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A NOVEL APPROACH OF PARAMETER ESTIMATION OF SMART GRID BY KALMAN FILTER WITH TAYLOR EXPANSION

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ABSTRACT

The use of dynamic state estimation methods such as the Kalman filter provides an optimal solution to the process of real-time data prediction and reduces the problem based on non-linearity. Various extensions such as unscented and the extended forms of Kalman filter have also been developed that specifically work on non-linear systems. 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 research adopts a methodology to work on covariance prior base estimation using Bayesian approach along with the estimation of dynamic polynomial prior by Particle Swarm Optimization (PSO). The experimental analysis compares the results obtained from the basic Kalman filter, PSO optimized Kalman filter and Kalman filter Covariance Bayesian approach. Finally, the results obtained from the analysis highlights the fact that the PSO optimized Kalman filter is more effective than the Kalman filter with Covariance Bayesian approach.

I. INTRODUCTION

The problem of load flow is the main issue which occurs in power grid systems. To improve the performance, reduce the cost and enhance the reliability of power systems, smart grids have been proposed. In electricity distribution system, smart devices like smart meters are used for effective performance. The major issues with these devices is to protect the data from unauthorized parties and the occurrence of noise in data. Smart device reader acts as the bridge which connects the smart grid devices with smart grid clouds [1]. In most of the cases of circuit analysis, the network components are limited to the known value of impedances with a 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, because the behavior of the load in most of the cases is as a constant power load, assuming that voltages applied on them remain within acceptable ranges [2].

There are various methods which are used to solve these problems. Kalman filters are proposed to achieve - optimal performance on - smart grid devices. This filter identifies - device failures, unusual disturbances, and malicious data attacks [3]. Kalman Filter is a dynamic state estimation method which is mainly used in this paper for noise variation estimation. Particle filtering method is another method which is used along with Kalman filter method as a hybrid approach. Particle filtering methods are mainly used to solve the problems arising in signal processing. This technique estimates the internal state of dynamic systems when particle observations are made in the sensors.

II. LITERATURE REVIEW

The smart grid attack detection method proposed is named as cyber-physical fusion approach. It detects the attack by merging traffic flow features with physical laws in power system [5].

To ensure the integrity of the state estimation, bad data detection system is used. In this paper, the author proposed the principal component analysis method which detects the blind false data injection attack [6].

The author proposed a method of false data detection in smart grid by using Chi-square detectors and cosine similarity matching methods. Kalman filter estimation method is used to measure the variation from actual measurement. To detect the attacks and find the robustness of the proposed system, cosine similarity matching approach is used [7].

In this paper, the author analyzed the performance of smart meters for smart grids. In this method, firstly it identifies the channel 1 and 3 of metrology and then harmonics of metrology which has an impact on reliability. The author described the issues related to the security in smart grid networks [8].

The sequential detection method is used to detect - false data injections in - smart grids. Likelihood ratio method is used in sequential detectors. In this research paper, the author also introduced a method for wide area monitoring in smart grids. Level triggered sampling method is used for distributed sequential detector [9].

False data injection attacks are tracked by dynamic measurement variation. Kullback- Liebler Distance method is used to calculate the distance between the probabilities of measurement variations. The value of KLD is changed when - deviations - occur in previous data [10].

Dynamic energy management is performed on the smart grids to manage the energy and optimize power flow. DEM is performed to reduce the power cost in a smart grid environment. In this, the data analysis process is also performed on the data of smart meters. In this method, features are extracted on the basis of traditional factors and smart grid factors. Then map reduces parallel computing and the platform is used for forecasting [11].

The parallel dynamic state estimator works mainly in the processing of large datasets. For massive amounts of data, a two-level dynamic state estimator is introduced with an extended Kalman filter. It utilizes the control of supervision, acquisition of data and phasor measurement unit. The results of the proposed scheme are differentiated with multithreaded CPU-based code. The result shows the outcomes of iterative linear and direct solvers on the state estimation algorithms [12].

For the estimation of the state-of-charge of the Li-ion battery pack of the electric vehicle using an improved extended Kalman filter, it finds to the cell with similar characteristics. A model adaptive algorithm is applied to the strings of cells to reduce the cell to cell variation's effect. The value of each cell is updated by using this algorithm. The mean value of the updated cell value is used for a single unit cell model. The results of this paper show that voltage and state of charge do not exceed acceptable ranges. [13].

This paper presents the study of the demand prediction of the power consumption and monitoring in smart meters. The author proposed a short-term forecasting method for predicting load. It shows the prediction of power consumption in the next hour, next day and next week. This method of prediction is based on the kernel method for non-linear regression. It shows improved accuracy for large meter aggregation [14].

Subspace methods are proposed for data attacks on state estimation in smart grids. Two attack strategies are presented by using estimated system subspace. In this model, the first attack affects the system state by hiding attack vector in system subspace. The second attack misleads the bad data detection method so that data which is not under attack is removed [15].

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Cross-layer defense mechanism against GPS spoofing attacks on phasor measurement units is proposed by the author in this article. In this method, spoofing detection is based on GPS carrier to noise ratio. The spoofing attack is considered as bad data injection in the power system. The evaluation of the proposed method is based on the physical layer information and power grid measurements. It identifies the phasor measurement unit which is attacked [16].

III. PROPOSED 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 $\vec{w}$. 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 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 $\vec{x} \in \Re^{n}$ 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, $\boldsymbol{\tau}_c \in \Re^{nxw}$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.

