Bayesian Approach to Non Linear State Estimation For Improved Performance of Smart Grid

Nisha Tayal, Rintu Khanna

***Abstract:**The process of PMU-based monitoring improves the quality of the smart grid. Simultaneously, the implementation of PMU increases the dynamics of noise variance which further inflates the uncertainty in noise-based distribution. This paper presents a method to reduce the amount of uncertainty in noise by using a linear quadratic estimation method (LQE), usually known as Kalman filter along with Taylor expansion series but this process is time-consuming and is vulnerable to a large number of errors at the time of testing. The main reason behind this approach is the high complexity of the system which makes it very hard to derive the process. The proposed studies adopts a technique to work on covariance earlier based estimation using Bayesian method together with the estimation of dynamic polynomial prior by using Particle Swarm Optimization (PSO). The experimental evaluation compares the outcomes received from the primary Kalman filter, PSO optimized Kalman filter out and Kalman filter Covariance Bayesian method. Finally, the effects received from the analysis highlights the truth that the PSO optimized Kalman clear out to be more effective than the Kalman filter out with Covariance Bayesian approach.*

***Keywords:**Smart Grid, PMU,Bayesian,kalman,PSO,parameter estimation,Optimization*

I. INTRODUCTION

The smart grid at its core represents the use of rising technology in order to support the energy and the cost-based efficiency. A smartly designed energy network, reads in an automatic way and reacts to the changes of supply as well as the demand. This would enhance the efficiency as the customers easily adapt with their own demands on real time basis [1] [4]. Keeping this in mind, a target has been set by the EU which is that 80 percent of the already existing meters of electricity to be changed by 2020, leading to a possible reduction of emission across the EU to about 9 percent and the same reduction in case of annual consumption of ordinary energy. The ambition of EU is basically set out in innovation-led electricity-based system transformation and technology-based context. According to the reports of World Economic Forum, three of the significant trends have been identified that are going to rattle large conventional structures from the generation process beyond the smart meter [2] [6]. These are:

- Economical large sectors electrification such as heating and transport;
- The process of decentralisation, propelled by an acute fall in distributed form of energy resources cost like distributed generation, distributed storage, energy efficiency and flexible demand; and
- The process of digitalisation of both grids, with smart sensors, smart metering, process of automation and the other technologies based on digital type of network with arrival of Internet of Things (IoTs) and a large power surge consuming associated devices [27].

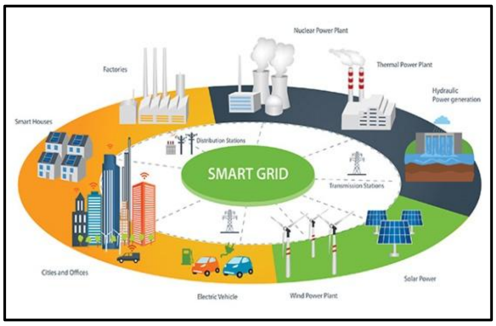

Figure 1: Smart Grid [27]

The technology of Smart Grid will help in allowing the utilities to drive the system-based electricity efficiently around them and makes the system economically possible. It will further allow the business and homeowner to use the systems' electricity economically [2] [3]. Smart Grid is generally built with a large number of technologies that are already in use by the electrical utilities but it further adds the control and communication capabilities that will help in optimizing the entire smart grid operation [24].

A. Smart Grid applications technologies

The process of transition of Smart Grids to replace the already existing grids involves significant form of revamping, like the use of new sensing technology, measurement, control, and automation technologies. Generally speaking, the technologies that are needed to properly implement the large basic needs of Smart Grid system consists of the following:

1. Advanced Metering Infrastructure (AMI): It is considered as one of the major part of Smart Grid technology that are operational already in various worldwide networks. Generally, the advanced monitoring infrastructure can be characterized as a communication of two-way type of network and represents the assimilation of smart energy meters, sensors, data management systems, and monitoring

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systems, which enables the collection and dissemination of informational data between the utilities and users' meters.

2. PMU (Phasor Measurement Units) and WAMPAC (Wide Area Monitoring Protection and Control) to ensure the security of the power system.

