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Dynamic State Estimation of a Power System Network with Wind Energy Integration Using Ensemble Kalman Filter

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Abstract

State estimation (S.E) is a technique used to find unknown values of the state variables based on some imperfect measurements. In power systems, state estimation is considered as a set of techniques able to provide a quantitative snapshot of the state of an entire network on the basis of partial or incomplete set of data.

With the increasing integration of weather-dependent and intermittent renewable energy sources (RES), the power systems become more dynamic. Thus, the static state estimation can no longer capture the dynamism of new modern power systems. This led to the development of the dynamic state estimation.

The dynamic state estimation (DSE) commonly uses the Kalman filter (KF) algorithm for linear systems and its non-linear variants for non-linear systems like the power systems. Thus, in this paper, the dynamic state estimation using one of these variants known as the Ensemble Kalman filter (EnKF) is investigated. The EnKF algorithm and its application to the estimation of the state variables (voltage magnitudes and phase angles) are explained. Simulations are carried out using MATLAB software to evaluate the accuracy of the algorithm whose inputs are the power flow results obtained by using MATPOWER. The performance of the EnKF is analyzed on a modified IEEE 14-bus test system with a wind distributed generator connected to the system.

Keywords: DSE, EnKF, Estimation, IEEE 14-bus, KF

I. INTRODUCTION

Since its presentation in 1960, the Kalman filter algorithm's contributions in the research on power system SE has been limited due to its higher complexity [1]. Many power system engineers focused rather on the static state estimation (SSE) based on the Weighted Least Squares (WLS) technique. In 1970, Schweppe introduced the WLS for static state estimation in [2]. Later on, many publications related to the static estimator have been written in and some textbooks have also made some contributions on it [3].

But as the power system grows, with the increasing penetration of renewable generation that has very high intermittency and variation, the system becomes extremely large for the static state estimation to be carried out at short intervals of time as it consumes heavy computing resources. Even if the SSE is important for power system monitoring, it is not adequate to capture the dynamic behavior of the power system. Hence, it has proved necessary to implement another set of algorithm called the "Dynamic State Estimation" (DSE) [4].

Power system DSE has been implemented by many types of Kalman filters. The Kalman filter is a recursive filtering method that uses only the current observed data and the estimate of the state at the last instant to estimate the state at the present instant.

Debs and Larsonn dedicated a paper to power system SE using KF in [5]. The Kalman filter (KF) [6] applied to nonlinear systems like the power system is in the form of extended Kalman filter (EKF) [6], which linearizes all nonlinear transformations.

Though EKF keeps the computationally efficient recursive update form of the KF, it is suitable only in a nonlinear environment due to the first-order Taylor series approximation for nonlinear functions [6]. It is sub-optimal and can easily lead to divergence.

In order to cope with the linearization problems of, the unscented transformation (UT) has been developed. Based on UT, Julier et al. [6] proposed the unscented Kalman filter (UKF) as a derivative-free alternative to EKF in the framework of state estimation. Thus, the UKF turns out to be an improvement of the EKF SE as it is much easier to implement than the EKF, because there is no need for the linearization and the derivation of Jacobian matrices. Valverde and Terzija showed the advantage of the unscented Kalman filter (UKF) over the EKF and WLS methods [7].The UKF has been applied to power system DSE, for which no linearization or calculation of Jacobian matrices is needed [7].

However, both EKF and UKF are not suitable to be applied in high-dimensional state-space models with the state vectors of size twenty or more, especially when there are high degree of nonlinearities in the equations that describe the state-space model, which is exactly the case for power systems [6].

As both EKF and UKF have some inconveniences, the researchers in power systems start to apply the ensemble Kalman filter for the dynamic state estimation. Zhou et al. [8] [DSE (ENKF)] proposed an ensemble Kalman filter (EnKF) method to simultaneously estimate the states and parameters. Ray and Subudhi in [9] proposed a new algorithm for the estimation of harmonics using EnKF.

