International Journal of Future Generation Communication and Networking
Vol. 13, No. 2, 2020 pp.1404-1418

State Estimation Of Pmsm Using Unscented Kalman Filter (Ukf)

R. Laxman[1], A.R.Vijay Babu[2], K. Mounika[2], K. Bhargavi[2], K. Meghana[2]
[1]*Scientist 'D', Research Centre Imarat, DRDO Laboratory, Hyderabad, Telangana, India*
[2]*Department of Electrical & Electronics Engineering, Vignan's Foundation for Science, Technology & Research, Guntur, Andhra Pradesh, India*
Email Ids: laxman.R@rcilab.in, 202vijay@gmail.com, mounikakanna254@gmail.com, bhargavikonda12@gmail.com, kokatammeghanareddy333@gmail.com

Abstract

In this paper a sensorless control is modeled for permanent magnet synchronous motor utilizing UKF in order to estimate the position of rotor and speed in accurate manner. In this thesis we have chosen PMSM over induction motors and DC motors due to its high speed operation, longer life time, high power density, higher efficiency and simple in construction. In industrial applications, we assimilate/integrate different sensors for control of PMSM motors in estimating the rotor position and speed. Generally we use Encoders and Hall sensors to measure the rotor angle increasing the complexity and burden on the system which in succession increases the overall cost of the drive. This control method circumvents the use of sensors thereby reducing its complexity, cost and load on the system.

The project presents speed or position sensorless control based on Kalman Filter (KF), Extended Kalman Filter (EKF), and Unscented Kalman Filter (UKF) method, implemented using MATLAB code, Kalman Filter(KF) is a recursive Filter applied to linear – dynamic systems. It estimates the state of the system by considering a series of measurements but the output generated will have considerable errors in measurement and process noise. Kalman Filter is preferred for linear systems but PMSM is a non linear model. These drawbacks can be sorted out with use of Extended Kalman Filter (EKF), a modified and non linearized version of Kalman Filter (KF). In EKF, the non linearized relationships can be linearized by obtaining the partial derivatives of noises with the use of Taylor Series. EKF will produce some noise in speed estimation and this process involves calculation of Jacobian matrices which consumes more time. These liabilities are rectified with Unscented Kalman Filter (UKF). It is derivative free filter which adopts a minimum number of sample points called Sigma points for accurate estimation.

Index terms: *Modelling of PMSM and assumptions, Park and Clarke Transformation, Kalman Filter (KF), Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF)*

1. INTRODUCTION

In the last few years PMSM motors are widely used in medium power applications in the field of industrial drives because of their power capability and higher efficiency. To control the PMSM motors we are using Kalman filter and its extensions thereby eliminating the use of mechanical sensors.

This paper will significantly satisfies the need of sensorless control of PMSM motor and it can be further extended to control over other industrial drives such as brushless DC motors, Induction motors etc. This paper makes use of State Space Analysis. State space model can be applid to both non liner and time invariant system which helps in estimating the internal condition of the system. In most of the sensorless control techniques of PMSM, the position of rotor is measured by computing the electrical quantities. But to obtain accurate rotor position we require advanced algorithms Kalman Filter is ome among them. This algorithm is based on computing the mean and covariance matrices and in each iteration we will predict and update the measurement and process noises. In EKF we have the ability to re-adjust the initial position of rotor which is inconvenient in commercialized simulation collections. When compared with KF we can estimate the optimized results in EKF and is best suitable during starting of motors. In Complex systems, we use UKF for obtaining more accurate results where the computations are very less, thereby reducing the complexity, weight and cost of the drive.

ISSN: 2233-7857 IJFGCN

2. MODELLING OF PMSM AND ASSUMPTIONS

PMSM motor is an AC synchronous motor where its stator contain a 3 phase winding placed in the slots of the stator and the rotor contain permanent magnets. With the help of permanent magnets we can produce torque at zero speed. PMSM is a high torque, low speed motor which further results in some advantages such as zero maintenance, improved precision of rotor position, reversal of load and low noise. Based on the type of rotor, we can utilize it for different applications. Surface PMSM (SPMSM) is used in small and moderate power applications and Interior PMSM (IPMSM) is used in high power applications. The Fig 1. below shows the closed loop PMSM control.

PMSM has been modeled with some assumptions with respect to rotor frame of reference. They are:

a) Saturation is neglected in the ferrite core of electric motor.
b) Hysteresis and Eddy current losses are neglected.
c) Induce EMF is assumed to be sinusoidal in nature.
d) Effects of damper winding are absent.

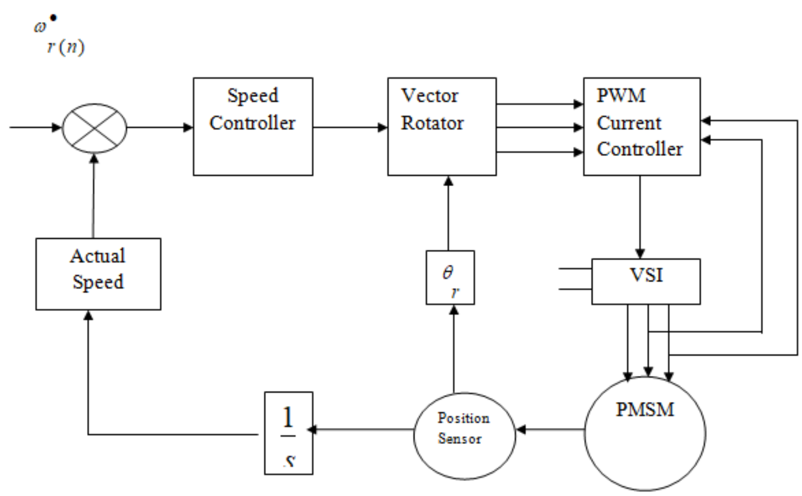

Fig.1. Closed loop control of PMSM

The direct and quadrature axis voltages are given by the following two equations:

$$V_d = R_s.I_d + \frac{d\lambda_d}{dt} - N_p.w_r.\lambda_q \tag{1}$$

$$V_q = R_s.I_q + \frac{d\lambda_q}{dt} + N_p.w_r.\lambda_d \tag{2}$$

$$T_e = \frac{3}{2} N_p.[\lambda_r I_q - (L_q - L_d).I_d.I_q] \tag{3}$$

$$\frac{dw_r}{dt} = \frac{1}{J}.(T_e - T_L - D.w_r) \tag{4}$$

ISSN: 2233-7857 IJFGCN

$$\frac{d\theta_e}{dt} = w = N_p.w_r \tag{5}$$

The flux linkages can be expressed as follows:

$$\lambda_d = L_d.I_d + \lambda_r \tag{6}$$

$$\lambda_q = L_q.I_q \tag{7}$$

Where the parameters are known as follows:

I_d , I_q are d, q axis currents

R_s : rotor resistance

N_p : pole pairs

w_r : Mechanical angular speed of rotor

θ_e : Rotor electrical angular position

λ_r : Rotor magnetic flux

D : frictional coefficient associated with rotor speed

J : moment of inertia of the rotor.