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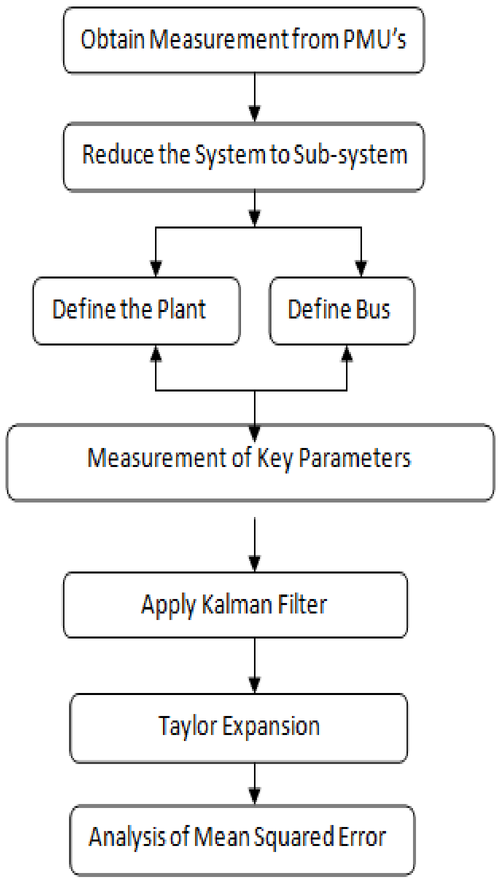

Figure 1.1 Flow chart of the proposed Methodology

IV. SIMULATION OF RESULTS

In this paper, implementation of Kalman filter with Taylor expansion method using MATLAB platform is done. 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 also tested by the Kalman with the Bayesian method.

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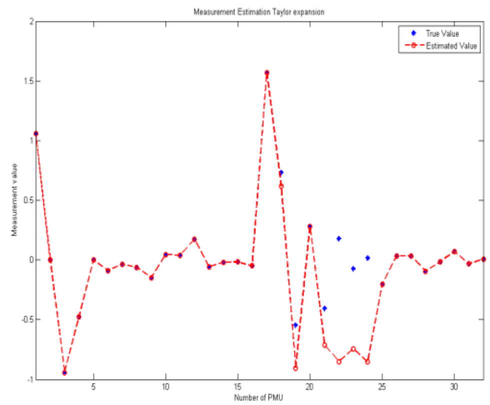

Figure 1.2 Graph between the True Value and estimated value

The above Figure 1.2, 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 polynomiality.

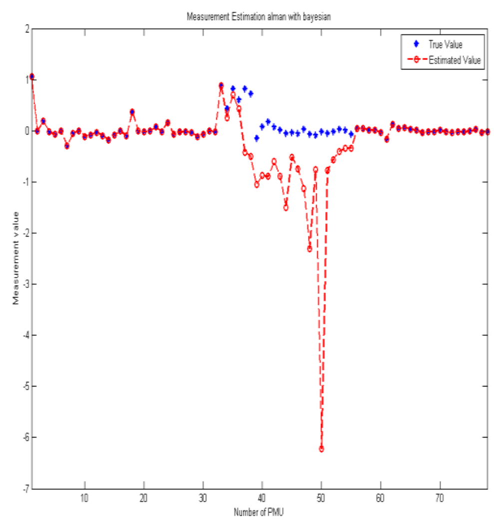

Figure 1.3 Graph between the True Value and estimated value using Kalman with Bayesian

The above Figure 1.3 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.

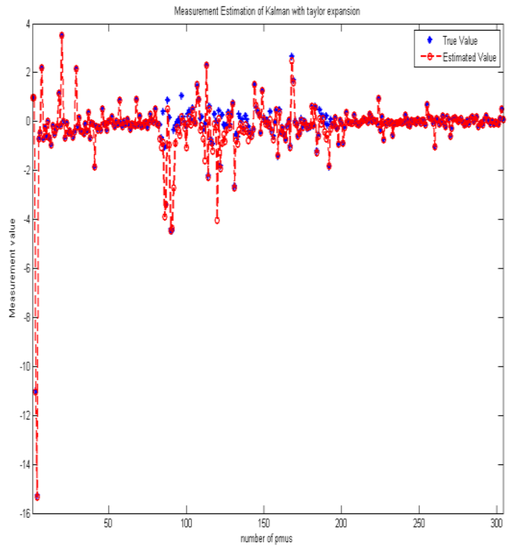

Figure 1.4 Graph between the True Value and estimated value using Kalman with Taylor expansion

The above figure 1.4 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.

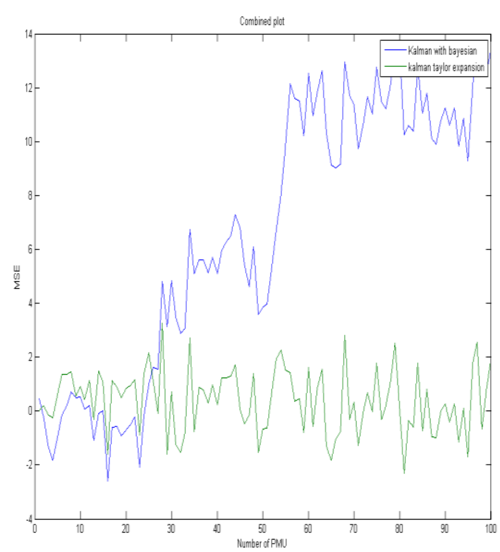

Figure 1.5 Graph between the True Values and estimated values using Kalman with Bayesian and Kalman with Taylor expansion

The above figure 1.5 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. CONCLUSION

This paper tested and compared one of the most popular-Kalman filter technique against a novel method Kalman filter with Bayesian learning.

In this paper, we also used the Taylor expansion of Kalman, which reduces the nonlinearity and improves the mean square error and noise. The concrete logic behind this paper is to reduce the nonlinearity and find the latent features which help in reducing noise.

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