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RESEARCH ARTICLE

NEW TOPOLOGIES OF KALMAN FILTERS FOR DYNAMIC POWER SYSTEM ESTIMATION

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ABSTRACT

Power system state estimation requires error less data to estimate the exact states of the power system. The Estimation process is done by Energy Management System (EMS) at the control centre with the help of estimated data. In practical conditions, collected data contain the measurement and process errors. These errors are due to high speed measuring devices and Phasor Measurement Units (PMU) installed on different buses. Due to communication errors, different filtration techniques are required at the control centre to get the best estimated data. For nonlinear power system, new improved Kalman filter techniques are introduced in this paper. Emerging Extended Kalman Filter (E-EKF) and Emerging Unscented Kalman Filter (E-UKF) based on the exponential description function are proposed in this paper. The effectiveness of these improved techniques is compared with the conventional nonlinear filterson the basis of elapsed time and Root Mean Square Error (RMSE). The performance of these filters is tested on standard IEEE-30 bus test system.

INTRODUCTION

The vector consisting of bus voltage magnitudes and phase angles is called the state of an electric power system. The concept of state estimation was introduced into the field of power systems in 1947 (Schweppe, 1968; Schweppe, 1970 and Schweppe, 1970). Estimation of the dynamic state of a power system is the first prerequisite for control and stability prediction under transient conditions (Miller, 1971). The inputs from static estimation are necessary for many applications like Automatic Generation Control (Saxena, 2012), contingency (Soni, 2016), and Voltage stability assessment (Akash Saxena and Ankit Kumar Sharma, 2016). The great importance of the 'Dynamic State Estimation (DSE)' in system monitoring and control of power systems, especially with the introduction of Phasor Measurement Units (PMUs) (Jain and Shivakumar, 2008; Xue et al., 2007; Jain and N. Shivakumar, 2008; Shivakumar and A. Jain, 2008 and Jain and N. R. Shivakumar, 2009). A dynamic state estimator for power system networks is firstly addressed by Debs and Larson (Debs, 1970). In this work, the state change is represented by Gaussian noise. Then, a novel method for detecting and ascertaining anomalies as the occurrence of bad-data, changes in network configuration and sudden variation of states, in dynamic state estimation for electric power systems was proposed (Nishiya, 1982). Simple dynamic models for the state vector comportment, combined with linearized measurement equations, have been anticipated and the estimations have been attained through Kalman Filtering Theory. Through the application of Kalman Filter techniques, at a first state, the set of measurements is used to estimate the state model parameters and at a second stage, estimate the state vector. New algorithms considering exponential smoothing and least-squares estimation techniques are used for forecasting and filtering the state vector for power systems (Leite da Silva, 1983). One of the most widely used methods is Extended Kalman Filter (EKF) in power system dynamic state estimation which takes into account both the incoming measurements and the predicted state to acquire a prime estimate of the state (Mandal, 1995). The feasibility of smearing Extended Kalman Filter techniques to include dynamic state variables (generator rotor speed and rotor angle) in the state estimation process is well investigated on a multi-machine system with both large and small disturbances (Huang, 2007). The extended Kalman Filter with unknown inputs, referred to as EKF-UI, is proposed for estimating the states and the unknown inputs of the synchronous machine (Ghahremani and I. Kamwa, 2011). A novel framework to perform EKF based dynamic state estimation in a distributed way is considering complexity associated with increasing renewable resources and novel smart-grid technologies (Du,

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2001). According to it, DSE can be implemented in a distributed environment by decomposing the systems into subsystems to increase the computational speed of DSE process in large scale power systems. The EKF is one of the most widely used estimation algorithms for nonlinear systems. It is difficult to implement, difficult to tune and only reliable for systems that are almost linear on the time scale of the updates [20]. In order to overcome the difficulties and drawbacks of the EKF algorithm which mainly arise from its use of linearization, the Unscented Transformation (UT) is developed as a method to propagate mean and covariance information through nonlinear transformation (Julier, 2004). The UKF has higher accuracy and easy to implement in estimating the dynamics of generators (Gao and S. Wang, 2010 and Valverde and V. Terzija, 2011). The performance of the UKF technique is derived, demonstrated and compared with the performance of classical EKF technique by using three different test power systems under typical network and measurement conditions (Valverde and V. Terzija, 2011).

