Improved Dynamic Parameter Estimation by Optimize Kalman Filter using Swarm Intelligence in PMU

Sahil Sharma
AP Vibhuti, Electrical, SSCET, Pathankot, INDIA

Abstract- Load flow is the main issue which occurs in power grid systems. To improve the performance, reduce the cost and enhance the reliability in power systems, smart grids have been proposed. In electricity distribution system, smart devices like smart meters are used for effective performance. The real concern in these devices is to protect the data from unauthorized parties and noise occurring in data. Smart device reader acts as the bridge which connects the smart grid devices with smart grid clouds. In most of the cases of circuit analysis, the network components are limited to the known value of impedances with current and voltage source. But the load flow problem is different in the sense that instead of impedances, the known quantities are active and reactive powers at most network buses, since the behavior of most of the load in a lot of cases are as constant power loads, assuming that voltages applied on them remain within acceptable ranges. There are various methods which are used to solve these problems. Kalman filters are proposed to achieve the optimal performance on the smart grid devices. This filter identifies the device failures, unusual disturbance, and malicious data attacks. The analysis of real-time data depends on Phasor Measuring Units (PMU) which plays a significant role in power transmission and distribution processes due to their ability to monitor the power flow within a network. 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 adopt 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: *PMU, Bus, Filters, Kalman, PSO, Taylor expansion, Voltage*

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. It offers a large potential for maintenance of large security of the supply system with the help of efficiency. When these are linked or coupled with the smart meter roll-out, then the possible efficiency is always larger as the customers easily adapt with their own demands on real time basis and usually increase the renewable energy integration into the grid [1, 2]. Keeping it in mind, a target has been set by the EU has set a target of around 80 percent of the already existing meters of electricity i.e. to be changed by 2020, guessing 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 ambitions of EU's were basically set out in innovation-led electricity-based system transformation and technology-based context.

1.1 Smart Grid Technology

The Smart Grid usually refers to an improved supply chain of electricity that is driven from the major power plant making an efficient way inside our home. In United States, there are large number of power plants approximately in thousands throughout that help in generation of electricity nuclear energy, coal, nuclear, wind, hydro and a large number of other kind of resources. The station that performs the process of generation produces the energy electricity at a specified voltage of electricity. Such a voltage gets further increased or stepped down to high voltages, like 500,000 volts, in order to boost the efficiency of power transmission over large regions apart on the basis of distance. In this case, once the electrical power is available near to your city or town, then the electrical voltage is decrease or stepped-down in a utility-based substation to a very low distribution voltage near around your city or town. As such an electrical power of the system reaches close to the user home, it is further stepped-down to the voltage to be used in the house with the help of another transformer [4] [8, 10]. This amount of power generally enters the home through the user-based electrical meter. The home voltage is typically around 110-120 volts in case of most of the house-hold appliances, but it may also lie from 220-240 volts for air conditioner, electric dryer, etc.

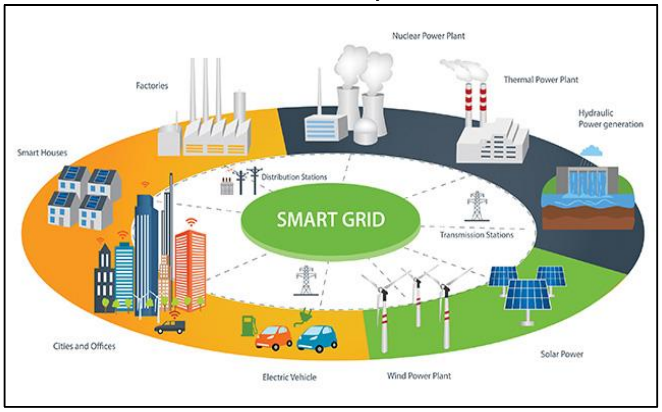

Fig.1: Smart Grid [16]

