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A Novel Techniques for Speed and Rotor Position Estimation of Brushless DC Motor with an Extended Kalman Filter by using Matlab Simulation

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***Abstract*— This paper describes a method of speed and rotor position estimation of a brushless dc motor (BLDCM). The estimation of motor state variables is obtained by using an extended Kalman filter (EKF) technique by only using stator line voltages and currents. At first while estimation the voltage and current measuring signals are not filtered over here rather than other kinds of similar methods usually done. By combining measurements and calculations, the average value of voltage during sampling intervals is obtained owing to the application of predictive current controller which is based on the mathematical model of motor. The parameters considered for the estimation algorithm consist of two parts, one consist of speed and rotor position are estimated with constant motor parameters and other the stator resistance is estimated simultaneously with motor state variables. From the results it is seen that it's quite possible for BLDCM to estimate speed and rotor position with sufficient accuracy in both steady state and dynamic operation. By the introducing of stator resistance estimation, the accuracy is increased especially working at low speeds.**

Keywords-Brushless dc motor, digital signal processor, extended Kalman filter, predictive current controller, speed and rotor position estimation.

I. INTRODUCTION

The brushless dc motor (BLDCM) has trapezoidal electromotive force (EMF) and quasi-rectangular current waveforms. Three Hall sensors are usually used as position sensors to perform current commutations every 60 electrical degrees. In addition, for servo drive applications with high stationary accuracy of the speed and rotor position, the BLDCM requires a rotor position sensor, such as resolver or absolute encoder. All the sensors mentioned increase the cost and size of the motor and reduce its sturdiness. Because of these reasons, the BLDCM without position and speed sensors has attracted wide attention and many papers have reported on it. In most existing methods, the rotor position is detected every 60 electrical degrees, which is necessary to perform current commutations. These methods are based on: 1) using the back EMF of the motor [1], [2]; 2) detection of the conducting state of freewheeling diodes in the unexcited phase [3]; and 3) the stator third harmonic voltage components [4]. Since these methods cannot provide continual rotor position estimation, they are not applicable for the sensorless drives in which high estimation accuracy of the speed and rotor position is required. In that case, it is necessary to estimate rotor position continually, not only every 60 electrical degrees. In [5], the rotor position of the BLDCM is estimated continually using measured motor voltages and currents with the aim of estimating flux linkage. At each time step, the motor current is estimated in two stages to correct the predicted rotor position and the estimated flux linkage. The estimation results have been obtained using offline- measured voltages and currents with a 10- s sampling time. The accuracy of the rotor position estimation depends significantly on the motor parameter variation and accuracy of measured voltages and currents. In [6] and [7], the rotor position and speed of the permanent-magnet (PM) motor have been estimated by the extended Kalman filter (EKF). This method is applied to the motor with trapezoidal EMF and sinusoidal waveform currents, and is not directly applicable to the motor with rectangular currents. In this paper, a method is presented by means of which the speed and rotor position of the BLDCM are continually estimated. This method is based on the application of the EKF, which is an optimal recursive estimation algorithm for nonlinear systems that are disturbed by random noise. The EKF approach appears to be a viable and computationally efficient candidate for the online estimation of the speed and rotor position of the PM motors [8]. This is possible since mathematical models of motors are sufficiently well known. As is different from most of the similar methods dealing with estimation of the electric machine variables, in which the measuring voltages and currents are filtered in order to eliminate high, harmonic components [6], [8], with this method, voltages and currents are measured without previous filtering. A special procedure is applied to obtain the line voltages average value combining measurements and calculations, which is made possible owing to the application of the predictive current controller. The experimental results of the speed and rotor position estimation are obtained using two variants of the estimation algorithm. In the first of them, the speed and rotor position are estimated with constant motor parameters and, in the second variant, the motor variables and stator resistance are estimated simultaneously. At the end of this paper, the characteristics of the sensorless drive are analyzed.

Sensorless control of a brushless dc motor drive essentially means vector control of the motor without any speed sensor. An incremental shaft mounted speed encoder usually a optical type is used here for the closed loop speed or position control in both vector and scalar controlled drives, a speed signal is also required in indirect vector control in the whole speed ranges, and in the direct vector control for low speed ranges, including zero speed start up operation, a speed encoder is undesirable in a drive because it adds cost and reliability problems, besides the need of shaft extensions and mounting arrangements. It is possible to estimate the speed signal from machine terminal voltages and currents with the help of DSP processors.