It is proved by using the performance indices that the UKF has higher filtering capacities during slow dynamic changes than EKF estimator (Valverde and V. Terzija, 2011). A new parameter estimation method for frequency, amplitude and phase tracking based on UKF is presented and it is shown that UKF method has high estimation accuracy both under normal and noisy conditions (Novanda, 2011 and Wang, 2012). A derivative-free approach to Kalman filtering is introduced and applied to state estimation-based control of a class of nonlinear dynamical systems in (Rigatos, 2012). A new method for the simultaneous estimation of power components and frequency is presented based on UKF method (Regulski and V. Terzija, 2012). The forecasting ability of dynamic state estimation has tremendous advantages, as security analysis can now be performed one-time stamp ahead and hence allows more time for the operator to take control actions, especially in cases of any emergency (Do CouttoFilho, 1993 and SunitaChohan, 1993). Hence, DSE algorithms for power systems form an important branch of power system state estimation techniques, with a potential to impact the very nature of operation of the real-time monitoring and control of power systems. On the basis of the review of the literature, following objectives are framed for this manuscript.

- To mathematical modeling and suggest modifications in existing Kalman filters on the basis of exponential description function.
- To carry out DSE of voltage, angle, real and reactive powers for standard electrical power systems and check the robustness of the proposed estimator against measurement and process noise.
- To present the decisive evaluation of filtering performance of proposed filter with the conventional filters based on the calculation of Elapsed timeand standard error index Root Mean Square Error (RMSE).

The remaining part of this paper is presented as follows; in following sections the problem of the state estimation, filter algorithm equations, simulation results and effectiveness of proposed filters over traditional filters are presented. The overall conclusion and future scope associated with proposed framework is presented.

PROBLEM FORMULATION

The information of the system is provided by the state differential equations and the measurement captured after the change in the system measurements. Figure 1 shows the working procedure of state estimation for making appropriate control action for remain system in stable.

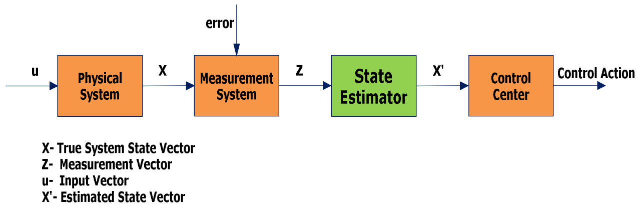

Figure 1. General block diagram of state estimation

Considering the nonlinear filtering problem given below which is defined by discrete time instant given by k=1,2,..N

$$x_k = f\left(x_{k-1}, \Theta,\ u_{k-1}\right) + w_k$$
$$Z_k = h\left(x_{k-1}, \Theta,\ u_{k-1}\right) + v_k \quad \text{………………(1)}$$

where 'x' is the state vector, 'u' is the control input and 'Z' is the measurement vector. The 'f' and 'h' are nonlinear functions of state and measurement equations respectively. The injected noise, are assumed to be the random noise of the order of state and measurement matrix order and are identically and independently distributed.

$$E\left[w_k w_j^T\right] = \boldsymbol{Q}\delta(k-j)\ \&\ E\left[w_k\right] = 0$$
$$E\left[v_k v_j^T\right] = \boldsymbol{R}\delta(k-j)\ \&\ E\left[v_k\right] = 0 \quad \text{…………..(2)}$$
$$E\left[w_k v_j^T\right] = 0 \forall j,k = 1,2,\ldots N$$

Where R, Q are covariance of error, δ is Kronecker delta function

$$\delta(k-j) = \begin{cases} 0 & if\ k \neq j; \\ 1 & if\ k = j; \end{cases} \quad \text{……………..(3)}$$

The parameter vector 'Θ' is augmented as

$$\begin{bmatrix} x_k \\ \Theta_k \end{bmatrix} = \begin{bmatrix} f\left(x_{k-1},\ \Theta_{k-1}, u_{k-1}\right) \\ \Theta_{k-1} \end{bmatrix} + \begin{bmatrix} w_k \\ 0 \end{bmatrix} \quad \text{………………(4)}$$

The nonlinear filtering problem is now defined as

$$X_k = f\left(X_{k-1}\right) + w_k$$
$$Z_k = h\left(X_k\right) + v_k \quad \text{…………………(5)}$$

where 'X' and 'w' are respectively the augmented state and process noise vector.The power system is a nonlinear system, which changes its state dynamically as illustrated in above equation.