Table1: Conventional vs. Smart Grid

	CONVENTIONAL GRID SYSTEM	SMART GRID SYSTEM
Metering Operation	Solid State, Electromechanical	Microprocessor/Digital
Communication	Either One way or Two-way communication	Integrated/Global two-way communication
Interaction of customer	Limited	Extensive
Control system	Limited contingencies of control systems	Pervasive control system
System Reliability	Cascading outages, Estimated: prone to failures	Predictive: Pro-active real time islanding and protection
Topology	Radial	Network
Generation	Centralized	Distributed and Centralized generation
Monitoring	Blind	Self-Monitoring
Maintenance & operation	Check equipment manually	Monitor equipment remotely
Restoration	Manual	Self-healing, Automated
Control of power flow	Control systems, Limited protection, and monitoring	Adaptive protection, WAMPAC.

1.2 Smart Grid Technologies

Generally speaking, the technologies are needed to properly implement the large basic needs of Smart Grid system that would consist the following:

*1. Advanced Metering Infrastructure (AMI):*It is considered as one of the major parts 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 systems, which enables the collection and dissemination of informational data between the utilities and users' meters.

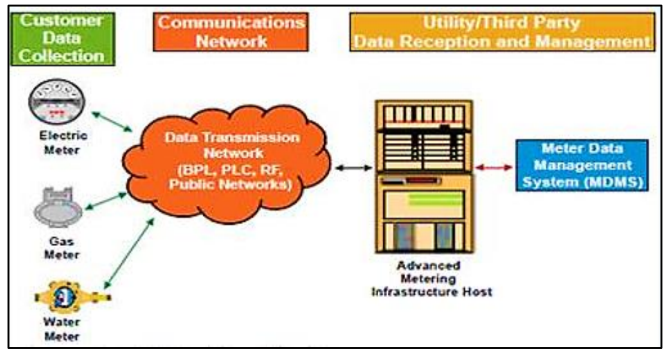

Fig.2: AMI components [17]

2. PMU and WAMPAC: Synchronized phasor measurements are 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] [6] [9]: 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.For making Indian grid smart wide area measurement (WAM) based on PMU i.e. Phasor measurement Unit is an important technology which plays a key role for making grid smarter [12, 13]. This technology of WAM may be employed for the following:

- Blackouts Threat and Scope Reduction
- State Based Measurement
- Increasing the Capacity of Transmission Line
- Calibration of Instrument Transformers
- Integration of Renewable Resources

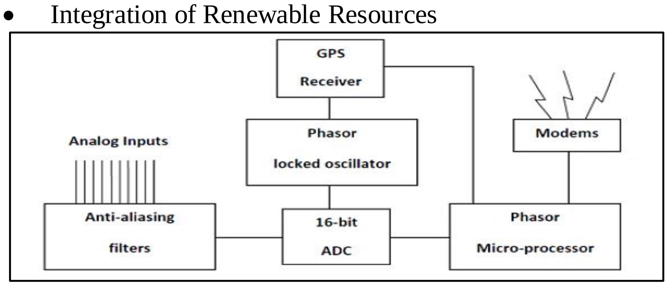

Fig.3: PMU (Different Components) [14] [15]

1.3 Wide Area Monitoring

The architecture of WAMS is generally classified as Distributed, Centralized, and Decentralized architecture [3]. The factors distinguishing among such type of dataflow or information between data acquisition location, the decision selective location and the place where the action are based on certain decisions performed. The section below deeply describes distinct types of wide area monitoring systems i.e. WAMS architecture

1. Centralized Architecture of WAMS: In an architecture of WAMS (centralized), the data analysis PMU-based data acquisition, and performance of therapeutic activity is generally performed at the central type of location. Figure 3 encloses the architecture of WAMS (centralized). The phase monitoring units (PMUs) from certain operating substations forwards the phasor data to the PDSC Central part where concentration of data and the time alignment of all the received PMUs activity of the data takes place. The data concentrated is generally used for the process of visualization and analytics. The corrective actions derived from such type of analysis is forwarded to the primary devices.

