Advantage of extended kalman filter over discrete kalman filter in dynamic state estimation of power system network

Article *in* International Journal of Control Theory and Applications · January 2016

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IJCTA, 9(10), 2016, pp. 4795-4800

Advantage of Extended Kalman Filter Over Discrete Kalman Filter In Dynamic State Estimation of Power System Network

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Abstract : The Kalman filter is a set of mathematical equations which are used to estimate the state of a system to minimize the mean of the squared error. In this paper Kalman filtering is used for the estimation of states of IEEE 14 bus power system network. We considered Voltage and its angle at all buses as states of the system. This paper presents the advantages of EKF over DKF by comparing both estimation methods. In EKF the exact nonlinear Process and measurement functions can be considered for estimation where it is limited to only linear functions in case of DKF. Because of this limitation using DKF we can estimate only one state of the power system but not both. The approximation of actual for applying DKF leads to the presence of single state i.e the angle of voltage at all buses of the network. In addition to this limitation, accuracy can also be improved from DKF to EKF. As voltage and its angle are not dynamic in nature the measurements are taken as constant at all instants of time during our observation.

Keywords : *Kalman Filter, Power System, Estimation*

I. INTRODUCTION

It is very important to control and monitor the power system as it is becoming the most complex system because of the integration of several renewable energy resources with it. It was initially formulated by F. C. Schweppe**.** In [1], discussion covers the overall problem, mathematical modelling, and general algorithms for state estimation, detection, and identification. In [2], same procedure has been done by considering an approximate mathematical model. In [3], the authors are discussed about various implementation problems. There are three types of state estimation techniques as Static State Estimation (SSE), Tracking State Estimation (TSE) and Dynamic State Estimation (DSE) in literature. In case of SSE we consider only one measurement set at a point of time and the corresponding state is estimated. But the problem with this method is that the iterative process of algorithm starts every time with the flat values. So it takes heavy computations and we can't execute it in short intervals of time. To avoid that problem TSE was introduced which is dynamic in time[4]. In TSE the estimation starts from the last estimated state which leads to the quick estimation of the state. But in both SSE and TSE the state estimates are calculated using one set of measurements and use only one step for estimation. After that a two step method of estimation i.e. DSE has been introduced to include several advantages apart from estimating states which has been discussed in [5-7]. In first step the predicted states are calculated which is known as prediction step. In the next step with the help of calculated predicted states and the acquired measurement values the actual states of the system are calculated which is known as Correction step. Because of this extra step involved in DSE power system operator gets extra time for making control decisions during emergency conditions. So DSE consider both measurement set and predicted state variables for estimation process. That means at an instant, in first step of

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estimation the next instant state will be predicted and in next step the state at that particular instant will be corrected using predicted states and measurement set values. The main challenge of DSE is that if there are any sudden changes in the load and generation, there is a large transition in the state variables in the area which is close to the affected area. In that case if you consider now at instant '*t*',

1. To predict the states for instant '$t + 1$'
2. Using the predicted state variables of instant '*t*' which were calculated previous instant and measurements at instant '*t*' states at instant '*t*' are estimated.

Suppose in between t^{th} and $t + 1^{\text{th}}$ instants if there is a sudden change in the system, [8] the state values which have already been predicted don't have the effect of sudden change. If those predicted states and the present instant measurement set is used, surely erroneous results will be obtained at the end of the estimation process. If this happens the entire DSE performance will degrade subsequently. To avoid this innovation analysis is used to know whether sudden change has occurred or not in the system and to take any further action. In 1960, R.E. Kalman published his famous paper regarding the recursive solution to the discrete-data linear filtering problem [9]. The Discrete Kalman Filter (DKF) deals with the problem of estimating the state $X \in R$ of a discrete time controlled process that is governed by the linear stochastic difference equation where as EKF addresses nonlinear stochastic difference equation. In [10], an IEEE-14 bus test system is used for finding static states using kalman filtering algorithm. The various algorithms are compared in [11] by considering power system stability problem as a case study. In this paper DKF and EKF methods of state estimation are used to estimate the static states of IEEE 14 bus network. Finally the advantages of EKF over DKF are presented. Section II describes the working methodology. Section III and IV describes the algorithm of DKF and EKF respectively. Section V and VI the simulation results for both the cases considered and conclusions respectively.

2. METHODOLOGY

A. Prerequisites for applying the working methodology

Choose the power system network for which you want to find states, IEEE-14 bus test system is considered [10] which consists of 5 generator buses and 11 load buses as shown in Fig. 1. Bus 1 is considered as slack bus.

