Novel Adaptive Approach using Particle Swarm Optimization in Parameter Estimation for Improved Performance of Smart Grid

Nisha Tayal[1, 2], Rintu Khanna[3]
[1] Research Scholar, I.K. Gujral Punjab Technical University, Kapurthala, India
[2] Assistant Professor, University of Engineering and Technology, Panjab University, Chandigarh, India
[3]Associate Professor, Punjab Engineering College, Chandigarh, India

Abstract - In the proposed paper, the problem of static estimation of the parameters of smart grid with real-time measurement by PMU data has been addressed. In Classical approaches, two adaptive predictors are used one of them for linear parameter and second for the non-linear parameter . For estimation Bayesian and Kalman filters are used respectively. In this proposed approach, both classic approaches (Gaussian and Kalman filter) are hybrid with PSO. To resolve the issue of load uncertainty,the proposed method is used with IEEE-30 bus system which provides the effective results.

Keywords - *Bayesian, PSO, Kalman, Load, Optimize*

I. INTRODUCTION

Smart Grid is a group of technologies, methods and transformers and more that delivers the power from the power plant to the houses, industries, and offices. Smart grid consists of different controls like automation, computers, and resources connected with internet and in this case, these technologies work with electrical grid to respond digitally and speedily. Smart grid uses the I.T approaches to optimize the use of capital asset and thus also helps in minimizing the maintenance costs. The whole idea of making our grids smart is achieved through combining the IT sector with the Power System. This means that prediction of loads and power system parameters in advance helps in accurate decision making. The problem of load flow in power system forms an example of classic engineering problems in power system. In most cases of circuit analysis, the network components are limited to the known value of impedances with current and voltage sources. 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 most of the load in a lot of cases are as constant power loads, assuming that voltages applied on them remain within acceptable ranges. The set of unknowns producing power balance at all of the specified buses in the system is solved by the load flow algorithm. The power balance equation is given by equation

$$P_i^{given} + jQ_i^{given} = P_i^{comp} + jQ_i^{comp}$$

Where

$$P_i^{comp} + jQ_i^{comp} = V_i I_i^* \ .$$

Stated otherwise, the specified power at a particular bus must be same as that of the power flowing into the system. The power which is generated is taken as positive power, which makes it consistent with KCL equation YV=I.

II. RELATED WORK

Introduced a novel approach of adaptive Kalman Filter to have a prediction on dynamic and smart grid state. To abstract the process and management factor there is a utilization of two tests termed as normalized innovation and residual test . The simulation study demonstrates the capability of the given approach under sup-optimal conditions [1]. The author reviewed the optimal and sub-optimal Bayesian algorithm for non-linear Gaussian tracking problem. In this paper author also discussed the Particles filter which is based on the Monte Carlo methods. Different types of particle filter algorithms are also defined such as SIR, ASIR, and RPF. These all are compared with Extended Kalman Filter (EKF) [2].Author reviewed the impact of reliability on smart grid resources such as storage and demand response. When these resources are mixed the reliability is changed. In this paper, a, model is presented to solve these problems which also provides cyber security. The given model was used to support the collection of geographical and temporary co-ordinates for hierarchical control and monitoring action over time scales from milliseconds and up [3].In this paper, particle filters are used for the positioning, tracking, and navigation. Kalman filter is used to estimate all the derivatives. In this author demonstrates how the map matching is used in aircraft elevation to a digital elevation of the car. By using simulation, it also determines how the particle filters are used for positioning based on cellular phone measurements [4].This combines the Gaussian particle filter and sum filter for the purpose of dynamic state-space model with non-gaussian noise. By using the given model Gaussian mixture, the given model will be estimated by banks of Gaussian noise model. These Gaussian mixtures are enhanced by using the same algorithm that is used to enhance Gaussian noise DSS models. The simulation result shows that this model works very effectively [5].A mathematical model to provide the robust security for the power grid, Kalman filter is used to estimate the variables of the state processes. It estimated the reading and fed them into the x^2 detectors. These detectors are called as Euclidean detectors which are used to detect the attacks and faults in the power system. It also detects the denial of service, data injection attack and replay attacks. The relationship among dependent variables and predictor variables is measured by using Kalman filter [6].The parallel dynamic state estimator works mainly on the processing of large datasets. For the massive amount of data ,two-level dynamic state estimator is introduced with extended Kalman filter. It utilized the control of supervisory, acquisition of data and Pharos 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 [7]. For the estimation of the state-of-charge of the li-ion battery pack of the electrical vehicle using improved extended Kalman filter. It finds the cell with similar characteristics. A model adaptive algorithm is applied on the cells of strings to reduce the cell to cell variation's effect. The value of each cell is updated by using this algorithm. The means value of the updated cell value is used for single unit cell model. The results of this paper show that voltage and State of Charge do not exceed [8]. In this paper, the study is on the demand prediction of the power consumption monitoring in smart meters. The author proposed 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 the improved accuracy at larger meter aggregation [10]. Proposed the sensor for the state estimation of the power system. This method uses the two state sampling rate for the measurements. In this model two estimators are also developed for the estimation of the values. BAR-Shalom formula is used for combining the values of the estimator. Proposed method effectively tracks the faults by using fusion based estimator [11].