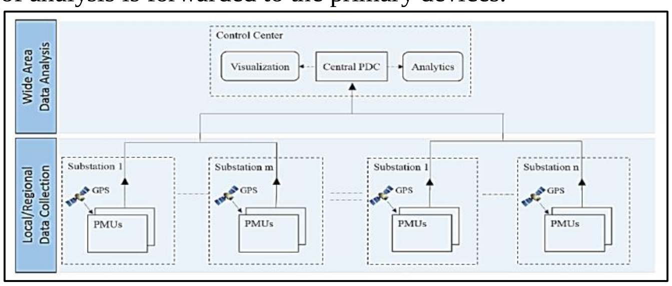

Fig.4: Centralized WAMS Architecture [7]

2. WAMS Decentralized Architecture: In an architecture of WAMS (decentralized), the area of monitoring is generally divided into small multiple type of areas and the PDCs perform local control of such small regions locally with the help local type of data. The system controllers built locally are linked to each other if they have the capability or the requirement to resolve the problems of larger area. Figure 4 encapsulates the decentralized architecture of WAMS.

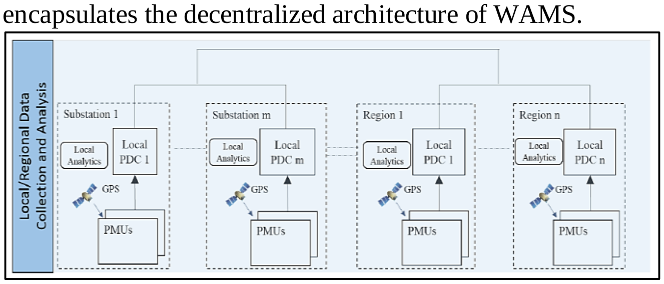

Fig.5:Decentralized WAMS Architecture [7]

3. WAMS Distributed Architecture: The architecture of WAMS (distributed) can be usually mapped between the architectures of

decentralized and centralized form. It involves local as well as the central type of controllers. It is depicted as a centralized type of control with its decentralized form of running stage. Figure 5encloses the architecture of distributed type of WAMs. It is usually comprised of PDC (local) placed at region level or substation and the master form of PDC placed at central controlling station.

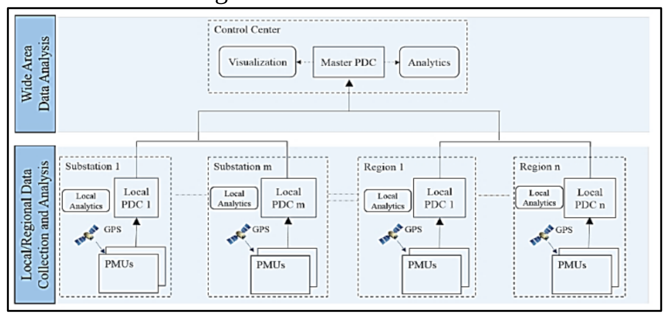

Fig.6: Distributed WAMS Architecture [7]