MATHEMATICAL FRAME WORK OF FILTERS

The Extended Kalman Filter (EKF) Equations: The EKF algorithm works on the discrete nonlinear system model, where noises are Gaussian distribution noises with known parameters. The extended algorithm is almost similar with KF algorithm.

The EKF state estimation algorithm is presented below:

Initialization step

Initial estimated state vector $\tilde{\underline{x}}_0 = E\{\underline{x}_0\}$
Initial covariance matrix: $\tilde{P}_{0,x} = E\{(\underline{x}_0 - \tilde{\underline{x}}_0).(\underline{x}_0 - \tilde{\underline{x}}_0)^T\}$

Linearizing the nonlinear model functions andcalculate the following matrices:

$$\varnothing_k = \begin{bmatrix} \frac{\partial F_1}{\partial x_1} & \cdots & \frac{\partial F_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial F_n}{\partial x_1} & \cdots & \frac{\partial F_n}{\partial x_n} \end{bmatrix}_{x=\tilde{\underline{x}}_{k-1}}$$

$$C_k = \begin{bmatrix} \frac{\partial G_1}{\partial x_1} & \cdots & \frac{\partial G_1}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial G_p}{\partial x_1} & \cdots & \frac{\partial G_p}{\partial x_n} \end{bmatrix}_{x=\tilde{\underline{x}}_{k-1}} \quad \ldots\ldots\ldots\ldots\ldots(6)$$

The linearization method utilizes just the first term in the Taylor expansion of the nonlinear functions

Calculation of the predicted state mean and covariance (time update)

$$\tilde{\underline{x}}_{\bar{k}} = F\left(\tilde{\underline{x}}_{k-1}, \underline{u}_{k-1}\right)$$
$$\tilde{P}_{\bar{x},k} = \varnothing_k.\tilde{P}_{x,k}.\varnothing_k^T + Q \quad \ldots\ldots\ldots\ldots\ldots\ldots(7)$$

The filter gain vector:

$$K_k = \tilde{P}_{\bar{x},k}.C_k^T.(C_k.\tilde{P}_{\bar{x},k}.C_k^T + R)^{-1} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(8)$$

Correction step: The estimates are updated with the latest observation (measurement update)

$$\tilde{\underline{x}}_k = \tilde{\underline{x}}_{\bar{k}} + K_k.\left(y_k - G\left(\tilde{\underline{x}}_{\bar{k}}.u_k\right)\right)$$
$$\tilde{P}_{x,k} = \left(I - K_k.C_k\right).\tilde{P}_{\bar{x},k} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots(9)$$

The EKF gives an approximation of the optimal estimate (Gol and A. Abur, 2012).

The Unscented Kalman Filter (UKF) Equations: The state distribution is also represented by Gaussian random variables, but this method is using a minimal set of carefully chosen sample points. These points are called sigma points and they are completely capture the true mean and covariance of the system states and are propagated through the nonlinearity.
The standard UKF state estimation algorithm is presented below:

Initialization step at k=0:

Initial estimated state vector: $\tilde{\underline{x}}_0 = E\{\underline{x}_0\}$
Initial covariance matrix: $\tilde{P}_{x,0} = E\{(\underline{x}_0 - \tilde{\underline{x}}_0).(\underline{x}_0 - \tilde{\underline{x}}_0)^T\}$

Sigma points' calculation

$$A_{k-1} = \left[\tilde{x}_{k-1}\tilde{x}_{k-1} + \gamma.\sqrt{\tilde{P}_{x,k-1}}\tilde{x}_{k-1} - \gamma.\sqrt{\tilde{P}_{x,k-1}}\right] \ldots\ldots\ldots(10)$$

Propagation of the sigma points

Transform the sigma points through the state-update function:

$$A_k^* = F\left(A_{k-1}.u_{k-1}\right) \quad \ldots\ldots\ldots\ldots\ldots\ldots(11)$$