II SPEED ESTIMATION METHODS USING AN EXTENDED KALMAN FILTER

The extended Kalman filter is basically a full order stochastic observer for the recursive optimum state estimation of non linear dynamical systems in real time by using signals that are corrupted by noise; the EKF can also be used for unknown parameters estimation such as rotor resistance R_r or joint state or parameter estimation. The luenberger observer is a deterministic observer without noise in comparison with EKF, and is applicable to linear time invariant systems. The noise source in EKF takes in to account measurement and modeling inaccuracies. Normally EKF are applicable to non linear systems.

The augmented machine model is given by

$$\frac{d(X)}{dt} = AX + BV_s \tag{1}$$

$$X = [ids^s \; iqs^s \; \psi dr^s \; \psi qr^s]^T \tag{2}$$

$$V_s = [vds^s \; vqs^s \; 0 \; 0]^T \tag{3}$$

Where,

$ids^s \; iqs^s$ - Stator current

$\psi dr^s \; \psi qr^s$ - Rotor flux

$vds^s \; vqs^s$ - Stator voltage

V_s - Input vector

ω_r - Rotor speed

$$A = \begin{bmatrix} \frac{-(Lm^2\,Rr+Lr^2Rs)}{\sigma L_s L_s{}^2} & 0 & \frac{L_m R_r}{\sigma L_s L_s{}^2} & \frac{L_m \omega_r}{\sigma L_s L_s} \\ 0 & \frac{-(Lm^2\,Rr+Lr^2Rs)}{\sigma L_s L_s{}^2} & -\frac{L_m \omega_r}{\sigma L_s L_s} & \frac{L_m R_r}{\sigma L_s L_s{}^2} \\ \frac{L_m R_r}{L_r} & 0 & \frac{-R_r}{L_r} & -\omega_r \\ 0 & \frac{L_m R_r}{L_r} & \omega_r & \frac{R_r}{L_r} \end{bmatrix} \tag{4}$$

$$B = \begin{bmatrix} \frac{1}{\sigma L_S} & 0 \\ 0 & \frac{1}{\sigma L_S} \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{5}$$

III MACHINE MODEL OF EKF DEVELOPMENT

The kalman filter algorithm uses the full machine dynamic model, where the speed ω_r is considered as parameter as well as a state.

$$Y = CX \tag{6}$$

Where,

$$A = \begin{bmatrix} \frac{-(Lm^2\,Rr+Lr^2Rs)}{\sigma L_s L_s{}^2} & 0 & \frac{L_m R_r}{\sigma L_s L_s{}^2} & \frac{L_m \omega_r}{\sigma L_s L_s} & 0 \\ 0 & \frac{-(Lm^2\,Rr+Lr^2Rs)}{\sigma L_s L_s{}^2} & -\frac{L_m \omega_r}{\sigma L_s L_s} & \frac{L_m R_r}{\sigma L_s L_s{}^2} & 0 \\ \frac{L_m R_r}{L_r} & 0 & \frac{-R_r}{L_r} & -\omega_r & 0 \\ 0 & \frac{L_m R_r}{L_r} & \omega_r & \frac{-R_r}{L_r} & 0 \\ 0 & 0 & 0 & 0 & 0 \end{bmatrix}$$

$$X = [ids^e \; iqs^s \; \psi dr^s \; \psi qr^s \; \omega_r]^T \tag{7}$$

$$B = \begin{bmatrix} \frac{1}{\sigma L_S} & 0 \\ 0 & \frac{1}{\sigma L_S} \\ 0 & 0 \\ 0 & 0 \\ 0 & 0 \end{bmatrix} \tag{8}$$

$$C = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \end{bmatrix} \tag{9}$$

$$Y = [ids^s \quad iqs^s]^T = i_s \tag{10}$$

Here $v_{s=[vds^s \quad vqs^s]^T}$ is the input vector. Is of the fifth order, where speed ω_r is a state as well as a parameter. If the speed variations is considered negligible, then $d\omega_r/dt = 0$. This is a valid consideration if the computational sampling time is small or load inertia is high. With speed ω_r as a constant parameter, the machine model used in EKF is linear. The block diagram of EKF algorithm,

