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PARTICLE SWARM OPTIMIZATION OF AN EXTENDED KALMAN FILTER FOR SPEED ESTIMATION OF PMSM DRIVE USING PARTICLE SWARM OPTIMIZATION

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ABSTRACT

This paper shows a speed estimation procedure for Permanent Magnet Synchronous Motor (PMSM) in light of Extended Kalman Filter (EKF). Molecule Swarm Optimization (PSO) technique is utilized to improve the clamor covariance networks of EKF, consequently guaranteeing channel dependability and exactness in speed estimation. The proposed strategy will be performed in two stages; in the to start with the covariance grids are upgraded in disconnected way and after that in the second step these mistake covariance frameworks values are infused into EKF to appraise rotor speed. Recreation comes about demonstrates that the covariance frameworks enhance the union of estimation process and nature of the framework execution.

Keywords: Permanent Magnet Synchronous Motor, Extended Kalman Filter, Particle swarm optimization, Objective function.

1.INTRODUCTION

Current industry patterns advocate the PMSM as the primary inclination for engine control application planners. Its unparallel highlights, for example, high power thickness, quick unique reaction and high effectiveness in correlation with other engines in its class, together with diminished assembling costs and enhanced attractive properties, make the PMSM a decent suggestion for huge scale item execution [1-2]. Be that as it may, ordinary engine control needs a speed sensor or an optical encoder to gauge the rotor speed with better precision. Sensors introduces a few weaknesses, for example, drive cost, machine size, unwavering quality and clamor invulnerability; along these lines, a sensorless control without position and speed sensors for PMSM drive turn into a well known research theme in writing [3-4]. Different control calculations like Sliding Mode Observer (SMO) [5], lessened request spectator [6], Full request eyewitness [7], Extended Kalman Filter(EKF) [8-9], Model Reference Adaptive System (MRAS) [10], Fuzzy rationale [11] and Artificial Neural Systems [12] are proposed in the writing for speed and position estimation of PMSM. Among the proposed calculations EKF is one of the promising eyewitnesses, if the commotion covariance grids are known; offers most ideal sifting of the commotion in estimation and of the framework. In the event that the rotor speed considered as an expanded state and is consolidated in the dynamic model of a PMSM then the EKF can be utilized to re-linearize the non-direct state show for each new estimation of gauge. Thus, EKF is the best answer for the speed estimation of a PMSM. Yet, EKF estimation for the most part relies

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upon commotion covariance lattices Q and R. They can be acquired by considering the stochastic properties of the comparing clamors. Since these are generally obscure, much of the time the EKF networks are composed what's more, tuned by experimentation systems. Be that as it may, it is a tedious procedure, to conquer this issue the covariance networks are tuned utilizing Genetic calculation [13]. In this paper, another elective technique mix of EKF-PSO is utilized to tune the covariance lattices Q and R. In the initial step, finding the ideal estimations of covariance lattices in disconnected technique lastly these qualities are put in the comparing networks and keep running in on-line to appraise rotor speed.

2.MATHEMATICAL MODELING

The voltage equations for a PMSM in the rotor reference frame can be expressed as [14].

$$V_d = R_s i_d + L_d p i_d - \omega_e L_q i_q \quad \text{--- (1)}$$

$$V_q = R_s i_q + L_q p i_q + \omega_e L_d i_d + \omega_e \psi_f \quad \text{--- (2)}$$

The electromagnetic torque of PMSM is described as

$$T_e = \left[\frac{3}{2} P_n i_q \left(\psi_f - \left(L_q - L_d\right) i_d\right)\right] \quad \text{--- (3)}$$