Calculate the apriori state estimate and apriori covariance, where the weights $W_i^{(m)}$and $W_i^{(c)}$are defined in accordance with relations:

$$\tilde{x}_{\bar{k}} = \sum_{i=0}^{2n} W_i^{(m)}.\left(A_k^*\right)_i$$
$$\tilde{P}_{x,k} = \sum_{i=0}^{2n} W_i^{(c)}.(\left(A_k^*\right)_i - \tilde{x}_{\bar{k}}).(\left(A_k^*\right)_i - \tilde{x}_{\bar{k}})^T + Q \quad \ldots\ldots..(12)$$

Update of the output vectors

Transform the sigma points through the measurement-update function:

$$Y_k^* = G(A_{(k-1)}, u_k) \quad \ldots\ldots\ldots\ldots(13)$$

calculate the mean and covariance of the measurement vector:

$$\tilde{y}_{\bar{k}} = \sum_{i=0}^{2n} W_i^{(m)}.\left(Y_k^*\right)_i$$
$$\tilde{P}_{\bar{y},k} = \sum_{i=0}^{2n} W_i^{(c)}.(\left(Y_k^*\right)_i - \tilde{y}_{\bar{k}}).(\left(A_k^*\right)_i - \tilde{x}_{\bar{k}})^T + R \quad \ldots\ldots(14)$$

Calculate the cross covariance matrix:

$$\tilde{P}_{x,y,k} = \sum_{i=0}^{2.n} W_i^{(c)}.\left(\left(x_k^*\right)_i - \tilde{x}_{\bar{k}}\right).\left(\left(y_k^*\right)_i - \tilde{y}_{\bar{k}}\right)^T \quad \ldots\ldots\ldots(15)$$

Calculation of the Kalman filter gain vector:

$$K_k = \tilde{P}_{x,y,k}.\left(\tilde{P}_{\bar{y},k}\right)^{-1} \quad \ldots\ldots\ldots..(16)$$

Calculate the estimated state in accordance with the standard Kalman filter algorithm:

$$\tilde{x}_k = \tilde{x}_{\bar{k}} + K_k.\left(y_k - \tilde{y}_{\bar{k}}\right) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(17)$$

The most computationally intensive operation in the UKF corresponds to calculating the new set of sigma points at each time update (Julier and J. K. Uhlmann, 2004; Ghahremani and I. Kamwa, 2011 and Wang, 2012).

The Emerging EKF and Emerging UKF Algorithm Equations: The Emerging EKF and Emerging UKF algorithms are based on exponential description function for reducing covariance of the filter in every dynamic step according to the previous calculation done. With the exponential description, the exponential function covariance updates the system covariance, which effects on gain calculated through Kalman filter. Due to this, system efficiency and accuracy will update in every time period which upgrades the overall accuracy of the filter for estimate the state vectors. The exponential description is used in EKF for make Emerging EKF is shown below:

$$RR = R^{-1}$$

$$RR = RR^{*} * \mathrm{e}_{(mean)}(\text{Performance})_{(\text{filter})}$$

$$R^{*} = RR^{-1}$$

$$K_k^{*} = \tilde{P}_{\bar{x},k}.C_k^T.(C_k.\tilde{P}_{\bar{x},k}.C_k^T + R^{*})^{-1} \qquad \ldots\ldots\ldots\ldots(18)$$

$$\tilde{x}_k = \tilde{x}_{\bar{k}} + K_k^{*}.\left(y_k - G\left(\tilde{x}_{\bar{k}}.u_k\right)\right)$$

$$\tilde{P}_{x,k} = \left(I - K_k^{*}.C_k\right).\tilde{P}_{\bar{x},k}$$

Where R^{*} is emerging noise covariance, K_k^{*} is emerging Kalman gain and ε shows the performance of the filter which dispirits from actual to estimated. Due to the mean measurement function variation, the performance ofthe filter will improve due to gain reduce. The Emerging UKF performs better and it defines as:

$$\mathrm{RR}^{*} = \mathrm{RR}_{\mathrm{pre}} * \mathrm{sqrt}^2\,(\varepsilon)_{(\mathrm{filter})}$$

$$\tilde{P}_{\bar{y},k}^{*} = \sum_{i=0}^{2n} W_i^{(c)}.((Y_k^{*})_i - \tilde{y}_{\bar{k}}).((A_k^{*})_i - \tilde{x}_{\bar{k}})^T + RR^{*}$$

$$K_k^{*} = \tilde{P}_{x,y,k}.\left(\tilde{P}_{\bar{y},k}^{*}\right)^{-1}$$

$$\tilde{x}_k^{*} = \tilde{x}_{\bar{k}} + K_k^{*}.\left(y_k - \tilde{y}_{\bar{k}}\right) \qquad \ldots..(19)$$