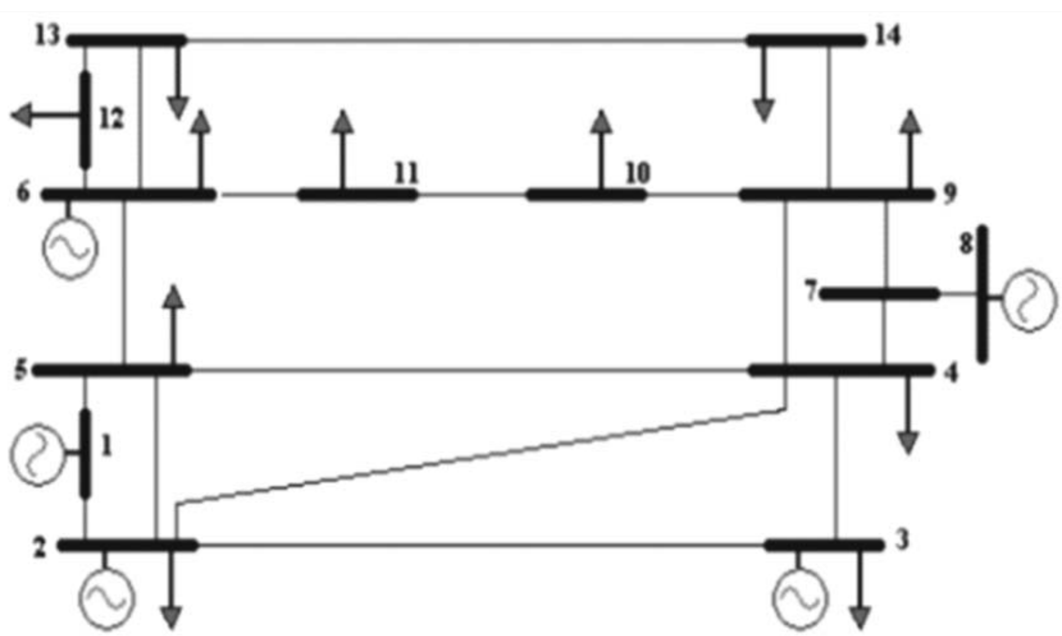

Fig. 1. IEEE 14 bus network

1. Consider the input data.
   (*a*) Bus data

- Phasor voltage of buses *i.e*. Voltage and its angle at all buses.
- Injected Real and Reactive power at all buses
- Load Real and Reactive power at all buses

(*b*) Line data, Generator dynamic data

- Line reactance and resistances & shunt admittance values

(*c*) Measurements

- Real and Reactive power injections
- Real and Reactive power flows

2. Decide the output *i.e*. which states you want to estimate. Here we are considering static states *i.e*. Voltage and its angle at all buses.

3. DISCRETE KALMAN FILTER

The linear difference equations [12] of both discrete time controlled process with measurement is given by

$$x_k = Ax_{k-1} + Bu_{k-1} + w_{k-1}$$
$$z_k = Hx_k + v_k \tag{1}$$

Static states include both voltage a1nd its angle so and so the actual power injection equation is

$$V_i \sum_{j \in N_{L_i}} V_i (g_{ij} \cos(\delta_{ij}) + b_{ij} \sin(\delta_{ij})) \tag{2}$$

Where

Xk is the Vector of state variables.

Wk is the Process noise

Vk is the Measurement noise

H is Measurement function

Zk is Vector of Measurements

For applying DKF algorithm the above equation has to be approximated by assuming δ_{ij} small, loss less lines and voltage magnitude of 1 pu at all buses. Then it becomes linear which results into

$$\sum_{j \in N_{L_i}} b_{ij}\delta_{ij} \tag{3}$$

where

δ_{ij} is the voltage angle between the buses i, j

b_{ij} is the susceptance between the buses i, j

g_{ij} is the conductance between the buses i, j

N_{L_i} indicates number of buses connected to i^{th} bus

As there is no control input B = 0 and measurements considered are also constant as we are not considering any fault case, A = I *i.e*. Identity matrix.