A phasor diagram represents sinusoidal wave mathematically. Time is taken as reference to determine the phase angle at a known frequency. The values of phasor that represent sinusoidal waveforms of power system in reference to the given coordinated universal (UTC) time and power system frequency are known as Synchro phasors [14] [15]. Waveform, the system frequency, and the instant of measurement determines the phase angle of a synchro phasor. Thus, power system phase angles can be accurately measured throughout a power system with a precise universal reference of time. This can also be achieved economically by global positioning system (GPS) technology. By using GPS technology, the main advantage is that synchronization can be accurately detected by its receiver. Synchronized phasor measurements is provided by a device known as PMU i.e. Phasor Measurement Unit. The widely distributed number of PMUs in power system may be employed for [5] [18]: controlling generation of distributed form, congestion management, voltage and angular stability, analysis of Post-Mortem on the basis of faults and disturbances, real time monitoring, and state estimation control and protection. Digital signal-processing components are used in PMUs i.e. Phasor Measurement Units that represents the electronic-based devices, for measurement of AC waveforms and transforming them into required phasors, in accordance to frequency of the system and synchronizing such measurements under the GPS reference based source control.

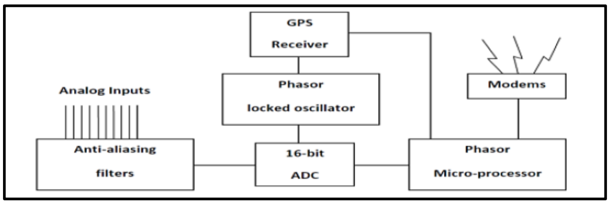

Figure 2: PMU (Different Components) [25]

A recursive phasor algorithm is used for sampling and processing of the analog signals for generation of current and voltage phasors [9]. PMU unit having distinct type of components is shown by a block diagram in fig. 1. The initial commercial form of PMU i.e. the Macrodyne 1690 generally performed the function of data recording only and was introduced in 1991. PMUs that had the ability of real time measurement were developed by the year 1997.The PMUs which are presently used help in providing data rate of samples 6-60 per second. In this measurement range, the higher data range may cover the local type of oscillations, actions of generator shafts, generator shafts etc. [17] [10] while the range on the basis of lower end may present the dynamics of power system inter area region. The data sample based Aime window is used for estimation of parameters of the phasor with the help of algorithms in order to compute phasors from measured signals. Only the angle of the phasor and magnitude is computed by simple algorithm which assumes a fixed nominal frequency.

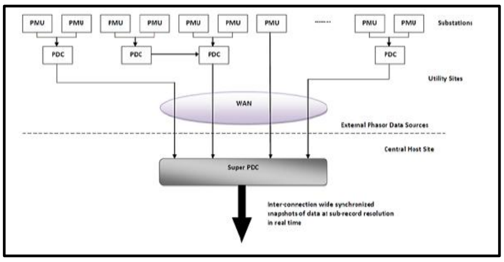

Figure 3: WAM System Based on PMU [17]

The other type of methods like the artificial neural networks or Kalman filter [11] helps in estimating the phasor diagram. The (PDC) Phasor Data Concentrator placed at the controlling center is generally provided with data from distinct distributed PMUs placed in the smart grid premises. The PDC waits for the data arrival having the slowest range and it gathers and collects and further helps in data sorting by a time stamp method until the slowest data arrival. In the control center the concentrated form of data by the PDC is further utilized for distinct types of applications. Now the super PDC collects the data from several PDCs distributed over a particular area. The PMU based conceptual measurement block diagram for wide area measurement is shown in figure 3.

B. Kalman Filter Based Parameter Estimation

The combination of certain methods of dynamic estimation of state like the Kalman filters with practical (real) time-based data collected by the digital type of meters likewise the phasor measurement units (PMUs) can lead to progressive form of techniques that improves the quality of controllability and monitoring in the technology of smart grids. The Kalman filters (KF) of classic form generally achieves the optimized performance with ideal model of the system that is really hard to achieve practically with sudden type of device failures, disturbances, and the data attacks of malicious form. The concept of Kalman filters (KF) is considered [24] to be the most famous technique for dynamic state estimation that has found applications in large number of fields, basically from the process of weather forecasting to the process of missile tracking. In real knowledge, the statistics of noise is not known properly. The system-based measurements are also corrupted with some errors due to malicious attacks done to data, or even failure of the device. In order to carry the activities of illegal form such as energy theft, the attackers of the system design or model a bad type data that bypasses the mechanisms of detecting bad data in the power systems [24] [25]. This gives rise to overwhelming impacts such as wrong rustle (dispatch) in the case of power system distribution and the breakdown of device during the generation of power.