Where $\tilde{P}_{\bar{y},k}^{*}$ is updated cross covariance which improves Kalman Gain in Emerging and update state vectors.

RESULTS

The effectiveness of proposed Kalman filters is evaluated on different cases on the standard IEEE 30 bus system. The standard IEEE 30 bus system represents a portion of the American Electrical Power System since December 1961. This system maintains 30 buses, 6 generators and 24 load buses. The algorithm has been written in MATLAB 2014 and same has been simulated over Intel core i5, 2.9 GHz, 4.00 GB RAM processor. In case 1 the dynamic cycle for the system is chosen 50 cycles, in case 2 it is considered 100 cycles and in the case 3 the estimation is proceeded on 200 dynamic cycles. In every dynamic cycle, the state vector interacts with random number which is Gaussian in nature and updates the value to state vectors with zero mean and standard covariance.The standard deviation is also increase with the increase in number dynamic cycles. Figure 2 shows the standard deviation of state vectors of voltage and angle in different dynamic cycle and figure 3 illustrate the average of standard deviation.

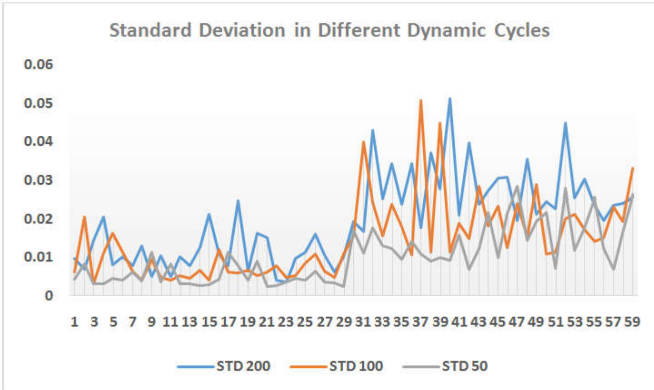

Figure 2. Standard Deviation in different dynamic cycles

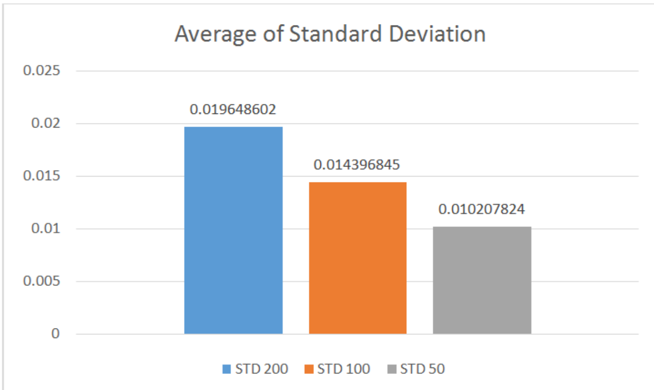

Figure 3. Average of standard deviation

According to figure 3 the standard deviation is decrease to 70.90% from standard deviation of 100 cycles to standard deviation of 50 cycles and standard deviation is decrease to 73.27% from standard deviation of 200 cycles to standard deviation of 100 cycles. It means in every 50% of dynamic cycles the standard deviation decrease to about 72% of its value.

Case-1 when dynamic cycle= 50 times

The state vectors of the electrical systems are voltage and angle. By the use of these vectors, the other parameters of the systems (active and reactive powers on the nodes, active and reactive power flows on the line) can be calculated. In regular condition, these parameters are also called the state vectors. Figure 4 shows the state vectors values estimated by different nonlinear filters. Figure 5 represents the variation of outputs of different filters from without filter output. The maximum variation shows the maximum value of communication error. Here according to figure 5 maximum errors are associated with EKF filter. It means at the higher values of dynamic cycles of error, the EKF filter fails to estimate exact values of parameters. But in the case of other filters results are comparatively better and it is best in E-UKF filter.

