International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 3 Issue 4, April - 2014

Unscented Kalman Filter Based Observer for Vector Controlled Induction Motor

Prashant Bhopale[1], Swati Dhobaley[2], D. R. Mehta[3]
[1,2,3] Dept. of Electrical Engg. Veermata Jijabai Technological Institute,
Mumbai-19., India.

***Abstract*—The extended kalman filter(EKF) suffers from 1st order approximation error which causes deviation in the mean and covariance of estimation while Unscented kalman Filter(UKF) uses the nonlinearity in the system without linearization to overcome this errors. The nonlinear approach of unscented transform has been used for rotor flux estimation in the presence of white Gaussian noise and results inferred.**

***Keywords*—Extended Kalman Filter; Unscented Kalman Filter; nonlinear;white gaussian noise.**

I. INTRODUCTION

The induction motor drives are widely used in industrial application due to the advantages in terms of robustness and prize, hence the motor control industry has become a strong and aggressive sector. During the last few decades the field of controlled electrical drives has undergone rapid expansion hence better estimation of the control parameter and states of control vectors are necessary. The Vector control induction motor consists of controlling the stator currents represented by a vector. The different methods of speed and flux estimation needs model which is sensitive and based on machine parameters and also require apriori knowledge of electrical and sometimes mechanical characteristics.

Some type of speed estimation is essential for speed control of induction motor. Magnetic saliencies depending speed estimation like rotor slotting [1], variation of leakage reactance [2] or rotor asymmetries [3] which are considered as true measurement and independent of machine parameters. Due to reduced range of frequency they are not widely used. Although machine model dependent estimations which uses open loop speed calculators[4,5],Model reference adaptive system(MRAS)[6,7,8,9] and Extended Kalman Filter[10]. Also deriving machine flux used methods are from machine models are integration of back emf [4,5], flux observer [6,7,8,9, 11], Extended Luenberger Observer [12], Monitoring local saturation effect [13] and extended kalman filter [13,14,15,16,17]. But the above mentioned methods which are model dependent have considered the linearized model of induction motor, although where 1st order approximation using EKF can introduce mean and covariance errors.

In practice, the rotor currents or fluxes are not easily available and measurable. Therefore an observer is required to estimate the unknown states and can also provide better estimates of known current states that are contaminated by noise in some circumstances,. In this paper we propose the UKF based observer for flux estimation of vector controlled induction motor which takes into account the nonlinearity of the model using nonlinear approach of unscented transform [22]Julier showing nonlinear estimation gives better performance than linearized strategies like EKF.

This paper is organized as follows. The fundamental model of vector control induction machine is described in Section II together with the theoretical basis for FOC strategy. The UKF algorithm is presented in Section III. In section IV MATLAB/Simulink simulation results obtained with the proposed algorithm applied on an ideal model of the machine is provided. In Section VI conclusions are drawn.

II. SYSTEM DESCRIPTION.

A. *Vector Controlled Induction Motor Drive*

First, The block diagram of the proposed system is shown in Fig.1 The continuous-time mathematical model of the induction machine can be described in state-space form, with rotor speed treated as a time-varying parameter,

$$\dot{x}_i = f_i(x,t) + Du + u(k) \qquad (1)$$

$$Where\ i = 1,2, \dots 4$$

x is state variable and the input voltage vector u are given as $x = [i_{ds}\ i_{qs}\ \Psi_{dr}\ \Psi_{qr}]$ where s and r stands for stator and rotor and d and q are vectors of respective fixed stator frame and $u(k)$is process noise.

B. *Mathematical Modelling of Vector Controlled Induction Motor Drive*

The four first order differential equations resulting from the expansion of eqn. 1 are:

$$\dot{x}_1 = -\left(\frac{R_s}{L_\sigma} + \frac{R_r L_m^2}{L_r^2 L_\sigma}\right)x_1 + \frac{R_r L_m}{L_r^2 L_\sigma}x_3 + \frac{w_r L_m}{L_r^2 L_\sigma}x_4 + \frac{1}{L_\sigma}u_{ds} \quad (2)$$

$$\dot{x}_2 = -\left(\frac{R_s}{L_\sigma} + \frac{R_r L_m^2}{L_r^2 L_\sigma}\right)x_2 - \frac{w_r L_m}{L_r^2 L_\sigma}x_3 + \frac{R_r L_m}{L_r^2 L_\sigma}x_4 + \frac{1}{L_\sigma}u_{qs} \quad (3)$$

