Sensorless control of PMSM drive using extended Kalman filter and fuzzy logic controller

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Abstract: This paper describes the estimation and control of rotor speed of a permanent magnet synchronous motor (PMSM) drive. The estimation is done through the use of extended Kalman filter (EKF). The EKF uses the dynamic state space model of the PMSM to estimate the speed and fluxes through a set of mathematical equations. The mathematics of which is dependent on the knowledge of stator voltages and currents. Besides, a fuzzy logic controller (FLC) is used for speed control of PMSM in this paper that aids against load and speed variations. Also, space vector pulse width modulation (SVPWM) is implemented for optimal performance of the drive. Simulation of a 1.7 Nm, 220 Vdc, 3,750 rpm PMSM is presented in this paper and speed tracking is achieved under different operating conditions.

Keywords: extended Kalman filter; EKF; permanent magnet synchronous motor; PMSM; fuzzy logic controller; FLC; sensorless vector control.


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1 Introduction

Synchronous motor drives are finding increased use in industrial applications. They have better efficiency than the induction motor drives. However, the high cost of these drives is the main disadvantage. The permanent magnet synchronous motor (PMSM) drive performance is highly improved by the use of vector control technique. The vector control of PMSM drives is nearly similar to that of the induction motor drives except for the absence of slip speed and flux vector (Bose, 2003). With vector control being one of the main area of interest currently, a lot of improvement is taking place. The sensorless vector control strategy is one such area where a lot of improved techniques have been proposed.

The sensorless vector control does not consist of the speed sensor. A speed sensor is undesirable as it increases the cost and reliability problems. In PMSM drives, the poles are fixed on the rotor, hence, the position measurement is absolute using position sensors. So with sensorless vector controlled PMSM drives, the estimation of speed and position is done from the measured stator voltages and currents. The computation is however complex and mainly machine parameter dependent (Bayoumi, 2013, 2014).

A number of methods are proposed in literature for speed estimation (Vas, 1998; Yousfi et al., 2009; Borsjie et al., 2005). Amongst the different sensorless estimation techniques, primarily the observer-based methods are adopted. The observer-based parameter estimation methods provide robustness and accuracy over wide speed range. In
this paper, an extended Kalman filter (EKF) is discussed for rotor speed and position estimation.

EKF has been widely used in AC drive systems (Shi et al., 2002; Cernat et al., 2000; Bolognani et al., 2003). The EKF estimator uses the stochastic principle for estimation purposes wherein disturbances are taken into consideration. All of the system noise disturbances are assumed as white-noise (i.e., the process noise is uncorrelated at all instants). The EKF uses the nonlinear motor model for speed estimation. EKF has been used in PMSM drives in a variable fashion (Aydogmus and Sünter, 2012; Xu et al., 2013).

Besides the use of a robust observer for speed/position estimation in a PMSM motor, the sensorless control scheme is highly dependent on speed controller for efficient operation. In case of load variations, EKF and unscented Kalman filter (UKF) give poorer performance (Chan et al., 2009). Hence, this paper presents the use of fuzzy logic controller (FLC) along with EKF for speed control. The FLC offers advantages in nonlinear systems with better dynamic performance.

Since current measurements are necessary for estimation, a distortion less current would be required. Modulation is therefore carried out through the implementation of space vector pulse width modulation (SVPWM) method. SVPWM is highly advanced PWM strategy with numerous advantages, most importantly the harmonic distortion in current is reduced (Chikhi and Benmessaoud, 2015).

Following the introduction, PMSM model is presented in Section 2. In Section 3, the EKF algorithm is presented. The modelling of the control strategy is discussed in Section 4 followed by simulation results in Section 5. The conclusions are presented finally in Section 6.

2 Extended PMSM model

The EKF implementation requires the development of a state space model of the PMSM. The model is developed in stationary reference frame (Vas, 1998) and represented through equations (1) to (8). Discretised representation of the same is represented in (9) to (12)

\[
\dot{x} = AX + BU
\]

\[Y = CX\]

where

\[X = \begin{bmatrix} i_{d} & i_{q} & \omega_e & \theta_e \end{bmatrix}^T\]

\[Y = \begin{bmatrix} i_{d} & i_{q} \end{bmatrix}^T\]

\[U = \begin{bmatrix} v_{d} & v_{q} \end{bmatrix}^T\]