According to the figures shown in case 2 and case 3, figure 7 and figure 9 validate the effectiveness of emerging filters over traditional filters used. In case 2, there is 100 dynamic cycles andin case 3, it is 200 cycles for add Gaussian noise in filters.

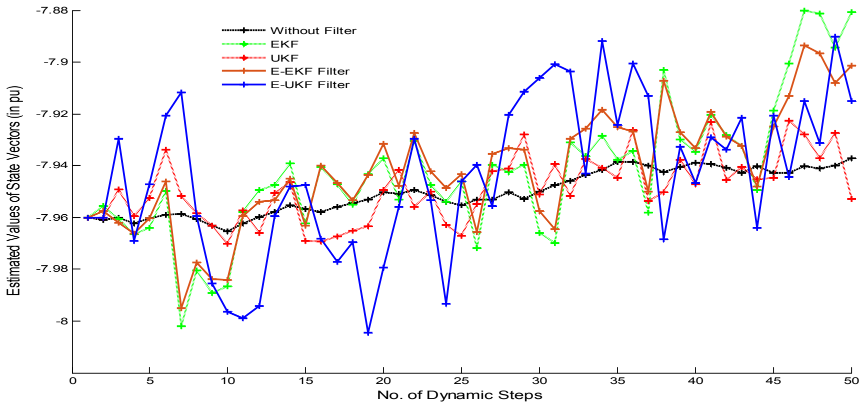

Figure 4. Estimated State vectors of the system when N=50

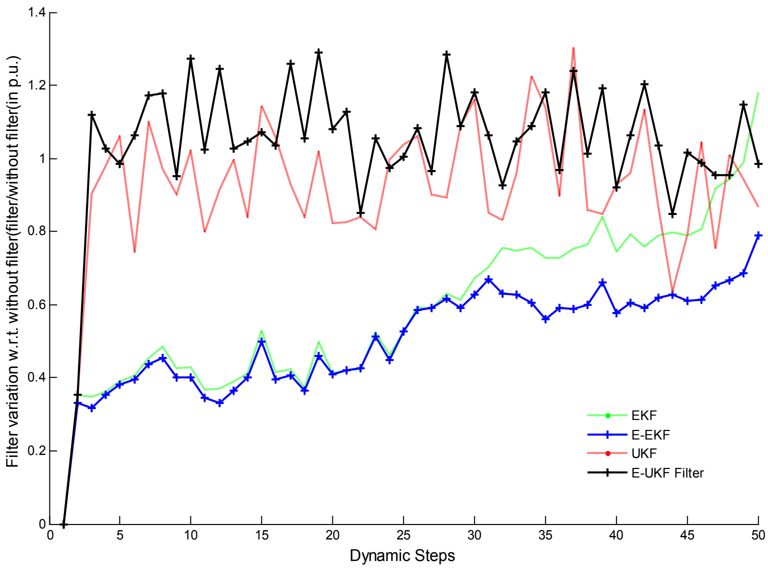

Figure 5. Filter variation from without filter estimation when N=50

Case-2 when dynamic cycle= 100 times

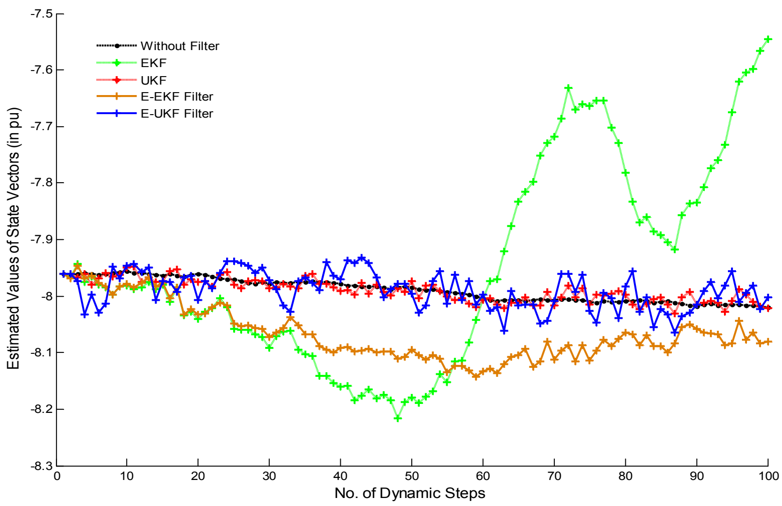

Figure 6. Estimated State vectors of the system when N=100

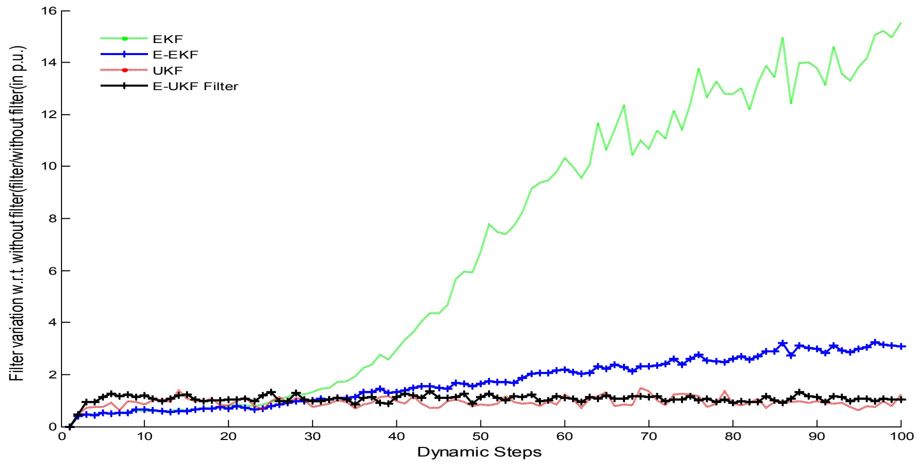

Figure 7. Filter variation from without filter estimation when N=100

Case-3 when dynamic cycle= 200 times

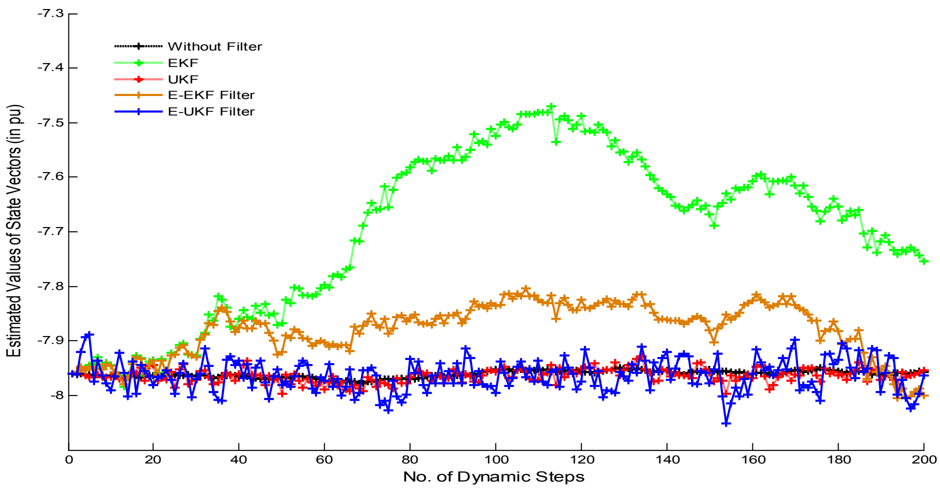

Figure 8. Estimated State vectors of the system when N=200