In this paper, the EnKF is applied to the dynamic state estimation of state variables of a modified IEEE 14-bus test system with wind generator considered as distributed generator connected to the system. The performance of the EnKF is analyzed in terms of accuracy and computational time.

II. RESEARCH METHODOLOGY

II.I Dynamic state estimation

Dynamic state estimation techniques took place in power system to replace the static state estimation. The power system is considered as a quasi-static system changing slowly in function of time. The DSE is a more accurate state estimation technique characterizing the time varying nature of the power system [10].

Dynamic state estimation uses the actual state of the power system to predict the state vector for the next time instant. Then, once the new measurements at the next instant of time reach, the predicted values are filtered to obtain a more accurate estimate of the states. This prediction feature of the DSE provides many benefits in system operation, control, and decision making. DSE is composed of two stages: prediction and estimation [10].

- Prediction (Forecasting)

In this step, the prediction of the current state is made based on the dynamic of the system and the last estimate. Obtaining the mathematical equation for the time evolution of the state is crucial in order to develop a dynamic state estimator. It is also difficult to be done because the model must have the correct knowledge on the future behavior of the loads, generator etc.

- Estimation (Filtering)

In this step, the estimation of the current state is made based on the measurement and the predicted state.

II.II Ensemble Kalman Filter algorithm

The ensemble Kalman filter is a particular type of the Kalman filter suitable to be applied in large power systems where the EKF and UKF are not appropriated due to the highly computed time [11].

The Ensemble Kalman Filtering method uses the two methods of prediction and estimation.

- In the prediction step, the method starts by generating a finite number of estimate points for the state parameter x_t from an a priori distribution. Let us denote this predicted ensemble of state estimates by X_t^p and let the fixed sample size be N :

$$X_t^p = \left\{ x_t^{p_i} \right\}, i = 1, ..., N \tag{1}$$

An ensemble of the same size N consisting of measurements generated by adding small perturbations to the current measurement is denoted by Y_t^p:

$$Y_t^p = \left\{ y_t^{p_i} \right\}, i = 1, \ldots, N \tag{2}$$

With $y_t^{p_i} = H_t x_t^{p_i} + v_t^{p_i}$

The samples for the state model ensemble may be drawn using the following rule:

$$x_t^{p_i} = f(\hat{x}_{t-1}^{p_i}) + w_{t-1}^{p_i} \tag{3}$$

Where $\hat{x}_{t-1}^{p_i}$ is the updated estimate at the instant $t-1$ and $w_{t-1}^{p_i}$ is a random noise with covariance Q_{t-1}.

The state ensemble error matrix $E_{x,t}^p$ and the measurement ensemble error matrix $E_{y,t}^p$ are then defined as follow:

$$E_{x,t}^p = \left[x_t^{p,1} - \bar{x}_t^p, \ldots, x_t^{p,N} - \bar{x}_t^p \right] \tag{4}$$

$$E_{y,t}^p = \left[y_t^{p,1} - \bar{y}_t^p, \ldots, y_t^{p,N} - \bar{y}_t^p \right] \tag{5}$$

Where $\bar{x}_t^p$, $\bar{y}_t^p$ are the ensemble averages for the states and the measurements given by:

$$\bar{x}_t^p = \frac{1}{N} \sum_{i=1}^{N} x_t^{p_i} \tag{6}$$

$$\bar{y}_t^p = \frac{1}{N} \sum_{i=1}^{N} y_t^{p_i} \tag{7}$$

- In the estimation step, the estimated error covariance $\bar{P}_{xy,t}^p$ and the estimated measurement covariance $\bar{P}_{yy,t}^p$ are given by the equations below:

$$\bar{P}_{xy,t}^p = \frac{1}{N-1} E_{x,t}^p \left[E_{y,t}^p \right]^T \tag{8}$$

$$\bar{P}_{yy,t}^p = \frac{1}{N-1} E_{y,t}^p \left[E_{y,t}^p \right]^T \tag{9}$$

Finally, the updated estimates for each trajectory are computed using the following equations:

$$\hat{x}_{t,ensemble}^i = x_t^{p_i} + \left[\bar{P}_{xy,t}^p \right] \left[\bar{P}_{yy,t}^p \right]^{-1} \left(y_t^i - H_t x_t^{p_i} \right) \tag{10}$$

