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MODEL PREDICTIVE CONTROL OF A PERMANENT MAGNET LINEAR SYNCHRONOUS MOTOR

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Abstract

Linear motors have many advantages compared to rotary motors due to directly creating linear motion without gears or belts. The difficulties of designing the controller are that we need the tracking of position and velocity and to guarantee that the voltage control and its variation are small enough. Model predictive control (MPC) is an advanced method of control that needs the corresponding predictive model. This work proposes the model predictive control with the constraints of voltage control and its variation. The numerical simulation validates the performance of the proposed controller.

Keywords: MPC, Linear Motor, PMLSM.

1. INTRODUCTION

In recent years, control for Linear motor has been the focus of active research. Many nonlinear control laws have been applied for linear motors, such as the adaptive fuzzy-neural network method in [1]. The rotor-position-tracking proportional-integral (PI) controller is used to estimate rotor velocity to control the position error converge to zero [2]. In [3] presented the adaptive backstepping control law for linear induction motor in the presence of friction dynamic effects. Process control has widely adopted predictive model control (MPC) to address optimization problems. A nonlinear model predictive control (NMPC) strategy requires formulating an optimization problem. In linear models, the MPC problem is typically a quadratic or linear program, and there is a variety of numerical methods and software [4]. In [5], the control design used a linearized state-space represented for the nonlinear dynamic model that describes the dynamics and a quadratic programming (QP) procedure to solve the resulting online optimization problem. However, the numerical complexity of linear MPC may be a good challenge, and it is limited in its industry, such as motor control. We propose the control law based on combining multi-parametric programming is described as the offline MPC solution is approached by employing the principles of multi-parametric nonlinear programming and in particular optimality conditions [5]. In this paper, the authors use the model based on cascade structure. The current loop (inner loop) is designed on the dynamic coordinate dq.

2. CONTROL DESIGN

We consider the modeling of the linear motor as in [6-9]:

$$\begin{cases} \dfrac{di_{sd}}{dt} = -\dfrac{R_s}{L_{sd}} i_{sd} + \left(\dfrac{2\pi}{\tau} v\right) \dfrac{L_{sq}}{L_{sd}} i_{sq} + \dfrac{U_{sd}}{L_{sd}} \\ \dfrac{di_{sq}}{dt} = -\dfrac{R_s}{L_{sq}} i_{sq} - \left(\dfrac{2\pi}{\tau} v\right) \dfrac{L_{sd} i_{sd} + \psi_p}{L_{sq}} + \dfrac{U_{sq}}{L_{sq}} \\ F = \dfrac{3\pi}{p\tau} \left[\psi_p i_{sq} + (L_{sd} - L_{sq}) i_{sd} i_{sq} \right] \\ \dfrac{dv}{dt} = \dfrac{p}{m} \left(F - F_c \right) \\ \dfrac{dx}{dt} = v \end{cases} \tag{1}$$

In this study, multi-parametric programming is applied to control the current loop (inner loop).

2.1 Control design for the current loop

Consider the current loop model:

$$\begin{cases} \dfrac{di_{sd}}{dt} = -\dfrac{R_s}{L_{sd}} i_{sd} + \left(\dfrac{2\pi}{\tau} v\right)\dfrac{L_{sq}}{L_{sd}} i_{sq} + \dfrac{U_{sd}}{L_{sd}} \\ \dfrac{di_{sq}}{dt} = -\dfrac{R_s}{L_{sq}} i_{sq} - \left(\dfrac{2\pi}{\tau} v\right)\dfrac{L_{sd}}{L_{sq}} i_{sd} - \left(\dfrac{2\pi}{\tau} v\right)\dfrac{\psi_p}{L_{sq}} + \dfrac{U_{sq}}{L_{sq}} \end{cases} \quad (2)$$

Define the tracking error variables for the inner loop as: $e_{sd} = i_{sd} - i_{sd}^d$, $e_{sq} = i_{sq} - i_{sq}^d$.

By using the coordinate transformation (3), we obtain the exact linearized PMLSM is described in (4):

$$w = \begin{bmatrix} \dfrac{U_{sd}}{L_{sd}} \\ \dfrac{U_{sq}}{L_{sq}} \end{bmatrix} + \begin{bmatrix} \left(\dfrac{2\pi}{\tau} v\right)\dfrac{L_{sq}}{L_{sd}} i_{sq} - \dfrac{R_s}{L_{sd}} i^d{}_{sd} - \dfrac{di_{sd}^d}{dt} \\ -\left(\dfrac{2\pi}{\tau} v\right)\dfrac{L_{sd} i^d{}_{sd} + \psi_p}{L_{sq}} - \dfrac{R_s}{L_{sq}} i^d{}_{sq} - \dfrac{di_{sq}^d}{dt} \end{bmatrix} \quad (3)$$

$$\begin{bmatrix} \dfrac{de_{sd}}{dt} \\ \dfrac{de_{sq}}{dt} \end{bmatrix} = \begin{bmatrix} -\dfrac{R_s}{L_{sd}} & 0 \\ 0 & -\dfrac{R_s}{L_{sq}} \end{bmatrix} \begin{bmatrix} e_{sd} \\ e_{sq} \end{bmatrix} + w \quad (4)$$