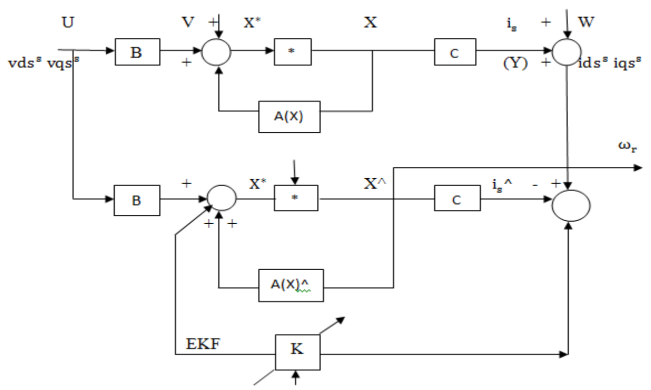

Figure 1 Show that Extended Kalman Filter for Estimation of Speed

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Where,

V, W - noise

K - Kalman gain

For digital implementation of the EKF the model must be discredited in the following form,

$$X(k+1)= A_d X(k) + B_d U(k) \quad (11)$$

$$Y(k)=C_d X(k) \quad (12)$$

The brushless dc motor with the noise sources, V and W, which correspondingly give the model equations in discrete forms as

$$X(K+1)= A_d X(k) + B_d U(k) + V(k) \quad (13)$$

$$Y(k) = C_d X(k) + W(k) \quad (14)$$

Where,

V(k), W(k) - Zero mean

X(k), Y(k) - Gaussian noise vectors

Both these parameters are independent each other. The statistics of noise and measurement are given by three covariance matrices. The sequence of EKF includes basic computational expressions. Basically it has two main stages prediction stage and filtering stage. In prediction stage, the next predicted values of states X^*(k+1) are calculated by the machine model and the previous values of the estimated states. In vector Q. in the filtering stage, the next estimated state $X^\wedge$(K+1) are obtained from the predicted state X^*(k+1) by adding the correction term eK (correction term) where e = Y(K+1) – $Y^\wedge$(K+1) and k = kalman gain. the kalman gain is optimized for state estimation errors. The EKF computations are done in recursive manner so that e approaches 0. The algorithm required for the design of the system is mentioned below consisting of six steps.

A.Extended Kalman Filter Flow Diagram

Step 1 Initialize state vector and covariance matrices

$X(0), Q_o, R_0, P_0$

$vds^s \; vqs^s$

Step 2 Predict the state vectors

$$X^*(k+1,k) = X^*(k+1) = A_d X^\wedge(k) + B_d U(k)$$

Step 3 Estimate P(k+1) covariance matrix

$$P^*(k+1) = f(k+1)\, P^\wedge(k) f^T(k+1)+Q$$

Where

$$f(k+1) = \frac{\delta}{\delta X}[A_d X + B_d U]$$

Step 4 Compute kalman filter gain K

$$K(k+1) = P^*(k+1)\; h^T(k+1)[\; h(k+1)\; P^*(k+1)\, h^T(k+1)+R\;]^{-1}$$

$$H(k+1) = \frac{\delta}{\delta X}[C_d X]_{x=x^*(k+1)}$$

$ids^s \; iqs^s$

Step 5 Estimate state vectors

$$X^\wedge(k+1) = X^*(k+1) + K(k+1)[Y^\wedge(k+1)] \longrightarrow \omega_r$$

Step 6 Update error covariance matrixes

$$P^\wedge(k+1) = P^*(k+1) - K(k+1)\, h(k+1)\, P^*(k+1)$$

B. Block Diagram of Bldc Motor With Extended Kalman Filter Flow Diagram

The block diagram representation of the experimental setup is shown in the figure.2 The blocks consist of a PID controller, non-linear controllers, switching table, inverter, extended kalman filter, digital to analog converter and of course brushless DC motor connected via hall sensors.