III. PROPOSED METHODOLOGY

It is an emerging population–based meta –heuristic algorithm used for optimization on the basis of bird flocking and fish schooling. The term Swarm means a collection of particles. PSO is used to optimize the value of an objective function. That value has some point in the search space. Every particle in the space is moving to determine the point at which objective function is optimized. These particles have some position and velocity at the moving time in the search space. Initially, position and location of particles are assigned randomly. After each iteration the position and location of particles are updated by using an equation:

$$V_{i,d}(t+1) = \alpha(t)V_{i,d}(t) + \beta_p ran_p(t)(persbest_{i,d}-P_{i,d}(t)) + \beta_g ran_g(t)(globest_d-P_{i,d}(t)) \quad (1)$$

$$P_{i,d}(t+1) = P_{i,d}(t) + V_{i,d}(t) \quad (2)$$

Every particle has its local and global best position in the space. Global best position is the position of a particle which is close to optimal value and all the particles move towards the global best position. The global position of particle will vary with the motion of particles.

Bayesian Filter with PSO

It is a technique used to estimate or predict the location of particles. It is used to represent the probability distribution by sets of particles. It is an algorithm used to evaluate the chances of multiple beliefs to permit a robot to infer its position and orientation. Bayes filter permits the robot to continuously update their most likely position within the coordinate system on the basis of currently obtained sensor data. It consists of two parts 1) prediction and update steps.

Prediction step: It used the state updated model by using

$$P[u_i| \ v_{1:i}] = \int p \ (u_{i|} \ u_{i-1} \ ) \ p \ (u_{i-1}| \ v_{1:i-1}] \ d \ u_{i-1} \quad (3)$$

Update step: with measurement used to update the prior using bayes rule:

$$P[u_i| \ v_{1:i}] = \frac{p(v_i|u_i)p\,(u_v|v_{1:i-1})}{p(\,v_i|v_{1:i-1})} \quad (4)$$

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 $\overrightarrow{x}$ 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. 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.

Proposed Algorithm
Step 1: By using phasor measurement unit obtain measurements.
Step 2: Reduction of system into sub-system by defining plant and bus.
Step 3: Identification of key parameters
Step 4: Implementation ofparticle swarm optimization to optimize the evaluated value using the formula: $V_{i,d}(t+1) = \alpha(t)V_{i,d}(t) + \beta_p ran_p(t)(persbest_{i,d}-P_{i,d}(t)) + \beta_g ran_g(t)(globest_d-P_{i,d}(t))$ $P_{i,d}(t+1) = P_{i,d}(t) + V_{i,d}(t)$
Step 5: PSO used to change the particle into a fitness function and upgrade the objective.
Step 6: If, updating is not completed, then, restart the process by Applying PSO algorithm.   Or   If completed, we apply the Bayesian filter for estimation of location by using the equation $P[u_i \| v_{1:i}] = \int p\ (u_{i\|}\ u_{i-1}\ )\ p\ (u_{i-1}\| \ v_{1:i-1}]\ d\ u_{i-1}$ $P[x_k\| \ z_{1:k}] = \frac{p(v_i\|u_i)p\,(u_v\|v_{1:i-1})}{p(\,v_i\|v_{1:i-1})}$
Step 7: The result obtains from Bayesian are used to analyze for the mean square error.

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. The goal of this paper is to solve the issue of the estimation of parameters for improved performance of smart grids. Non-linear extensions of Kalman Filter will be developed which will utilize a probabilistic approach to the problem. Several Extensions like Extended Kalman Filter, Recursive Bayesian Filter have been developed for state estimation in other areas of engineering, especially space programs. The main aim is to apply various new Bayesian filters like Particle Filter, Unscented Kalman Filter etc. for the performance improvement of smart grids in terms of quality and security. A novel hybrid of these filters will also be developed and a comparative analysis of these will be done.