Define:

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} e_{sd} \\ e_{sq} \end{bmatrix}, \; A_c = \begin{bmatrix} -\dfrac{R_s}{L_{sd}} & 0 \\ 0 & -\dfrac{R_s}{L_{sq}} \end{bmatrix}, \; B_c = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}.$$

we receive the model (4) in state-space as follows:

$$\frac{dx}{dt} = A_c x + B_c w. \quad (5)$$

For using the results of MPC, discretize above model, we obtain:

$$x(k+1) = Ax(k) + Bw(k) \quad (6)$$

where $A = e^{A_c T_s}$, $B = A_c^{-1}(A - I)B_c$ and T_s is the sample time.

The predictive model of (6) at k as follows:

$$\begin{cases} x(k+l+1 \mid k) = Ax(k+l \mid k) + Bw(k+l) \\ x(k \mid k) = x(k) \\ l = 0, \ldots N-1 \end{cases} \quad (7)$$

With N is the prediction horizon. The sake of designing an MPC controller is to optimize the under cost-function:

$$J = \sum_{j=1}^{N} x(k+j \mid k)^T Q x(k+j \mid k) + \sum_{j=0}^{N} w(k+j)^T R w(k+j) \quad (8)$$

$$\text{s.t. } \begin{cases} x(k+l+1 \mid k) = Ax(k+l \mid k) + Bw(k+l) \\ i_{s\min} \le i_s \le i_{s\max} \\ u_{\min} \le u \le u_{\max} \end{cases} \quad (9)$$

Where Q, $R > 0$.

We denote that

$$W = \begin{bmatrix} w(k)^T & w(k+1)^T & \cdots & w(k+N-1)^T \end{bmatrix}^T$$

and

$$X = \begin{bmatrix} x(k+1)^T & x(k+2)^T & \cdots & x(k+N)^T \end{bmatrix}^T.$$

From predictive model:

$$\begin{aligned} & x(k+1 \mid k) = Ax(k) + Bw(k) \\ & x(k+2 \mid k) = Ax(k+1) + Bw(k+1) \\ & \quad = A^2 x(k) + ABw(k) + Bw(k+1) \\ & \ldots \\ & x(k+N \mid k) = Ax(k+N-1 \mid k) + Bw(k+N-1) \\ & \quad = A^N x(k) + A^{N-1} Bw(k+N-1) \ldots + ABw(k+1) \\ & \quad + Bw(k). \end{aligned}$$

So that, we rewrite:

$$X = \hat{A}x(k) + \hat{B}W$$

Where:

$$\hat{A} = \begin{bmatrix} A \\ A^2 \\ A^3 \\ \vdots \\ A^N \end{bmatrix} \quad \hat{B} = \begin{bmatrix} B & 0 & 0 & 0 & 0 \\ AB & B & 0 & 0 & 0 \\ A^2 B & AB & B & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & 0 \\ A^{N-1}B & A^{N-2}B & \cdots & AB & B \end{bmatrix}.$$

And substituting into (8), we obtain:

$$J = \left(\frac{1}{2} W^T H W + x_0^T F W\right) \quad (10)$$

Rewrite the above conditions on the whole of the prediction horizon, one gets:

$$I_{s\min} - \underline{a} \le X \le I_{s\max} - \underline{a} \quad (11)$$

We see that $X = \hat{A}x_0 + \hat{B}W$, so (11) become:

$$I_{s\min} - \underline{a} - \hat{A}x_0 \le \hat{B}W \le I_{s\max} - \underline{a} - \hat{A}x_0$$

Consider the constrained conditions of voltages in (9):

$$u_{\min} \le u \le u_{\max}$$

With $w = \begin{bmatrix} \dfrac{U_{sd}}{L_{sd}} \\ \dfrac{U_{sq}}{L_{sq}} \end{bmatrix} + b$

where:

$$b=\begin{bmatrix} \left(\frac{2\pi}{\tau}v\right)\frac{L_{sq}}{L_{sd}}i_{sq}-\frac{R_s}{L_{sd}}i^d{}_{sd}-\frac{di_{sd}^d}{dt} \\ -\left(\frac{2\pi}{\tau}v\right)\frac{\psi_p}{L_{sq}}-\left(\frac{2\pi}{\tau}v\right)\frac{L_{sd}i^d{}_{sd}}{L_{sq}}-\frac{R_s}{L_{sq}}i^d{}_{sq}-\frac{di_{sq}^d}{dt}\end{bmatrix}$$

we refer to:

$$\begin{bmatrix}\frac{U_{sd\min}}{L_{sd}}\\ \frac{U_{sq\min}}{L_{sq}}\end{bmatrix}+b\le w\le\begin{bmatrix}\frac{U_{sd\max}}{L_{sd}}\\ \frac{U_{sq\max}}{L_{sq}}\end{bmatrix}+b$$