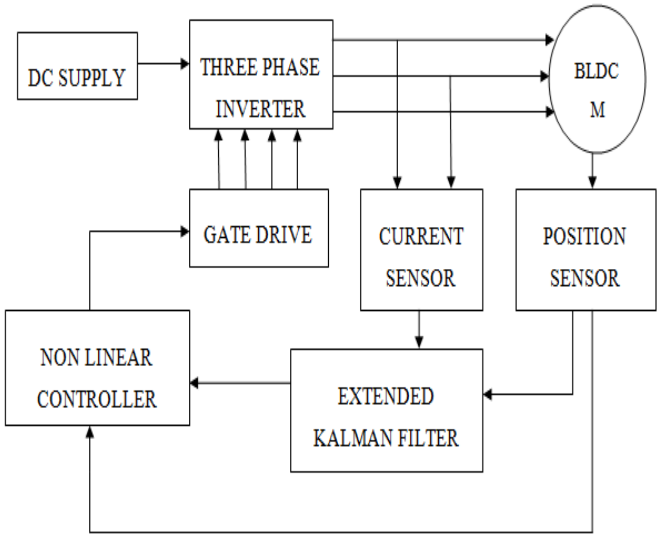

Figure 2 Show that Block Diagram BLDC Motor with Extended Kalman Filter

Here the brushless DC motor which is actually a synchronous motor is used. The motor is exited with a trapezoidal wave input in which it is obtained by a switching analogy which is made by proper switching made by the switching logic table. At first it is made worked by giving dc input to the system and then it is applied to the MOSFET control switch. Then to the inverter, BLDC is made run. The part of kalman filter is to generate estimated values of stator linkage flux, actual velocity of rotor and position and stator flux phasor using measured values of currents and voltage from motor terminals. From these estimated values it is feed backed to the PID controllers and then to the switching logic table. The PID controller makes reference of electromagnetic torque. From the Hall Effect sensors which are feed backed to the MOSFET switches is one which works on stator and rotor position of the BLDC motor. These sensors sense the position of the system by sensing the electromagnetic force obtained by the stator and rotor positions. Hence these positions are made in to zeros and one's and fed back to the controllers via digital to analog converters. The non-linear system takes these references and then makes proper switching to the motor. The extended kalman filter in which it is a non-linear version of kalman filters which linearizes about an estimator of the current mean and covariance. In case of well-defined transition model EKF is used. It generates estimated values of stator linkage flux, actual velocity of rotor and position of stator flux phasor using measured values of current and voltage from motor terminals. From these values the torque ripple is controlled by the PID controller on the brushless DC motor and hence the ripple is minimized.

IV. SIMULATION MODEL OF PROPOSED BLDC MOTOR WITH AN EXTENDED KALMAN FILTER TECHNIQUE

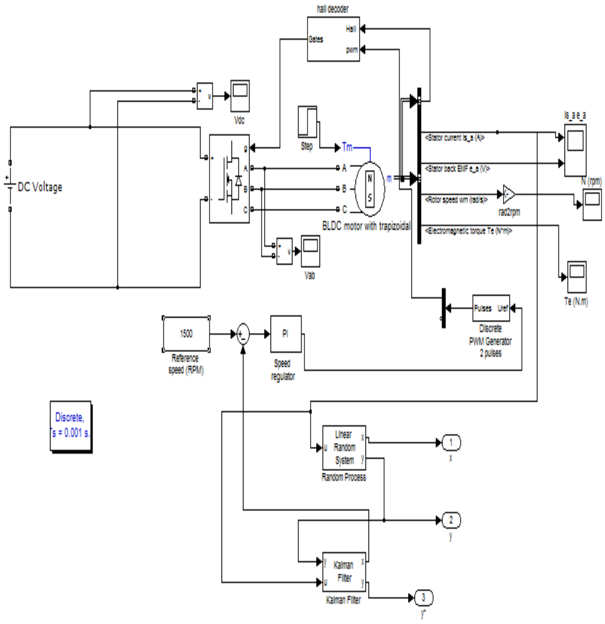

Figure 3 show that Simulation of BLDC Motor with an Extended Kalman Filter Technique.

Simulink tool is used to obtain the model of brushless DC motor using an extended kalman Filter technique. Here apart from normal BLDC motor speed controls the stator flux and mechanical state estimated values are detected by the extended kalman filters. It generates estimated values of stator linkage flux, actual velocity of rotor and position of stator flux phasor using measured values of current and voltage from motor is taken and fed back to the switching logic gates. For well defined transition model extended kalman filter technique is used and in common they are used in non-linear systems. The stator current and rotor speed are taken and given to the linear random systems. These systems take the values randomly by analyzing the systems and fed to the kalman filters. These filters are state observers specially designed for non linear systems in which estimation of mechanical states, in order to achieve sensorless control of synchronous machines or DC machines with electromagnetic excitation and starting cage. In principle kalman filter is a state observer that establishes the best approximation by minimization of square error for the state variable of a system, subjected at its both input and output to the random disturbances.