In research purposes, we will assume PMSM motors as non-salient motors. Therefore $L = L_d = L_q$

$$\frac{dI_d}{dt} = \frac{V_d}{L} - \frac{R_s}{L}.I_d + N_p.w_r.I_q \tag{8}$$

$$\frac{dI_q}{dt} = \frac{V_q}{L} - \frac{R_s}{L}.I_q - N_p.w_r.I_d - \frac{1}{L}N_p.w_r.\lambda_r \tag{9}$$

$$T_e = \frac{3}{2}N_p.\lambda_r.I_q \tag{10}$$

3. PARK AND CLARKE TRANSFORMATION

This transformation also known as frame transformation is frequently used in 3 phase AC machines to acquire effective control of drive systems by remodeling a time variant system to time invariant system. The stator of PMSM is supplied with 3Φ which cause 3Φ currents (abc) in the stator. The Clarke transformation converts 3Φ time domain components in abc frame to stationary (αβ) frame of 2 components. Similarly it is converted to arbitrary frame (dq) with 2 components from αβ frame by park transformation. This modification helps in simplifying mathematical calculations to obtain conventional control. These components are again altered to 3Φ elements of stator.

ISSN: 2233-7857 IJFGCN

$$\begin{bmatrix} F_\alpha \\ F_\beta \end{bmatrix} = \frac{2}{3}\begin{bmatrix} 1 & -1/2 & -1/2 \\ 0 & \sqrt{3}/2 & -\sqrt{3}/2 \end{bmatrix}\begin{bmatrix} F_a \\ F_b \\ F_c \end{bmatrix} \Rightarrow \begin{bmatrix} F_a \\ F_b \\ F_c \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ -1/2 & \sqrt{3}/2 \\ -1/2 & -\sqrt{3}/2 \end{bmatrix}\begin{bmatrix} F_\alpha \\ F_\beta \end{bmatrix}$$

(11)

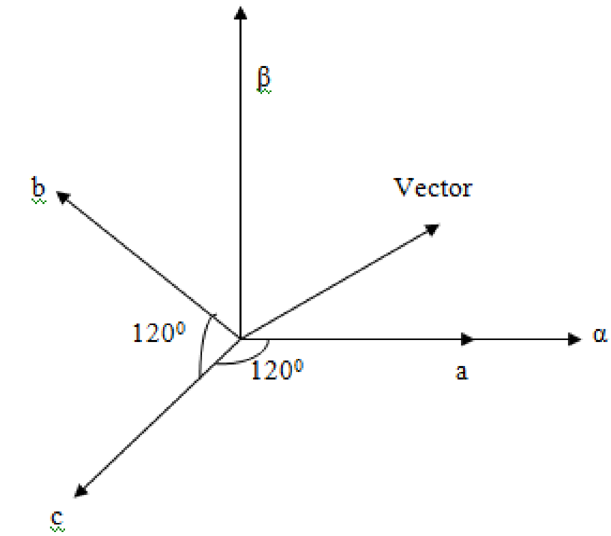

Fig 2.Vectors in abc and αβ reference frames

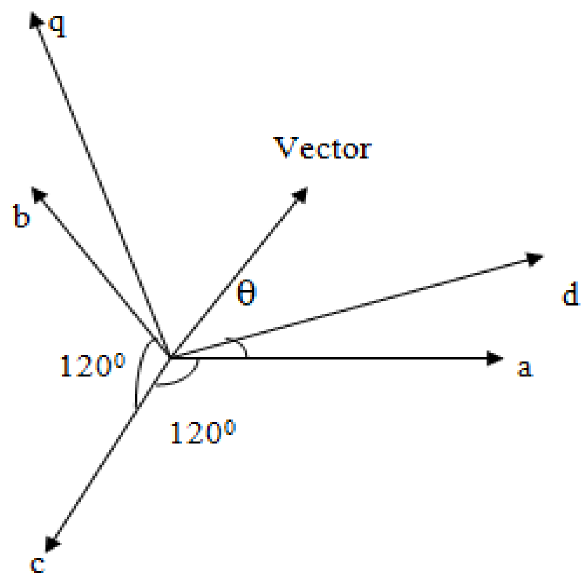

Fig 3.Vectors in abc and dq reference frames

$$\begin{bmatrix} F_d \\ F_q \end{bmatrix} = \frac{2}{3}\begin{bmatrix} \cos\theta & \cos(\theta - 2\pi/3) & \cos(\theta + 2\pi/3) \\ -\sin\theta & -\sin(\theta - 2\pi/3) & -\sin(\theta + 2\pi/3) \end{bmatrix}\begin{bmatrix} F_a \\ F_b \\ F_c \end{bmatrix}$$

(12)

ISSN: 2233-7857 IJFGCN

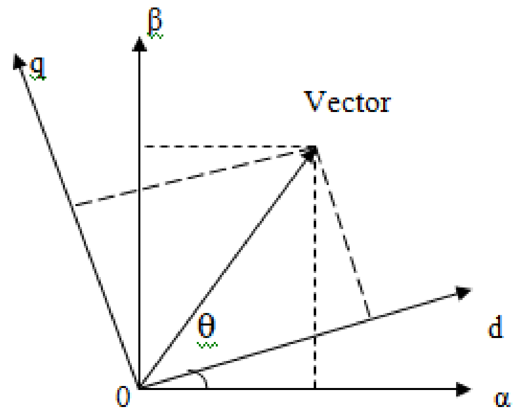

Fig 4.Vectors in αβ and dq reference frames

$$\begin{bmatrix} F_d \\ F_q \end{bmatrix} = \begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} F_\alpha \\ F_\beta \end{bmatrix} \tag{13}$$