The motion equation is expressed as follows as

$$J\frac{d\omega_r}{dt} + B\omega_r + T_l = T_e \quad \text{--- (4)}$$

3.PROPOSED SCHEME OF EKF BASED SENSOR LESS SPEED CONTROL OF PMSM DRIVE

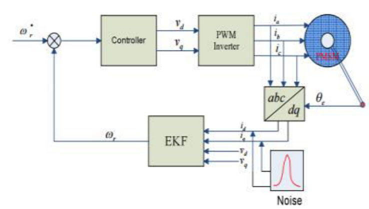

Figure 1 Block diagram of proposed speed estimation system of PMSM

3.1 Extended Kalman Filter (EKF)

Kalman Filter is a scientific model that keeps running in parallel to the genuine framework and gives the estimation of the conditions of straight frameworks. In any case, the disadvantage of Kalman channel is that it is a tedious procedure when connected for nonlinear frameworks. For the execution of nonlinear frameworks, these elements of the state factors change with each time venture, thus the cycle can't be pre-figured. Deficiencies of this model can be overwhelmed by utilizing Expanded Kalman channel (EKF). In the model portrayed by conditions (1), (2) and (3), the streams of dq-pivot and the speed are chosen as state factors, and the information variable u and yield variable y are characterized as takes after:

$$x = \begin{bmatrix} i_d \\ i_q \\ \omega_r \end{bmatrix}, \; u = \begin{bmatrix} V_d \\ V_q \end{bmatrix}, \; y = \begin{bmatrix} i_d \\ i_q \end{bmatrix}$$

The discrete time system equations are

$$x_k = f_{k-1}(x_{k-1}, u_{k-1}, w_{k-1}) \quad \text{--- (5)}$$

$$y_k = h_k(x_k, v_k) \quad \text{--- (6)}$$

Where xk is state vector, uk is input vector, wk is random state noise, yk is the noisy

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observation or measured variable vector and vk is the measurement noise.

3.2 EKF Algorithm

Step 1: State vector and covariance matrices are initialized

i.e. $x(0)$, P(0), Q, R

Step 2: Find Jacobian matrices k 1 f − and k h using

$$F_{k-1}=\frac{\partial f_{K-1}}{\partial x_k} \quad \text{--- (7)}$$

$$H_k=\frac{\partial h_K}{\partial x_k} \quad \text{--- (8)}$$

Step 3: Prediction of state matrix and error covariance matrices

$$x_{k-1}=f_{k-1}(x_{k-1},u_{k-1})+x(0) \quad \text{--- (9)}$$

$$P_{k-1}=F_{k-1}P_{k-1}F_{k-1}^{T}+Q_{k-1} \quad \text{--- (10)}$$

Step 4: Correction state

• Calculation of Kalman gain matrix

$$K_k=P_{k-1}H_k^{T}/\left(H_kP_{k-1}H_k^{T}+R_k\right) \quad \text{--- (11)}$$

• Update state prediction

$$x_k=x_{k-1}+K_k\left(y_k-H_kx_{k-1}\right) \quad \text{--- (12)}$$

• Estimation of error covariance matrix

$$P_k=\left(I-K_kH_k\right)P_{k-1} \quad \text{--- (13)}$$

3.3 EKF estimation for PMSM drive

The dynamic state equations of PMSM are

$$\frac{di_d}{dt}=\frac{1}{L_d}\left[-R_si_d+P_n\omega_rL_qi_q\right]+\frac{V_d}{L_d} \quad \text{--- (14)}$$

$$\frac{diq}{dt}=\frac{1}{L_q}\left[-R_si_q-P_nW_rL_di_d-P_n\omega_r\psi_f\right]+\frac{V_q}{L_q} \quad \text{--- (15)}$$

$$\frac{d\omega r}{dt}=\frac{1}{J}\left[\frac{3}{2}P_ni_q\left(\psi_f-\left(L_q-L_d\right)i_d\right)\right]-\frac{B}{J}\omega_r-\frac{T_l}{J} \quad \text{--- (16)}$$