Rewrite it for the whole of the prediction horizon we obtain:

$$\bar{U}_{\min}+B\le W\le\bar{U}_{\max}+B \tag{12}$$

Where

$$B=\begin{bmatrix}0&1&0&1&\cdots&0&1\\1&0&1&0&\cdots&1&0\end{bmatrix}^T_{2\times 2N}b$$

and

$$\bar{U}=\begin{bmatrix}0&1&0&1&\cdots&0&1\\1&0&1&0&\cdots&1&0\end{bmatrix}^T_{2\times 2N}\begin{bmatrix}\frac{U_{sd}}{L_{sd}}\\ \frac{U_{sq}}{L_{sq}}\end{bmatrix}.$$

Summary, multi-parametric programming is used to solve:

$$\begin{aligned}W^*(\theta)&=\arg\min_W J(W,\theta)\\ &=\arg\min_W\left(\frac{1}{2}W^THW+x_0^TFW\right)\end{aligned}$$

Subject to:

$$GW\le\bar{W}+S\theta$$

The optimal control variable at *k:*

$$u^*(k)=\begin{bmatrix}L_{sd}&0\\0&L_{sq}\end{bmatrix}\left(w(k,\theta)-b\right)$$

2.2. Control design for the outer-loop

From (1), the control law for this subsystem is chosen:

$$\begin{cases}v_c=\dot{x}_r-k_1\left(x-x_r\right)\\ i_{sq}^r=\dfrac{\hat{F}_c+\frac{m}{p}\dot{v}_c-k_2\left(v-v_c\right)}{\frac{3\pi}{p\tau}\left[\psi_p+\left(L_{sd}-L_{sq}\right)i_{sd}\right]}\end{cases}$$

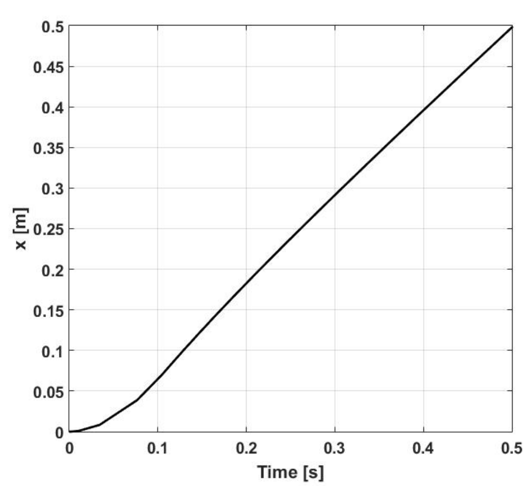
3. SIMULATION RESULTS

This section implements our simulation studies to verify the proposed control law. The parameters of PMLSM is given in the following table:

Parameter	***Value***
Number of Pole	2
Pole step	80 mm
Rotor mass	4.54kg
Phase coil Resistance	3.2 Ω
d-axis inductance	2.7 mH
q-axis inductance	2.74 mH
Flux	0.85Wb

Table 1. The parameters of PMLSM P01-48x210/690x840-C

Considering the desired trajectory of motors is expressed by: $x_d(t)=t$, we obtain the following efficient:



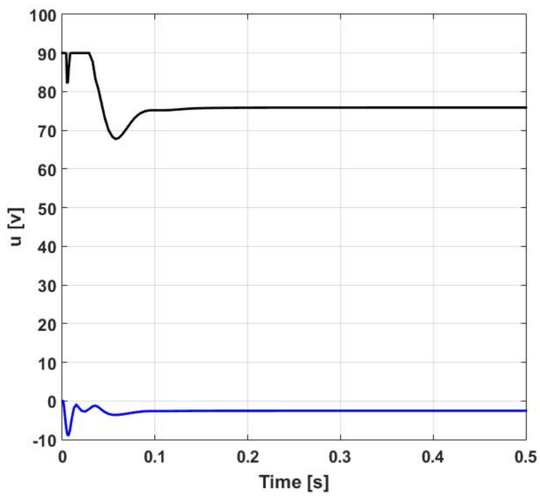


Figure 1. actual trajectory and control signal with constrainted MPC

Figure 1 describes responses of PMLSM in case of the desired trajectory is $x_d(t) = t$ and constraint conditions responses of the motor when the input voltage is limited by $u_{sq\max} = 90V$.

3. CONCLUSIONS

In this study, the MPC controller is designed for the linear motor with constraints on voltage inputs and state variables. The MPC controller is designed for the linear motor with voltage inputs and state variables constraints. The multi-parametric programming method is applied to solve the optimal offline problem. This work enables to development the application of MPC for motion control problems.

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