II. RELATED WORK

Helder RO Rocha, et al [1] presented a new approach for designing the WAMS i.e. Wide Area Measurement Systems. An algorithm based on topological analysis in the basis of Variable Neighbourhood Search heuristic was tested and proposed in various type of networks, that includes IEEE testing networks and the Brazilian 5804-bus transmission system. The analysis of the results has shown the effectiveness, scalability, and flexibility of the proposed framework on comparing it with presented literature-based research. Morteza, Sarailoo et al [2] was to accurately infer the isolated PMUs-based synchro phasors in order to hide the spoofing effects on the basis of real-time functions in respect to the network of PMU. As presented in the framework, a solution of deterministic form usually requires more redundant form of PMUs and lots of interconnections in the environment based on the circuits of physical transmission. Therefore, the cost (defensive) rapidly develops with increase amount of attacks based on aggressive spoofing. In order to address this kind of problem, various future-based directions have been considered. Shahriar Amani, et al [3] was to use a new method in order to determine the optimized alterative and minimized PMU number in the network on the basis of PSO based algorithm. Considering the system from the PMUs based perspective, the process of location optimization was mainly performed on estimation mode for control and voltage variables in a distributed network with multiple loads and DG resources. The main purpose of this work was to determine the minimum number of PMUs and the voltage-based differences on the basis of algorithm in the network premises. MariappanSaravanan, et al [4] proposed the application of power domination integrity to an electric network of power system. A phasor measurement unit was used for analyzing and controlling the energy system by measurement of voltage phase in transmission lines and electrical nodes. For achieving this, the graph theory concept of domination was applied to energy-based networks by redefining the vertex "adjacency" as an "observed" vertex. The domination powers number helps in identifying the PMU number to be placed. The concept proposed the integrity of power domination that not only provides minimum number of PMUs but also helps in identifying the optimized locations for the placement of PMU in an electric network of power system.Tapas Kumar Maji. et al [5] introduced a concept to solve the OPP-based problem, an algorithm of EBPSO was proposed and it was tested on distinct type of systems, like IEEE 118- bus, 57-bus, 14-bus, and practical system based on NRPG 246-bus. Due to coefficient of exponential inertia-based weight, two useful and innovative sigmoid function (SFs), two techniques based on Social Media Optimization (SMO) and logical 'filtration', multiple solutions are usually obtained. The coefficient based on exponential inertia weight was introduced for improving the capability based on swarm searching.Nadia HanisAbd Rahman, et al [6] uses V-shaped sigmoid function and mutation strategy that improved the diversity of population, which further minimized the number of particle chances of being trapped in the region of local optima, therefore leading to a solution based on quality. For validating the effectiveness of the solution, the obtained results by the proposed methodology were compared with other existing techniques in order to demonstrate the validity and accuracy of the technique that was proposed. The IEEE 300-bus system results show that the method proposed managed effectively to reduce the number of PMUs required. Carlos A. Lozano, et al [7] presented a comparison and review of several methods for placement of PMU in power systems. The researchers have included a classification in accordance to the type of obtained observability and considered the method-based application. Finally, a method to monitor the stability of voltage in power systems was selected and tested on IEEE39 bus system by using MATLAB-PSAT, where PSAT represents the Power System Analysis Toolbox.N. M. Manousakis, et al [8] provided a broad literature-based review on the problem of OPP along with its possible methodological solutions. In this field, a large number of materials has been published, so the most ideal and classical papers were reviewed. The techniques proposed can be divided into three of the major categories: heuristic, metaheuristic, and conventional. The reviewing literature further presented will be useful for the analysts for discovery purpose as well as for applying new approaches for solving the issues related to optimal phasor.SaikatChakrabarti, et al [9] presented a method for using the synchronized kind of measurements for the process of complete power system observability. The PMU placement that utilizes the measurements of time-synchronized measurements of current and voltage phasors, was studied in this framework. An approach named integer quadratic programming was mainly used for minimizing the needed PMUs in total number, and to further maximize the redundancy-based measurement at the buses of power system. P.S. SreenivasaReddy, et al [10] aimed to provide an extensive survey on optimized placement of phasor measurement unit (PMU) for the rising development of power system. The process includes the use of distinct type of algorithms for optimum placement of PMU and it deeply explained the methods adopted for the proposed work. B. Mohammadi-Ivatloo, et al [11] presented an algorithm based on optimized PMU-based placement for the achieving the observability of power system and it also increased the performance of secondary voltage control scheme. The optimal placement problem (OPP) is formulated such that to minimize the number of PMU installations subject to full network observability and monitoring pilot buses of the system to improve secondary voltage control performance. The BB i.e. branch and bound method of optimization was adopted for solving the problem of OPP that was suitable for the problems with Boolean and integers variables. Chunhua Peng, et al [12] was optimized as the placement of PMU for full power network observation and the minimized number of PMUs. It usually provides a speedy and a general method of analyzing the topology of power network observation on the basis of properties of phase measurement unit and structural information based on the topology of the power network, and resolution of the object function by improved version of binary PSO algorithm that was further combined with a mechanism on the basis of information based on immune system information. MadhaviKavaiya, et al [13] presented a methodology based on integer based linear programming for optimal PMU placement in a known network for achieving the full network observability. Firstly, a complete conventional observability of the given network was mainly designed and then the bus constraints based on zero were added in previously designed formulation. The results obtained from modified and conventional formulation were compared further. However, minimized problem of PMU placement may contain multiple network solutions, so in order to decide the best solution, two of the indices were proposed, SORI and BOI, where SORI is System Observability Redundancy Index and BOI is Bus Observability Index. Results over IEEE 14, 9 bus were presented.

