Assisted State Estimator”, *Power & Energy Society General Meeting, 2009. PES '09. IEEE*, July 2009.

[42] P Kozierski, “Particle filter in power system state estimation – bad measurement data and branch disconnection”, June 2015. *aee.czasopisma.pan.pl/images/data/aee/wydania/No_2.../6%20aee-2015-0020.pdf. (Date:25/11/2016 time: 10.42 AM)*

[43] Thomas B.Schon.. Solving nonlinear state estimation problems using particle filters–an engineering perspective. *Technical Report. Automatic Control at Linkopings Universitet*, 2010.

[44] N. Wiener, I Am a Mathematician, *MIT Press*, Cambridge, Massachusetts, 1956.

[45] N. Gordon, D. Salmond, and A. Smith, “Novel approach to nonlinear/non- Gaussian Bayesian state estimation,” *IEEE Proceedings-F*, 140(2), pp. 107- 113, April 1993.

[46] https://creately.com/jupiter/diagram/image/gzpnvehl (time: 11:18 PM and date: 18/11/2016)

[47] Ryan E. Guerra, Tahir N. Saleem, Terrance D. Savitsky, “ Imprtance Sampling” , Rice University, Nov 2008. www.ece.rice.edu/~vc3/elec633/ImportanceSampling.pdf *(time 8:48 PM, Date: 20 Nov 2016.*

[48] Liu, J. S., Chen, R., “Sequential Monte Carlo Methods for Dynamic Systems”, *Journal of the American Statistical Association*, vol. 93, no. 443, pp. 1032-1044, Sep. 1998.

[49] Emin Orhan, “Particle Filtering”, *www.cns.nyu.edu/~eorhan/notes/particle-filtering.pdf (time: 8.50 PM date: 22/11/2016)*

[50] Arnaud Docucet, Adam M. Johansen, “A Tutorial on Particle Filtering and Smoothing: Fifteen Years Later”, *Version: 1.1, Dec 2008.*

[51] *PMU data in the Coding for state estimation of the power system. Data from year 2012. "120103,010000000,UT,Austin,3378,Phasor", projects.ece.utexas.edu/grady/120103,010000000,UT,Austin,3378,Phasor.zip*

[52] Haseltine, E. L., Rawlings, J. B., Critical Evaluation of Extended Kalman Filtering and Moving-Horizon Estimation, *Ind. Eng. Chem. Res.*, vol. 44, no. 8,2451-2460, 2005.

[53] Julier, S. J., Uhlmann, J. K., New extension of the Kalman filter to nonlinear systems, *Proc. SPIE*, vol. 3068, no. 182, 1997.

