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Torque Ripple Minimization of Permanent Magnet Synchronous Motor Using Iterative Learning Control

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Abstract

Permanent Magnet Synchronous Motor (PMSM) produces the large torque ripples. It leads the system to be non-linear. Due to the presence of the airgap flux harmonics, undesirable torque pulsations occur in the motor. In this paper, Iterative Learning Control (ILC) algorithm is implemented in order to reduce the ripples that occur in the system. Iterative Learning Control is an adaptive control method which is used to reduce the ripples by repetitive learning. Most commonly used ILC schemes such as Proportional type ILC (P-ILC) and Model Predictive Control ILC (MPC-ILC) have the lower Torque Ripple Factor (TRF) and convergence. These not only reduces the torque ripples but also speed up the response of the system. The proposed algorithms are test over the permanent magnet synchronous motor and results are obtained.

Keywords: Permanent magnet synchronous motor; Torque ripple; Iterative learning control; Proportional type controller; Model predictive control

Introduction

Permanent Magnet Synchronous Motor (PMSM) is widely used in many applications such as actuators, machine tools, robotics, aerospace and large telescope. It is considered in high power applications such as vehicular propulsion and industrial drives. Even though PMSM has many advantages, some of the disadvantages may also occur in it. One of the main issues that remain in permanent magnet motor is the presence of oscillations of torque. These oscillations reflect throughout the system which is in the form of ripples. The ripples which occurs in torque is commonly known as “torque ripple”. Due to the non-uniformity of the torque distribution, the deviations in speed and efficiency are occurred. Apart from the speed oscillations, it also produces noise in the mechanical part of the motor due to the trigger of resonance. It is the effect which occurs in much electric motor design. It refers to the periodic increase or decrease in output torque as the motor shaft rotates. The torque ripple factor is expressed in the percentage. It can be measured by the difference of maximum and minimum torque over one complete revolution.

It occurs due the flux harmonics, current offsets, cogging torque and torque cogging. In order to minimize torque ripples, different methods can be proposed. Developing the coherent and general theoretical approach to the algorithm design for Iterative Learning Control. It is based on the quadratic optimization and the use of operator representations [1]. The study regarding the maintenance and fault diagnosis in Permanent Magnet Synchronous Motor has been proposed [2]. Different adaptive control method has been proposed to reduce the torque ripple occurs in permanent magnet synchronous motor by Fei Q et al. [3], Toloue SF et al. [4] and improve the fast response and strong robustness. The finite-time control algorithm is designed and implemented in order to improve the dynamical performance of the PMSM and disturbance rejection ability [5]. Speed tracking performance in the transient and steady state of PMSM is proposed [6]. A voltage feed-forward compensation method based on an ILC is proposed and the harmonics of estimated back EMFs and position estimation error gets eliminated and also improves the performance of sensor less control [7]. The P-type ILC is proposed to control Distributed Parameter System with non-collocated sensor-actuated networks [8]. This approach can be used only for the torque ripple components which are observable from the electrical subsystem but the ripples caused due to the mechanical part such as cogging torque, flux harmonics, DC offset and load oscillations cannot be controlled or observed [9]. Robust iterative learning control is proposed to improve the performance of the system [10, 11]. The torque and current ripples of surface-mounted permanent magnet synchronous motor can be reduced by the concept of duty cycle and only one voltage vector can be used instead of applying two vectors as in conventional Model Predictive Current Control during the transient period [12]. The torque ripple produced by the stator slot harmonics and it is reduced through some feed-forward compensation signals which are calculated using three different hybrid methods [13].

The outline of this paper is as follows. In section II mathematical model of PMSM is explained. Section III describes the design process of the Proportional type controller combined with ILC and the MPC combined with ILC. In section IV simulation results are illustrated. Section V gives the conclusion of this paper.

Mathematical Model of PMSM

In order to minimize the torque ripples of PMSM, various methods have been proposed. The most common method of controlling the PMSM is by Field Oriented Control (FOC). This section covers the dynamic modeling of the PMSM.