The Kalman filters (KFs) are very useful in the applications of real world involving: robotics, GPS, communication systems, chemical-based plant control, weather prediction, aircraft tracking, satellites, inertial navigation, ships, multi-sensor based data fusion, rockets, etc, in addition it includes some of the reluctant applications (for example, prediction of stock market). Also, the Kalman

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filters (KFs) are easy to code and model, and they regularly help to provide accuracy in estimation process. Differently, the accuracy of Kalman filter can be exceptionally bad for most of the real applications, for various reasons, consisting of: 1) equation-based nonlinearities describing the system physical state, 2) covariance matrix ill-conditioning process, and 3) incomplete or inaccurate models of pointing out the problems in physical form.

II. RELATED WORK

A significant component of distribution-based intelligence is the response and the outage detection. Presently, most of the utilities generally rely on the calls of the consumer in order to know the affected areas of distribution System effected by a power-outage [1] [15]. With the help [6] of smart meters, distribution-based intelligence will surely help to rapidly point out the power outage sources so that maintenance crews can dispatch immediate services to the problem area. A response to outage can also be improved. Most of the utilities rely on manual switching and power distribution complex schemes in order to continue the flow of power to the consumers, even when the power lines are destroyed and damaged. However, such an approach [6] [15] has its own drawbacks, and in most of the cases a system that is of automated form responds faster and could continue the power flow to more consumers. In order to determine the best solution to power outage, the system requires sensors indicating the function joining intelligent systems with an automated switching.

Parameter Estimation

In 1970, pioneering work conducted by F.C. Schweppe consists of the work done on static estimation (SE). It plays a significant function in supervised planning and control of electric power grids. It serves to monitor the state of the grid and enables energy management systems (EMS) to perform various important control and planning tasks like establishment of nearby network models on the basis of real-time for proper functioning of the grid, optimization of power flows, and bad data analysis/detection One more SE-based utility example involves SE-based assessment of security/reliability that is basically deployed for analyzing various contingencies of the system and it determines the desired preventive actions against possible failures in power systems research area.

Power System Monitoring with PMUs

The deployment of PMU has developed a paradigm-based shift from state estimation (SE) to the determination of state. In India, the experience of synchro-phasor is very promising and enriching and has led to an excellent understanding of grid events. Precise time stamping of data has enabled operators to have a signature of the grid. The utilities are likely to be benefitted with advanced static and dynamic contingency analysis.

a. Optimized PMUs Placement in Power System: Bei Gou (2008) has stated [26] a generalized form of integer-based linear programming method for an optimized placement of phasor measurement units (PMUs) considering redundancy of PMUs location, incomplete and full observability process. A specific method for finding out the minimized PMUs number and their optimized positions for enabling the whole network system to become observable. This kind of methodology grants the loss of multiple or single PMUs enabling the whole network of the system to be observable. The analysts in [16] has provided an approach based on the immunity-based genetic algorithm (GA) for optimized PMU placement for the system to become completely observable. This methodology represents optimized placement of PMUs without any contingency-based measurement.

PMUs-Based Applications for State Estimation

The state estimation of power system using PMUs has been examined on critical basis. The inaccurate measurement and the model of the system generally represents the system that gives rise to anxiety or uncertainty. The function of state estimation represents a basic tool for real-time data measurement received from the controlling substations. AliAbur et al (2005) investigated [31] the problem of state estimation in multi-area systems. It involves a central type of entity coordinator that accesses possible solution of SE-based area, data from measurement of synchronized phasor from each of the bus and the raw-type measurements from boundary area. M. R. Irving et al 2005 overviewed a comparative analysis among two of the methods for the process of power system state estimation with intervals of uncertainty [30].

III. PROPOSED METHODOLOGY

In this section, we discussed the proposed approach and the methodology used to achieve the results.

(A) Proposed methodology

The Extended Kalman filters, popularly known as EKFs were generally developed for non-linearized discrete time-based processes. It provides an optimal estimate of approximation. The nonlinearities of system-based dynamics are usually estimates in approx. by the linear version of non-linearized system model around the estimation of the last state. For a valid type of approximation, this process of linearization using the first order taylor series should be presented as a good approximation of non-linearized model in global uncertain domain linked with the estimation of state. The concept of EKFs faces various challenges from the use of linearization process like challenges of implementation, tuning difficulty, issues related to reliability, etc. In order to overcome such issues, unscented transformations (UTs) were popularized to proliferate covariance and mean information through the non-linear type of transformations. The EKF flaws and its advancement through the UKF can be overviewed here. Such a UKF application extends the application to areas like dual estimation, neural networks, machine learning, non-linear identification of the system, etc.