The above matrix can be expanded as:

$$F_d = F_\alpha \cos\theta + F_\beta \sin\theta \tag{14}$$

$$F_q = -F_\alpha \sin\theta + F_\beta \cos\theta \tag{15}$$

We have obtained the following state equations from modeling of PMSM:

$$\frac{dI_d}{dt} = \frac{V_d}{L} - \frac{R_s}{L} I_d + N_p.w_r I_q \tag{16}$$

$$\frac{dI_q}{dt} = \frac{V_q}{L} - \frac{R_s}{L} I_q - N_p.w_r I_d - \frac{1}{L} N_p.w_r \lambda_r \tag{17}$$

Similarly by applying frame transformation to currents and voltages,

$$I_d = I_\alpha \cos\theta + I_\beta \sin\theta \quad ; \quad I_q = -I_\alpha \sin\theta + I_\beta \cos\theta \tag{18}$$

$$V_d = V_\alpha \cos\theta + V_\beta \sin\theta \quad ; \quad V_q = -V_\alpha \sin\theta + V_\beta \cos\theta \tag{19}$$

Substitute above frame transformation expressions wherever required in the state equations and deduce them by simple mathematics.

We obtain following equations:

$$\frac{dI_\alpha}{dt} = \frac{V_\alpha}{L} - \frac{R_s I_\alpha}{L} + N_p w_r I_\beta + \frac{1}{L} N_p w_r \lambda_r \sin\theta \tag{20}$$

ISSN: 2233-7857 IJFGCN

$$\frac{dI_\beta}{dt}=\frac{V_\beta}{L}-\frac{R_s I_\beta}{L}-N_p w_r I_\alpha-\frac{1}{L}N_p w_r \lambda_r \cos\theta \tag{21}$$

$$\frac{dw_r}{dt}=0\ ;\ \frac{d\theta_e}{dt}=w=N_p.w_r \tag{22}$$

Express the above state equations in form of matrices

$$\frac{d}{dt}\begin{bmatrix} I_\alpha \\ I_\beta \\ w_r \\ \theta_e \end{bmatrix}=\begin{bmatrix} -\frac{R_s}{L} & 0 & \frac{N_p\lambda_r}{L}\sin\theta_e & 0 \\ 0 & -\frac{R_s}{L} & -\frac{N_p\lambda_r}{L}\cos\theta_e & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & N_p & 0 \end{bmatrix}\begin{bmatrix} I_\alpha \\ I_\beta \\ w_r \\ \theta_e \end{bmatrix}+\begin{bmatrix} \frac{1}{L} & 0 \\ 0 & \frac{1}{L} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \text{ and } \begin{bmatrix} I_\alpha \\ I_\beta \end{bmatrix}=\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}\begin{bmatrix} I_\alpha \\ I_\beta \\ w_r \\ \theta_e \end{bmatrix} \tag{23}$$

Let us assume

$$\overset{\bullet}{x}=\frac{d}{dt}\begin{bmatrix} I_\alpha \\ I_\beta \\ w_r \\ \theta_e \end{bmatrix};x=\begin{bmatrix} I_\alpha \\ I_\beta \\ w_r \\ \theta_e \end{bmatrix};u=\begin{bmatrix} V_\alpha \\ V_\beta \end{bmatrix};v=\begin{bmatrix} I_\alpha \\ I_\beta \end{bmatrix} and \tag{24}$$

$$A=\begin{bmatrix} -\frac{R_s}{L} & 0 & \frac{N_p\lambda_r}{L}\sin\theta_e & 0 \\ 0 & -\frac{R_s}{L} & -\frac{N_p\lambda_r}{L}\cos\theta_e & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & N_p & 0 \end{bmatrix};B=\begin{bmatrix} \frac{1}{L} & 0 \\ 0 & \frac{1}{L} \\ 0 & 0 \\ 0 & 0 \end{bmatrix};H=\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{25}$$

The Parameters of PMSM are as follows :

$R_s = 2.8\Omega\ L = 1.2mH\ , N_p = 4\, , w_r = 0.28Wb\, , \theta_e = 60^\circ$

$$A=\begin{bmatrix} -90.1600 & 0 & 61.4720 & 0 \\ 0 & -90.1600 & -30.7360 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 4 & 0 \end{bmatrix}\ ;\ B=\begin{bmatrix} 80 & 0 \\ 0 & 80 \\ 0 & 0 \\ 0 & 0 \end{bmatrix}\ ;\ C=H=\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix} \tag{26}$$

4. KALMAN FILTER

ISSN: 2233-7857 IJFGCN

Kalman filter (KF) offers recurrent solution in solving linear discrete time control systems. For a given sequence of measurements, Kalman filter provides a optimal estimation of required quantities. It will not store the previous data, but it recovers all the data in each iteration i.e, it operates using the present state measurements , state matrices and earlier Kalman filter algorithm typically comprises of two processes – Prediction, Updation which is shown in Fig 5.

Kalman Filter Algorithm:

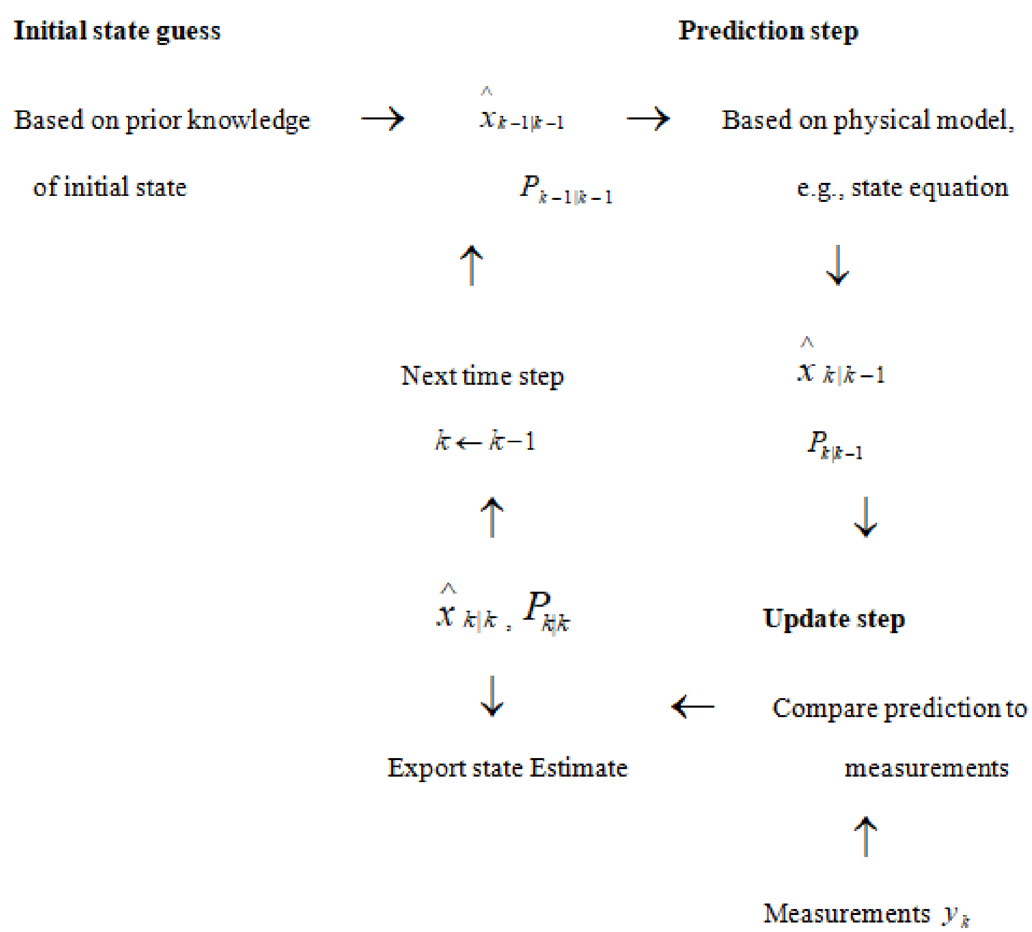

Fig 5.Kalman Filter algorithm

Prediction: In this step Kalman filter generates approximation of present state parameters in addition to their unpredictabilities.

Updation : With the entry of new measurement, the estimates are updated after computing the Kalman gain using weighted average technique. Similarly error covariance is updated.

Solution to KF is obtained with the following:

Time update equations: It uses present state as well as error covariance to prevail prior estimation to obtain next moves.

Measurement update equations: In this step we assimilate a current measurement into priori approximation to prevail posteriori estimate**s.**

Prediction Step

ISSN: 2233-7857 IJFGCN

$$\hat{x}(k \mid k-1) = \phi \hat{x}(k-1 \mid k-1) + \Gamma u(k-1)$$

$$P(k \mid k-1) = \phi P(k-1 \mid k-1)\phi^T + \Gamma_d Q_d \Gamma_d^T \tag{27}$$

Kalman Gain

$$L^*(k) = P_{\varepsilon e}(k) P_e(k)^{-1}$$

$$L^*(k) = P(k \mid k-1)C^T [CP(k \mid k-1)C^T + R]^{-1} \tag{28}$$

Update Step

$$e(k) = [y(k) - C\hat{x}(k \mid k-1)]$$

$$\hat{x}(k \mid k) = \hat{x}(k \mid k-1) + L^*(k)e(k) \tag{29}$$

$$P(k \mid k) = (I - L^*(k)C]P(k \mid k-1) \tag{30}$$

5. EXTENDED KALMAN FILTER

Kalman Filter is only applicable for linear models where PMSM is non linear process and noise in errors could be manipulated. These issues can be resolved by employing its extended model i.e, Extended Kalman Filter (EKF). EKF is a non linear model of Kalman Filter which makes it linear with reference to present mean and covariance. EKF adapt Taylor series expansion model to get a linearized model about an operating position by considering the partial derivatives i.e, jacobians of measurement and process noise.

The fig 6. Given below is a flowchart which describes the procedure and steps of Extended Kalman Filter.

ISSN: 2233-7857 IJFGCN

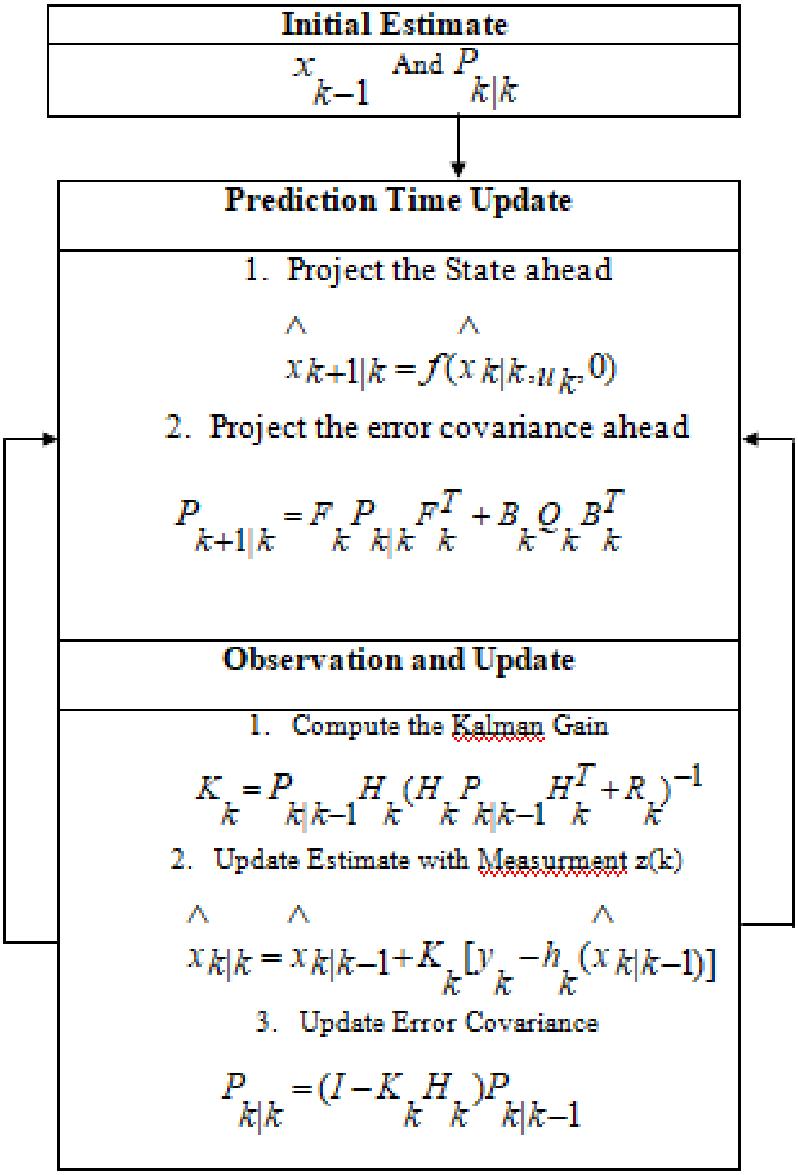

Fig 6. Flowchart of EKF

Prediction: $\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_k)$ **Covariance:** $P_{k|k-1} = \phi_k P_{k|k-1} \phi_k^T + Q_k$

