Fuzzy Logic Vector Control of PMSM with Fuzzy Kalman Filter for the Estimation of Speed and Rotor Position

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Abstract—In this paper a fuzzy logic based intelligent Extended Kalman filter (EKF) is used for the estimation of speed, rotor position, direct and quadrature axis current of permanent magnet synchronous motor thereby eliminating the problem of design and tuning of process covariance matrix in EKF algorithm. Unlike in the previous approaches the present work uses only the sensed line currents as measurements, and thus following a blind system identification approach. A fuzzy logic control technique is utilized for control purpose. The results show the improvement in convergence of EKF algorithm when intelligent technique is introduced in it.

Index Terms—Permanent magnet synchronous motor, Fuzzy logic speed control, Intelligent Extended Kalman filter, Blind system identification.

I. INTRODUCTION

High torque to inertia ratio, superior power density, high efficiency and many other advantages made PMSM the most widely acceptable electrical motor in industrial applications. The invention of Vector control made the ac drives equivalent to DC drives in the independent control of flux and torque. To facilitate vector control the stator quantities are resolved into components which rotate in synchronism with the rotor. For this transformation of stator quantities into synchronously rotating frame, the accurate knowledge of speed and rotor position is required. It usually requires mechanical sensors for measurement of speed in variable speed applications. But these types of shaft mounted mechanical sensors will make the system more complex and moreover reduces the reliability of the drive system. Accordingly, sensor less operation of PMSM has been receiving wide attention recently [1] in variable speed drives. The extended Kalman filter algorithm is an optimal recursive estimation algorithm for nonlinear systems [2]. The Kalman filter is essentially a set of mathematical equations that implement a predictor corrector type estimator that is optimal in the sense that it minimizes the estimated error covariance when some presumed conditions are met. The present method addresses the whole problem as that of blind system identification eliminating the requirement of prior information of input voltages. This approach is found to be well suited to the state estimation of a PMSM, from the convergence properties of the flux vector position and the rotor speed. The well established dynamics defined in terms of familiar state variables and the relationship of the stator currents with the state variables shows itself the utilization of the Kalman filter based algorithms, for inverting the rotor flux position and the synchronous speed from the dynamic behavior. The design and tuning of the covariance matrices in EKF algorithm makes the Kalman filter algorithm a laborious process. In order to solve this an intelligent technique can be incorporated in the system [3]. It is proposed to introduce fuzzy technique to automatically adjust the diagonal element corresponding to speed in the process covariance matrix in EKF algorithm. The results of the conventional EKF and intelligent EKF are compared to show the effectiveness of the latter. The introduction of intelligence in the conventional Kalman filter completely puts an end to the struggling in manual designing of the covariance matrices in EKF. Fuzzy control is different from the traditional PI control in the sense that it does not depend on precise system mathematical model [4]. The fuzzy logic technique has become very popular in the control of ac drives because of the flexibility in accommodating overlapping information in the definition of terms. Standard algorithm computes a fuzzy function on the basis of the error and change in error of the set speed and the estimated speed using a set of rules. In this paper as in the case of usual approach of fuzzy, all the rules are assigned equal weightings. The performance evaluation of the fuzzy-extended Kalman filter with online estimation of the speed and rotor position and fuzzy control of a PMSM is presented with simulation results and the results are compared with conventional Kalman filter to show the faster convergence.

II. MATHEMATICAL MODEL OF PMSM

The dynamic model developed on a synchronously rotating reference frame describes better the behavior of the motor for the vector control. Therefore the stator variables are transformed into a synchronously rotating d-q frame. The stator of the PMSM is similar to that of the wound rotor synchronous motor. The back emf produced by a permanent magnet is similar to that produced by an excited coil. A PMSM can be mathematically represented by the following equation in the d-q axis synchronously rotating rotor reference frame for assumed sinusoidal stator excitation [5].

\[
\begin{bmatrix}
v_d \\
v_q \\
q_d \\
q_q
\end{bmatrix} = \begin{bmatrix}
R + pL_q & p\omega_r & L_d & 0 \\
-p\omega_r & R + pL_q & 0 & L_q \\
0 & 0 & R + pL_q & 0 \\
0 & 0 & 0 & R + pL_q
\end{bmatrix} \begin{bmatrix}
v_d \\
v_q \\
q_d \\
q_q
\end{bmatrix} + \begin{bmatrix}
P & \omega_r & \varphi_f
\end{bmatrix} (1)
\]
\[
\begin{align*}
\frac{d\theta}{dt} &= P\omega_r \\
T_e &= 3P/2 \left[ \varphi_f \left( i_d + (L_d - L_q) i_d i_q \right) \right] \\
T_e &= J_m P\omega_r + B_m \omega_r + T_L
\end{align*}
\]