The above equations written in the form of state space representation

$$\begin{bmatrix}\frac{di_d}{dt}\\ \frac{di_q}{dt}\\ \frac{d\omega_r}{dt}\end{bmatrix}=\begin{bmatrix}\frac{-R_s}{L_d} & \frac{P_n\omega_rL_q}{L_d} & 0\\ \frac{-P_n\omega_rL_d}{Lq} & \frac{-R_s}{L_q} & \frac{-P_n\psi_f}{L_q}\\ \frac{-3P_n\left(L_q-L_d\right)i_q}{2J} & \frac{3P_n\psi_f}{2J} & \frac{-B}{J}\end{bmatrix}\begin{bmatrix}i_d\\ i_q\\ \omega_r\end{bmatrix}+\begin{bmatrix}\frac{1}{L_d} & 0\\ 0 & \frac{1}{L_q}\\ 0 & 0\end{bmatrix}\begin{bmatrix}V_d\\ V_q\end{bmatrix} \quad \text{--- (17)}$$

Discrete time representation of above equation is

$$f_{k-1}\left(x_{k-1},u_{k-1},w_k\right)=\begin{bmatrix}1-\frac{R_s}{L_d}T_s & \frac{P_n\omega_rL_q}{L_d}T_s & 0\\ \frac{-P_n\omega_rL_d}{Lq}T_s & 1-\frac{R_s}{L_q}T_s & \frac{-P_n\psi_f}{L_q}T_s\\ \frac{-3P_n\left(L_q-L_d\right)i_q}{2J}T_s & \frac{3P_n\psi_f}{2J}T_s & 1-\frac{B}{J}T_s\end{bmatrix}\begin{bmatrix}i_d\\ i_q\\ \omega_r\end{bmatrix}+\begin{bmatrix}\frac{1}{L_d}T_s & 0\\ 0 & \frac{1}{L_q}T_s\\ 0 & 0\end{bmatrix}\begin{bmatrix}V_d\\ V_q\end{bmatrix} \quad \text{--- (18)}$$

The Gradient matrix is given as

$$F_{k-1}=\frac{\partial f_{K-1}}{\partial x_k}=\begin{bmatrix}1-\frac{R_s}{L_d}T_s & \frac{P_n\omega_rL_q}{L_d}T_s & 0\\ \frac{-P_n\omega_rL_d}{Lq}T_s & 1-\frac{R_s}{L_q}T_s & \frac{-P_n\psi_f}{L_q}T_s\\ \frac{-3P_n\left(L_q-L_d\right)i_q}{2J}T_s & \frac{3P_n\psi_f}{2J}T_s & 1-\frac{B}{J}T_s\end{bmatrix} \quad \text{--- (19)}$$

$$H_k=\frac{\partial h_K}{\partial x_k}=\begin{bmatrix}1 & 0 & 0\\ 0 & 1 & 0\end{bmatrix} \quad \text{--- (20)}$$

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4. PARTICLE SWARM OPTIMIZATION (PSO)

Molecule swarm streamlining, a swarm knowledge based worldwide arbitrary pursuit calculation, is proposed by Kennedy and Eberhart propelled from manufactured life explore comes about [15]. It respects all people in the populace as particles without mass and volume in the D-dimensional pursuit space and every molecule moves at a specific speed to the best position of its own history Pbest and the best position of its neighborhood history gbest in the arrangement space, keeping in mind the end goal to accomplish the advancement of hopeful arrangements.