Correction: $\tilde{y}_k = z_k - h(\hat{x}_{k|k-1})$; $S_k = h_k P_{k|k-1} h_k^T + R_k$ (31)

Kalman gain: $K_k = P_{k|k-1} h_k^T S_k^{-1}$;- $\hat{x}_{k|k} = \hat{x}_{k|k-1} + \tilde{y}_k K_k$; $P_{k|k} = (I - K_k h_k) P_{k|k-1}$ (32)

The drawback of this Filter is evaluation of jacobians in each iteration which extends the complication in mathematical computations. This difficulty can be sorted out with UKF.

ISSN: 2233-7857 IJFGCN

6. UNSCENTED KALMAN FILTER

Unscented Kalman Filter (UKF) is derivative free filter where we consider a set of sample points on the original Gaussian. These samples are known as sigma points, passed through a non linear model subsequently we will compute mean and covariance and then we map them on Gaussian surface. These sample points constitute the whole didtribution. Precision increases with number of samples. We are not converting the system to a linearized model, since we are not computing jacobians which successively assists in minimizing complexity in UKF.

UKF Algorithm

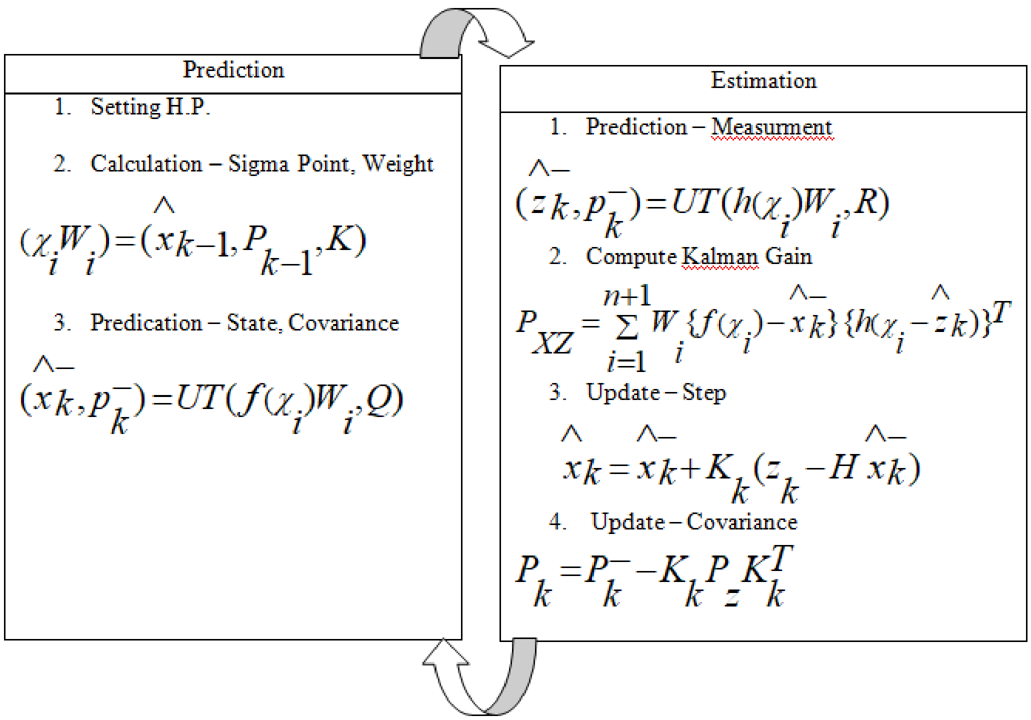

Fig 7. Algorithm of UKF

Prediction:

$$x^a_{k-1|k-1} = \begin{bmatrix} \hat{x}^T_{k-1|k-1} & E\langle w_k^T \rangle & E\langle v_k^T \rangle \end{bmatrix}^T \quad ; \quad P^a_{k-1|k-1} = \begin{bmatrix} P_{k-1|k-1} & 0 & 0 \\ 0 & Q_k & 0 \\ 0 & 0 & R_k \end{bmatrix} \qquad (33)$$

Correction:

$$\tilde{y}_k = z_k - h(\hat{x}_{k|k-1}) \quad ; \quad \hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(z_k - \hat{z}_k) \quad ; \quad P_{k|k} = P_{k|k-1} - K_k P_{z_k z_k} K_k^T \qquad (34)$$

7. RESULTS AND DISCUSSIONS:

Figures 8 and 9 shows the comparison of estimated states of PMSM with KF, EKF, UKF