A. Algorithm of DKF

1. Time update equations

$$x_k^{pri} = x_{k-1}^{post}$$
$$P_k^{pri} = IP_{k-1}I^T + Q\backslash \tag{4}$$

2. Measurement update equations

$$K_k = P_k^{pri}H^T (HP_k^{pri}H^T + R)^{-1}$$
$$P_k^{post} = x_k^{pri} + K(z_k - Hx_k^{pri})$$

$$x_k^{post} = (\mathrm{I} - \mathrm{K}_k \mathrm{H})\mathrm{P}_k^{pri}$$

Where

x_k^{pri} is the Priori State Estimate

P_k^{pri} is the priori estimate error covariance

x_k^{post} is the Posteriori State Estimate

P_k^{post} is the posteriori estimate error covarience

4. EXTENDED KALMAN FILTER

We have discrete time controlled process that is governed by the non-linear stochastic difference equation

$$\begin{aligned} x_k &= f(x_{k-1}, u_{k-1}, w_{k-1}) \\ z_k &= h(x_k, v_k) \end{aligned} \tag{6}$$

As EKF can be applied to non-linear process here there is no need to approximate power injection equation *i.e*.

$$\mathrm{V}_i \sum_{j \in \mathrm{N}_{\mathrm{L}_i}} \mathrm{V}_i (g_{ij} \cos(\delta_{ij}) + b_{ij} \sin(\delta_{ij})) \tag{7}$$

So using EKF we can estimate both the state variable without approximating the the above non linear equation which is the main advantage of EKF over DKF.As there is no control input B = 0 and measurements considered are also constant as there is no fault case, A = I *i.e*. Identity matrix. Similarly consider noise variables as mentioned in earlier chapter. Then apply DKF algorithm by considering table as follows

A. Algorithm of EKF

1. Time update equations

$$x_k^{pri} = x_{k-1}^{post}$$

$$\mathrm{P}_k^{pri} = \mathrm{IP}_{k-1}\mathrm{I}^{\mathrm{T}} + \mathrm{WQW}^{\mathrm{T}} \tag{8}$$

2. Measurement update equations

$$\mathrm{K} = \mathrm{P}_k\mathrm{H}^{\mathrm{T}} (\mathrm{HP}_k\mathrm{H}^{\mathrm{T}} + \mathrm{VRV}^{\mathrm{T}})^{-1}$$

$$\mathrm{X}_k^{post} = \mathrm{X}_k^{pri} + \mathrm{K}(z_k - h)(\mathrm{X}_k^{pri}, 0))$$

$$\mathrm{P}_k^{post} = (\mathrm{I} - \mathrm{KH})\mathrm{P}_k^{pri} \tag{9}$$

5. RESULTS

In this study, static states i.e. the voltage and its angle at all buses of the IEEE 5 generator, 14 bus systems are estimated by performing DKF and EKF algorithms through MATLAB coding and the results have been shown in following figures and table. Fig. 2 shows the calculated active power flows values using estimated state variables by DKF algorithm. Similarly Fig. 3 shows calculated active power flows values using estimated state variables by EKF algorithm. Table I. gives the calculated Average Error using DKF and EKF through estimates and measurements.

Calculate the estimated and measured square error by using (10) and (11) respectively. The following table 5.1 gives the calculated square errors at one sample point through estimates and measurements respectively using both DKF and EKF respectively.

$$\text{Estimated Square Error} = (x - x^{est})^2 \tag{10}$$

$$\text{Measured Square Error} = (x - x^{meas})^2 \tag{11}$$

where

$(x - x^{est})^2$ is the square of the difference between the true quantity and the estimated quantity at an instant

$(x - x^{meas})^2$ is the square of the difference between the true quantity and the measured quantity at an instant

Table 1. Comparison of DKF and EKF.

Algorithm	*Estimated Square Error*	*Measured Square Error*
DKFEKF	7.93730.0460	0.13060.1009

