

Multi parametric model predictive control based on laguerre model for permanent magnet linear synchronous motors

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ABSTRACT

The permanent magnet linear motors are widely used in various industrial applications due to its advantages in comparisons with rotary motors such as mechanical durability and directly creating linear motions without gears or belts. The main difficulties of its control design are that the control performances include the tracking of position and velocity as well as guarantee limitations of the voltage control and its variation. In this work, a cascade control strategy including an inner and an outer loop is applied to synchronous linear motor. Particularly, an offline MPC controller based on MPP method and Laguerre model was proposed for inner loop and the outer controller was designed with the aid of nonlinear damping method. The numerical simulation was implemented to validate performance of the proposed controller under voltage input constraints.

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1. INTRODUCTION

The Permanent Magnet Linear Synchronous Motors (PMLSM) is extensively used in various industries due to the ability to directly create linear motion without gears or belts. Although the mediate mechanical actuators are eliminated, the system become weak robustness, in that external impact such as frictional force, end – effect, changed load and non-sine of flux cause damage to control performances. Generally, principle operation of synchronous linear motor is similar to permanent magnet synchronous motor; however their physical construction is different in [1]-[5], and various applications such as CNC Lathe [6], sliding door [7].

In recent years, there has been many researches for control problem of permanent magnet linear motor. An adaptive fuzzy neural network in [8] was proposed to control the permanent magnet linear synchronous motor. The authors in [9] presented a control design to regulate velocity based on PI – self tuning combining with appropriate estimation technique at slow velocity zone, but if load is changed, PI – self tuning controller will be not efficient. In order to overcome changed load, model reference control method based on Lyapunov stability theory employed in [10]. Additionally, the backstepping technique in [11], was applied to reduce influence of frictional force and controller is designed based on appropriate frictional estimated model. In [12], the advantage of that the sliding mode control applied in Linear Motor is that real position value tracks set point. However, the disadvantages of this method is that sliding surface is complicated and chattering problem occurred. It is clear that the previous researches do not mention position, velocity and current constraints. To solve this problem, the MPC approach in [13] was proposed as a single

controller for speed control. The authors in [14] built a new mathematic model and use optimal control approach to result in linear quadratic regulation (LQR). However, the considered model did not include disturbance load as well as friction force. In addition, the implementation of this MPC controller on a microcontroller is very difficult because of calculation burden.

In this paper, we apply cascade control strategy to synchronous linear motor including an inner and an outer loop. The offline MPC controller based on MPP method in [15] was proposed for inner loop to make motor current to follow the reference signal from the outer controller. We modify optimization problem in the MPC controller by using a Laguerre Model approach in [13] to reduce the number of optimal variables. The major advantage of our MPC controller lies in the ability to solve constraints problem and reducing amount of calculation because the optimal problem is offline solved. The outer controller was designed based on nonlinear damping method in [16] to guarantee the error between real and reference velocity converge to arbitrary small value.

2. PRIMARY RESULTS

2.1. Laguerre orthogonal polynomials

As represented in [13] Laguerre polynomials are defined as follows:

$$l_i(z) = \sqrt{(1-a^2)} \frac{(z^{-1}-a)^{i-1}}{(1-az^{-1})^i} \quad (1)$$

where a is a positive constant, $0 \leq a < 1$ and $i = 0, 1, \dots$. The application of Laguerre polynomials is mainly in the area of system identification, in which the discrete-time impulse response of a dynamic system is represented by a Laguerre model (see Wahlberg, 1991). In this work, based on Wang 2009, we obtain the main result: Suppose that the impulse response of a stable system is $H(k)$, then with a given number of terms N , $H(k)$ is written as:

$$H(k) = c_1 l_1(k) + c_2 l_2(k) + \dots + c_N l_N(k) \quad (2)$$

with c_1, c_2, \dots, c_N are the coefficients to be determined from the system data. The discrete-time Laguerre functions are orthonormal functions, and with these orthonormal properties, the coefficients of the Laguerre network are defined by the following relation:

$$c_i = \sum_{k=0}^{\infty} H(k) l_i(k), \quad \forall i \in \{0, 1, \dots, N\} \quad (3)$$

2.2. Model predictive control based on Laguerre function

In this section, we consider this discrete time linear system described by:

$$x_m(k+1) = A_m x_m(k) + B_m u(k) \quad (4)$$

In which, x_m is vector of state variable and $u(k)$ is the input at the time k .