$$\dot{x}_3 = \frac{R_r L_m}{L_r}x_1 - \frac{R_r}{L_r}x_3 - w_r x_4 \quad (4)$$

$$\dot{x}_4 = \frac{R_r L_m}{L_r}x_2 + w_r x_3 - \frac{R_r}{L_r}x_4 \quad (5)$$

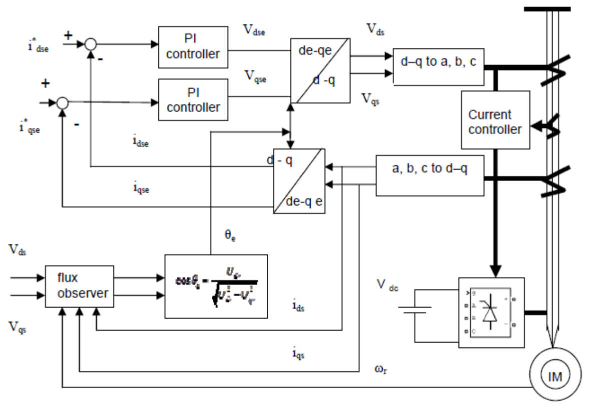

Fig.1 Indirect Vector Control Drive

Where L_σ is linkage inductance i.e.

$$L_\sigma = L_s - \left(\frac{L_m^2}{L_r}\right) \quad (6)$$

The states x_1 and x_2 are the stator d-q axis currents, which are usually measurable. The statesx_3 and x_4 are the d-q axis rotor fluxes, which are not easily measurable and require estimation. Sometimes, the measured stator currents are contaminated by noise, and require to be estimated as well. In some circumstances the estimates can be more reliable.

An output or observation equation is required by the state space model and for the practical case in which stator and rotor flux are chosen as measurements:

$$y(k) = h(x(k)) \quad (7)$$

$$y(k) = [\,\Psi_{dr}\ \Psi_{qr}]^T \quad (8)$$

III. Algorithm of Unscented Kalman Filter

Unscented Kalman Filter (UKF) also known as Sigma Point Kalman Filter[22], priory needed to created sigma points which are selected by priory knowledge of previous state and covariance matrices. 2L+1 Sigma points are more useful when creating sigma points for L dimensional state vector. Following are the steps for UKF algorithm.

A. Sigma Points:

The m dimensional random variable x with mean $\bar{x}$ and co-variance P_{xx} is approximated by $2m+1$ weighted points given by,

$$x_0 = \bar{x}$$

$$x_i = \bar{x} \pm \left(\sqrt{(n+\lambda)P_{xx}}\right)_i \quad for\ = 1,2,3, \ldots \ldots 2m \quad (9)$$

$$W_0^m = \frac{\lambda}{m+k}, \quad W_0^c = \frac{\lambda}{m+k} + (a - \alpha^2 + \beta) \quad (10)$$

$$W_i^m = W_i^c = \frac{1}{2(m+\lambda)} \quad for\ \ i = 1,2,3, \ldots \ldots 2m \quad (11)$$

Where,

$$\lambda = \alpha^2(m + k_i) - m \quad (12)$$

k_i determines the spread of sigma points around $\bar{x}$ and usually set to a small positive value. k_i is a secondary scaling parameter which is usually set to 0 and β is a parameter used to incorporate any priory knowledge about the distribution of x. $\left(\sqrt{(n+\lambda)P_{xx}}\right)_i$ is the ith row or column of the matrix square root of $\left(\sqrt{(n+\lambda)P_{xx}}\right)$ and W_i is the weight which is associated with the ith point. These sigma points are propagated through the function.

B. Implementation of UKF

For L dimension state vector, 2L+1 sigma points are related as follows,

Step1: Creating Sigma Points

$$\chi_{k-1} = \left[\hat{x}_{k-1} \quad \hat{x}_{k-1} + \zeta\sqrt{\hat{P}_{k-1}} \quad \hat{x}_{k-1} - \zeta\sqrt{\hat{P}_{k-1}}\right]$$
(13)

Where, $\zeta = \sqrt{L+\lambda}$ and $\lambda = \alpha^2(L + k_i) - L$

Step 2: Propagating Sigma Points or Prediction

$$\chi_{i,k} = f(\chi_{i,k-1}), \qquad for\ \ i = 1,2, \ldots \ldots, 2L+1$$
(14)

Step 3: Calculating Mean & Covariance

$$x_{k/k-1} = \sum_{i=0}^{2L} W_i^m\, \chi_{i,k} \quad (15)$$

$$P_{xx} = \sum_{i=0}^{2L} W_i^c \left[\chi_{i,k} - x_{k/k-1}\right]\left[\chi_{i,k} - x_{k/k-1}\right]^{*T} + Q_{k-1}$$
(16)

$$Y_{i,k} = h(\chi_i, k)$$
(17)

$$y_{abs} = \sum_{i=0}^{2L} W_i^m Y_{i,k}$$
(18)

$$P_{xy} = \sum_{i=0}^{2L} W_i^c \left[\chi_{i,k} - x_{k/k-1}\right][Y\_(i,k) - y\_abs]^{*T}$$
(19)

$$P_{yy} = \sum_{i=0}^{2L} W_i^c \left[y_{i,k} - y_{abs}\right]\left[Y_{i,k} - y_{abs}\right]^{*T} + R_{k-1}$$
(20)