Where \(v_d\) and \(v_q\) are the d, q axis voltages, \(L_d\) and \(L_q\) are the d,q axis inductances and \(i_d\) and \(i_q\) are the d,q axis stator currents, respectively. The other parameters are:

- \(R\): the stator resistance per phase
- \(\varphi_f\): the constant flux linkage due to rotor permanent magnet,
- \(\omega_r\): the angular rotor speed,
- \(\theta_e\): the rotor position in electrical degrees,
- \(P\): the number of pole pairs of the motor,
- \(p\): the differential operator,
- \(T_e\): the developed electric torque,
- \(T_L\): the load torque,
- \(B_m\): the rotor damping coefficient,
- \(J_m\): the inertia constant

The current control is made possible through a vector control approach. In order to make the PMSM system linear, the d axis current is set to zero. So control of PMSM will become as easy as that of a DC motor. The d-q axis currents are related to the three phase stator currents by the equation

\[
\begin{bmatrix}
i_d \\
i_q
\end{bmatrix} =
\begin{bmatrix}
-\sin \theta_e & \cos \theta_e \\
\cos \theta_e & -\sin \theta_e
\end{bmatrix}
\begin{bmatrix}
i_d \\
i_q
\end{bmatrix}
+ \begin{bmatrix}
0 \\
1/\sqrt{3} \\
-1/3 \\
-1/\sqrt{3}
\end{bmatrix}
\begin{bmatrix}
v_d \\
v_q
\end{bmatrix}
\]

III. ESTIMATION OF SPEED AND ROTOR POSITION USING EXTENDED KALMAN FILTER

The Extended Kalman filter [6] is an optimal recursive algorithm suitable to estimate the state of nonlinear dynamic systems. The system is described by the following state equations

\[
\begin{align*}
x_{k+1} &= f(x_k, u_k) + w_k + Bu_k \\
Z_k &= h_k x_k + v_k
\end{align*}
\]

where \(x\) are the zero mean white Gaussian noise. And the state vector, \(x = [i_d, i_q, v_d, v_q]\). The measurements are the three phase stator currents \([i_d, i_q, v_d, v_q]\). In discrete form the augmented state model is represented as

\[
\begin{bmatrix}
i_d(k) \\
i_q(k) \\
\omega_r(k) \\
\omega_e(k)
\end{bmatrix} =
\begin{bmatrix}
1 - R_{t/1} & \omega_Tz_e & 0 & 0 \\
-\omega_Tz_e & 1 - R_{t/1} & (-\varphi_f/L)T_e & 0 \\
0 & (L_d/2) & P^2T_e & (-\varphi_f/L)T_e & 0 \\
0 & 0 & T_e & 0
\end{bmatrix}
\]

The mathematical model of PMSM is typically coupled and hence nonlinear [9]. In the present work, an Extended Kalman filter is used for estimating the speed and the rotor position, from the non linear system given in (8), based on the measured values of line currents. For a given sampling time \(Ts\), both the state estimate \(\hat{x}_k/k\) and its covariance matrix \(P_{k|k}\) are generated by the filter through a two step loop predictor corrector process.

The corrector algorithm starts with an initial value of \(x, P_{0/|0}\) and follows as below

1. Computation of the Kalman gain

\[
K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R)^{-1}
\]

where \(K_k\) is the Kalman gain for \(k\)th iteration and \(H_k = \frac{\partial z}{\partial x}\) and \(R\) is a constant measurement noise covariance matrix.

2. Update estimate with the measurements

\[
x_{k|k} = x_{k|k-1} + K_k (Z_k - h_k x_{k|k-1})
\]

3. Updating the error covariance as

\[
P_{k|k} = (I - K_k H_k) P_{k|k-1}
\]

where \(I\) is an identity matrix.

The predictor algorithm involves

1. Projecting the state error covariance matrix ahead for the next iteration as

\[
P_{k|k-1} = A_k P_{k-1|k-1} A_k^T + Q,
\]

where \(A_k = \frac{\partial f}{\partial x}\) and \(Q\) is a constant process covariance matrix.