The process is discretized and the discretized form of the process model can be expressed as:

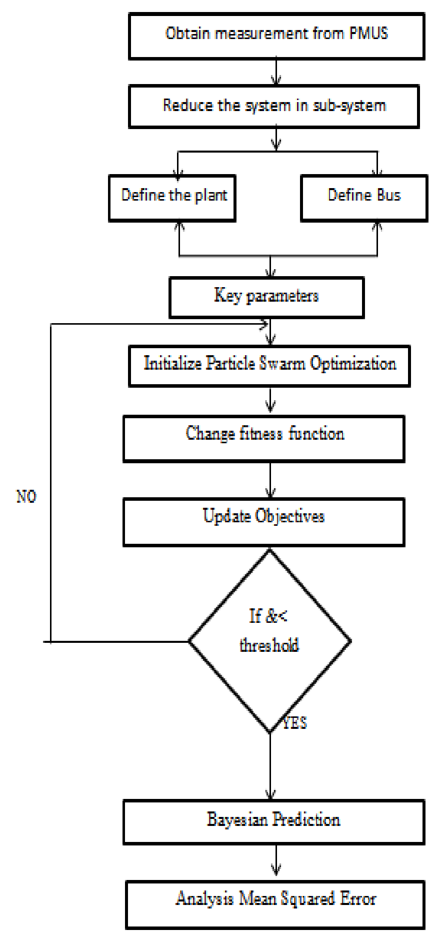
$$\vec{x}_k = \boldsymbol{F}_{k-1}\vec{x}_{k-1} + \vec{w}_k$$

Where $\vec{w}_k$ *a discrete white noise and F is* given by:

$$\mathbf{F}=e^{\mathbf{A}T} = I + AT + \left(\frac{AT^2}{2!}\right) + \cdots (4.1)$$

Here only terms up to second order are considered and higher order terms are neglected for the expansion of the state transition matrix. Using the process model, the states are propagated (predicted) in time and the measurements are used to correct thepredicted estimates.

Proposed Methodology (flow chart):



IV. SIMULATION RESULTS

In this section several simulation results are reported for a preliminary evaluation of the proposed Gaussian and Kalman filter PMU parameter estimation with particle swarm optimization. Simulation parameter on IEEE-30 bus system on MATLAB.

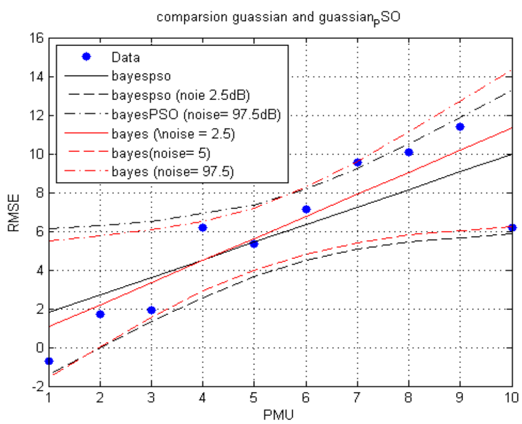


Fig.1: Comparison graph on Gaussian and GaussianPSO

Fig1 represents the prediction of PMU by Gaussian and Gaussian with PSO. The Gaussian PSO reduces the noise because of PSO and it sets adaptive prior for Gaussian prediction for noise. Red line shows Gaussian with PSO prediction which is approximate overlaps the blue point which is actual value.

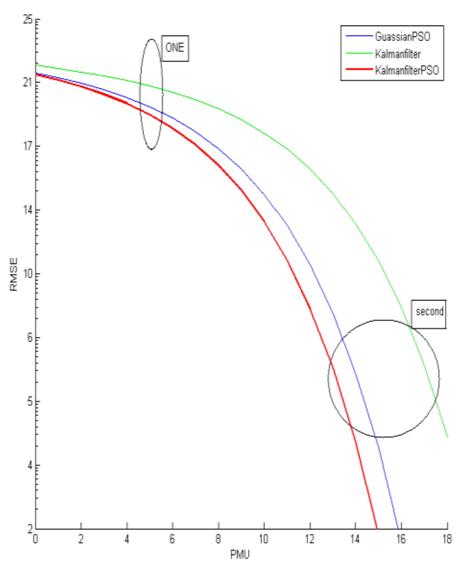


Fig 2: Comparison of RMSE on proposed methods

In Fig 2 X- axis represents the PMU values and Y-axis represents the RMSE values. In given graph two rectangles show the variation between the proposed and previous approaches. On analyzing we see the initial condition where the number of PMU is less and RMSE error increases. PMU in Kalman with PSO (Red line) performs better due to its non-linearity property which is optimized by PSO.