III. SIMULATION RESULTS

An IEEE 14-bus test system, as shown in Fig. 1, is used for this study. The test system consists of five generators and eleven load buses. The simulation is carried out using MATPOWER and MATLAB. MATPOWER is a power system analysis software, which has many features including power flow and continuation power flow [12]. Using power flow feature of MATPOWER, the power flow of the test system is investigated.

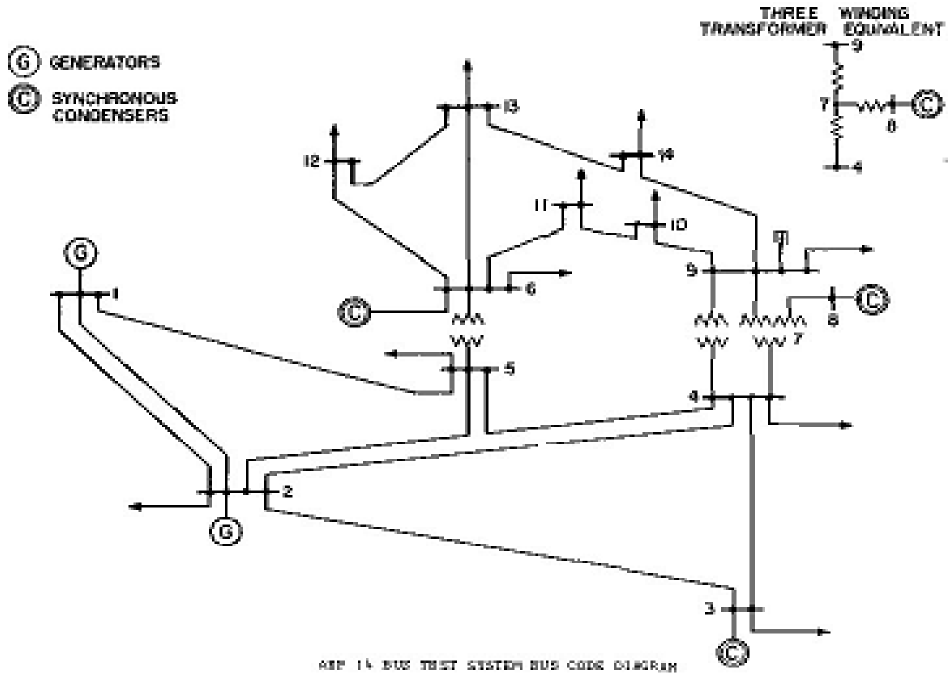

Fig 1: Benchmark of IEEE 14-bus test system [13]

The load flow calculations are analyzed using the usual Newton-Raphson method for the determination of magnitudes and phase angles of voltages at all buses. The load flow outputs are considered as true values to which a random noise is added to form the input measurement of the state estimator based on EnKF for the dynamic state estimation. The main point of this study is thus, to improve the estimation accuracy by effectively filtering the measurement noise.

The performance of the EnKF algorithm is investigated on a modified IEEE 14-bus test system. This test network is modified from the traditional IEEE 14-bus test system with the following simplifications and adjustments:

- A wind generator considered as distributed generator is connected to different PQ buses of the system.
- The size of the distributed generator is taken as 10% of the total real and reactive power.

The basic idea of a state estimation function in this paper is to determine the most likely system state vector **x** for the system states (i.e voltage magnitude and voltage angle):

$$X = [V_1,\ldots,V_N,\theta_1,\ldots,\theta_N]^T \qquad (11)$$

The evaluation of the accuracy of the EnKF algorithm can be made based on the performance index ε given by:

$$\varepsilon = \frac{\sum_{i=1}^{N}(x_i - x_i)^2}{\sum_{i=1}^{N}(x_i)^2} \qquad (12)$$

Where x_i and x_i are the true and estimated states respectively.

