ROBUST CONTROL OF A SPEED SENSORLESS PERMANENT MAGNET SYNCHRONOUS MOTOR DRIVE

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Abstract *- This paper presents the application of the Linear Quadretic Gaussian (**LQG**) controller to the state estimation and feedback of a speed sensorless permanent magnet synchronous motor (**PMSM**) drive system. The nonlinear model of the motor has been linearized on the basis of field orientation principle. The standard Kalman filter technique has been used to estimate the speed, position, and load torque by measuring only the stator current. The optimal state feedback gains and the Kalman state space model have been calculated off-line in order to reduce the computational burden. The proposed controller has the advantages of robustness, easy implementation and adequate performance in the face of uncertainties. Moreover, the load disturbance can be rejected without affecting the overall performance.*

Computer simulations have been carried out in order to validate the effectiveness of the proposed scheme. The results show that accurate tracking performance of the PMSM has been achieved.

Index Terms: *permanent magnet synchronous motor – Linear Quadretic Gaussian controller- Kalman filter.*

NOMENCLATURE

v_d , v_q d-q stator voltages,

v_α , v_β $\alpha-\beta$ stator voltages,

i_d, i_q d-q stator currents,

i_α, i_β $\alpha-\beta$ stator currents,

R_s stator resistance/phase,

L_d, L_q d-q stator inductances,

ω_r Motor angular speed,

ω_e electrical angular speed,

p differential operator,

P number of pole pairs,

ϕ permanent magnet flux linkage,

D viscous friction coefficient,

T_L Load torque,

j moment of inertia

1. INTRODUCTION

In recent years, permanent magnet synchronous motor drives have been widely used in many industrial applications such as robots, rolling mills and machine tools. The inherent advantages of these machines include high power density, low inertia, and high speed capabilities. However, the control performance of the PMSM is greatly affected by the uncertainties of the plant which usually are mismatched motor parameters, external load disturbance, and unmodelled and nonlinear dynamics [1].

Advanced control techniques such as nonlinear control [2], adaptive control [3], robust control [4], variable structure control [5], and intelligent control [6, 7] have been developed to deal with plant uncertainties under various operating conditions. In these control schemes, the speed or position signal is necessary for establishing the outer speed loop feedback and also in the flux and torque control algorithms.

From the viewpoints of reliability, robustness, and cost, several approaches have been proposed that address the elimination of the mechanical sensors. Some approaches are based on the motor equations in order to express rotor positions and speed as functions of terminal quantities [8, 9]. However, the sensitivity to motor parameters is a major drawback of this method. In other approach, sensorless PMSM drives have been developed on the basis of state observers [2,10,11]. However, the overall stability may not be guaranteed in these schemes due to certain assumptions introduced, complicated controller design, and feedback linearization. In a third approach, the estimation of the rotor position and speed have been proposed using the extended Kalman filter technique [12-15]. However, this method has some inherent disadvantages such as the effect of noise characteristic, the computational burden, parameter sensitivity, and the absence of design and tuning criteria.

In this paper, the PMSM drive has been controlled using the LQG controller. The structure of the LQG consists of a Kalman filter estimator and optimal state feedback gains. The nonlinear model of the motor has been linearized according to the field orientation principle. All the system states including the speed, position, and load torque have been estimated using the standard Kalman filter. The stator current is the only measured signal. The computational burden has been minimized to a large extent by computing the optimal state feedback gains and the Kalman state space model off-line. Computer simulations have been carried out in order to evaluate the effectiveness of the proposed scheme. The results proved that the proposed controller can give better overall performance regarding to high estimation accuracy, quick recover from load disturbance, good tracking ability and simple implementation.

2. Mathematical Model

The dynamic model of the LBDCM can be described in the d-q rotor frame as follows [14]:

$$V_d = R_s i_d + p\lambda_d - \omega_e \lambda_q \quad (1)$$

$$V_q = R_s i_q + p\lambda_q + \omega_e \lambda_d \quad (2)$$

Where:

$$\lambda_d = L_d i_d + \phi \quad (3)$$

$$\lambda_q = L_q i_q \quad (4)$$

$$\omega_e = P\omega_r \quad (5)$$

The mechanical motion of the PMSM can be expressed as:

$$T_e = jP\omega_r + D\omega_r + T_L \quad (6)$$

Where T_e is the electromagnetic torque developed by the machine which is given by:

$$T_e = (3/2)P\,[\lambda_d i_q + (L_d - L_q) i_d i_q] \quad (7)$$

3. Linearised Model

The basic principle in controlling the PMSM is based on field orientation. This is obtained by letting the permanent magnet flux linkage be aligned with the d-axis, and the stator current vector is kept along the q-axis direction. This means that the value of i_d is kept zero in order to achieve the field orientation condition. Since the permanent magnet flux is constant, therefore the electromagnetic torque is linearly proportional to the q-axis current which is determined by closed loop control. As a result, maximum torque per ampere can be obtained from the machine in addition to the achievement of high dynamic performance. Applying the field orientation concept by letting $i_d = 0$ in equations (1-7), the linearised model of the PMSM can be described in a state space form as :