- In the EKFs, the observation models and the transition state, don't need to be linear functions of the state but may instead be differentiable functions.
- System equations are given as:

The equations of the system are presented as follows:

State equation: $x_{k+1} = f(x_k, u_k) + w_k$ …………….…..1 (a)

Observation equation: $y_k = h(x_k) + v_k$ ………….…….1 (b)

Where,

h = computes the predicted measurement from the predicted state.

f = computes the predicted state from the previous estimate.

However, both the h and f are not applicable to the covariance on direct basis. Rather a partial derivative (the Jacobian) matrix is usually computed. At each step of time, the Jacobian matrix is computed with present predicted form of states. Such type of matrices are used in the equations of Kalman filter. This type of process necessarily helps to linearize both the current estimate and the non-linearized function. The Kalman filter (KF) represents a method of linear state estimation. On the other hand, the power systems is extremely of non-linear nature. For applying the KF to original state estimation of power system, an individual needs to perform system linearization. The EKF is generally based on the process of linearizing the non-linear type of equation with the use of Taylor Series where higher order and quadratic terms are erased. The algorithm in detail is provided by Huang et al (2007) and it presents the following equations:

Prediction: $\hat{x}_{k+1} = f(\hat{x}_k^{+}) + q_k$ (2)

$P_{k+1}^{-} = F_k P_k^{+} F_k^{T} + Q_k$ (3)

Correction: $K_{k+1} = P_{k+1}^{-} H_{k+1}^{T} (H_{k+1} P_{k+1}^{-} H_{k+1}^{T} + Rk+1-1$ (4)

$\hat{x}_{k+1} = \hat{x}_{k+1}^{-} K_{k+1} \left(z_{k+1} - h(\hat{x}_{k+1}^{-})\right)$ (5)

$P_{k+1} = (1 - K_{k+1} H_{k+1}) P_{k+1}^{-}$ (6)

$F_k = \frac{\delta f\ (x_k)}{\delta x_k},\ H_{k+1} = \frac{\delta h\ (x_{k+1})}{\delta x_{k+1}}$

The EKF represents the main methodology that is used for estimating the state of power system on current basis. But there are few drawbacks: The Linearization of continuous discrete (CD) will cause filtering instability if the time interval of calculation is not limited enough.

- For complex systems and large scale systems, the calculation of Jacobian matrix is consideredto be complicated that is to be executed in case of real time.
- The disregard of higher and quadratic order terms make estimation and the prediction less correct/precise.

A.1 Proposed Flowchart

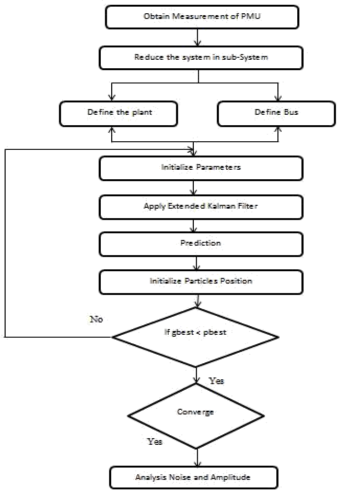

Figure 4: Flow chart of Proposed Methodology

IV. EXPERIMENTAL AND RESULTS ANALYSIS

Figure 5 depicts the noise level according to the actual level and the level with different approaches. The figure represents the noise level of Extended Kalman filter, EKF_PSO, EKF_Bayesian. The curves in the EKF and EKF Bayesian are tilted more and it shows high noise level. The noise level in EKF_PSO is slightly changed than the actual level so it shows better results.