Step 4: Correction

$$K = P_{xy} P_{yy}^{-1}$$
(21)

$$x_k = x_{k-1} + K(y_k - \overline{y_k})$$
(22)

$$\hat{P}_k = P_{xx} - K P_{yy} K^{*T}$$
(23)

Process noise $\boldsymbol{w(k)}$ and Measurement noise $\boldsymbol{v(k)}$ are characterized by

$$E\{w(k)\} = 0 \quad \& \quad E\{v(k)\} = 0$$
(24)

$$E\{w(k)w(k)^{\boldsymbol{T}}\} = Q\delta_{kj} Q \geq 0 \ \&$$

$$E\{v(k)v(k)^T\} = R\delta_{kj} R \geq 0$$
(25)

IV. SIMULATION AND ESTIMATION

The rotor flux estimation is obtained by applying UKF algorithm. The UKF used the nonlinear model (2)-(5) The simulation results for UKF is shown in Fig.2 where 9 sigma points are created by considering 4 state including rotor and stator current along with rotor and stator flux as augmented states which are estimated by observer. Scaling parameters and process and measurement noise of UKF are selected as [23]. Sampling time taken 0.01sec and simulation carried out for 10 sec when motor accelerates from rest to 255 rpm.

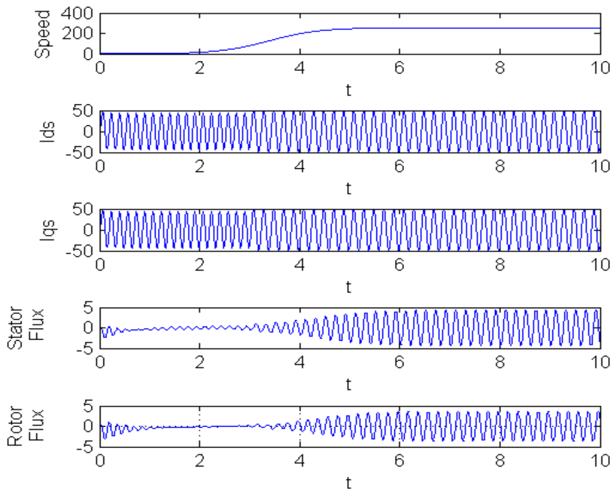

Fig.2 Results obtained by UKF observer

V. CONCLUSIONS

In this paper, we have implemented nonlinear model of indirect vector control induction motor without linearization, and simulation results are presented. The UKF based flux observer is created and performance of observer is presented in the presence of noise. Result shows that the Stator and Rotor flux of Vector Control Induction Motor can be successfully estimated by observer designed using UKF.

VI. ACKNOWLEDGMENT

The authors would sincerely like to acknowledge the support of Mr. Pratik K. Bajaria, VJTI, Matunga, Mumbai, India, for his valued contributions to this paper.

APPENDIX

Rating and Parameters of Induction Motor used for simulation
4 Poles,60 Hz,220 V,20 Hp
Rotor Resistance(R_r) = 1.772Ω
Stator Resistance(R_s)=1.282Ω
Stator Inductance(L_s)=0.282mH
Rotor Inductance(L_r)=0.101mH
Mutual Inductance(L_m)=0.161mH

VII. REFERENCES

[1] Atkinson,DJ; Acarnley,PP;Finch,JW,"Observer for Induction-Motor State and Parameter-Estimation",IEEE Transaction on Industry Application,1991,Vol.27,No.6,pp.119-1127

[2] Jansen, P.L.; Lorenz, R.D., "Transducerless position and velocity estimation in induction and salient AC machines," *Industry Applications, IEEE Transactions on* , vol.31, no.2, pp.240,247, Mar/Apr 1995
doi: 10.1109/28.370269

[3] Holloday,D,,Fletcher,J.E. and William,B.W.," non-invasive rotor position and and speed sensing of Asynchronous Motor",Proceeding of EPE '95,Sevilla,1995 Vol.1,pp. 1.333-1.337

[4] Xingyi Xu; Novotny, D.W., "Implementation of direct stator flux orientation control on a versatile DSP based system," *Industry Applications, IEEE Transactions on* , vol.27, no.4, pp.694,700, Jul/Aug 1991
doi: 10.1109/28.85484