In this case, the significance of the performance index ε is that it provides the accuracy of the estimation algorithm. Small value of ε corresponds to more accurate estimation and vice- versa. For this study, the value of the performance index is $7.8679e\text{-}05$ *and* $1.4023e\text{-}05$ for the voltage magnitude and the voltage angle respectively.

III.I Convergence of the algorithm

The twentieth state corresponds to the voltage angle at bus 6. The state variable value is expressed in radian. It is seen at the Fig. 2 that the true state and the estimated one coincide around the tenth time slot (or number of iterations). This means that after the tenth iteration, the algorithm starts to converge.

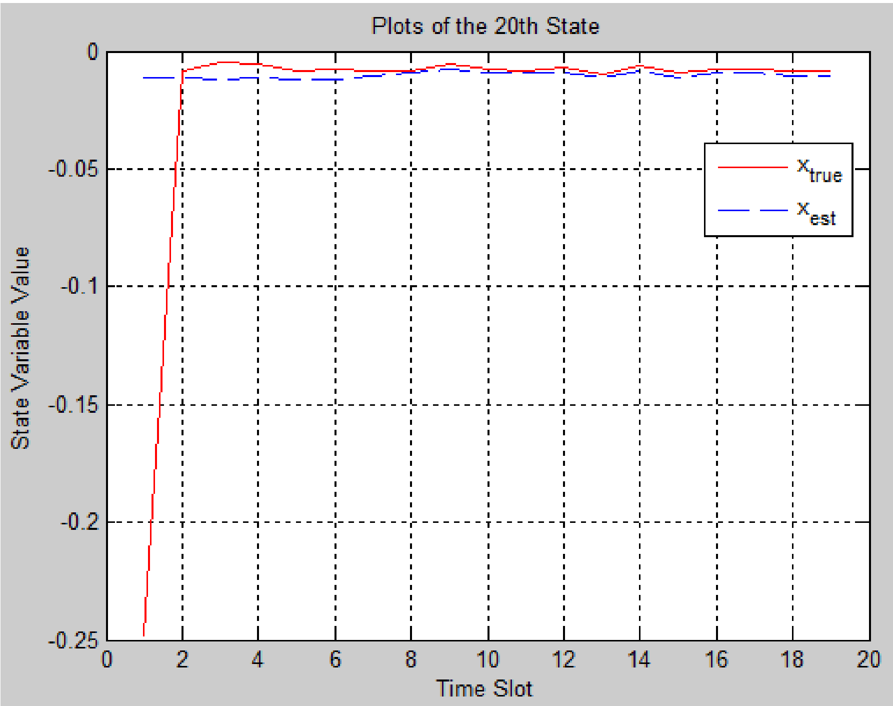

Fig. 2: Plot of the twentieth state

The Fig. 3 shows the plots of the true and estimated voltage magnitude on all buses of the test system studied. The distributed generator is placed on bus 5. It is noted that the plot of the estimated values matches well the one of the true values. This means that the ensemble Kalman filter algorithm used performs an accurate estimation by filtering the noise introduced by the measurements. The noise is considered as a random process with noise level factor NLF=10%.