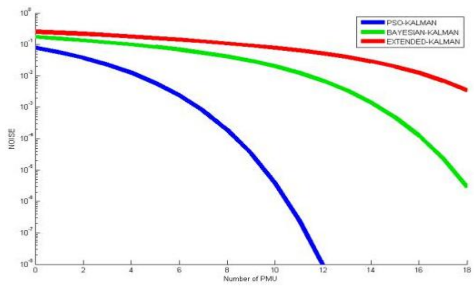

Figure 5: Noise in EKF_PSO, EKF_Bayesian and Extended Kalman filter

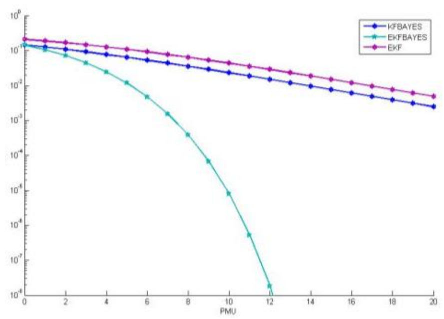

Figure 6: Noise curve in KF_BAYES, EKFBAYES, EKF

Figure 6 represents the noise curve of three different approaches on the different number of PMUs. In this graph Purple line represents the Extended Kalman filter, Blue represents the Kalman filter with Bayesian form and sky Blue Line represents the Extended Kalman filter with Bayesian. The curve of Extended Kalman filter shows less noise and stability but the curve of the Kalman filter with Bayesian has high noise level.

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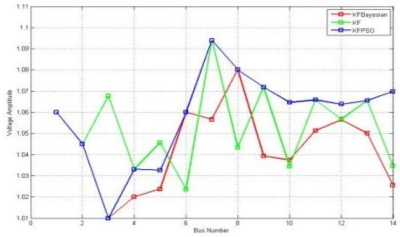

Figure 7: Voltages and amplitude level of Kalman filter, extended kalman Filter and Kalman with PSO

The above given figure 7 represents the voltage and amplitude level on Kalman filter, extended kalman Filter and Kalman with PSO. The Red line represents the Kalman with Bayesian, Green represents Kalman filter and Blue represents the Kalman with PSO. The Blue line curve shows the maximum stability in the voltage and amplitude level when the number of buses is increased.

Extended Kalman Filter with particle swarm Optimization

An Extended Kalman Filter needs to be designed based on Taylor series expansion around a nominal value which is taken as the previous estimate in this case. The state transition matrix **F** is given by the Jacobian vector function $f(\vec{x},\vec{w})$about state $\vec{x}$ and the noise scaling matrix τ is given by the Jacobian vector function $f(\vec{x},\vec{w})$about state w. Since the process dynamics are continuous while the measurements are usually discrete in nature, a hybrid continuous-discrete EKF model is developed. The EKF equations of discrete time cannot be used directly and for continuous time EKF equations have to be derived. Also, since the measurements are discrete in nature, a hybrid of both is developed and described below. An observable, non-linear dynamical system, with the continuous process dynamics and discrete measurement of dynamics is explained as:

Here $\vec{x} \in \Re^n$ shows the n-dimensional state vector of the system, $f(.)\ D_x \rightarrow \Re^n$ is a finite non-linear mapping of system states to system inputs, $\vec{z}_k \in D_z \subset \Re^p$denotes the *p*-dimensional system measurement, $h(.)\ :D_x \subset \Re^n \rightarrow \Re^p$ is a non-linear mapping of system states to output, $\tau_c \in \Re^{nxw}$denotes the continuous process noise scaling matrix ,$\vec{w} \in D_w \subset \Re^w$denotes the *w*-dimensional random process noise and $\vec{v} \in D_v \subset \Re^v$denotes the *v*-dimensional random measurement noise.

In this section different simulation results are evaluated by using proposed extended Kalman filter with particle swarm optimization on IEEE-30 bus system on MATLAB. The analysis is done on the basis of Noise.

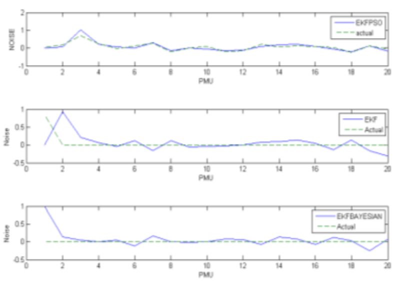

Figure 8: Noise in EKF_PSO, EKF_Bayesian and Extended Kalman filter

Figure 8 depicts the noise level according to the actual level and the level with different approaches. The figure represents the noise level of Extended Kalman filter, EKF_PSO, EKF_Bayesian. The curves in the EKF and EKF Bayesian are tilted more and it shows high noise level. The noise level in EKF_PSO is slightly changed than the actual level so it shows better results.

Kalman filter with Taylor expansion method using MATLAB

Kalman filter is applied to the key parameters and then on results using Taylor expansion. In this section of the paper, the simulation of results is shown below. PMU measured values were used for the performance evaluation of the Kalman Filter with Taylor expansion and it is also tested by the Kalman with Bayesian method.