Convert the Equation (4) as follows:

$$\Delta x_m(k+1) = A_m \Delta x_m(k) + B_m \Delta u(k) \quad (5)$$

Where: $\Delta x_m(k+1) = x_m(k+1) - x_m(k)$, $\Delta u(k) = u(k) - u(k-1)$

From (4), (5) and by letting $x(k+1) = [\Delta x_m(k+1) \quad x_m(k+1)]^T$, the Equation (5) becomes:

$$x(k+1) = Ax(k) + B\Delta u(k) \quad (6)$$

With: $A = \begin{bmatrix} A_m & \Theta_{n \times n} \\ A_m & I_{n \times n} \end{bmatrix}, \quad B = \begin{bmatrix} B_m \\ B_m \end{bmatrix}$

Predictive model of (6) at k_i as follows:

$$\begin{cases} x(k+i+1|k) = Ax(k+i|k) + B\Delta u(k+i|k) \\ i = 0, 1, \dots, N \\ x(k|k) = x(k) \end{cases} \tag{7}$$

N is prediction horizon. From (7), the sake of designing the MPC controller is finding the sequence of input signal $u(k)$ minimizing this under cost function:

$$J = \sum_{j=1}^{N_p} x(k+j|k)^T Qx(k+j|k) + \sum_{j=0}^{N_p} \Delta u(k+j)^T R\Delta u(k+j) \tag{8}$$

Where Q, R are positive definite matrices.

Denote that:

$$\begin{aligned} X &= [x(k+1|k)^T \quad x(k+2|k)^T \quad \dots \quad x(k+N|k)^T]^T \\ U &= [\Delta u(k|k)^T \quad \Delta u(k+1|k)^T \quad \dots \quad \Delta u(k+N-1|k)^T]^T \end{aligned} \tag{9}$$

Putting (7) into a form admitting variable (9) as;

$$X = \hat{A}x_0 + \hat{B}U \tag{10}$$

Where:

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

and $x_0 = x(k)$ is initial state of prediction horizon. Substituting (10) into the cost function (8):

$$J = \left(\frac{1}{2} U^T H U + x_0^T F U + x_0^T \hat{A}^T \hat{Q} \hat{A} x_0 \right) \tag{11}$$

Where:

$$H = 2(\hat{B}^T \hat{Q} \hat{B} + \hat{R}), \quad F = 2\hat{A}^T \hat{Q} B^T, \quad \hat{Q} = \begin{bmatrix} Q & \Theta & \Theta & \Theta \\ \Theta & Q & \Theta & \Theta \\ \vdots & \vdots & \ddots & \Theta \\ \Theta & \Theta & \Theta & P \end{bmatrix}, \quad \hat{R} = \begin{bmatrix} R & \Theta & \Theta & \Theta \\ \Theta & R & \Theta & \Theta \\ \vdots & \vdots & \ddots & \Theta \\ \Theta & \Theta & \Theta & R \end{bmatrix},$$

In this work, we regard the sequence of signals $\Delta u(k|k), \Delta u(k+1|k), \dots, \Delta u(k+N-1|k)$ can be approximated by the by a discrete Laguerre polynomial functions. In other words, a set of Laguerre functions $l_1(k), l_2(k), \dots, l_M(k)$ are used to capture the input $\Delta u_i(k+i|k)$ in prediction horizon:

$$\Delta u_i(k+i|k) = \sum_{j=1}^M c_j l_j(i) \quad (12)$$

Where c_j are the coefficients which depend only on the initial of prediction horizon. $l_j(i)$ are the orthogonal Laguerre functions having form as following:

$$\eta = \begin{bmatrix} c_1^1(k) & c_2^1(k) & \dots & c_M^1(k) \\ c_1^2(k) & c_2^2(k) & \dots & c_M^2(k) \\ \vdots & \vdots & \ddots & \vdots \\ c_1^n(k) & c_2^n(k) & \dots & c_M^n(k) \end{bmatrix}^T, \quad L = \begin{bmatrix} l_1(0) & l_2(0) & \dots & l_M(0) \\ l_1(1) & l_2(1) & \dots & l_M(1) \\ \vdots & \vdots & \ddots & \vdots \\ l_1(N-1) & l_2(N-1) & \dots & l_M(N-1) \end{bmatrix}^T$$