The system matrix \(A\), the input matrix \(B\) and the output matrix \(C\) are given by:

\[
A = \begin{bmatrix} -\frac{R}{L_d} & \frac{\omega_e}{L_q} & 0 & 0 \\ -\frac{\omega_e}{L_q} & -\frac{R}{L_q} & -\frac{\dot{\omega}_e}{L_q} & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}
\]

\[
B = \begin{bmatrix} \frac{1}{L_d} \\ 0 \\ 0 \\ 0 \end{bmatrix}
\]

\[
C = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}
\]

The model represents a higher order system. This offers a drawback in the implementation of the EKF algorithm in real-time. Nevertheless, the EKF implementation does not require the measurement of rotor speed and flux, thus reducing the system implementation cost and increasing reliability. Also, the parameter estimation is possible through the use of EKF algorithm.

The motor equations (1) to (8) are to be discretised for the digital implementation of EKF as:

\[X(k+1) = A_d X(k) + B_d U(k)\]

\[Y(k) = C X(k)\]

\[A_d = I + AT\]

\[B_d = BT\]

where ‘\(T\)’ represents the sampling time.

3 EKF algorithm

Estimation of state variables is necessary for increasing the reliability of the system. In sensorless PMSM drives, rotor speed and position is estimated through the use of observers. The observers can also be used for rotor resistance and other parameter estimation. The most commonly used observers are Luenberger and Kalman types (Bose, 2003).

Kalman filter is only applicable to linear stochastic systems, but for nonlinear systems the EKF is used. The EKF is a recursive filter. The EKF model is applied to a nonlinear time varying stochastic system. The EKF model depends on the knowledge of both the state parameters and noise which includes system and measurement modelling noises. EKF offers the advantage to vector controlled PMSM drives as it is insensitive to parameter changes and disturbances in the system modelling.
An EKF can be used for the state and parameter estimation in real-time by monitoring Gaussian distributed noisy signals. The assumption made for EKF model is that the measurement noise and system noise are uncorrelated. Here, the system noise is assumed as \( w(k) \) (\( w \) is the noise vector of states) which is a zero-mean white-Gaussian noise and independent of \( x(k) \) with a covariance matrix \( Q \) (a 4x4 positive semi definite matrix). The measurement noise, which also is a zero-mean white-Gaussian noise and independent of \( y(k) \) (noise in the measured stator currents), independent of \( y(k) \) and \( w(k) \) with a covariance matrix \( R \) (a 2x2 positive definite matrix). The nonlinear state equation of the PMSM motor is represented in discrete form thus as

\[
X(k+1) = F(x(k), u(k)) + w(k)
\]

\[
Y(k) = h(x(k)) + v(k)
\]

where

\[
F(x(k), u(k)) =
\begin{bmatrix}
1 & 0 & \frac{\lambda T}{L_s} \sin(\theta_e) & \frac{\omega_s \lambda T}{L_s} \cos(\theta_e) \\
0 & 1 & -\frac{R}{L_s} T & \frac{\omega_s \lambda T}{L_s} \sin(\theta_e)
\end{bmatrix}
\]

(15)

EKF algorithm is based on two stages, prediction and filtering. In the first stage of the calculations, the state variables are predicted by using the system model which is the PMSM motor model given in (6) to (8) and the knowledge of previous estimates. The next stage involves the iterative correction of the estimated value through the use of feedback filter. In certain cases, a low pass filter can also be introduced for further noise reduction. The filtering makes use of actual measured states, by adding a term to the predicted states. The EKF provides an optimum output value at the next input instant as the correction term is

\[
\text{Kalman gain computation}
\]

The Kalman filter gain is computed as:

\[
K(k+1) = P^*(k+1)H^T(k+1)[H(k+1)P^*(k+1)H^T(k+1)+R]^{-1}
\]

(19)

\[
H(k+1) = \frac{\partial}{\partial x}[C_x X]_{x=x^*(k+1)} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}
\]

(20)

\[
\text{State vector estimation}
\]

The predicted state-vector is added to the innovation term multiplied by Kalman gain to compute the state-estimation vector. The filtering at time \( k \) is determined as:

\[
\hat{X}(k+1) = X^*(k+1) + K(k+1)[Y(k+1) - \hat{Y}(k+1)]
\]

(21)

\[
\hat{Y}(k+1) = C_d X^*(k+1)
\]

(22)

\[
\hat{P}(k+1) = P^*(k+1) - K(k+1)H(k+1)P^*(k+1)
\]

(23)

After all steps executed, set \( k = k + 1 \) and start from the Step 2 to continue the computation recursively.
However, the tuning of EKF parameters is tiresome. The tuning involves the modification of the machine parameters and covariance matrices \( Q \) and \( R \) in order to yield the best estimate of the states. Changing the covariance matrices \( Q \) and \( R \) affect both the transient and the steady-state operation of the filter.