2. And the state is projected ahead as

\[
x_{k|k-1} = f(x_k) x_{k|k-1}
\]

Beginning the iteration with an initial value of \(x\) is \(X(0)\) and the Covariance \(P_{0/0}\), the Kalman filter estimates the values of flux angle \(\theta_e\) and the speed \(\omega_e\). The convergence of Kalman filter is highly affected by the choice of \(P_{0/0}=X(0), Q\) and \(R\). Usually these matrices are chosen by trial and error approach.

In this paper fuzzy logic technique is utilized for the design
of process covariance matrix $Q$.

IV. COVARIANCE MATRIX DESIGN USING FUZZY LOGIC

Usually covariance matrices $P$, $Q$ and $R$ are assumed to be diagonal. The matrix $Q$ describes statistically the drive model. Increase in $Q$ indicates heavy system noise or increased parameter uncertainty. It has been found that the element that mostly influences the EKF convergences are $q_{3,3}$, the element corresponding to speed of the motor. In this paper fuzzy logic technique [7], is utilized to update this element in terms of speed error , $e$ and change in error, $\Delta e$. The fuzzy variables of input ie $e$ and $\Delta e$ and fuzzy variable of output i.e. “Q are scaled to [-1, 1]. The fuzzy system is realized in terms of 5 variables viz. NB, NS, ZE, PS and PB as in Fig. 1(a). In this paper triangular membership function is used to represent the fuzzy set.

![Figure 1(a) Membership function for computing “Q](image)

Rules for computing “Q are shown as below.

<table>
<thead>
<tr>
<th>$\Delta Q$</th>
<th>$e$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta e$</td>
<td>NB</td>
</tr>
<tr>
<td>NB</td>
<td>NB</td>
</tr>
<tr>
<td>NS</td>
<td>NB</td>
</tr>
<tr>
<td>ZE</td>
<td>NS</td>
</tr>
<tr>
<td>PS</td>
<td>ZE</td>
</tr>
<tr>
<td>PB</td>
<td>ZE</td>
</tr>
</tbody>
</table>

In this paper $P_{0.1}$ and $R$ are assumed constant. Initially $q_{3,3}$ is set to zero. The process covariance matrix $Q$ is

$$Q = \begin{bmatrix}
10 & 0 & 0 & 0 & 0 & 0 \\
0 & 10 & 0 & 0 & 0 & 0 \\
0 & 0 & Q_{2} & 0 & 0 & 0 \\
0 & 0 & 10 & 0 & 0 & 0 \\
0 & 0 & 0 & 10 & 0 & 0 \\
0 & 0 & 0 & 0 & 10 & 0
\end{bmatrix}$$

$Q_{2}$ is updated as, $q_{3,3} + \Delta Q$.

V. FUZZY LOGIC SPEED CONTROLLER

The over control of the speed is also realized in terms of $e$ and $\Delta e$. The error in speed and the rate of change of speed error are considered as the input linguistic variables and the quadrature axis current is considered as the output linguistic variable. The support for all the fuzzy variables viz. $e$ and $\Delta e$, variable of output $i_q$ is scaled to [-1, 1]. In this case 7 membership functions are used, viz., NB, NM, NS, ZO, PS, PM, PB as shown in Fig. 1(b).

![Figure 1(b) Membership function for computing quadrature axis current](image)

Rules for computing the quadrature axis current is given below

<table>
<thead>
<tr>
<th>$i_q$</th>
<th>$\Delta e$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta e$</td>
<td>NB</td>
</tr>
<tr>
<td>NB</td>
<td>NB</td>
</tr>
<tr>
<td>NM</td>
<td>NB</td>
</tr>
<tr>
<td>NS</td>
<td>NB</td>
</tr>
<tr>
<td>ZO</td>
<td>NB</td>
</tr>
<tr>
<td>PS</td>
<td>NM</td>
</tr>
<tr>
<td>PM</td>
<td>NS</td>
</tr>
<tr>
<td>PB</td>
<td>ZO</td>
</tr>
</tbody>
</table>

The block diagram representation of the controller is shown in Fig 2.