The equation (12) is rewritten to:

$$\Delta u(k_i+k) = L(k)^T \eta \quad (13)$$

Substituting (13) model (4), we can obtain:

$$x(k_i+j|k_i) = A^j x(k_i) + \sum_{i=0}^{j-1} A^{j-i-1} B \Delta u(k+i) = A^j x(k) + \sum_{i=0}^{j-1} A^{j-i-1} B L(i)^T \eta = A^j x(k) + \phi(j)^T \eta$$

$$\text{Where } \phi(j)^T = \sum_{i=0}^{j-1} A^{j-i-1} B L(i)^T$$

Substituting into the cost function we obtain:

$$\begin{aligned} J &= \sum_{j=1}^{N_p} \left(A^j x(k_i) + \phi(j)^T \eta \right)^T Q \left(A^j x(k_i) + \phi(j)^T \eta \right) + \sum_{j=0}^{N_p} \left(L(k_i+j)^T \eta \right)^T R \left(L(k_i+j)^T \eta \right) \\ &= \eta^T \left(\sum_{j=1}^{N_p} \phi(j) Q \phi(j)^T + \sum_{j=0}^{N_p} L(k_i+j) R L(k_i+j)^T \right) \eta + 2\eta \left(\sum_{j=1}^{N_p} \phi(j) Q A^j \right) x(k_i) + \sum_{j=1}^{N_p} x(k_i)^T (A^T)^m Q A^m x(k_i) \end{aligned}$$

$$\text{Let: } \Omega = \sum_{j=1}^{N_p} \phi(j) Q \phi(j)^T + \sum_{j=0}^{N_p} L(j) R L(j)^T; \quad \psi = \sum_{j=1}^{N_p} \phi(j) Q A^j$$

We set the optimization problem as:

$$\eta^* = \arg \min \left(\eta^T \Omega \eta + 2\eta^T \psi x(k_i) \right) \quad (14)$$

▪ *Unconstrained MPC controller*

In this case, (7) was considered without any constraints on inputs and state variables:

$$\frac{\partial J}{\partial \eta} = 2\eta^T \Omega + 2\psi x(k_i)$$

Which is equivalent:

$$\eta^* = -\Omega^{-1} \psi x(k_i) = - \left(\Omega = \sum_{j=1}^{N_p} \phi(j) Q \phi(j)^T + \sum_{j=0}^{N_p} L(j) R L(j)^T \right)^{-1} \sum_{j=1}^{N_p} \phi(j) Q A^j x(k_i)$$

So that, the optimal input signal at time k_i :

$$\Delta u(k_i) = L(0)^T \eta^*$$

▪ *Constrained MPC controller*

We suppose that (14) has constraints as follows:

$$\begin{aligned} u_{\min} &\leq u(k) \leq u_{\max} \\ x_{m\min} &\leq x_m(k) \leq x_{m\max} \end{aligned} \tag{15}$$

We consider prediction model (7) and constraints (15) at time k_i :

$$\begin{aligned} u_{\min} - u(k_i - 1) &\leq \Delta u(k_i | k_i) \leq u_{\max} - u(k_i - 1) \\ \begin{bmatrix} x_{m\min} - x_m(k_i) \\ x_{m\min} \end{bmatrix} &\leq x(k_i + 1 | k_i) \leq \begin{bmatrix} x_{m\max} - x_m(k_i) \\ x_{m\max} \end{bmatrix} \end{aligned} \tag{16}$$

(15), (16) deduce to:

$$\Delta U_{\min} \leq \Delta u(k_i) \leq \Delta U_{\max} \tag{17}$$

Furthermore, by using $\Delta u(k_i) = L(0)^T \eta$, rewriting (17):

$$M\eta \leq \gamma \tag{18}$$

Thus, the optimization problem (14):

$$\begin{aligned} \min J &= \min \eta^T \Omega \eta + 2\eta^T \psi x(k_i) \\ \text{s.t. } M\eta &\leq \gamma \end{aligned} \tag{19}$$