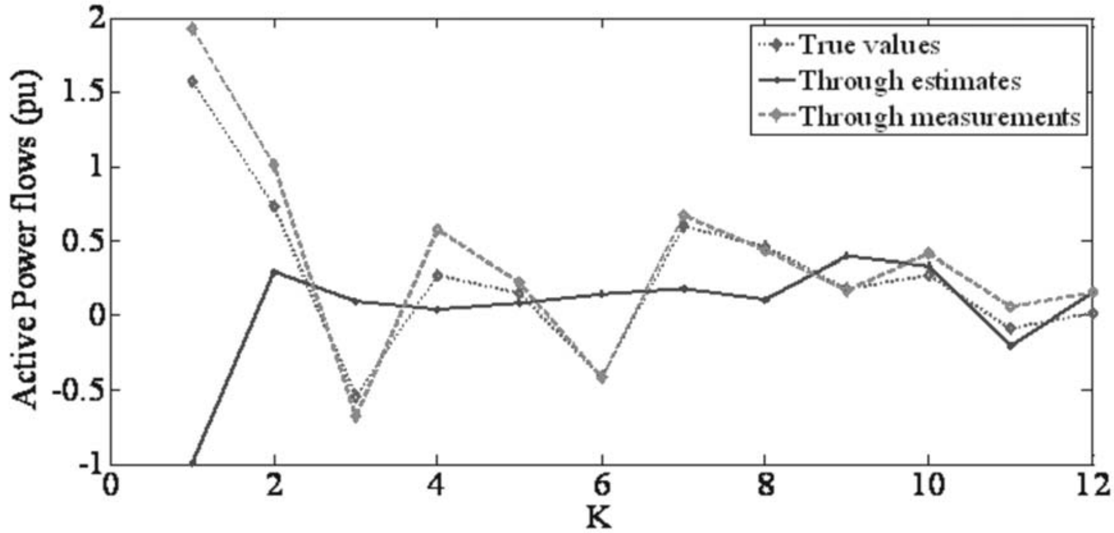

Fig. 2. Calculated Power flows using DKF Algorithm

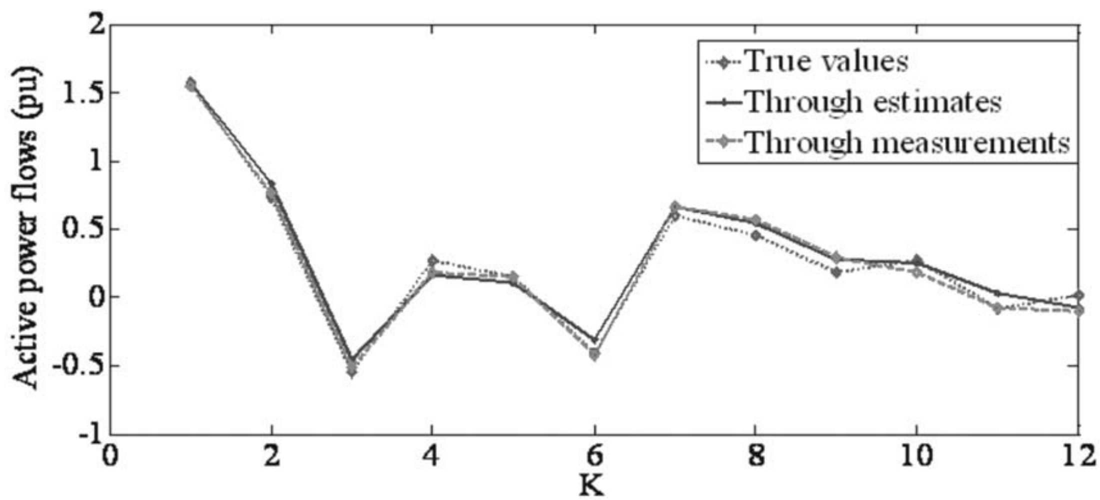

Fig 3. Calculated Power flows using EKF Algorithm

6. OBSERVATIONS AND CONCLUSIONS

A. Observations

1. From Fig. 2, it is observed that the calculated pu active power flow values using estimated states by DKF algorithm are not following the true pu active power flow values. This is because of the approximation of the nonlinear power injection equation to linear equation to perform DKF.
2. From the Table. I, it is observed that the calculated estimated square error value 7.9373 using DKF algorithm more than the measured square error 0.1306, which is not a favourable case. So it is necessary to go for non linear filter so that estimated square error will be less than measured square error.

3. From Fig. 3, it is observed that the calculated pu active power flow values using estimated states by EKF algorithm are closely following the true pu active power flow values. This is because EKF is a non linear filter exact non linear equation can be used for estimation without approximating it to linear equation as in the case of DKF.
4. From the Table. I, it is observed that the calculated estimated square error value 0.0460 using EKF algorithm is less than the measured square error 0.1009, which is a favourable case.

B. Conclusions

The MATLAB results shown above for static states estimation conclude that for nonlinear functions EKF is far better than DKF even though the nonlinear equation is approximated to linear function for applying DKF. The Error values obtained using EKF and DKF confirm that the approximation of the actual nonlinear power equations to find state estimates using DKF is not preferable which results in more erroneous values than measured values.

7. ACKNOWLEDGEMENT

The author would like to thank Dr. Debashisha Jena for his guidance and advice throughout this work which led to conduct additional analysis, establish deeper insight, and make well-informed conclusions.

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