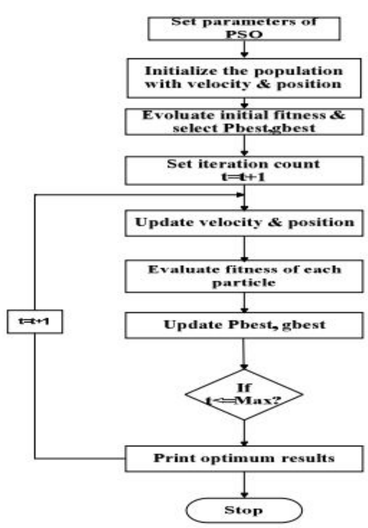

Figure 2 Flow chart of particle swarm optimization

5. TUNING OF EKF USING PARTICLE SWARM OPTIMIZATION

The basic advance in a Kalman channel configuration is to get a numerical assessment of the channel parameters determined by the introductory state x (0), and the covariance networks P(0), Q and R. This procedure is called tuning and it includes an iterative scan for the coefficient esteems that yield the most ideal estimation execution. Changing the covariance networks Q and R influences both the transient and the relentless state operation of the channel. Expanding Q would show increment in either clamor driving the framework or vulnerability in the model. This will build the estimations of the state covariance components. The channel additions will likewise increment along these lines weighting the estimations all the more intensely, and the channel transient execution is quicker. Correspondingly, expanding the covariance R shows that the estimations are subjected to a more grounded corruptive clamor and ought to be weighted less by the channel. Therefore the estimations of the pick up framework K will diminish, and the transient execution is slower. For the underlying state covariance network Po, the slanting terms speak to fluctuations or mean squared mistakes in learning of the underlying conditions. Shifting P (0) yields an alternate extent transient trademark. The transient term will be the same and the relentless state conditions are unaffected. The covariance networks Q, R and P (0) are thought to be inclining because of need of adequate factual data to assess their off-askew terms. The principle target capacity of this paper is determination of ideal estimations of Q and R. These qualities are chosen physically by utilizing trial and mistake strategy. However, this is extremely tedious process. To surmount this issue, covariance frameworks are tuned by utilizing Particle Swarm Advancement (PSO).

The objective function F= w1e1+w2e2+w3e3

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Where

$$e_1 = \int \left(i_{d-act} - i_{d-est}\right)^2$$
$$e_2 = \int \left(i_{q-act} - i_{q-est}\right)^2$$
$$e_3 = \int \left(\omega_{r-act} - \omega_{r-est}\right)^2$$

Proper selection of weights is essential in tuning else these weights may lead to large errors. These weights are selected as follows w1=0.125, w2=0.05, w3=0.00167.

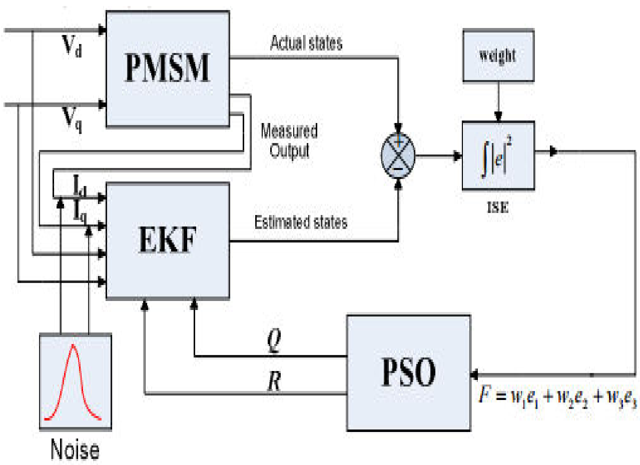

Figure 3 EKF-PSO block diagram

6. RESULTS AND DISCUSSIONS

In the simulation d i , q i , d v , q v are input variables of EKF algorithm and d i , q i ,ωr are the estimated state variables. In order to mimic the condition of real system Gaussian white noises are added to feedback values of d i , q i are set to 3×10-6 and sample time of the white noise block is set to 2×10-5 sec. It should be noted that the convergence of the PSO method to the optimal solution depends on the parameters c1, c2, wmin, and wmax values. During the simulation, these values are set to c1=2, c2=2, wmin,=0.5 and wmax =0.9 respectively

Table 1: PSO-EKF estimations

Number of iterations = 50(PSO)			
Number of Generations	Diagonal matrix *Q*	Diagonal matrix *R*	Objective function value
5	[18.6932 6.4571 95.5391]	[1319.2855 1255.226]	0.0341
10	[21.8921 4.3835 111.8467]	[4294.768 1745.057]	0.0337
20	[47.8346 7.2033 131.0535]	[1220.123 2067.458]	0.0320