APPENDIX

```
%% Particle Filter

% Here we are estimmating the state of the voltage for bus 1 and

% for the estimation we are using PMU data and for that

% we are loading a file which has PMU measureed data for 5 bus

%%

clear all;

close all;

clc;

% load data of PMU data to matlab

data=xlsread('120103,010000000,UT,Austin,3378,Phasor.csv');

% loading voltage data of bus 1

voltageData=data(:,2);

% generate no of entries in voltageData

n=length(voltageData);

h=ones(1,1);

   for i=1:n

       o(1,i)=randn;

   end

variable=h*o;

t=1:(n/1000);


   for d=1:n;

       voltage(1,d) =voltageData(d,1);   % initial state
```

```
end

voltagehat = voltage;
Q = 1;              % it is covariance of the process noise
R = 1;              % it is noise covariance of measurement
tf = 200 ;          % length of simulation
N = 200;            % generation of particles in the particle filter number=200
P = 2;              % initial estimation variance declaration
voltagehatPart = voltage;        % define the vectors of particles
j= 10*variable.*(sqrt(P));

for i=1:n
   voltagedata(i,1)=(voltage(1,i)) +j(1,i);
end
figure;
plot(t,voltagedata(1:108),'b',t,voltageData(1:108),'r');
legend('Error state','True state');
xlabel('Time Step'); ylabel('Voltage State');

% Particle Filter Initialization

for i = 1 : N
% generate random particles based on the Guassian Distribution
%from the initial Prior
```

```
        voltagepart(1,i) = voltage(1,i) + sqrt(P) * randn;
    end

%generation of the observation based on the given function,
%from the random particle selection

    voltageArr = [voltage];                  %the actual output vector for measurement values.
    voltageoutputArr = [voltage.^2 / 20 + sqrt(R) * randn];
%the actual output vector for measurement values.
    voltagehatArr = [voltage];              % time by time output of the particle filters estimate
    PArr = [P];
    voltagehatPartArr = [voltagehatPart];            % the vector of particle filter estimates.
        % System simulation
    for k = 1 : tf
        for kk =1:tf
            voltage(1,kk) = 0.5 * voltage(1,kk) + 25 * voltage(1,kk) / (1 + voltage(1,kk).^2) + 8 *
cos(1.2*(kk-1)) + sqrt(Q) * randn;
            y(1,kk) = voltage(1,kk).^2 / 20 + sqrt(R) * randn;
        end

        % Extended Kalman filter

        for mm=1:tf
            F(1,mm) = 0.5 + 25 * (1 - voltagehat(1,mm).^2) / (1 + voltagehat(1,mm).^2)^2;
            P = F(1,mm)* P * F(1,mm)' + Q;
```

```
        H = voltagehat(1,mm) / 10;

        K = P * H' * (H * P * H' + R).^(-1);

        voltagehat(1,mm) = 0.5 * voltagehat(1,mm) + 25 * voltagehat(1,mm) / (1 +
voltagehat(1,mm).^2) + 8 * cos(1.2*(k-1));

        voltagehat(1,mm) = voltagehat(1,mm) + K * (y(1,mm) - voltagehat(1,mm).^2 / 20);

        P = (1 - K * H) * P;

    end


  % Particle filter

    for i = 1 : N


        %given the prior set of particle (i.e. randomly generated locations

        %the quail might be), run each of these particles through the state

        %update model to make a new set of transitioned particles.


        xpartminus(1,i) = 0.5 * voltagepart(1,i) + 25 * voltagepart(1,i) / (1 +
voltagepart(1,i)^2) + 8 * cos(1.2*(k-1)) + sqrt(Q) * randn;


        %with these new updated particle locations, update the observations

        %for each of these particles.


        ypart = (xpartminus(1,i)^2 / 20) + R;

        %particles weight generation.

        %These weights are based upon the probability of the given observation for a particle,
for given the actual observation.
```

```
        %That is, if we observe a location ypart, here we have added Gaussian error  variance
R, then the probability of seeing a given

        %q centered at that actual measurement is


        vhat(1,i) = (y(1,i) - ypart);

        w(1,i) = (1 / sqrt(R) / sqrt(2*pi)) * exp(-vhat(1,i).^2 / 2 / R);

    end



  % Normalization of the prior estimation

    wsum = sum(w);

    for i = 1 : N

        w(i) = w(i) / wsum;

    end

  % Resample

        %this coding creates randomaly and unifomrmally generated particles sample from

        %the CDF of the probability distribution

        %generated by the weighted vector q.  If you sample randomly over

        %this distribution, you will select values based upon there statistical

        %probability, and thus, on average, pick values with the higher weights

        % it will store this newly generated particle and it will iterate for the next iterations


    for i = 1 : N

        u = rand;                    %it will give uniform distribuition between 0 and 1

Wtemporarysum = 0;
```

```
        for j = 1 : N
            Wtemporarysum = Wtemporarysum + w(j);
            if Wtemporarysum >= u
                voltagepart(i) = xpartminus(j);
                break;
            end
        end
    end

% The particle filter estimate is the mean of the particles.
    voltagehatPart = mean(voltagepart);

% Plot the estimated pdf's at a specific time.

        if k == 100

    % Particle filter pdf
            pdf = zeros(401,1);
            for m = -200 : 200
                  for i = 1 : N
                      if (m <= voltagepart(i)) && (voltagepart(i) < m+1)
                            pdf(m+201) = pdf(m+201) + 1;

                      end
```

```
            end
        end

        figure;
        m = -200 : 200;
        plot(m, pdf / N, 'r');
        hold;
        title('Estimated pdf at k=100');
        disp(['min, max xpart(i) at k = 100: ', num2str(min(voltagepart)), ', ',
num2str(max(voltagepart))]);

        % Kalman filter pdf
        for mm=1:tf
            pdf = (1 / sqrt(P) / sqrt(2*pi)) .* exp(-(m - voltagehat(1,mm).^2 / 2 / P));
        end
        plot(m, pdf, 'b');
        legend('Particle filter', 'Kalman filter');
    end

  % Save data in arrays for later plotting
    voltageArr = [voltageArr voltage];
    voltageoutputArr = [voltageoutputArr y];
    voltagehatArr = [voltagehatArr voltagehat];
    PArr = [PArr P];
    voltagehatPartArr = [voltagehatPartArr voltagehatPart];
```

```
 end
t = 0 : tf;

%figure;
%plot(t, xArr);
%ylabel('true state');

figure;
plot(t(1:101), voltageArr(1:101), 'b-', t(1:101), voltagehatArr(1:101:10201),'g-');
set(gca,'FontSize',12); set(gcf,'Color','White');
xlabel('time step'); ylabel('Voltage State');
legend('True state', 'EKF estimate');

figure;
plot(t(1:101), voltageArr(1:101), 'bs', t(1:101), voltagehatPartArr(1:101), 'k-
',t(1:101),voltagedata(1:101),'y');
set(gca,'FontSize',12); set(gcf,'Color','White');
xlabel('Time Step'); ylabel('Voltage State');
legend('True state', 'Particle filter estimate','Error state');

figure;
plot(t(1:101), voltageArr(1:101), 'bs', t(1:101), voltagehatPartArr(1:101), 'k-
',t(1:101),voltagedata(1:101),'y',t(1:101), voltagehatArr(1:101:10201),'g-');
set(gca,'FontSize',12); set(gcf,'Color','White');
xlabel('Time Step'); ylabel('Voltage State');
```

```
legend('True state', 'Particle filter estimate','Error state','EKF Estimate');


VoltagehatRMS = sqrt((norm(voltageArr - voltagehatArr))^2 / tf)/100;

VoltagehatPartRMS = sqrt((norm(voltageArr(1:108001) -
voltagehatPartArr(1:108001)))^2 / tf);

disp(['Extended Kalman filter RMS error = ', num2str(VoltagehatRMS)]);

disp(['Particle filter RMS error = ', num2str(VoltagehatPartRMS)]);
```

BIO-DATA

Dipesh Shirishbhai Doshi received Bachelor of Engineering degree in Electrical Engineering from Lukhdhirji Engineering College, Affiliated with Gujarat Technological University, Morbi, Gujarat, India, in 2014. He received his M.Tech degree in Electrical Engineering from Lovely Professional University, Punjab, India, in 2017. Area of interest is power system state estimation, protection and optimization, renewable resources.

- **“Recent developments in optimal placement of Phasor Measurement Units considering in incomplete observability”,** published in **SCOPUS** journal “**Indian Journal of Science and Technology (IJST)**”.
- **“Particle Filter Based State Estimation of Power System”,** accepted at **ICRTEECT 2017 IEEE** conference at **S. R. Engineering College**, Warangal, Telangana”.
- “**State Estimation of Power System Based on Particle Filter**”, submitted to **SCOPUS** journal The **International Journal of Applied Engineering Research (IJAER)**