Since J is the quadratic function, optimal issue in (19) can be solved by Quadratic Programming (QP) to obtain the solution η^* , the control signal is calculated by:

$$\Delta u(k_i) = L(0)^T \eta^* \tag{20}$$

2.3. Multi parametric programming

In this section, we remind the results of multi parametric programming method (MPP) in [11]. The basic idea is that the space of parameter is separated into critical regions in that each critical regions, the solution of optimization problem is in the same form. Consider the quadratic cost function:

$$\begin{aligned} V^* &= \min_z \left(\frac{1}{2} z^T H z \right) \\ \text{s.t. } Gz &\leq W + S\theta \end{aligned} \tag{21}$$

with $z \in \mathbb{R}^s$ is the vector of optimization variables. $\theta \in \mathbb{R}^n$ is the vector of parameters, and the matrices: $H \in \mathbb{R}^{s \times s}$, $G \in \mathbb{R}^{q \times s}$, $W \in \mathbb{R}^q$, $S \in \mathbb{R}^{q \times n}$. Let D be a polytopic set of parameters. In multi parametric programming, we consider finding the solution of optimizing V on D . By using first order Karush-Kuhn-Tucker (KKT) optimality conditions we obtain:

$$Hz + G^T \lambda = 0, \lambda \in \mathbb{R}^q \tag{22}$$

$$\lambda_i (G^i z - W^i - S^i \theta) = 0, i = 1, 2, \dots, q \tag{23}$$

$$\lambda \geq 0 \quad (24)$$

where i is the row index. From (22) we have:

$$z = -H^{-1}G^T \lambda \quad (25)$$

Substituting into (23) we arrive at the conditions as follow:

$$\lambda_i (-G^i H^{-1} G^{iT} \lambda_i - W^i - S^i \theta) = 0, \quad i = 1, 2, \dots, q \quad (26)$$

Let $\tilde{\lambda}$ and $\tilde{\lambda}$ are the Lagrange multiples corresponding to the inactive constraints and active constraints respectively. With the inactive constraints we have $\tilde{\lambda} = 0$. With the active constraints we receive:

$$\tilde{\lambda} = -(\tilde{G}H^{-1}\tilde{G}^T)^{-1}(\tilde{W} + \tilde{S}\theta) \quad (27)$$

Where \tilde{G} , \tilde{W} , \tilde{S} are the matrices corresponding to the active constraints. There exist $(\tilde{G}H^{-1}\tilde{G}^T)^{-1}$ because the rows of \tilde{G} is linear independence. Substituting $\tilde{\lambda}$ from (24) into (21) we obtain:

$$z^*(x) = H^{-1}\tilde{G}^T(\tilde{G}H^{-1}\tilde{G}^T)^{-1}(\tilde{W} + \tilde{S}\theta) \quad (28)$$

And from (20), $\tilde{\lambda}$ in (24) must be satisfied:

$$\tilde{\lambda} = -(\tilde{G}H^{-1}\tilde{G}^T)^{-1}(\tilde{W} + \tilde{S}\theta) \geq 0 \quad (29)$$

The results (25) and (26) are the basic of multi parametric programming method in this case. Based on the above results, the main steps of the off-line mp-QP solver are outlined in the following algorithm [11]:

Step 1: Defining the current region be the whole space D of the vector of parameter θ .

Step 2: Choose vector θ_0 in the current region.

Step 3: With $\theta = \theta_0$, find the optimal solution (z_0, λ_0) by QP method.

Step 4: Define the active and inactive constraints in case of (z_0, λ_0) , and then build those matrices: $\tilde{G}, \tilde{W}, \tilde{S}$.

Step 5: Find $(\tilde{\lambda}, z^*)$ from (11) and (12).

Step 6: Characterize the CR_0 of x from (13) in which the optimal solution is in (12).

Step 7: Redefine the current region be the $D - CR_0$ and go to step 2.

Step 8: When all regions have been explored, exit.

3. MAIN RESULTS

3.1. MPC controller for current sub-system

As mentioned in [17], current loop model of permanent magnet linear synchronous motor is described by:

$$\begin{cases} \frac{di_{sd}}{dt} = -\frac{R_s}{L_{sd}}i_{sd} + \left(\frac{2\pi}{\tau}v\right)\frac{L_{sq}}{L_{sd}}i_{sq} + \frac{U_{sd}}{L_{sd}} \\ \frac{di_{sq}}{dt} = -\frac{R_s}{L_{sq}}i_{sq} - \left(\frac{2\pi}{\tau}v\right)\frac{L_{sd}}{L_{sq}}i_{sd} - \left(\frac{2\pi}{\tau}v\right)\frac{\psi_p}{L_{sq}} + \frac{U_{sq}}{L_{sq}} \end{cases} \quad (30)$$