III. THE PROPOSED METHOD

3.1Proposed Methodology

The Kalman filter is an advanced type of filter which is used to filter the measurement noise and provide the optimal estimation of a dynamic system's state. It is recursive in nature so that new measurements can be processed as they arrive. Kalman filter minimizes the MSE (Mean square error) of estimated parameters. An Extended Kalman Filter,based on Taylor series expansion around a nominal value which is taken as the previous estimate in this case needs to be designed. 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 $\boldsymbol{\tau}$ is given by the Jacobian vector function $f(\vec{x},\vec{w})$ about state $\boldsymbol{w}$. Since the process dynamics are continuous while the measurements are usually discrete in nature, a hybrid continuous-discrete EKF model is developed.

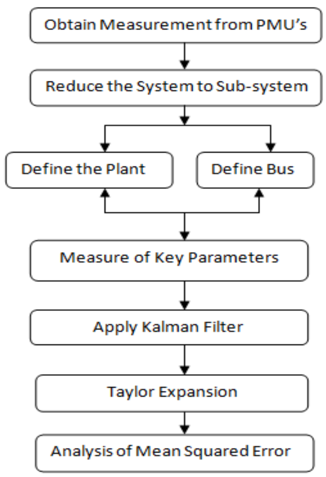

Fig.7: Proposed Steps

The EKF equations of discrete time cannot be used directly and thus 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 (repetitive data). An observable, non-linear dynamical system, with the continuous process dynamics and discrete measurement of dynamics is explained by: Here $\vec{x}$ □^{n} shows the n-dimensional state vector of the system, $f(.)$ $D_x \to \Re^n$ is a finite non-linear mapping of system states to system inputs, $\vec{z}_k D_z \subset$ □^{p} denotes the p-dimensional system measurement, $h(.)$ $:D_x$ □^{n} □^{p} is a non-linear mapping of system states to output, $\boldsymbol{\tau}_c$ □^{nxw} denotes the continuous process noise scaling matrix , $\vec{w}D_W$□^{W} denotes the w-dimensional random process noise and $\vec{v}D_v$□^{v} denotes the v-dimensional random measurement noise

3.2 Algorithm Used

UKF algorithm: The unscented Kalman filter (UKF) provides an impactful or effective recursive filter on the basis of discrete-time i.e. used for solving the problems of estimation as stated below:

$$x_k = f(x_{k-1}) + q_{k-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (1)$$

$$y_k = \square(x_k) + r_k \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (2)$$

Where,

x = state vector and;
y = measurement vector.
h and f functions = non-linear equations of the measurement and system, respectively.
q_{k-1} = system noises with zero covariance and mean matrices Q and R.
r_k = measurement noises with zero covariance and mean matrices Q and R.