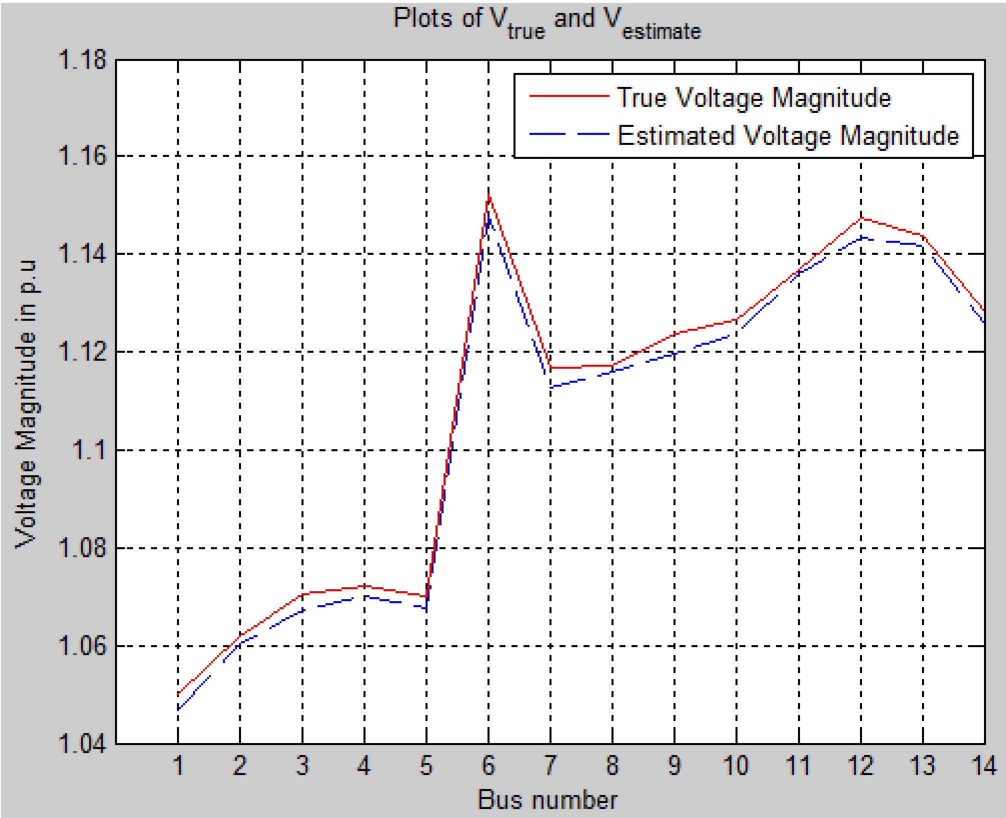

Fig 3: Plot of the true and estimated voltage magnitude

As the Fig. 3, the Fig. 4 shows the plots of the true and estimated voltage angle on all buses of the test system studied.