Denote that i_{sd}^d, i_{sq}^d are desired outputs and $e_{sd} = i_{sd} - i_{sd}^d, e_{sq} = i_{sq} - i_{sq}^d$. Substituting into (30):

$$\begin{cases} \frac{de_{sd}}{dt} = -\frac{R_s}{L_{sd}} e_{sd} + \left(\frac{2\pi}{\tau} v\right) \frac{L_{sq}}{L_{sd}} e_{sq} + \frac{U_{sd}}{L_{sd}} - \left(-\frac{R_s}{L_{sd}} i_{sd}^d + \left(\frac{2\pi}{\tau} v\right) \frac{L_{sq}}{L_{sd}} i_{sq}^d\right) \\ \frac{de_{sq}}{dt} = -\frac{R_s}{L_{sq}} e_{sq} - \left(\frac{2\pi}{\tau} v\right) \frac{L_{sd}}{L_{sq}} e_{sd} + \frac{U_{sq}}{L_{sq}} - \left(\frac{R_s}{L_{sq}} i_{sq}^d - \left(\frac{2\pi}{\tau} v\right) \frac{L_{sd}}{L_{sq}} i_{sd}^d + \psi_p\right) \end{cases} \quad (31)$$

Define:

$$A_m(t) = \begin{bmatrix} -\frac{R_s}{L_{sd}} & \left(\frac{2\pi}{\tau} v(t)\right) \frac{L_{sq}}{L_{sd}} \\ -\frac{R_s}{L_{sq}} & -\left(\frac{2\pi}{\tau} v(t)\right) \frac{L_{sd}}{L_{sq}} \end{bmatrix}, B_m(t) = \begin{bmatrix} \frac{1}{L_{sd}} & 0 \\ 0 & \frac{1}{L_{sq}} \end{bmatrix}, u(t) = \begin{bmatrix} \frac{U_{sd}}{L_{sd}} - \left(-\frac{R_s}{L_{sd}} i_{sd}^d + \left(\frac{2\pi}{\tau} v(t)\right) \frac{L_{sq}}{L_{sd}} i_{sq}^d\right) \\ \frac{U_{sq}}{L_{sq}} - \left(\frac{R_s}{L_{sq}} i_{sq}^d - \left(\frac{2\pi}{\tau} v(t)\right) \frac{L_{sd}}{L_{sq}} i_{sd}^d + \psi_p\right) \end{bmatrix}$$

The current error model (31) is rewritten as:

$$\frac{dx}{dt} = A_m(t)x(t) + B_m u(t) \quad (32)$$

Obtaining discrete time model from (32) by using ZOH method:

$$x(k+1) = \hat{A}_m(k)x(k) + \hat{B}_m u(k) \quad (33)$$

Where: $\hat{A}_m(k) = e^{A_m T_s}$ and $\hat{B}_m = \int_0^{T_s} B_m dt = T_s B_m$

Then, we can apply MPC controller designed in 2.1 to current loop and the optimal control signal is presented in (20).

3.2. Control design for outer loop

Let us consider model of PMLSM proposed in [18]:

$$\begin{cases} \frac{dv}{dt} = \frac{p}{m}(F - F_c) \\ F = \frac{2\pi}{\tau_p} \left[\psi_p i_{sq} + (L_{sd} - L_{sq}) i_{sd} i_{sq} \right] \\ \frac{dx}{dt} = v \end{cases} \quad (34)$$

Without loss of generality, we choose desired current in d - axis on d - q coordinate: $i_{sd}^d = 0$.

By letting $x_1 = x - x_d, x_2 = v - \dot{x}_d$ with x_d is desired position, we obtain the model in state space as:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = au + d - \ddot{x}_d \end{cases} \quad (35)$$

where $a = \frac{2\pi}{\tau_p} \psi_p, u = i_{sq}$ and $d = -\frac{F_c}{m}$.