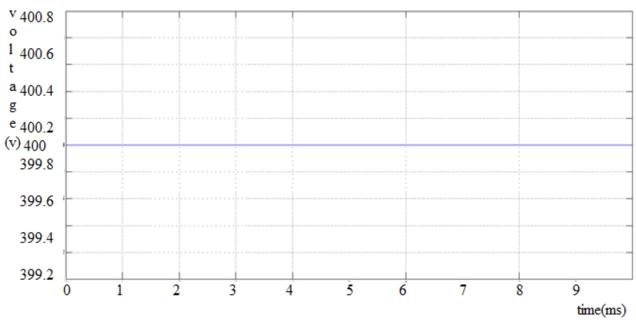

Figure 4 show the Input Voltage of the Proposed System

A. Speed of the Motor without Extended Kalman Filter Technique

The speed response of a brushless DC motor without an extended kalman filter technique is shown in the figure 5. Here the speed lies in (0 to 1000) rpm. But here steady speed is not maintained because of the torque ripple caused in the system. The speed Varies at each phase of time.

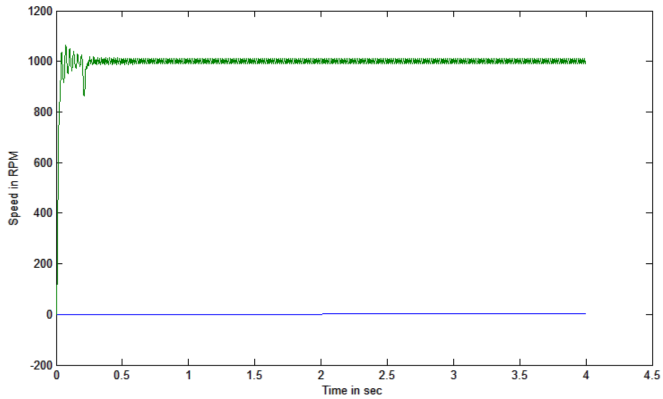

Figure 5 shows the Motor Speed without Using Kalman Filter

B.Torque Ripple Waveform of the Proposed BLDC Motor

Torque ripple produced in the system is caused by many factors such as cogging torque, interaction between MMF and air gap flux harmonics of mechanical imbalance. Thus it leads to minimization of the motor rated speed. Torque ripple should be minimized in order to obtain rated speed. Here an extended kalman filter technique is used in order to obtain stator flux and mechanical state estimation. It generates estimated values of stator linkage flux, actual velocity of rotor and position of stator flux phasor using measured values of current and voltage from motor terminals. The extended kalman filter method is specially designed for sensorless control of direct torque controlled motor hence by these technique the ripple is controlled in the system and thus the speed also controlled by using the proposed technique as the speed is directly proportional to speed.

Torque ripple produced in the system is caused by many factors such as cogging torque, interaction between MMF and air gap flux harmonics of mechanical imbalance. Thus it leads to minimization of the motor rated speed. Torque ripple should be minimized in order to obtain rated speed. The torque ripple is a major factor which affects the efficiency of the motor in means of its energy losses and in reduction of rated speed of the motor. The torque ripple of the system is obtained by different techniques like input voltage varying method, current control algorithm method and frequency control method, unipolar and bipolar control. Here an extended kalman filter technique is used to reduce the ripple in the system.

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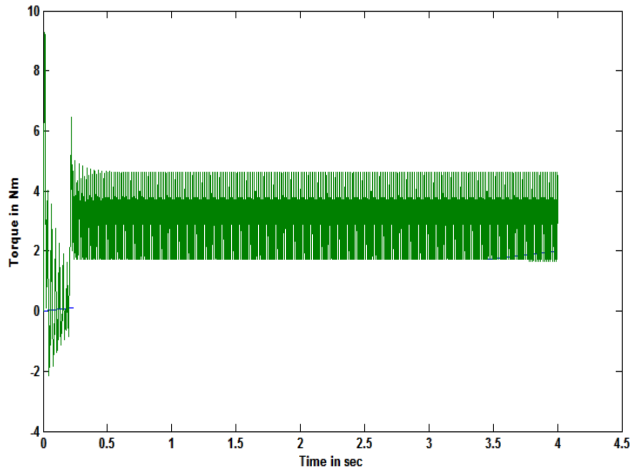