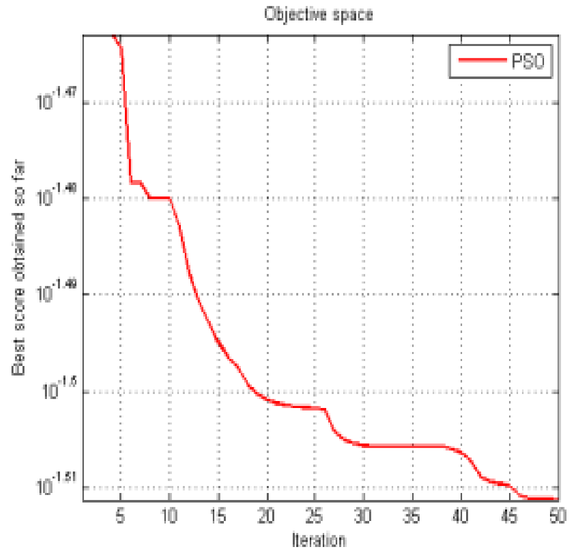

Figure 4 Evolution of fitness function relative to PSO-EKF

Optimized parameters of matrices Q & R of EKF with their corresponding ISEs obtained by proposed PSO-EKF method and its performance is given in Figure 4. Table 1 shows the convergence of PSO-EKF process and ISE is decreased with increasing of generation count. Here best objective function value is obtained for generation count 20, corresponding values are injected into EKF and run in online manner. Finally the states of the EKF is estimated as shown in below figures.

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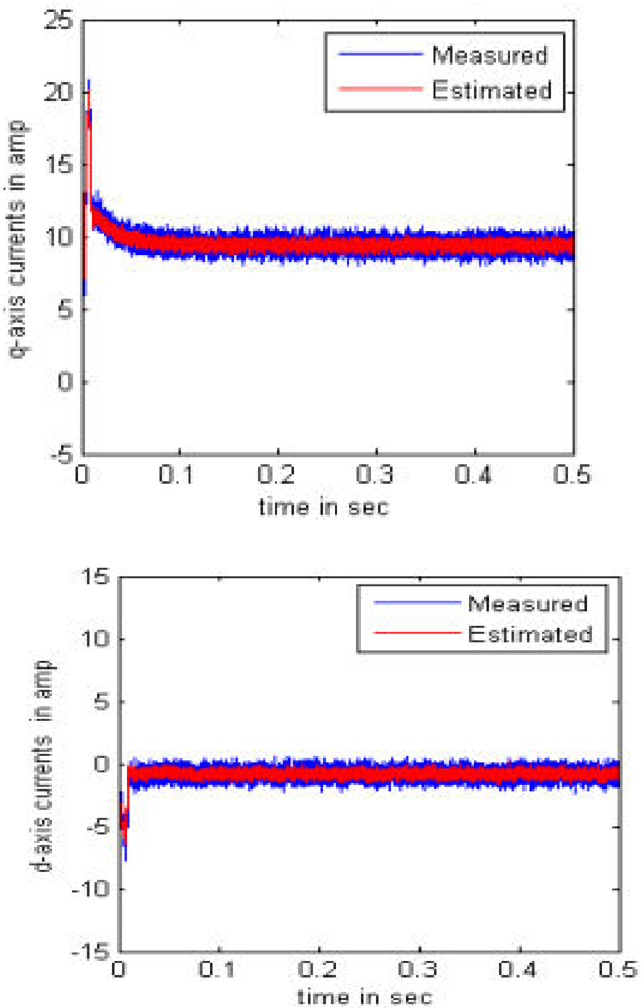