ISSN: 2233-7857 IJFGCN

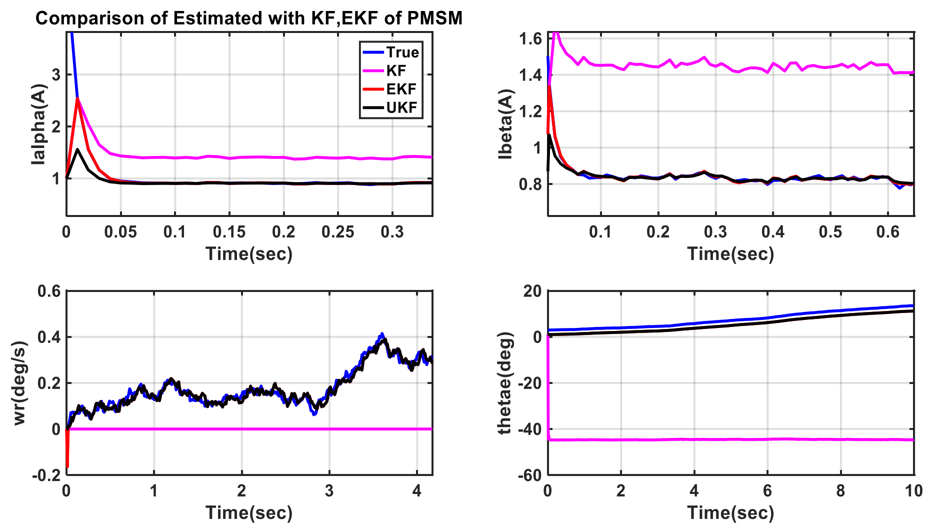

Fig 8. estimated states with 3 filters for Vα = 60v, Vβ = 60v

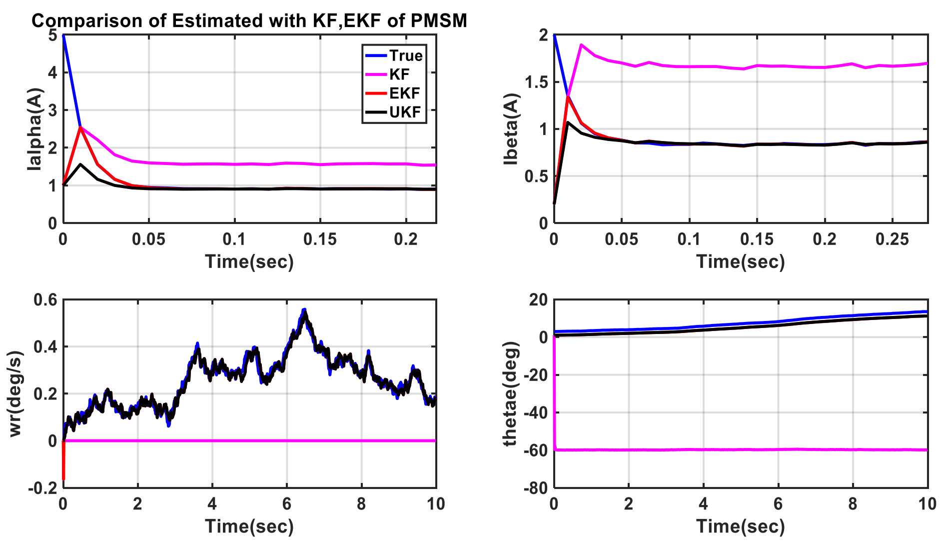

Fig 9. estimated states with 3 filters for Vα = 80v, Vβ = 80v

From figures 8 and 9 it is evident that during starting the performance of EKF is marginally better than that of UKF. But under speed reversal conditions, UKF has better performance. It is also clear that both the filters show similar and good steady state performance. The error tends to zero in both the filters after a transcient period.