$$pi_q = (1/L_q).(-R_s.i_q + v_q - \phi.\omega_e) \quad (8)$$

$$p\omega_e = (1/j).(1.5P^2\phi.i_q - D.\omega_e - P.T_L) \quad (9)$$

The rotor position dynamics can be expressed as:

$$p\theta = \omega_e \quad (10)$$

Assuming that the unknown load torque has a slow variation which can be modeled satisfactorily as [20]:

$$p.T_L = .0 \quad (11)$$

The state equations of the linearised model of the PMSM can be written in a matrix form as :

$$px = Ax + Bu \quad (12)$$

$$y = Cx \quad (13)$$

Where :

$$A = \begin{bmatrix} -R_s/L_q & -\phi/L_q & 0 & 0 \\ 1.5P^2\phi/j & -D/j & 0 & -P/j \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix},$$

$$B = \begin{bmatrix} 1/L_q & 0 & 0 & 0 \end{bmatrix}^T, \quad C = \begin{bmatrix} 1 & 0 & 0 & 0 \end{bmatrix}^T,$$

$u = v_q$ and $y = i_q$.

4. CONTROL STRATEGY

In this paper, the LQG controller has been employed to control a speed sensorless field oriented PMSM drive. The LQG is a modern state space technique for designing optimal dynamic regulators. It has the following advantages :

1) It enables to trade off regulation performance and control effort.
2) It takes into account the process disturbance and measurement noise.

The LQG controller consists of an optimal state feedback gain "k" and a Kalman state estimator. The optimal feedback gain is calculated such that the feedback control law

$$u = -kx = -k\begin{bmatrix} i_q & \omega & \theta & T_L \end{bmatrix}^T$$

minimizes the performance index :

$$H = \int_0^{\infty} \left(x^T Q x + u^T R u\right) dt$$

where Q and R are positive definite or semi definite Hermittian or real symmetric matrices. The optimal state feedback $u = -kx$ is not implementable without full state measurement. In our case, the states are chosen to be current, speed, position and load torque while the current is chosen to be the output measured signal. The Kalman filter estimator is used to drive the state estimation :

$$\hat{x} = \begin{bmatrix} \hat{i}_q & \hat{\omega} & \hat{\theta} & \hat{T}_L \end{bmatrix}^T \quad \text{such that} \quad u = -k\hat{x}$$

remains optimal for the output feedback problem. The state estimation is generated from [16]:

$$p\hat{x} = (A - Bk - LC)\hat{x} + Ly$$

Where L is the Kalman gain which is determined by knowing the system noise and measurement covariances Q_n and R_n . However, the accuracy of the filter's performance depends heavily upon the accuracy of these covariances. On the other hand the matrices A and B containing the motor parameters are not required to be very accurate due to the inherent feedback nature of the system.

The Kalman filter performs best for linear systems. Therefore, The nonlinear model of the PMSM has been linearised through the use of field orientation concept. The optimal state feedback gains and the Kalman state space model have been calculated off-line which results in great saving in computational burden. On this basis, the implementation of the proposed controller becomes easier and the hardware will be reduced to minimum.

4. SYSTEM CONFIGURATION

The block diagram of the sensorless field oriented PMSM with the proposed LQG controller is shown in figure (1). All the commanded values are superscripted with asterisk in the diagram. The system can be functionally divided into two parts: speed control system and LQG controller. The first part consists of three loops, one for the speed and the others for the d-q currents. The speed error is fed to the speed controller in order to generate the torque current command i_q^* . The flux current command i_d^* is set to zero to satisfy the field orientation condition. The reference currents i_d^* and i_q^* are compared with their respective actual currents. The resulted errors are used to generate the voltage commands v_d^* and v_q^* which are converted to three phase reference values v_a^* , v_b^* , and v_c^* in the stator frame. These voltage signals are compared with triangular carrier signal and the output logic is used to control the PWM inverter.

The second part of the system configuration is the LQG controller which consists of Kalman estimator in addition to optimal state feedback gains. The Kalman estimator uses the measured q-axis current in order to estimate all the states including current, speed, position and load torque. These states are multiplied by the corresponding optimal gains and summed to produce the control signal necessary to compensate for the load disturbance and system uncertainties.