The dynamic modeling can be obtained based on some assumptions:

1. The permanent magnet motor is unsaturated.

2. The torque produced in the rotor is proportional to the phase currents.

3. Eddy currents and hysteresis losses are negligible.

4. Back EMF is proportional to the angular velocity and it is independent of current.

By these assumptions, the equation of the motor is as follows:

$$\frac{d\theta_e}{dt} = \omega_e \qquad (1)$$

$$\frac{d\omega_m}{dt} = \frac{1}{J}(T - T_L - b\omega_m) \qquad (2)$$

$$v_s = R_s i_s + L_S \frac{di_s}{dt} - \lambda_S \omega_e \qquad (3)$$

Where θe is the electrical angular position of the rotor, ωe and ωm are the electrical and mechanical angular velocity of the rotor respectively, J is the mass moment of inertia, T and TL are the output torque and load torque respectively, vs is the stator voltage, Ls is the stator inductance, is is the stator current, Rs is the stator resistance and λS is the flux linkage due to the permanent magnets.

The equation for the electromagnetic torque for the three-phase system is,

$$T_{em} = \lambda_s \,.\, i_s \qquad (4)$$

Where, Tem is the dot product of the flux linkage and the stator current.

Some of the methods require electrical position and the angular velocity for the calculations. There will be some electrical revolution for each pair of poles of the motor. So that,

$$\theta_e = p\theta_m \qquad (5)$$

$$\omega_e = p\omega_m \qquad (6)$$

Where, p is the number of poles and θm is the rotor mechanical angular position.

Therefore, the output torque T is,

$$T = T_{em} - T_L \qquad (7)$$

PMSM has two transformations namely, clarke transformation and park transformation. If the magnitude of the flux is constant, then the torque is proportional to the armature current. By regulating the armature current, the motor can control the torque. The space orientation of the flux and the armature current is called d-axis and the q-axis respectively. Since the armature current of the PMSM is three-phase sinusoidal, it is necessary to transfer these currents into the rotating q-axis constant current.

So that, the park transformation is able to transfer the variables from a-b-c reference frame to d-q-0 reference frame. Then the transformation can be written as shown in Table 1,

$$P = \frac{2}{3}\begin{bmatrix} \cos(\theta) & \cos\left(\theta - \frac{2\pi}{3}\right) & \cos\left(\theta + \frac{2\pi}{3}\right) \\ \sin(\theta) & \sin\left(\theta - \frac{2\pi}{3}\right) & \sin\left(\theta + \frac{2\pi}{3}\right) \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{bmatrix} \qquad (8)$$

Due to this transformation, the equation 3 can be written in the rotor reference frame,

$$v_d = R_s i_d + L_d \frac{di_d}{dt} - \lambda_q \omega_e \qquad (9)$$

$$v_q = R_s i_q + L_q \frac{di_q}{dt} - \lambda_d \omega_e \qquad (10)$$

The relationship between the inductance with the flux linkages is,

$$T_{em} = \frac{3}{2} p\left(\lambda_d i_q - \lambda_q i_d\right) \qquad (13)$$

$$T_{em} = \frac{3}{2} p\left((L_d i_d + \lambda_m) i_q - L_q i_q i_d\right) \qquad (14)$$

$$T_{em} = \frac{3}{2} p\left[\lambda_m i_q + \left(L_d - L_q\right) i_d i_q\right] \qquad (15)$$

Symbol	Description	Value
P	Rated power	5 kW
T	Rated torque	1606 Nm
J	Inertia	3.4 kgm2
Kt	Torque constant	142.2 Nm/A
R	Armature resistance	2.44 Ω
L	Armature inductance	36.05 mH
P	Number of pole pairs	65

Table 1: Specifications of PMSM.

Design of Proposed Controller

ILC is a model-free control method which is based on memory. Therefore, it is considered as the memory-based control method. It can cause error signal tends to zero in a limited time through the continuous learning of periodic error signal. This approach is used to improve tracking performance of a system that repeats its operation over a fixed time interval. It is a memory-based control which stores the previous control effort and error in it and computes the new control effort based on the previous information. It is basically the error correction algorithm. The principle of ILC is a feed forward control which updates through the control signals and iterative learning at every repeated operation. Some of the standard assumptions or that the system should be stable dynamics. It returns to the same initial condition at the start of each trial, then the trail last for a fixed time. All these trails have the same length. As the number of hydrations increase, the system tracking error over the entire time period which includes the transient portion will get decrease and it may vanish.