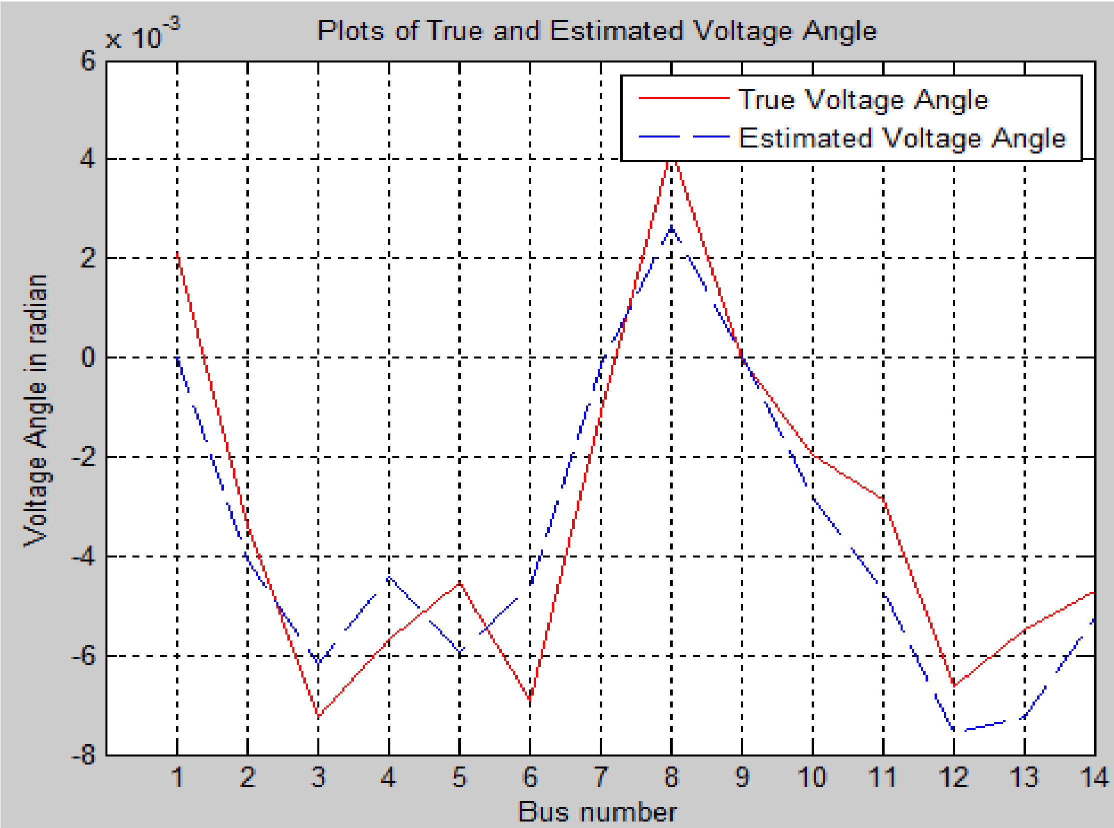

Fig 4: Plot of the true and estimated voltage angle

III.II Accuracy of the algorithm

For an adequate accuracy comparison, the mean absolute error (MAE) of voltage estimations is plotted. The MAE is an accuracy evaluation criteria in quantitative methods of prediction. The MAE is defined as:

$$MAE = \frac{\sum_{i=1}^{N} \| x_i - x_i \|}{N} \tag{13}$$

The Fig. 5 shows the mean absolute error plots of voltage magnitude and voltage angle.It is seen that the MAE of voltage magnitude has small values in term of 10^{-3}. This is an indice that the EnKF algorithm performs well the estimation.