The entire system has been simulated on the digital computer using the Matlab / Simulink / Powerlib software package. The motor used in the simulation procedure has the following specifications :

PMSM	: 1 kw, 2-pole, 1500 rpm
Stator resistance	: 1.55 ohm
Stator inductance	: 20.5 m.H.
Permanent magnet flux	: 0.22 N.m./amp.
Moment of inertia	: 0.0022 kg.m^2
Friction coefficient	: 0.0221 N.m.s/rad

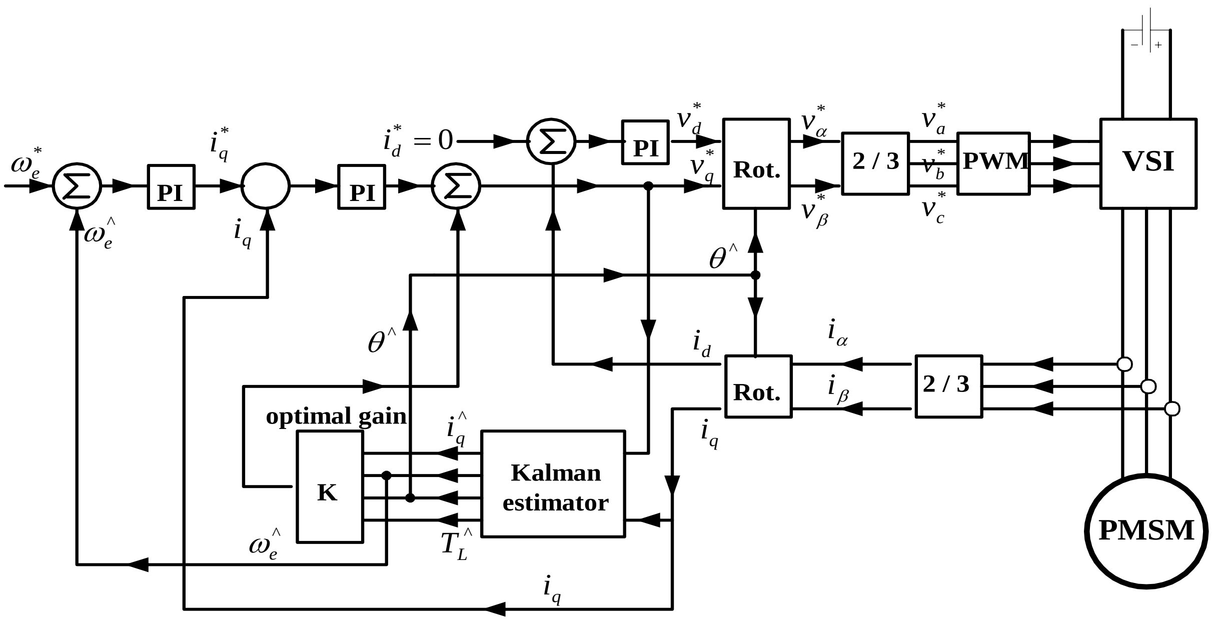


Fig. (1) Block diagram of the sensorless proposed scheme

The gains of the speed and current controllers are chosen as :

Speed loop : kp = 2 , ki = 3
d-q current loops : kp = 1 , ki = 30

The noise and measurement covariances are set as :
Q_n = 0.1 , R_n = 0.01

Also, the values of Q and R matrices which are necessary to calculate the optimal feedback gains are set as : Q = [20 100 10 1] , R = 1.

5. RESULTS

Computer simulations have been carried out in order to validate the effectiveness of the proposed scheme. The speed, current, rotor position, and torque responses are observed under various operating conditions such as change in reference speed, step change in load, and parameter variation.
Figure (2) shows the actual and estimated responses of the proposed PMSM sensorless scheme. The machine is started from rest and assumed to follow a certain speed trajectory. The reference speed is assumed to be linear during the first half second until 1000 rpm is reached, and then kept constant for 1.5 second. At time t=2 sec., the reference speed is increased linearly again with the same initial slope to 1500 rpm, and then kept constant during the remaining simulation time. A load torque of 4 N.m. is assumed to be applied initially on the machine and stepped to 6 N.m. at t=3.5 second. Also, the stator resistance is detuned to 120 % of nominal value. It is clear that the estimated speed tracks well the trajectory of reference one with good accuracy over the whole speed range except at starting. This is due to the imperfect estimation of the Kalman filter during the transient state where all the signals are distorted. Moreover, the high state feedback gains amplify the distortion of the estimated signals at starting. In addition, the assumption of zero initial rotor position is another source of error.

On the other hand, a speed dip is noticed at the instant of step increase in load torque, but it is successfully rejected within 0.15 sec.
Also, the following remarks can be concluded from the figure :
a) The unknown load torque is estimated fastly and accurately.
b) The d-axis current is well decoupled from the motor speed, and is regulated quite well to be zero.
c) The rotor position angle estimation is not affected by the parameter uncertainties, and a stable machine drive can be obtained.
d) The sinusoidal variation of the 3-phase stator currents responds quickly to the change in load.