ILC schemes have some of the following assumptions:

1. Each iteration has the fixed solution.

2. Throughout the process, the invariance of the system dynamics is maintained.

3. For each iteration, the system always starts with the same initial condition.

4. The dynamics of the system are deterministic.

5. The output can also be measured in a deterministic way.

The learning controller calculates the error between the actual output and the desired output and computes the new cycle which is stored in the memory for future use in the next cycle of operation.

The dynamic system for the ILC is,

$$\bar{x} = ax(t) + bu(t) + \eta(t) \tag{16}$$

$$y(t) = cx(t) + \xi(t) \tag{17}$$

where a and b are continuous in t for all, t belongs to (0, T), T is the time period of the desired output, c is the differentiable in x and t, η(t) is unstructured uncertainties due to the state perturbations and ξ(t) is the random output measurement noises. For the convergence of the ILC system, K is taken as the learning gain, the following criterion must hold.

$$\|1 - cbK\| < 1 \tag{18}$$

Since an angle-based iterative learning control is proposed, angular position information is required. According to this information, the torque ripple is compensated in order to improve the performance of the motor from the periodic disturbances.

The control algorithm is given as,

$$\hat{F}_{i+1}(\theta_{m,k}) = (1-\alpha)\hat{F}_i(\theta_{m,k}) + \Phi e_i(\theta_{m,k}) + \Gamma e_{i+1}(\theta_{m,k}) \tag{19}$$

Where, α is forgetting factor, Φ is the error feedback gain of previous cycle, Γ is the error feedback of current cycle, θm,k is the angle value at time k as shown in Figure 1.

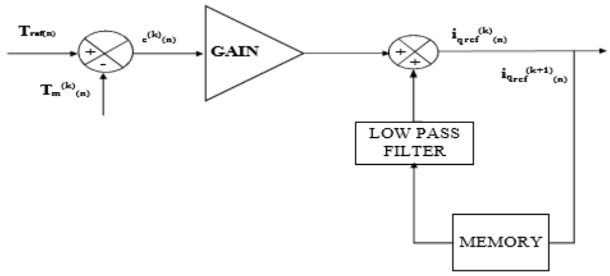

Figure 1: System configuration of ILC.

Design of P type ILC

It uses only the error signal with a proportional gain to potentially avoid amplifying small noise signal. It occurs through the differentiation and makes destabilizing the control system. The calculations of derivative enable great simplicity and ease of implementation. The law is given by,

$$u_{k+1}(t) = u_k(t) + Ke_k(t) \tag{20}$$

Where K is the proportional learning gain

Using PCF algorithm for the proportional-type ILC, the learning law is,

$$i_{qref}^{(k+1)}(n) = i_{qref}^{(k)}(n) + \beta_1 e^{(k)}(n) \tag{21}$$

Where the tracking error of the previous cycle is given as,

$$e^{(k)}(n) = T_{ref}(n) - T_m^{(k)}(n) \tag{22}$$

Where k is the kth repetitive operation of the system, n is the discrete time index and it belongs to (0, N), where N is the number of sampling intervals over one complete period of time taken by torque ripple, β1 is the controller gain.

From the torque-current relationship,

$$T_m(t) = K_t i_{ref_{(t)}} \tag{23}$$

Where Kt is the torque constant.

$$k_t = \frac{3}{2}\frac{p}{2}\lambda_{dm^{i}q}(t) \tag{24}$$

According to (18), the condition for the convergence can be obtained as,

$$\left\|1 - \frac{K_t}{J}\Phi\right\| < 1 \tag{25}$$

These inequality can be satisfied by the error feedback gain of previous cycle Φ, so that iterative learning control can achieve the stability and convergence of the system as shown in Table 2.

Symbol	Description	Value
K	Learning gain	0.95
A	Forgetting factor	0.1
Γ	Error feedback gain of current cycle	0.01
N	Number of iterations	10
Kp	P-type tuning	0.5

Table 2: Specifications of iterative learning control.