![Figure 2. Block diagram representation of the proposed system](image)

VI. SIMULATION AND RESULTS

Simulation of the given PMSM has been carried out using Simulink. The three phase stator currents are taken from the motor model, and given to the extended Kalman filter. The Extended Kalman filter estimates the instantaneous motor speed, rotor position, quadrature and direct axis currents and voltages. The estimated motor speed is compared with the
reference speed and the error produced and change in the error is given to the fuzzy speed controller and FLC. In FLC it undergoes fuzzy inference process according to the rule generated in TABLE1. FLC gives “Q as the output linguistic variable, which is given to Fuzzy EKF estimator to update the process covariance matrix. In Fuzzy speed controller, it undergoes the fuzzy inference process according to the rule generated in TABLE2. It gives quadrature axis current as the output linguistic variable. Fuzzy speed controller output is compared with the estimated quadrature axis current and the error produced is passed through a PI controller to produce quadrature axis voltage. The direct axis current reference is set to zero and this value is compared with the estimated direct axis current and the error produced is passed through another PI controller which produces direct axis voltage. The direct and quadrature axis voltages are converted into two axis stator voltages using the inverse park transformation. The two axis stator voltages are utilized to trigger the space vector PWM inverter. The space vector PWM inverter drives the PMSM. The approach towards the estimation of speed and rotor position is stable and converges very fast. It needs only the three phase stator current values which are easily available from the machine. The EKF algorithms is developed in Matlab and integrated with Simulink using embedded Matlab facility. The parameters used for simulation are discussed below. The PMSM parameter used in this paper is 1.1 KW, 4 poles, \( R = 2.875 \text{Ù} \), \( L = 0.423 \text{H} \), \( \varphi_f = 1.7 \text{wb/m}^2 \), \( J = 0.008 \text{Kg-m}^2 \). During the simulation, it was seen that convergence for the speed estimating Kalman filters is highly dependent on the initial values viz. \( X (0) \) and \( P (0/-1) \). The values of those matrices are given as:

\[
X (0) = \begin{bmatrix} 0;0;0;0;0;0 \end{bmatrix}
\]

\[
R = \text{dia} [10; 10; 10]
\]

\[
P (0/-1) = \text{dia} [200; 200; 200; 200; 200; 200]
\]

The sampling time chosen is 4.5 s. The values of proportional and integral gain constants used are:

\[
K_p = 60, K_i = 2; \text{ for inner quadrature axis current controller.}
\]

\[
K_p = 40, K_i = 2; \text{ for inner direct axis current controller.}
\]
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The estimator is stable and quick for all set speeds. The FLC could trace and reach all the set speeds very quickly. Once again FLC has proved its excellence in handling uncertain parameters and disturbances. The controller performance has been tested for various step changes in speed in Simulink environment and found stable.

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REFERENCES


Figure 7. Estimated rotor position of speed reference in Fig4 with fuzzy EKF

Fig 3 shows the step response of mechanical speed of PMSM with a Fuzzy EKF. from the result it is clear that the speed converges within 0.5 sec time with an error of 1%. hence it is very quick in operation compared to the conventional EKF. Fig 4 shows the same step response with conventional EKF. there it takes nearly 1 sec time to converge. Fig 5 and Fig 6 shows the estimated motor speed for the step speed change 100 rad/sec to 140 rad/sec with Fuzzy EKF and conventional EKF respectively. From the results it is clear that the intelligent technique incorporated along with EKF made it quicker compared to the conventional case. In the speed graph it is clear that the estimated speed is completely coincident with the running speed of motor. The slope of the estimated rotor position also changes when the speed steps into a new value. These step changes are required in electric vehicle applications, IEEE Press,1997.

One of the major difficulties of EKF, which we successfully crossed, is the tuning of the covariance matrices in EKF algorithm by incorporating intelligence and also with trial and error approach. With all these difficulties, the results demonstrate the competence of EKF algorithm as an estimator, simply from three stator current measurements. And the fuzzy logic technique to control the speed of the motor for all the set speeds.

VII. CONCLUSIONS

A Fuzzy EKF estimator along with Fuzzy logic speed controller has been successfully implemented in SIMULINK/MATLAB environment. The performance really shows that the controller can be used in electric vehicle applications in order to control both speed and position. The results clearly illustrate that the intelligence in EKF made it quicker compared to the conventional EKF. The results illustrate the efficacy of the Kalman filter algorithm as a blind system identification approach for estimation purposes.