However, it seems in figure (2) that there is a difference between the actual and estimated rotor position which adversely affects the decoupling between the d- and q- axes. This is may be attributed to the following reasons:

a) The Kalman filter model, and the optimal state feedback gains are determined on the basis of the linearised model of the motor.
b) Zero initial rotor position is assumed.

In order to reduce the discrepancy between the actual and estimated rotor position, a precise modeling of the system is required. Also, a good choice of the covariance matrices will improve the filter performance. In addition, the knowing of the initial rotor position would decrease the error to a large extent.

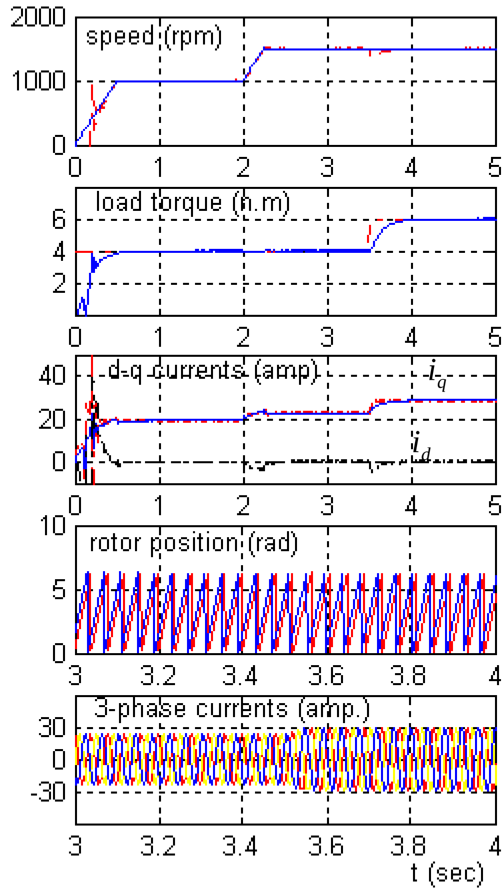
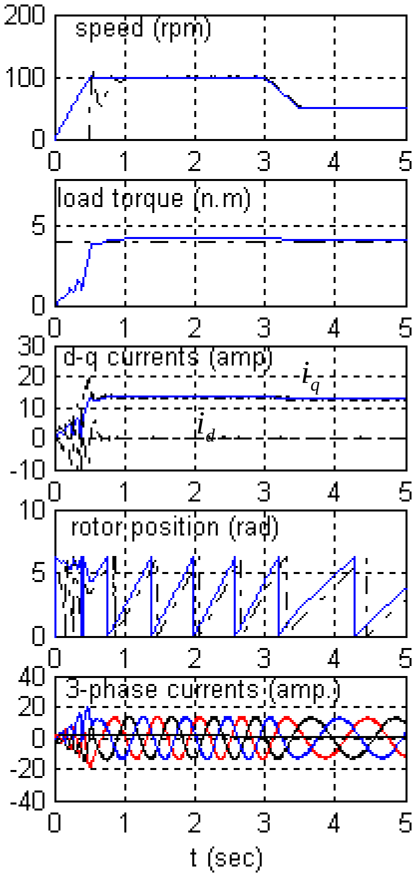


Fig. (2) Simulation waveforms of the proposed scheme at high speeds with stator resistance detuned to 120% of nominal value
(... actual - estimated)

The robustness of the proposed sensorless scheme has been tested at low speeds and mismatched parameters. Figure (3) shows the simulation waveforms when the speed is reduced linearly from 100 to 50 rpm (about 3.3% of its nominal). The load torque is assumed to be constant at 4 N.m. during the simulation period. Moreover, the stator resistance, moment of inertia, and friction coefficient are all detuned to 200% of their nominal values, while the stator inductance is detuned to 50% only. It is clear that good tracking capability and fast responses have been achieved in spite of the mismatched parameters. However, the difference between the actual and estimated rotor position, which has been noticed in the figure, is for the same reasons discussed above.



6. CONCLUSIONS

This paper presents the application of a high dynamic optimal regulator to control the speed and torque of the permanent magnet synchronous motor drive system without a speed sensor. The concept of the field orientation has been applied in order to linearise the nonlinear model of the motor. The standard Kalman filter technique has been employed to estimate the speed, position, and load torque by measuring only the stator current. The computational burden has been minimized to a great extent by computing the optimal state feedback gains and the Kalman state space model off-line. The proposed controller has the advantages of robustness, easy implementation and good performance in the face of uncertainties. Moreover, the load disturbance can be rejected without affecting the overall performance.

Computer simulations have been carried out in order to evaluate the effectiveness of the proposed controller. The results prove that accurate tracking performance of the PMSM has been achieved at low speeds as well as high speeds. Moreover, this scheme is robust against the parameters variation and eliminates the influence of modeling and measurement noises.

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