Design of MPC-ILC

The main goal of Model Predictive Control (MPC) in PMSM is to ensure the speed follows the reference speed accurately. MPC requires the discrete model of PMSM. It can be obtained by using the Euler's discretion method. Here, model predictive control can be used in parallel with the iterative learning control in order to obtain the better response.

The general torque equation of PMSM by considering the periodic disturbances can be written as,

$$J\frac{d\omega}{dt} = k_t i_q - B\omega + f(\omega, t) \qquad (26)$$

Where f(ω,t) is the unknown periodic function resulting from the torque ripple. This discrete mechanical equation can be obtained as,

$$\omega(k+1) = \left(1 - \frac{BT_s}{J}\right)\omega(k) + \frac{K_t T_s}{J} i_q(k) + \frac{T_s}{J} f(\omega, k) \qquad (27)$$

The above equation can be obtained by defining state variable as,

$$x(k) = \omega(k),\ \ u(k) = i_q(t) \qquad (28)$$

Therefore, equation (27) can be written as,

$$x(k+1) = A_m x(k) + B_m u(k) + C_m f(x, k) \qquad (29)$$

Where,

$$A_m = \left(1 - \frac{BT_s}{J}\right), B_m = \frac{K_t T_s}{J} \ and\ C_m = \frac{T_s}{J}$$

To design the prediction control system, it is necessary to calculate the output of the predicted plant by using the future control signals as the adjustable variable.

$$\begin{aligned} x(k+N_p|k) &= A_m x + B_m u + C_m(x, k+N_p-1) \\ &= A_m^{N_p} x(k) + A_m^{N_p-1} B_m u(k) + \cdots + \left(A_m^{N_p-N_c} B_m + \cdots + B_m\right) u(k+N_c-1) + A_m^{N_p-1} C_m f(\omega, k) + \cdots + C_m f(\omega, k+N_p) \end{aligned} \qquad (30)$$

Where Np is the prediction horizon and Nc is the control horizons.

Control horizon should always be less than the prediction horizons. The term x(k+Np|k) is the Npth step of the predicted state variable at the kth moment. The predicted state variable in the matrix form can be expressed as,

$$X = Gx(k) + KU + \varepsilon F \qquad (31)$$

Where

$$G = \begin{bmatrix} A_m \\ A_m^2 \\ A_m^3 \\ \vdots \\ A_m^{N_p} \end{bmatrix}$$

…

$$\varepsilon = \begin{bmatrix} A_m^{N_p-1} C_m \\ A_m^{N_p-2} C_m \\ A_m^{N_p-3} C_m \\ \vdots \\ C_m \end{bmatrix}$$

$$K = \begin{bmatrix} A_m & \cdots & 0 \\ \vdots & \ddots & \vdots \\ A_m^{N_c-1} B_m & 0 & B_m \\ A_m^{N_p-1} B_m & \cdots & \sum_{i=0}^{N_p-N_c} A_m^i B_m \end{bmatrix}$$

The control of speed-loop MPC has the objective to find the optimal control input U which minimizes the cost function and it is represented as,

$$J = \|W - X\|_Q^2 + \|U\|_R^2 \qquad (32)$$

Where, Q is the approximate dimensions of the output and R are the control weighing matrices. By using all the above equations, the performance and the cost index can be reduced and obtain the control algorithm for the convergence of the ILC system.

The ripples can be calculated by,

$$TRF = \frac{T_{r,rms}}{T_{avg}} * 100\% \qquad (33)$$

It is to determine how effective the various control methods are used to reduce the torque ripple. It is expressed in percentage.

Simulations Results and Discussion

The proposed controllers is applied to permanent magnet synchronous motor and simulated by using MATLAB platform. The gain of the proportional value can be chosen based on the trial and error method.

Therefore, five different values have been taken from 0.2 to 0.6.

Figure 2 shows the torque ripple factor at different Kp values. It is considered for different proportional gain values.

It is inferred that Kp=0.4 gives the better minimizing of torque ripples. When Kp increases, the Torque Ripple Factor (TRF) decreases. This shows that the convergence is also less when gain increases.