The UKF jointly combines the unscented transformation (UT) and classical Kalman filter (KF) theory. The major objective of using unscented Kalman filter (UKF) is the use of equations above that represents the model-based measurement and presents an exact system instead of linearized models as in case of EKF that generally avoids the loss related to information based on higher order. Additionally, no Hessian or Jacobian matrices are required that would help in reduction of needed CPUs and this results in offering advantages on the basis of computational over extended Kalman filter [84]. Rather, only restricted Sigma point number in (20) and (21) are significantly required in UKF. We can say that it helps to provide higher level of accuracy than in case of the EKF in similar computing circumstances. The steps of the UKF are stated as follows. Based on the theory of the UT i.e. unscented transformation as explained in earlier section, the Sigma points { x_{k-u} } are modelled/created and further evaluated (one by one) with the help of system-based equation.

$$X_k = f\left(\chi_{k-1,i}\right) \quad i = 0, \dots\dots, n \quad \dots\dots\dots\dots\dots\dots (3)$$

In the next step, one can compute the state mean (predicted) vector x_k^-, and the covariance (predicted) matrix P_k^- as states below:

$$x_k^- = \sum_{i=0}^{2n} W_i^m X_k^i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (4)$$

$$P_i^- = \sum_{i=0}^{2n} W_i^c \left[\left(X_k^i - x_k^-\right)\left(X_k^i - x_k^-\right)^T\right] + Q_{k-1} \dots (5)$$

Where,
X_k^i = Matrix X_k based $(i+1)^{t\square}$ column
$X_k = n \times (2n+1)$ matrix that contains the propagated form of sigma points.
Another step involves the build-up phenomenon of distinct sets of Sigma point $\{\chi_{k,j}\}$ that corresponds to P_k^- and x_k^- with UT same theoretical concept and compute the points of Sigma with the help of the given (below) measurement equation:

$$Y_i = \square\left(\chi_{k,j}\right) \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (6)$$

The measurement covariance S_k matrix and the mean evaluated points μ_k and C_k that represents the cross-covariance of the measurement and state are evaluated using the equations below:

$$\mu_k = \sum_{i=0}^{2n} W_i^m Y_k^i \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (7)$$

$$S_k = \sum_{i=0}^{2n} W_i^c \left[(Y_k^i - \mu_k)(Y_k^i - \mu_k)^T \right] + R_k. \dots\dots (8)$$

$$C_k = \sum_{i=0}^{2n} W_i^c \left[(X_k^i - x_k^-)(Y_k^i - x_k^-)^T \right] \dots\dots\dots\dots (9)$$

In the final step, the filter gain K_k, the updated forms of covariance P_k, and the state mean x_k are evaluated as follows:

$$K_k = C_k S_k^{-1} \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (10)$$

$$x_k = x_k^- + K_k(y_k - \mu_k) \dots\dots\dots\dots\dots\dots\dots\dots\dots (11)$$

$$P_k = P_k^- - K_k S_k K_k^T \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots (12)$$

IV. RESULT ANALYSIS

4.1 Result Analysis

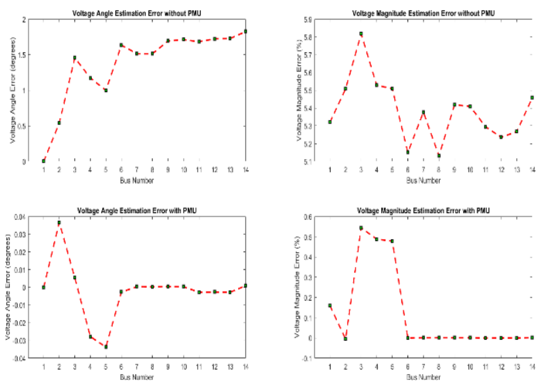

Fig.8: Proposed Approach Voltage profile

BUS	Voltage magnitude with PMU	Voltage angle with PMU
1	1.59E-03	-3.21E-12
2	-5.61E-05	0.036676933
3	0.005442012	0.005403532
4	0.004874977	-0.02779928
5	0.004787058	-0.033691186
6	8.88E-08	-0.002644996
7	1.16E-05	0.000370515
8	1.61E-05	0.00030468
9	1.33E-05	0.000438954
10	1.30E-05	0.000339254
11	-7.70E-06	-0.002787357
12	3.40E-08	-0.002688842
13	-1.47E-06	-0.002770346
14	1.84E-05	0.000921524