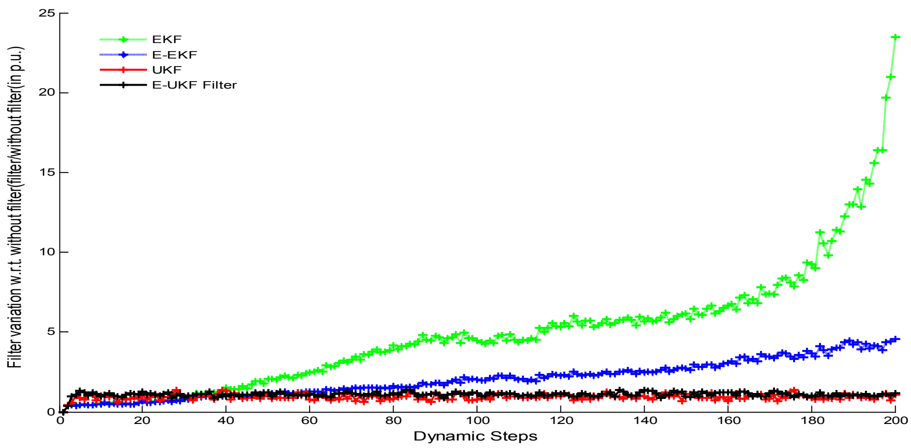

Figure 9. Filter variation from without filter estimation when N=200

With the increase of dynamic cycles, the error is also increasing and due to this, traditional methods are failing to estimate state vectors required. The robustness and effectiveness are greater in new emerging filters. Figure 10 shows the statistical analysis of different filters with respect to time elapsed for calculating parameters.

The statistical data for all four filterperformances are shown in figure 11. Figure 12 shows the Sum of RMSE calculated, which shows the performance of Emerging filters over traditional filters. The RMSE observed in E-EKF is 11.78% of EKF and in case of E-UKF, it is about 18.51 % of UKF.

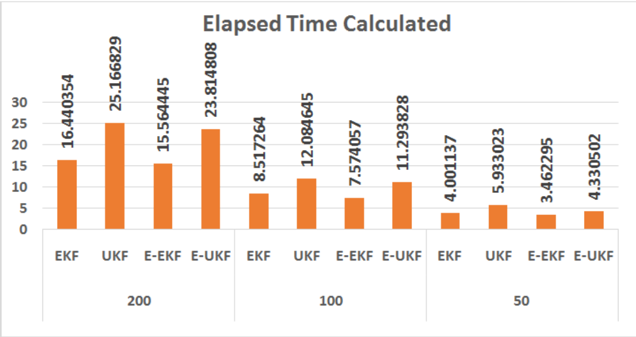

Figure 10. Elapsed time by each filter