Figure 5 Measured and estimated current of i_q and i_d

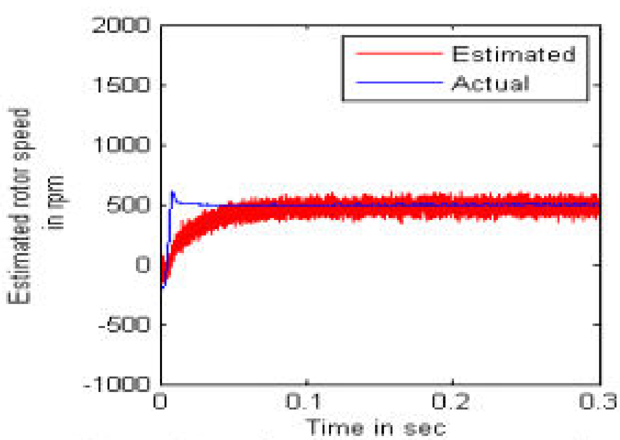

Figure 6 Actual and estimated rotor speed

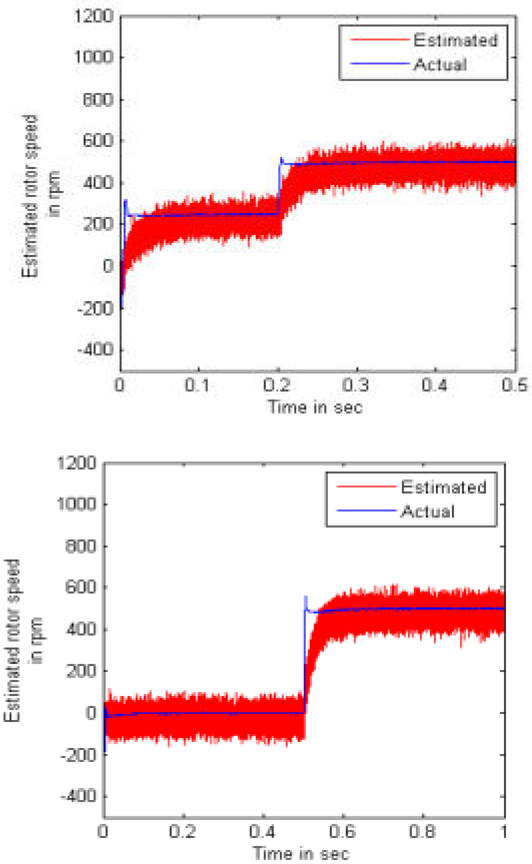

Figure 7 Actual and estimated rotor speed under variable speeds

The measured and estimated waveforms of id and iq are shown in figure 5. Due to convergence problem of state covariance matrix P, the estimated dq-axes currents having large ripples upto0.03 sec. After 0.03 sec matrix P is converges, then state variables id and iq are tracks the actual values. From Figure 6 it is evident that the estimated speed matches with the actual speed near 0.001 sec. The effectiveness of PSO-EKF method is evaluated under two cases, in one case the speed is varied from 200 rpm to 500 rpm at 0.5 sec and in another case motor is run at 500 rpm at 0.5 sec as shown in figure 7 and in both cases the

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estimated speed is converged accordingly due to precise values of matrices Q & R.

7. CONCLUSION

In this paper, EKF based sensorless speed control of PMSM drive has been exhibited to demonstrate the aftereffects of assessed estimations of speed and dq-tomahawks stator streams. The execution of EKF is for the most part relies upon blunder covariance lattices Q and R, which are reasonably chosen. These grids are enhanced the framework union and nature of estimation. The reproduction comes about demonstrate the predominant execution as far as settling time, lessening of commotion and general framework strength.

Appendix A:

Simulation Parameters values of PMSM drive:

Parameters	Symbol	Numerical value
Resistance of stator	R_s	0.675 ohm
Direct axis inductance of stator	L_d	0.0085 H
Quadrature axis inductance of stator	L_q	0.0085 H
Flux linkages	ψ_f	0.12 Wb
Inertia of rotor	J	0.0011 Kg/m^2
friction coefficient	B	0.0014 Nm/s^2
Pair of poles	P_n	3
Rated speed	ω	1000 rpm

References

[1]. R. Krishnan and A. J. Beutler, "Performance and design of an axial field permanent magnet synchronous motor servo drive", Proc. IEEE IAS Annu. Meeting, pp. 634-640, 1985.