ISSN: 2233-7857 IJFGCN

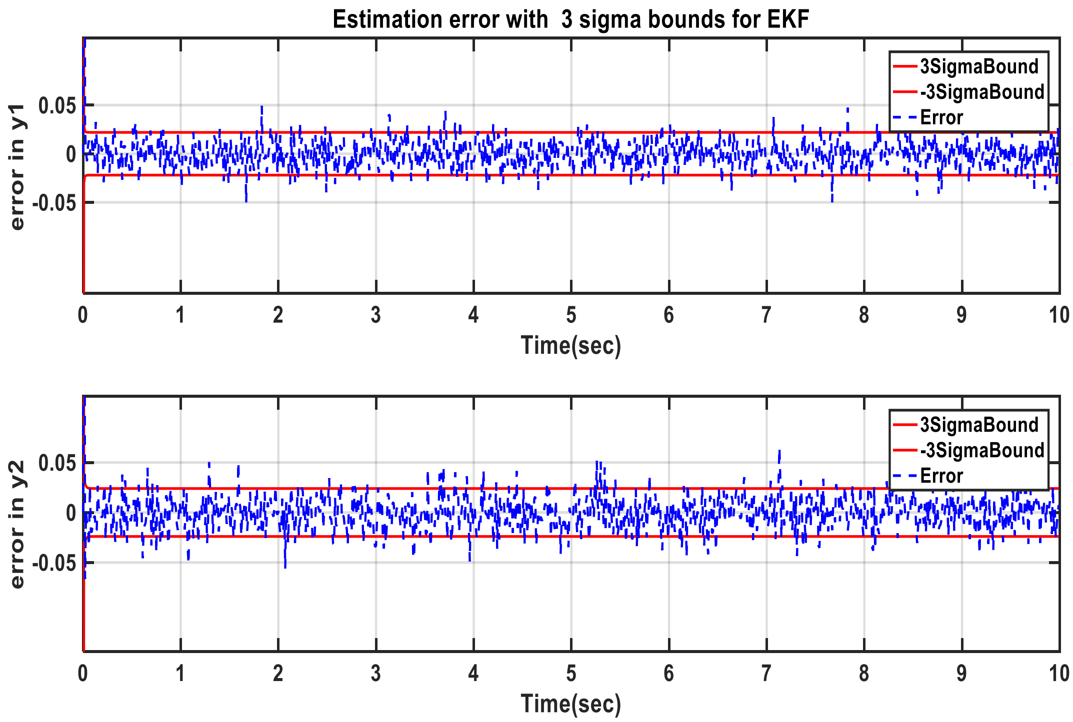

Fig 10. Estimation error with 3 sigma bounds for EKF for Vα = 60v, Vβ = 60v

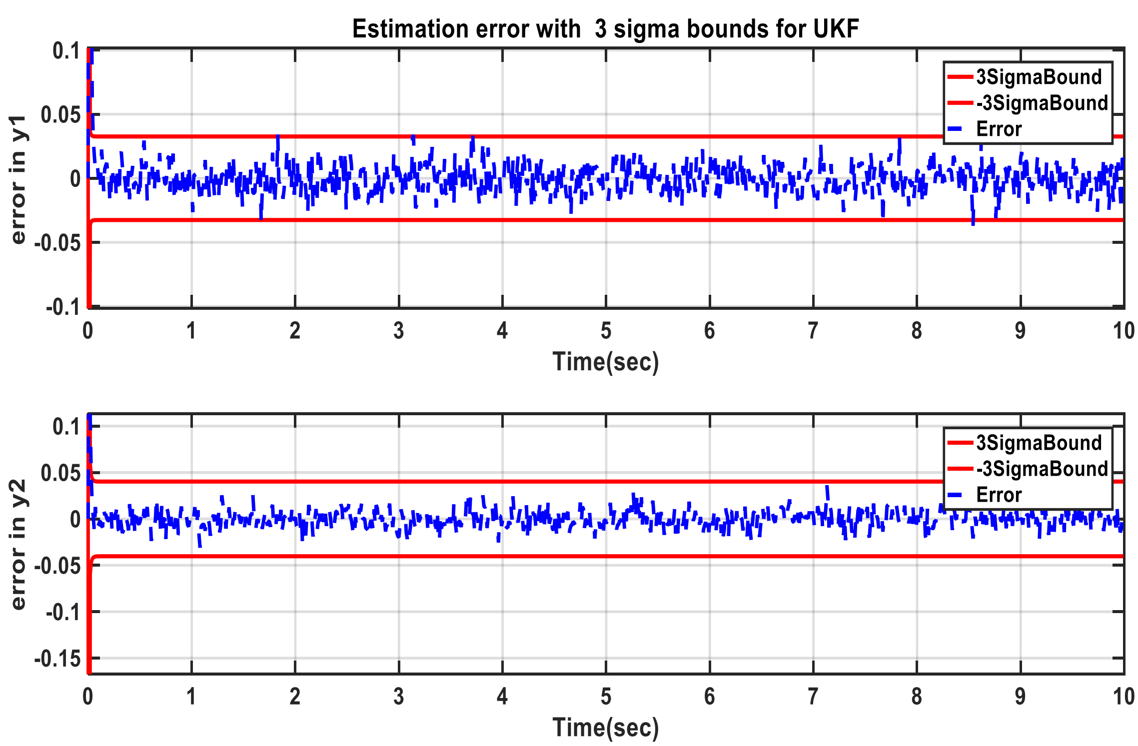

Fig 11. Estimation error with 3 sigma bounds for UKF for Vα = 60v, Vβ = 60v

ISSN: 2233-7857 IJFGCN

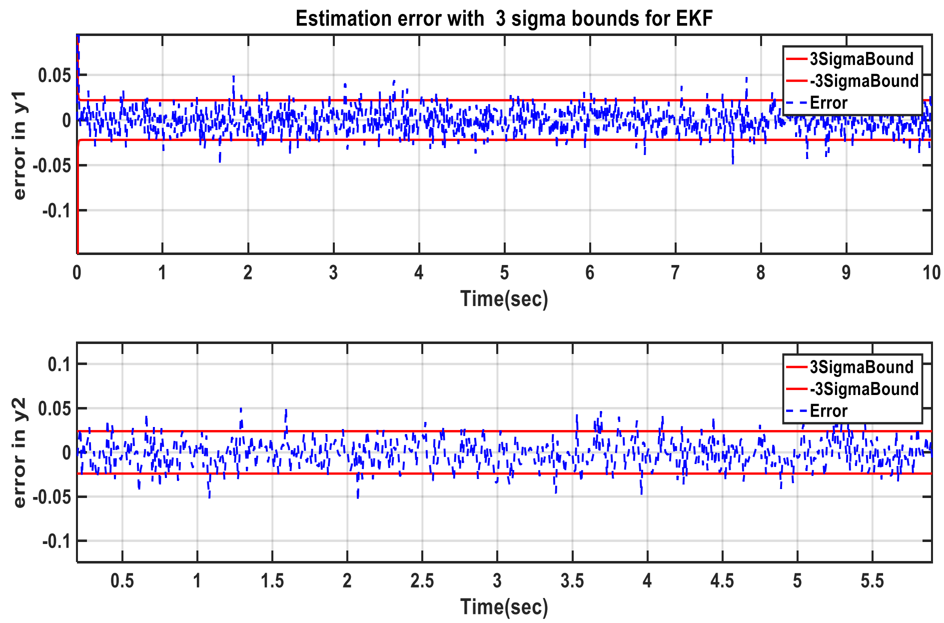

Fig 12. Estimation error with 3 sigma bounds for EKF for Vα = 80v, Vβ = 80v

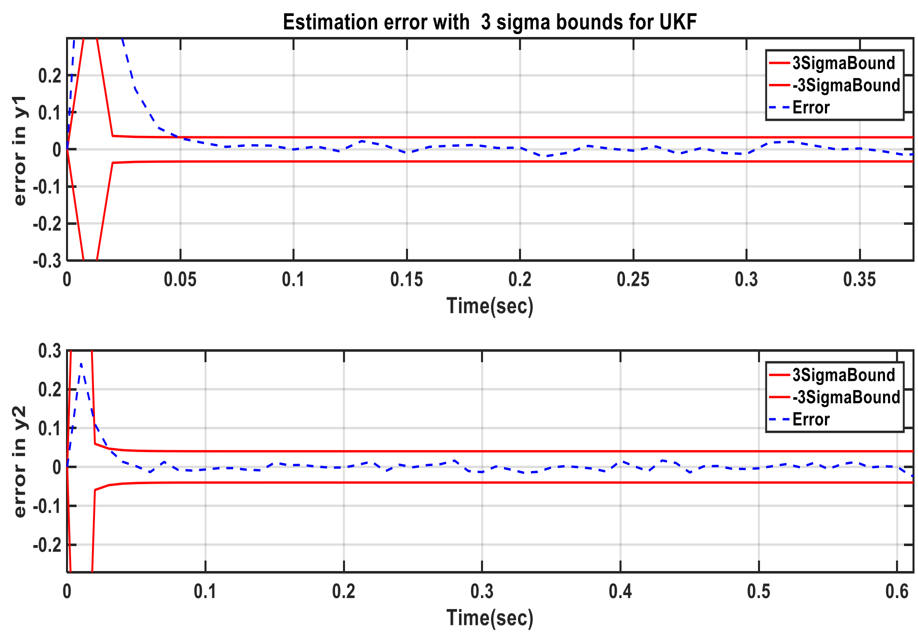

Fig 13. Estimation error with 3 sigma bounds for UKF for Vα = 80v, Vβ = 80v

Figures 10-13 shows estimation error with 3 sigma bounds. Usually 3 sigma bound is a statistical method to measure variability and measures how much deviation exists from a stastical mean or average. From figures deviation is more in EKF compared to that of UKF. There is slight deviation from bounds in UKF during startup whereas in steady state error is within the bounds but in EKF there are deviations throughout.