Figure 6 shows that Torque Ripple Obtained in a BLDC Motor

C.Speed of the Motor With An Extended Kalman Filter Technique

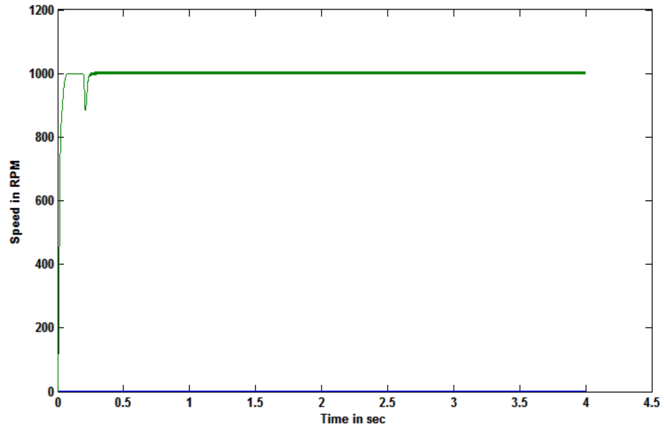

Figure7 shows that Speed of the Motor with An Extended Kalman Filter

Here the torque ripple of the BLDC motor without using an extended kalman filter technique is obtained from the figure 8 where from the figure the ripple lies between (+2 to -6) where the ripple is high.

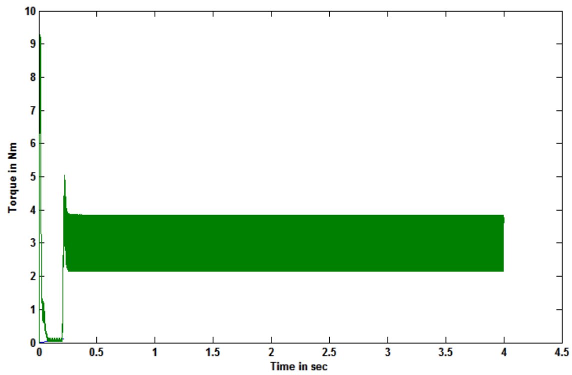

Figure 8 shows that Torque Ripple in Proposed System by Using Kalman Filter Technique

V. HALL SENSOR AND ITS SWITCHING LOGICS FOR PROPOSED SYSTEMS

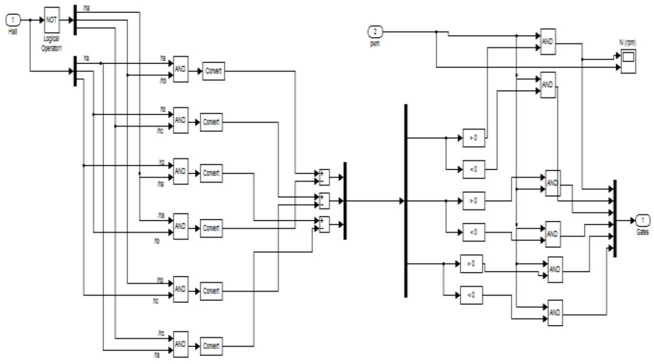

Figure 9 shows that Hall Sensors Simulation

Phases commutation depends on the hall sensor values. When motor coils are correctly supplied, a magnetic field is created and the rotor moves. The most elementary commutation driving method used for BLDC motors is an on-off scheme: a coil is either conducting or not conducting. Only two windings are supplied at the same time and the third winding is floating. Connecting the coils to the power and neutral bus induces the current flow. This is referred to as trapezoidal commutation or block commutation. To command brushless DC motors, a power stage made of 3 half bridges is used. For motors with multiple poles the electrical rotation does not correspond to a mechanical rotation. A four pole BLDC motor uses four electrical rotation cycles to have one mechanical rotation.

Table1. Switching States and Voltage Space Vectors

VSV	S_a	S_b	S_c
U1	1	0	0
U2	1	1	0
U3	0	1	0
U4	0	1	1
U5	0	0	1
U6	1	0	1
U7	0	0	0
U8	1	1	1

The Hall Effect sensors are usually positioned so that the magnets change its values before the rotor is actually in the next commutation position. This allows for the next commutation to be made before the rotor actually becomes stuck at one position. With Hall effect sensors, a simple BLDC control system needs only 9 pins from a microcontroller; six pins to control the H-bridge and three pins to sense the Hall effect switches. Software up to this point is also simple. A table in the memory is enough for the processor to determine the next commutation with the six-step process and the Hall effect sensor outputs. Table1.Shows the switching states of Hall Effect sensors.

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VI CONCLUSION

The paper develops the possibility of estimation of speed and rotor position of a BLDCM using an EKF, with sufficient accuracy in both steady state and dynamic modes of operations. The paper studies the interaction between closed loop and state observer. From the simulation results it is shown that the dynamic behavior of kalman filter based control system is quite good. Here the machine electrical and mechanical parameters are different from nominal values, which are used for the design of controllers and kalman filter and for initialization of incorrect estimated positions.

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