[2]. P. Ramana, K. Alice Mary, M. Surya Kalavathi and A.Swathi "Parameter Estimation of Permanent Magnet Synchronous Motor-A Review," i-manager's Journal on Electrical Engineering, Vol.9, No.4, (2015), 46-56.

[3]. Hoque M, A Rahman M. A. "Speed and position sensorless permanent magnet synchronous motor drives," Canadian Conference on Electrical and Computer Engineering, 1994,vol.2, pp. 689-692.

[4]. J. Kim and S. Sul, "New approach for high performance PMSM drives without rotational position sensors," IEEE Trans. Power Electron., Vol. 12, No. 5, pp. 904–911, Sep. 1997.

[5]. B. K. Kim, W. K. Chung, and K. Ohba, "Design and performance tuning of sliding-mode controller for high-speed and high-accuracy positioning systems in disturbance observer framework," IEEE Trans. Ind. Electron., vol. 56, No. 10, pp. 3798–3809, Oct. 2009.

[6]. P.Ramana, K. Alice Mary, M. Surya Kalavathi and J. Hareesh Kumar, "Design of a Non-linear Reduced and Full order Observers for an Inverter Fed Permanent Magnet Synchronous Motor Drive," Indian Journal of Science and Technology, Vol.9, No.10,(2016), 1-8.

[7]. S. Po-ngam and S. Sangwongwanich, "Stability and Dynamic Performance Improvement of Adaptive Full-Order Observers for Sensorless PMSM Drive," in IEEE Transactions on Power Electronics, vol. 27, no. 2, pp. 588-600, Feb. 2012.

[8]. S. Bolognani, L. Tubiana and M. Zigliotto, "Extended Kalman filter tuning in sensorless

PMSM drives," in IEEE Transactions on Industry Applications, vol. 39, no. 6, pp. 1741-1747, Nov.-Dec. 2003.

[9]. R. Dhaouadi, N. Mohan and L. Norum, "Design and implementation of an extended Kalman filter for the state estimation of a permanent magnet synchronous motor," in IEEE Transactions on Power Electronics, vol. 6, no. 3, pp. 491-497, Jul 1991.

[10].Zhang Bingyi, Chen Xiangjun, Sun Guanggui and Feng Guihong, "A Position Sensorless Vector-control System Based on MRAS for Low Speed and High Torque PMSM Drive," 2005 International Conference on Electrical Machines and Systems, Nanjing, 2005, pp. 1682-1686.

[11].Faa-Jeng Lin, Chih-Hong Lin and Po-Hung Shen, "Self-constructing fuzzy neural network speed controller for permanent-magnet synchronous motor drive," in IEEE Transactions on Fuzzy Systems, vol. 9, no. 5, pp. 751-759, Oct 2001.

[12].M. A. Rahman and M. A. Hoque, "On-line adaptive artificial neural network based vector control of permanent magnet synchronous motors," in IEEE Transactions on Energy Conversion, vol. 13, no. 4, pp. 311-318, Dec 1998.

[13].Shi KL, Wong YK, Ho SL, "Speed estimation of an induction motor drive using an optimized extended kalman filter.", IEEE Transactions on Industrial Electronics 49:124-133.

[14].D. Xu, S. Zhang, and J. Liu, "Very-low speed control of PMSM based on EKF estimation with closed loop optimized parameters ," Elsevier, ISA Transactions,Vol. 52, (2013) , 835–843.

[15].Yahia Laamari, Kheireddine Chafaa and Belkacem Athamena, "Particle swarm optimization of an extended Kalman filter for speed and rotor flux estimation of an induction motor drive," Electrical Engineering, Springer, Vol.97, (2015), 129–138.