### 4 Modelling of control strategy

The vector control drive strategy is shown in Figure 2. The control involves the use of EKF for the estimation of rotor speed and position. The speed control in the scheme is carried out by the use of FLC.

#### Figure 2 Block diagram of sensorless controlled PMSM drive

4.1 Fuzzy logic controller

The FLC model is shown in Figure 3 (Bose, 2003). Fuzzy logic is a branch of artificial intelligence which deals in reasoning algorithms based on human intelligence having a prior knowledge of the process under control. This knowledge is stored in the fuzzy system.

#### Figure 3 Block diagram of fuzzy logic based controller

Sensorless control drives suffer with speed and load variations. Hence, the drive requires a robust controller for speed control. With FLC implemented for speed control of the drive, it is possible to make a robust sensorless scheme. The fuzzy logic is successfully implemented for nonlinear systems and immune to disturbances.

The two inputs to the FLC are the speed error and the rate of change of speed error, which are calculated at every sampling time, \( t_s \), as

\[
\begin{align*}
    e(t_s) &= \omega_r^* (t_s) - \omega_r (t_s) \\
    ce(t_s) &= e(t_s) - e(t_s - 1)
\end{align*}
\]  

The fuzzification maps the error and change in error to linguistic labels of fuzzy sets (Bose, 2003). A Mamdani type FLC is designed for the control system. The inputs, i.e., the error ‘\( e \)’, change in error ‘\( ce \)’ and the output, \( \Delta i_q \) follow the membership function plot as shown in Figure 4.

#### Figure 4 Mamdani MF plots for (a) inputs (b) output

Knowledge base involves defining the rules represented as IF-THEN rules statements governing the relationship between input and output variables in terms of membership function. The input variables \( e(t_s) \) and \( ce(t_s) \) are processed by the inference mechanism that executes \( 7 \times 7 \) rules represented in rule base shown in Table 1. The proposed controller uses following linguistic labels NB, NM, NS, ZE, PS, PM, and PB. Each of the inputs and output contain membership function with all these seven linguistics. The membership function shown in Figure 4 can be modified through implementation of different MFs so as to obtain best performance from the PMSM drive.

4.2 Space vector modulation

The dynamic performance of the drive is further improved by the use of SVPWM strategy. The SVPWM method is an advanced PWM technique which involves intensive computations for variable frequency drive application (Bose, 2003). The SVPWM method offers advantages over current modulation with better DC bus utilisation and easier implementation.

Due to full utilisation of all available voltage vectors, the harmonic content in current is reduced due to proper
switching table. In Figure 5, inverter voltage vectors are represented in space ranging from $V_0$ to $V_7$ with each voltage vector resulting in operation of different combinations of semiconductor switch. With proper selection of switching algorithm, the harmonic content of the load can be optimised by considering the interaction of different phases.

<table>
<thead>
<tr>
<th>Table 1 Rule Base for the FLC</th>
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<tbody>
<tr>
<td>$e$</td>
</tr>
<tr>
<td>NB</td>
</tr>
<tr>
<td>NM</td>
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<tr>
<td>NS</td>
</tr>
<tr>
<td>Z</td>
</tr>
<tr>
<td>PS</td>
</tr>
<tr>
<td>PM</td>
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<tr>
<td>PB</td>
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</table>

The drive performance is further enhanced with the utilisation of SVPWM technique as it reduces the distortion in current. The current thus utilised by the EKF estimator has less distortion, the result of which is improved estimation of speed.

5 Simulation results

Simulation study of the vector controlled PMSM drive is performed to analyse the physical behaviour of the drive. The simulation of a 1.7 Nm, 300 Vdc, 3,750 rpm, three phase PMSM drive is carried out in MATLAB/Simulink to observe the dynamic behaviour of the motor using EKF for speed and position estimation and FLC for speed control. The covariance matrices chosen for the EKF filter are given in Appendix.

The specifications of the motor used in simulation are given in Table 2.