Table 1: Voltage profile with PMU

Figure 7 analyse the voltage profile, voltage magnitude, voltage magnitude error and voltage error of proposed approach using Kalman with particle swarm optimization in IEEE 14 bus system. In normal load configuration voltage error will increase without using PMU but error reduce when use PMU and voltage angle error and voltage magnitude error reduce and go to stable because PMU reduce the noise.

BUS	Voltage magnitude with PMU	Voltage angle with PMU
1	0.053207345	0
2	0.055077251	0.537399171
3	0.058174447	1.454713789
4	0.055276848	1.172617453
5	0.05508744	0.998183662
6	0.051502452	1.632914674
7	0.053766521	1.514229622
8	0.051304857	1.513151119
9	0.054181079	1.692424425
10	0.05409145	1.711613542
11	0.052940395	1.681591621
12	0.052350832	1.723007686
13	0.052673005	1.727032246
14	0.054580349	1.82495685

In figure 8 analysis the noise reduction with Kalman and Kalman PSO.I graph green color is noise and red line Kalman filter value and blue lineKalman with PSO but Kalman with PSO improve the accuracy of noise.

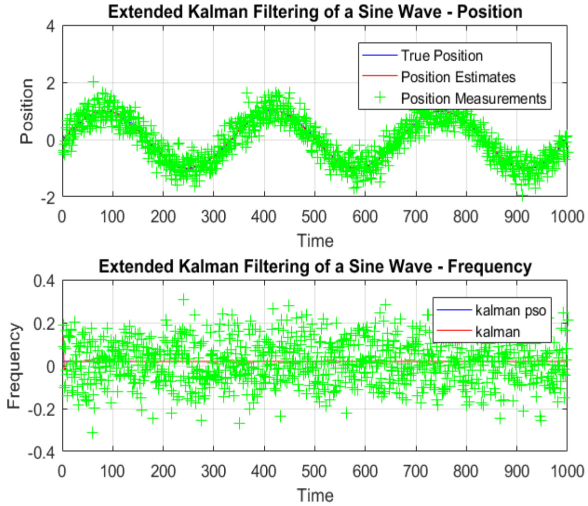

Fig.9: Comparison between Kalman and Kalman PSO ON Noise Reduction

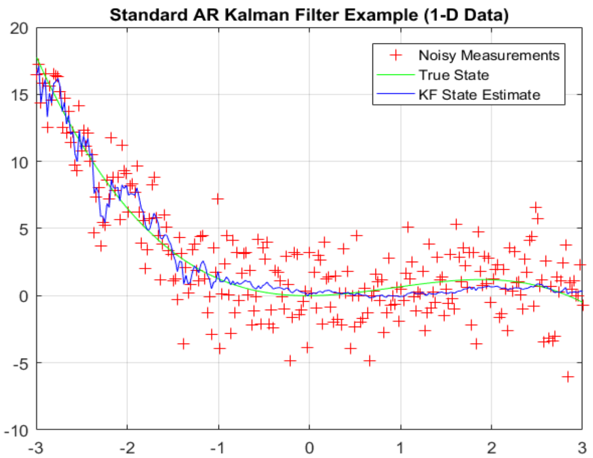

Fig.10: Comparison between Kalman noise reduction Prediction

Figure 9 analyse the noise reduction with Kalman and Kalman PSO. In graph green color is noise and red line Kalman filter value and blue line Kalman with PSO but Kalman with PSO improve the accuracy of noise.