ISSN: 2233-7857 IJFGCN

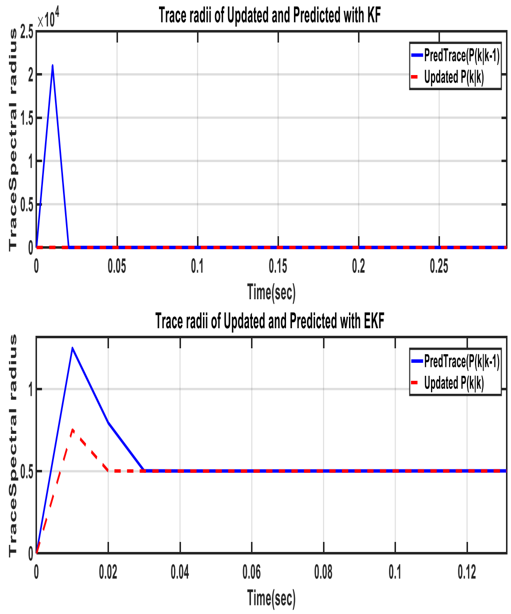

Fig 14. Trace radii of updated and predicted with KF and EKF for Vα = 60v, Vβ = 60v

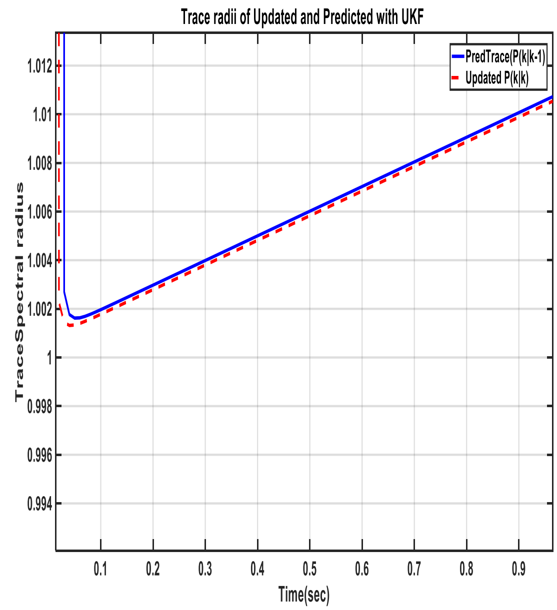

Fig 15. Trace radii of updated and predicted with UKF for Vα = 60v, Vβ = 60v

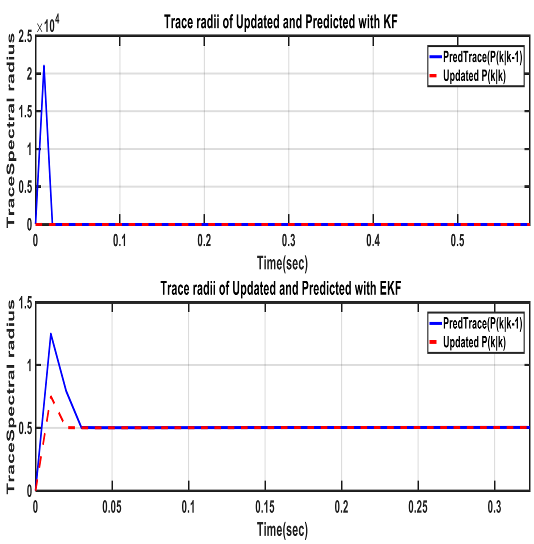

Fig 16. Trace radii of updated and predicted with KF and EKF for Vα = 80v, Vβ = 80v

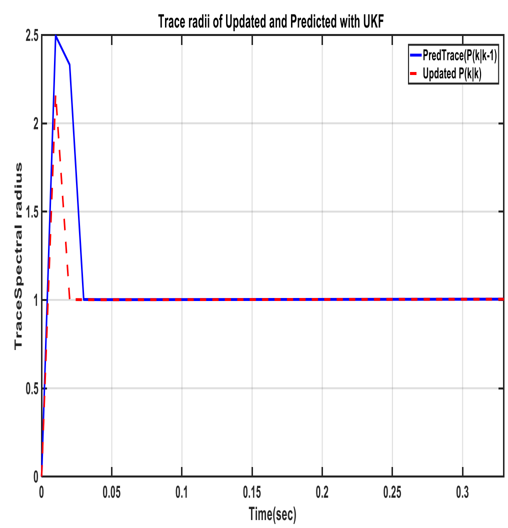

Fig 17. Trace radii of updated and predicted with UKF for Vα = 80v, Vβ = 80v

ISSN: 2233-7857 IJFGCN

Figures 14-17 depicts the trace radii of updated and predicted ststes with UKF. During startup, the UKF traces more precisely compared to EKF. But during steady state conditions both filters traces almost in a similar manner. So, we can choose any one of these filters in industrial applications where static state performance is crucial.

CONCLUSION

Both the filters (EKF and UKF) are preferable for controlling drives without sensors.. EKF discharges better characteristics at the time of starting of the motors whereas UKF exhibits superior characteristics in monitoring the speed, particularly in transients. Due to absence of Jacobian matrices, the computations will be much lesser in UKF thereby making it feasible to apply this estimation for highly non-linear, complex systems to obtain better filter characteristics. UKF provides promising features when compared to EKF under noisy conditions. The steady state characteristics of both the filters are much closer. UKF performs well during the speed reversal as it will result in less error.

REFERRENCES

[1] L.A. Jones and J.H. Lang, "A State Observer for the Permanent Magnet Synchronous Motor", IEEE transactions on industrial. Vol. 36, No. 3, pp. 374-382, August 1989.

[2] L. Salvatore and S. Stasi, "Application of EKF to Parameter and State Estimation of PMSM Drive", Elechic Power Applications, lEE Proceedings B, Volume: 139 pp- 87-95 Issue: 3, May 1992.

[3] Joohn-Sheok Kim and Seung-Ki Sul, "New Approach for tlie Low-Speed Operation of PMSM Drive Without Rotational Position Sensors", IEEE Transaction on Power Electronics, Vol. 11, No. 3, pp- 40-60 May 1996.

[4] Shigeo Morimoto, Yoji Takeda and Takao Hirasa, "Current Phase Control Methods for Permanent Magnet Synclii'onous Motors", IEEE Transactions on Power Electronics. Vol. 5, No. 2, pp- 27-42 April 1990

[5] K. L. Shi, Hassan Kojori and Bin Wu, "High-performance Sensorless PMSM Drive witli Extended Kalman Filter", 2002 SAE Power Systems Conference, October 2002, Florida.

ISSN: 2233-7857 IJFGCN