<table>
<thead>
<tr>
<th>Table 2 Specifications of PMSM</th>
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<tbody>
<tr>
<td>$V_{dc}$</td>
</tr>
<tr>
<td>$T_L$</td>
</tr>
<tr>
<td>$\omega_r$</td>
</tr>
<tr>
<td>$R_s$</td>
</tr>
<tr>
<td>$L_d$</td>
</tr>
<tr>
<td>$L_q$</td>
</tr>
<tr>
<td>$\Lambda$</td>
</tr>
<tr>
<td>$P$</td>
</tr>
<tr>
<td>$J$</td>
</tr>
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</table>

In Figure 7, position estimation can be observed. The motor is made to run for the same conditions as above. It can be seen that the estimated position and the measured position track each other with almost negligible error.
Figure 7  Estimated and measured rotor position in the PMSM drive (see online version for colours)

Figure 8  Error between measured and estimated speed in the PMSM drive for a load of 1.5 Nm at $t = 0.1$ sec

Figure 8 shows the error in the estimated speed and the measured speed of the PMSM drive. It is observed that initially the error is considerable but after $t = 0.06$ sec, the error reduces to zero. At $t = 0.1$ sec, the load is applied and increase in error is observed momentarily, which is compensated by the FLC quickly to reduce the error back to zero.

In Figure 6, an estimate of speed can be observed. The motor is initially made to run at no load for a reference speed of 180 rad/sec. At $t = 0.1$ sec, the load of 1.5 Nm is applied. The estimated speed is seen to track the reference speed irrespective of the load variation.

In Figure 9, speed variation under no load condition is observed with initially the motor made to run at $\omega = 180$ rad/sec and then after $t = 0.05$ sec, the speed is changed to $\omega = 350$ rad/sec. It is observed that the estimated speed tracks the reference speed.

Figure 10 shows the proposed speed control in reverse motoring mode. The EKF-based estimator is able to track speed, however, the proposed methodology suffers with slight oscillatory behaviour.
6 Conclusions

In this paper, the EKF model has been discussed for speed and position estimation in a vector controlled PMSM drive. The speed control has been carried out using a FLC. With the use of speed estimators, load and speed variations can cause problem in estimation. For this purpose, FLC is implemented alongside an EKF algorithm for speed estimation and control. Further current distortion can be reduced by utilising SVPWM.

The simulation of a 1.7 Nm, 300 Vdc, 3,750 rpm, three phase PMSM drive has been performed in MATLAB/Simulink. With vector control known to improve the drive’s dynamic performance, it has been observed that the speed and position estimation carried out using EKF method is very much accurate. The drive performance has been studied for varying load and varying speed conditions and it has been observed that the drive performance is improved with the use of FLC. However, the problem of sensorless control at low speed persists.

References


Appendix

Table 3  Symbols used

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>$I_d$</td>
<td>d-axis stator voltage</td>
</tr>
<tr>
<td>$I_q$</td>
<td>q-axis stator voltage</td>
</tr>
<tr>
<td>$V_d$</td>
<td>d-axis stator voltage</td>
</tr>
<tr>
<td>$V_q$</td>
<td>q-axis stator voltage</td>
</tr>
<tr>
<td>$R_s$</td>
<td>Stator phase resistance</td>
</tr>
<tr>
<td>$L_d$</td>
<td>d-axis stator inductance</td>
</tr>
<tr>
<td>$L_q$</td>
<td>q-axis stator inductance</td>
</tr>
<tr>
<td>$\lambda$</td>
<td>Flux linkage</td>
</tr>
<tr>
<td>$\omega_e$</td>
<td>Angular velocity at electric angle</td>
</tr>
<tr>
<td>$\theta_e$</td>
<td>Electrical angle/position</td>
</tr>
<tr>
<td>$T$</td>
<td>Sample time</td>
</tr>
<tr>
<td>$K$</td>
<td>Kalman filter gain</td>
</tr>
<tr>
<td>$P$</td>
<td>System state vector covariance matrix</td>
</tr>
<tr>
<td>$Q$</td>
<td>System noise vector covariance matrix</td>
</tr>
<tr>
<td>$R$</td>
<td>Measurement noise vector covariance matrix</td>
</tr>
</tbody>
</table>

$P_0 = \text{diag}[1, 1, 1, 1]$  
$i_0 = [0.1; 0.1; 0; 0]$  
$Q = \text{diag}[1e-6; 1e-6; 1e-1; 1]$  
$R = \text{diag}[70, 70]$  
$T = 20e-6$

Vector control sample time $t = 5e-6$. 