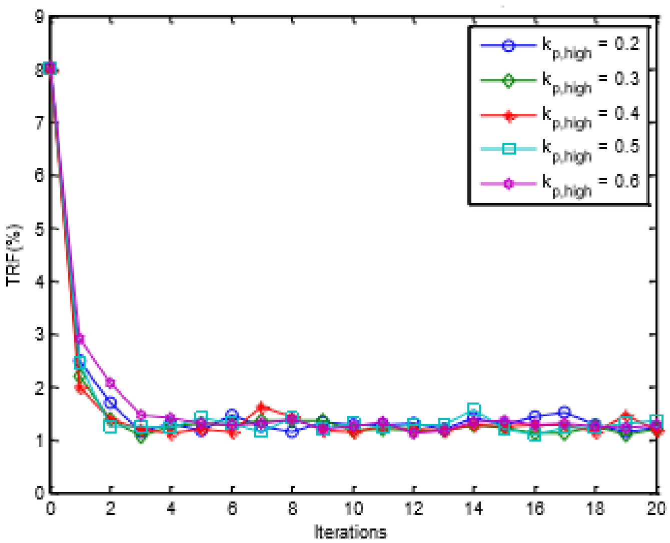

Figure 2: Torque ripple factor at different Kp values.

Figure 3 shows Torque ripple factor at different forgetting factors for Kp= 0.4. It is clear that the forgetting factor Kp=0.4 is taken as the constant value since it gives the better value for reducing the TRF.

In order to improve the performance further, different forgetting factor α is used. Here, the lowest value of α gives the better results. But still, the torque ripples are further minimized by the method MPC-ILC.

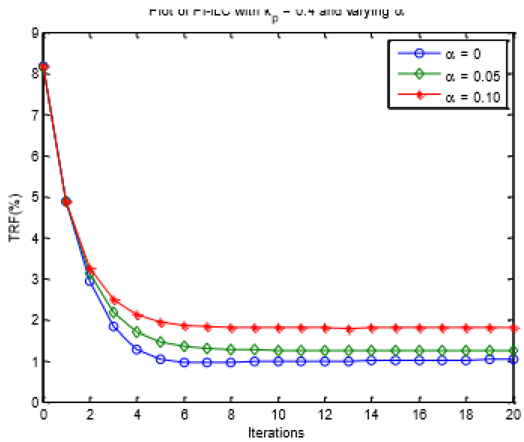

Figure 3: Torque ripple factor at different forgetting factors for Kp= 0.4

Figure 4 shows Torque ripple factor at different values of forgetting factor for Np=5 and Nc=1. It is clear that, in MPC type ILC, the iterative learning control is used in parallel with the model predictive control. By combining both the iterative control, the periodic pulsation is well suppressed. To suppress the high frequency noise, some of the low-pass filter is used. As number of iterations is increased, the torque ripple gets minimized.

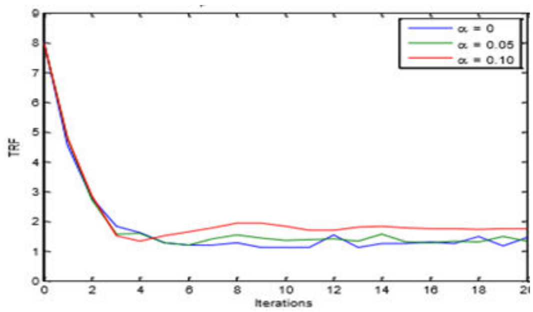

Figure 4: Torque ripple factor at different values of forgetting factor for Np =5 and Nc=1.

Conclusions

The proposed algorithm Iterative learning control gives the better performance of the PMSM drive system. It is also used to minimize the torque ripple of the system. The proposed control scheme suppresses the periodic velocity pulsation. It also increases the speed response time. The ratio of the peak to peak torque to the average torque gives the ripple minimization. Here, the ILC is combined with P-type and model prediction control that is P-ILC and MPC-ILC. Both the proposed methods are compared. MPC-ILC gives better performance when compared with the P-ILC. When the forgetting factor decreases, then the Torque Ripple Factor (TRF) also decreases. The convergence also gets reduced in MPC-ILC due to the less torque ripple. The torque ripples are minimized and the response time of the speed is improved in MPC-ILC method.

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