[5] Habetler, T.G.; Profumo, F.; Pastorelli, M.; Tolbert, L.M., "Direct torque control of induction machines using space vector modulation," *Industry Applications, IEEE Transactions on* , vol.28, no.5, pp.1045,1053, Sep/Oct 1992

[6] Jansen, P.L.; Lorenz, R.D., "Accuracy limitations of velocity and flux estimation in direct field oriented induction machines," *Power Electronics and Applications, 1993., Fifth European Conference on* , vol., no., pp.312,318 vol.4, 13-16 Sep 1993

[7] Kubota, K.; Matsuse, K.; Nakano, T., "DSP-based speed adaptive flux observer of induction motor," *Industry Applications, IEEE Transactions on* , vol.29, no.2, pp.344,348, Mar/Apr 1993

[8] Tajima, H.; Hori, Y., "Speed sensorless field-orientation control of the induction machine," *Industry Applications, IEEE Transactions on* , vol.29, no.1, pp.175,180, Jan/Feb 1993

[9] Yang, G.; Chin, T.-H., "Adaptive-speed identification scheme for a vector-controlled speed sensorless inverter-induction motor drive," *Industry Applications, IEEE Transactions on* , vol.29, no.4, pp.820,825, Jul/Aug 1993

[10] Sc Hroedl,M.,"Sensorless Control of Induction Motor at Low Speed and Standstill", Proceeding ICEM'92,1992,pp.863-867

[11] KubotMAtsuse,K.,"Speed sensorless field-orientation control of the induction Motor with Rotor Resistance Adaption",IEEE Industry Application Society Annual Meeting,1993,Vol.1,pp.414-418

[12] Du, T.; Brdys, M.A., "Implementation of extended Luenberger observers for joint state and parameter estimation of PWM induction motor drive," *Power Electronics and Applications, 1993., Fifth European Conference on* , vol., no., pp.439,444 vol.4, 13-16 Sep 1993

[13] Atkinson, D.J.; Acarnley, P.P.; Finch, J.W., "Observers for induction motor state and parameter estimation," *Industry Applications, IEEE Transactions on* , vol.27, no.6, pp.1119,1127, Nov/Dec 1991

[14] Henneberger,G.,Brunscach,B.J. and Klepsch,T.,"Field-Oriented Control of Synchronous and Asynchronous Drive Without Mechanical Sensors using Kalman Filter", Proceeding of the EPC conference,Firenze,1991,Vol.3,pp.664-671

[15] Brunsbach,BJ;Henneberger,G,"Field-Oriented Control of an Induction-Motor Without Mechanical Sensors using a Kalman-Filter",Archiv Fur Elektrotechnil 1990, Vol.73, No.5,pp.325-335

[16] Kim, Y.-R.; Seung-Ki Sul; Park, M.-H., "Speed sensorless vector control of induction motor using extended Kalman filter," *Industry Applications, IEEE Transactions on* , vol.30, no.5, pp.1225,1233, Sep/Oct 1994

[17] Loron,L. And Laliberte,G.,"Application of the Extended Kalman Filter to Parameter Estimation of Induction Motor",Proceeding of EPE conference,Brighton,1993,Vol.5,pp.85-90

[18] B.K.BOSE,"Power electronics and AC drives",(Prentice-Hall,1986).

[19] A K Chattopadhyay, "Advances in vector control of AC motor drives-a review"

[20] Finch, J.W.; Atkinson, D.J.; Acarnley, P.P., "Scalar to vector: general principles of modern induction motor control," *Power Electronics and Variable-Speed Drives, 1991., Fourth International Conference on* , vol., no., pp.364,369, 17-19 Jul 1990

[21] Kataoka, T.; Toda, S.; Sato, Y., "On-line estimation of induction motor parameters by extended Kalman filter," *Power Electronics and pplications, 1993., Fifth European Conference on* , vol., no., pp.325,329 vol.4, 13-16 Sep 1993

[22] Julier, S.J.; Uhlmann, J.K.; Durrant-Whyte, H.F., "A new approach for filtering nonlinear systems," *American Control Conference, Proceedings of the 1995* , vol.3, no., pp.1628,1632 vol.3, 21-23 Jun 1995

[23] Rigatos, G.; Siano, P., "Sensorless nonlinear control of induction motors using Unscented Kalman Filtering," *IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society* , vol., no., pp.4654,4659, 25-28 Oct. 2012

[24] Jafarzadeh, S.; Lascu, C.; Fadali, M.S., "Square Root Unscented Kalman Filters for State Estimation of Induction Motor Drives," *Industry Applications, IEEE Transactions on* , vol.49, no.1, pp.92,99, Jan.-Feb. 2013