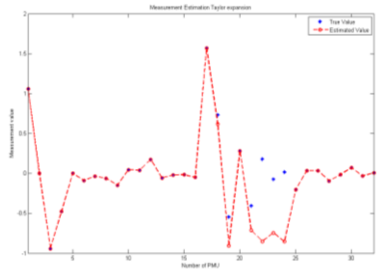

Figure 9: Graph between the True Value and estimated value

The above Figure 9, depicts the error of Taylor expansion, in the estimation of the number of PMU and measurement value or mean squared error which comes by noise. Taylor expansion makes a high polynomial degree of the infinite sum and is not able to generalize the prediction. So, the analysis of the graph: redlines (prediction of noise) and blue points (actual representation) shows that Taylor expansion is not able to predict because of high polynomial behavior.

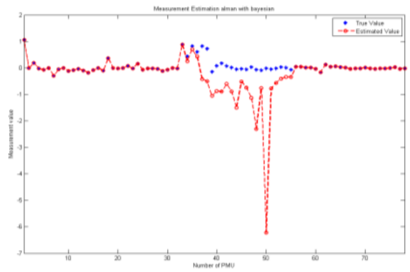

Figure 10: Graph between the True Value and estimated value using Kalman with Bayesian

The above Figure 10 depicts the error of Kalman with Bayesian prediction in estimation of number of PMU and measurement value or mean squared error which comes by noise. Bayesian makes a prior base for the prediction of noise and Kalman reduces the non-linearity in noise space. In the graph, the blue points show the actual data noise and the redline shows the noise predicted by Bayes Kalman filter combination but it is not able to predict as much because of the prior base not being static. So it is not able to predict non-linearity in noise.

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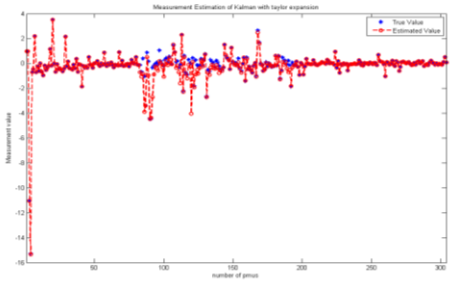

Figure 11: Graph between the True Value and estimated value using Kalman with Taylor expansion

The above figure 11 depicts the error of Kalman with Taylor expansion in the estimation of the number of PMU and measurement value or mean squared error which comes by noise. In Taylor expansion, the basic problem of reduction of prediction was the cause of non-linearity. In the hybridization of Kalman and Taylor, a dynamic prior is selected which was static in case of Bayesian approach. Prior will change if data noise varies. Analysis of graph: the red line is predicted and blue-original by the model which approximately overlaps because of dynamic prior.

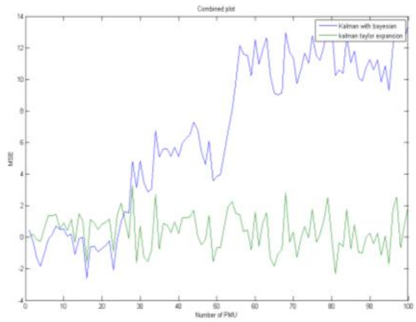

Figure 12: Graph between the True Values and estimated values using Kalman with Bayesian and Kalman with Taylor expansion

The above figure 12 depicts the comparison -between Kalman with Bayes and Kalman with Taylor expansion. The graph clearly shows that Kalman filter with Taylor expansion reduces the noise when the number of PMUs is increased.

V. CONLUSION

The phasor measurement method plays an important role in providing an efficient performance in the smart grid technology. But in spite of using such measurement methods, the system experiences a lot of inconsistencies during the measuring operations as the measured quantity is not defined properly resulting in excessive forms of divergent results. Phasor Measurement Unit (PMU) plays a very significant role in smart grid technology, where it contributes to measure the synchro phasors thus making it valuable to dynamically monitor different types of transient processes occurring in a system. Basically compares the popular Kalman filter technique with a novel method of Kalman filter Covariance Bayesian learning. A Taylor expansion of Kalman filter was used which reduces the non-linearity by using particle swarm optimization technique and the metrics based covariance which has improved the mean square error and the noise of the system. However, in this paper proposed work is done on PMU- parameter estimation by using an extended version of Kalman filter along with the optimization techniques. The proposed algorithm of Kalman filter used in the process helps in predicting the states of noise and covariance. Further, the optimization of the generated output is done using an intelligent PSO technique. The main logic behind the objective is to reduce the non-linearity and to pin-point the latent features that reduce the non-linearity of the system.

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