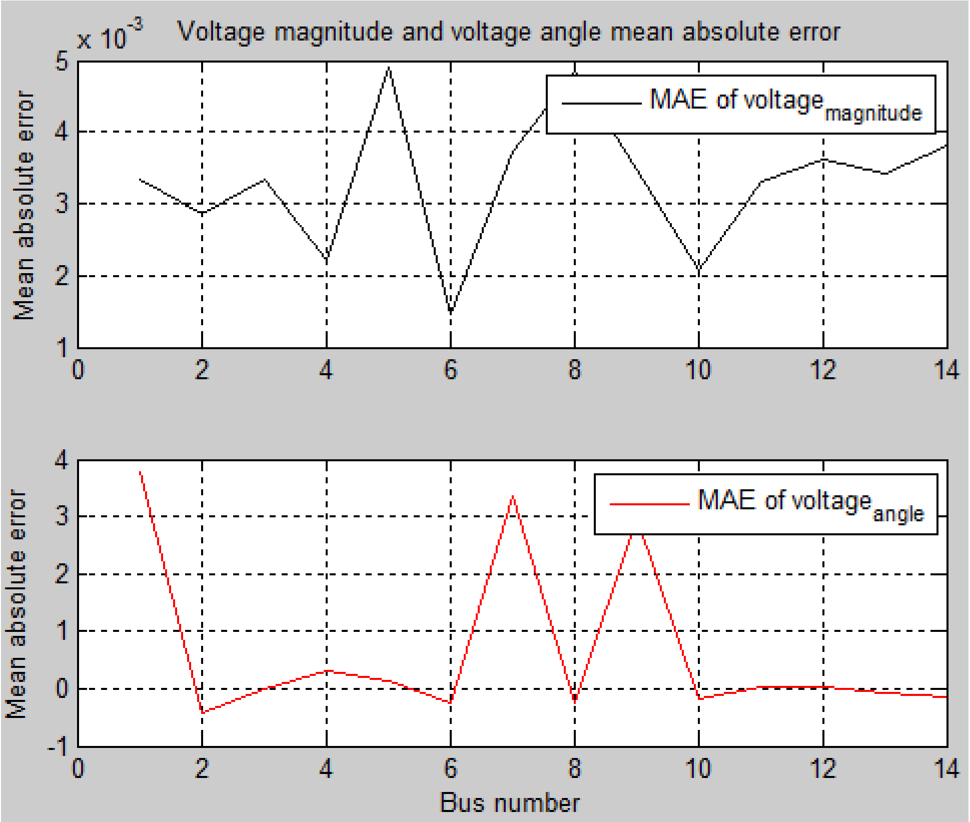

Fig 5: Plot of the mean absolute error

IV. CONCLUSIONS

This paper has addressed the important role of DSE in estimating accurate state variables at the right moment. An EnKF-based DSE has been introduced to tackle the dynamic nature of the modified IEEE 14-bus test system with distributed generator connected. The proposed approach requires less computational effort and is more accurate. Simulation results showed the feasibility of the EnKF in accurately estimating the dynamic states of the test system network taken into consideration. In the simulation, the estimated values matched well the true values which mean that the dynamic estimator used is accurate. Depending on the sampling time interval, this prediction can be used to provide advance information for secure operation of the network.

REFERENCES

[1] R. E. Kalman, A New Approach to Linear Filtering and Prediction Problems 1, *vol. 82, no. Series D*, pp. 35–45, 1960.

[2] F. C. Schweppe, Power System Static-State Estimation, Part I: Exact Model, *Trans. power Appar. Syst. IEEE, vol. PAS-89, no. 1*, pp. 120–125, 1970.

[3] A. Monticelli, *State estimation in electric power systems_ a generalized approach* (New York, Kluwer Academic Publishers Springer 1999).

[4] J. A. N.R Shivakumar, A Review of Power System Dynamic State Estimation Techniques, in Power System Technology and IEEE Power India Conference, March 2009, pp. 1–6.

[5] A. S. Debs and E. Robert, A dynamic estimator for tracking the state of a power system, *IEEE Trans. power Appar. Syst., vol. PAS-89, no. 7*, pp. 1670–1678, 1970.

[6] J. Qi, K. Sun, J. Wang, and S. Member, Dynamic State Estimation for Multi-Machine Power System by Unscented Kalman Filter with Enhanced Numerical Stability, IEEE Trans. Smart Grid, *vol. 2, no. 4*, pp. 1–13, 2016.

[7] G. Valverde and V. Terzija, Unscented Kalman filter for power system dynamic state estimation, IET Gener. Transm. Distrib., *vol. 5, no. 1*, pp. 29–37, 2011.

[8] N. Zhou, D. Meng, Z. Huang, and G. Welch, Dynamic State Estimation of a Synchronous Machine Using PMU Data : A comparative study, IEEE Trans. Smart Grid, *vol. 6, no. 1*, pp. 450–460, 2015.

[9] P. K. Ray and B. Subudhi, Ensemble-Kalman-Filter-Based Power System Harmonic Estimation, IEEE Trans. Instrum. Meas., *vol. 61, no. 12*, pp. 3216–3224, 2012.

[10] D. Pietaloka, *Distributed-dynamic state estimation with SCADA and PMU*, Delft University of Technology, 2015.

[11] S. D. Gupta, *A comparative study of the particle filter and the ensemble kalman filter*, University of Waterloo,Canada, 2009.

[12] Y. Kumar, V. K. Devabhaktuni, and S. Vemuru, Comparison of Power System Simulation Tools with Load Flow Study Cases, IEEE, pp. 290–294, 2015.

[13] https://www2.ee.washington.edu/research/pstca/pf14/pg_tca14bus.htm