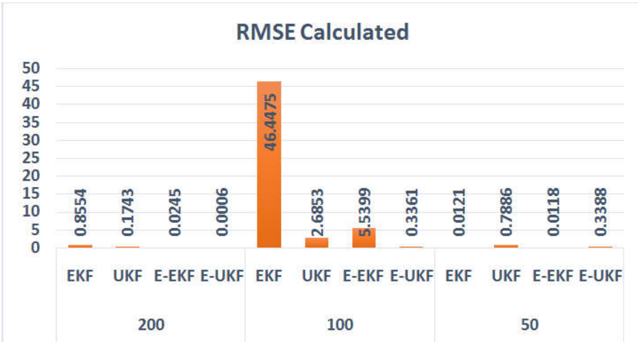

Figure 11. RMSE calculated by each filter

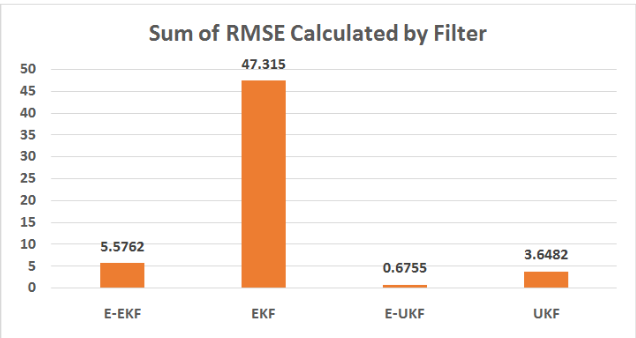

Figure 12. Sum of RMSE calculated

Conclusion

Two major conclusions can be derived with this simulation and analytical studies. Firstly, As per the variations of the measured state vectors from the actual state values, the Emerging EKF and Emerging UKF show promising results and performing well for calculate error is reduced. It has been observed with different case studies that these emerging filters are suitable for online applications at any EMS. Secondly, as per the time elapsed, emerging EKF presents swift results. Significant improvements are observed with the proposed modifications. Application of these filters in noisy environment lies in future scope of this manuscript.

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