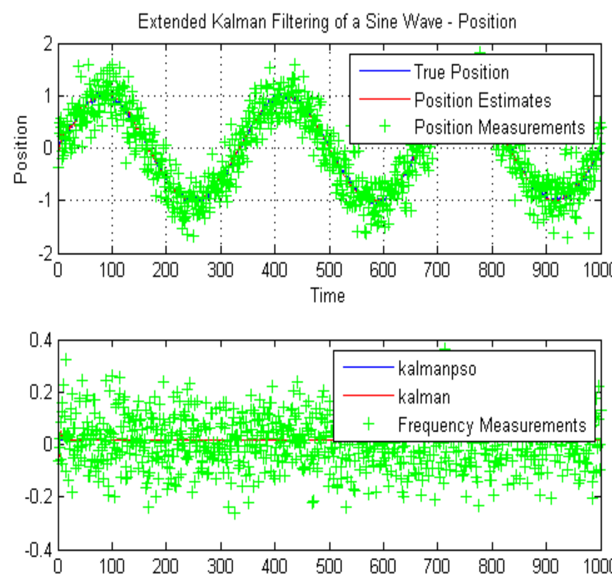


Fig 3: Graph of extended Kalman filter of a sine wave-position.

Fig 3 represents the noise prediction by using the Kalman with PSO. The upper part of the graph represents the non-linearity in prediction by both methods (kalman and kalman with PSO) in which red line represents the Kalman and blue line represent the Kalman with PSO. Blue line reduces the noise in both upper and lower graph.

V. CONCLUSION

In this paper, a comparison between the linear and non-linear parameters by using Bayesian and Kalman Filters respectively has been achieved. In the simulation result , filters are hybrid with PSO which increased the prior efficiently. Prior is a type of optimization information (threshold) which is given by the PSO by using iterative prediction. In the experiment, Fig 1 and Fig 3 show that Bayesian and Kalman Filter hybrid with PSO provided efficient parameter estimation which reduced the error or noise in PMU data.

VI. REFERENCES

[1]. Zhang, Jinghe, et al. "Kalman filters for dynamic and secure smart grid state estimation." *Intelligent Industrial Systems* 1.1 (2015): 29-36.

[2]. Arulampalam, M. Sanjeev, et al. "A tutorial on particle filters for online nonlinear/non-Gaussian Bayesian tracking." *IEEE Transactions on signal processing* 50.2 (2002): 174-188.

[3]. Moslehi, Khosrow, and Ranjit Kumar. "A reliability perspective of the smart grid."*IEEE Transactions on Smart Grid* 1.1 (2010): 57-64.

[4]. Gustafsson, Fredrik, et al. "Particle filters for positioning, navigation, and tracking." *IEEE Transactions on signal processing* 50.2 (2002): 425-437

[5]. Kotecha, Jayesh H., and Petar M. Djuric. "Gaussian sum particle filtering." *IEEE Transactions on signal processing*51.10 (2003): 2602-2612.

[6]. Manandhar, Kebina, et al. "Combating false data injection attacks in smart grid using kalman filter." *Computing, Networking and Communications (ICNC), 2014 International Conference on*.IEEE, 2014.

[7]. Karimipour, Hadis, and VenkataDinavahi. "Extended Kalman filter-based parallel dynamic state estimation." *IEEE transactions on smart grid* 6.3 (2015): 1539-1549.

[8]. Sepasi, Saeed, Reza Ghorbani, and BorYannLiaw. "Improved extended Kalman filter for state of charge estimation of battery pack." *Journal of Power Sources* 255 (2014): 368-376.

[9]. Chen, Rui, Dajun Du, and MinruiFei. "A Novel Data Injection Cyber-Attack Against Dynamic State Estimation in Smart Grid." *Advanced Computational Methods in Energy, Power, Electric Vehicles, and Their Integration*.Springer, Singapore, 2017.607-615.

[10]. Mirowski, Piotr, et al. "Demand forecasting in smart grids." *Bell Labs technical journal* 18.4 (2014): 135-158.

[11]. Ghosal, Malini, and VittalRao. "Fusion of Multirate Measurements for Nonlinear Dynamic State Estimation of the Power Systems." *IEEE Transactions on Smart Grid* (2017).