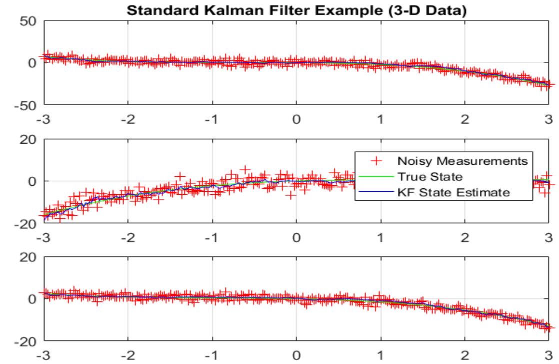

Fig.11: Analysis the noise reduction with Kalman

BUS	Actual noise	Noise Filter by Kalman	Noise filter By Proposed
1	0.053207345	0.032486348	0.00994737
2	0.055077251	0.033176182	0.009437114
3	0.058174447	0.033179578	0.008529099
4	0.055276848	0.03095558	0.007199665
5	0.05508744	0.030452138	0.006909189
6	0.051502452	0.029191277	0.00682263
7	0.053766521	0.030084152	0.007338085
8	0.051304857	0.030192462	0.007352554
9	0.054181079	0.030737641	0.007173315
10	0.05409145	0.030127559	0.006994566
11	0.052940395	0.029654744	0.007160938
12	0.052350832	0.030201395	0.007802807
13	0.052673005	0.030626677	0.008103513
14	0.054580349	0.031580349	0.008580349

Table 3: Noise reduction comparison between proposed and Kalman

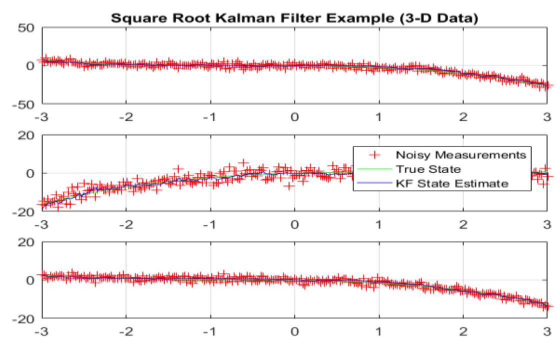

Fig.12: Analysis the noise reduction with Kalman-PSO

Figure 10 and 11 analyse the noise reduction with Kalman and Kalman PSO. In graph red color is noise and red line Kalman filter value and green line Kalman with PSO but Kalman with PSO improve the accuracy of noise.

Number of PMU	KALMAN	KALMAN PSO	Bayesian PSO
2	0.02	0.001	0.001
5	0.03	0.0001	0.0002
8	0.01	0.00001	0.0001
10	0.001	0.00002	0.00002
12	0.002	0.00001	0.00001
15	0.0001	0.000001	0.000002

Table 4: BER comparison

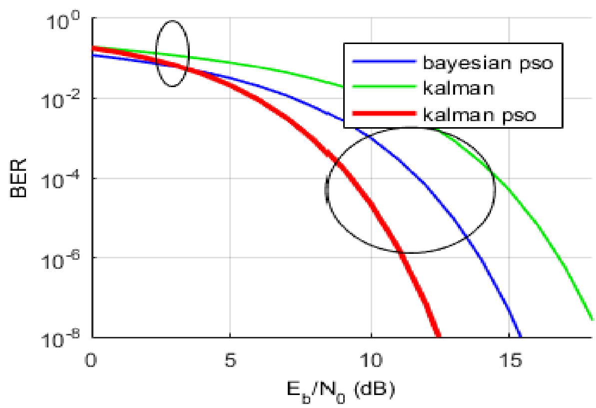

Fig.13: Comparison between BER and Number of PMUs in Different Approaches

Figure 13 analyse the noise reduction with Kalman and Kalman PSO. In graph green color is noise and red line Kalman filter value and blue line Kalman with PSO but Kalman with PSO improve the accuracy of noise.

V. CONCLUSION

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.

VI. REFERENCES

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