Lemma 1: As is presented in [7], by using controller (36) and disturbance observer (37), the state variables of system (35) converges to a ball centered at the origin.

$$u = \frac{1}{a} \left[-L_1 \tanh(x_2 + L_2 \tanh(x_1)) - \hat{d} + \ddot{x}_d \right] \quad (36)$$

$$\begin{cases} \hat{d}(t) = \xi + K_0 x_2 \\ \dot{\xi} = -K_0 \xi - K_0 (au - \ddot{x}_d + K_0 x_2) \end{cases} \quad (37)$$

Proof:

Let $\bar{u} = au - \ddot{x}_d$, we obtain:

$$\begin{cases} \dot{x}_1 = x_2 \\ \dot{x}_2 = \bar{u} + \tilde{d} + \xi + K_0 x_2 \\ \dot{\xi} = -K_0 \xi - K_0 (\bar{u} - K_0 x_2) \\ \hat{d}(t) = \xi + K_0 x_2 \end{cases} \quad (38)$$

where $\tilde{d} = d - \hat{d}$. Choose Lyapunov candidate function as follows:

$$V = \frac{1}{2} L_2^2 \tanh^2(x_1) + \frac{1}{2} [x_2 + L_2 \tanh(x_1)]^2 + \frac{1}{2} \tilde{d}^2 \quad (39)$$

Differentiating both side of (39) along solution of (38) with respect to t :

$$\begin{aligned} \dot{V} = & -L_2^3 \tanh^2(x_1) (1 - \tanh^2(x_1)) + [x_2 + L_2 \tanh(x_1)] (\bar{u} + \dot{d}) + \tilde{d} \dot{\tilde{d}} \\ & + L_2 (1 - \tanh^2(x_1)) [x_2 + L_2 \tanh(x_1)]^2 \end{aligned} \quad (40)$$

Substituting (36) into (40):

$$\begin{aligned} \dot{V} \leq & -L_2^3 \tanh^2(x_1) (1 - \tanh^2(x_1)) - L_1 [x_2 + L_2 \tanh(x_1)]^2 \\ & + k_1 [x_2 + L_2 \tanh(x_1)]^2 + \frac{\tilde{d}^2}{4k_1} + L_2 [x_2 + L_2 \tanh(x_1)]^2 + \tilde{d} \dot{\tilde{d}} \end{aligned} \quad (41)$$

From (38):

$$\dot{\tilde{d}} = \dot{\xi} + K_0 \dot{x}_2 = -K_0 \xi - K_0 (\bar{u} + K_0 x_2) + K_0 (\bar{u} + \tilde{d} + \xi + K_0 x_2) = K_0 \tilde{d}$$

Then, refer to:

$$\dot{\tilde{d}} = \dot{d} - K_0 \tilde{d} \quad (42)$$

Rewriting (42) with the aid of (41):

$$\dot{V} \leq -L_2^3 \tanh^2(x_1) (1 - \tanh^2(x_1)) + (-L_1 + L_2 + k_1) [x_2 + L_2 \tanh(x_1)]^2 + \left(\frac{1}{4k_1} - K_0 \right) \tilde{d}^2 + \tilde{d} \dot{d} \quad (43)$$

And using the relation: $\tilde{d}\dot{\tilde{d}} \leq k_2\tilde{d}^2 + \frac{\dot{\tilde{d}}^2}{4k_2}$, we finally get:

$$\dot{V} \leq -L_2^3 \tanh^2(x_1)(1 - \tanh^2(x_1)) + (-L_1 + L_2 + k_1)[x_2 + L_2 \tanh(x_1)]^2 + \left(\frac{1}{4k_1} - K_0 + k_2\right)\tilde{d}^2 + \frac{\dot{\tilde{d}}^2}{4k_2} \tag{44}$$

By selecting control parameter constant L_1, L_2, K_0 such that:

$$L_1 > L_2 + k_1, K_0 > k_2 + \frac{1}{4k_1}, k_1 > 0, k_2 > 0 \tag{45}$$

And assume that $|\dot{\tilde{d}}| < \infty$, since k_2 can be chosen arbitrarily large and from (59), Lemma 1 is proved.

4. RESULTS AND ANALYSIS

Base on the above conclusions, the simulation model of PMLSM and controller are constructed in Matlab environment. The parameters of PMLSM is given:

Parameter	Value
Number of Pole	2
Pole step	72mm
Rotor mass	3.5kg
Phase coil Resistance	3.1Ω
d-axis inductance	4.1mH
q- axis inductance	4.1mH
Flux	0.8Wb

Figure 1 and Figure 2 describe the responses of PMLSM in cases unconstrained and constrained MPC controller. In first case, Figure 1. display that actual trajectory's motor tracking designed trajectory very fast, but it requires the large started voltage. This is a reason to we must constraint the voltage input. Figure 2. shows responses of motor when the input voltage u_{sq} is limited by $u_{sq \max} = 90V$.

Considering the desired trajectory of motors is expressed by: $x^d(t) = t$, we obtain following efficients:

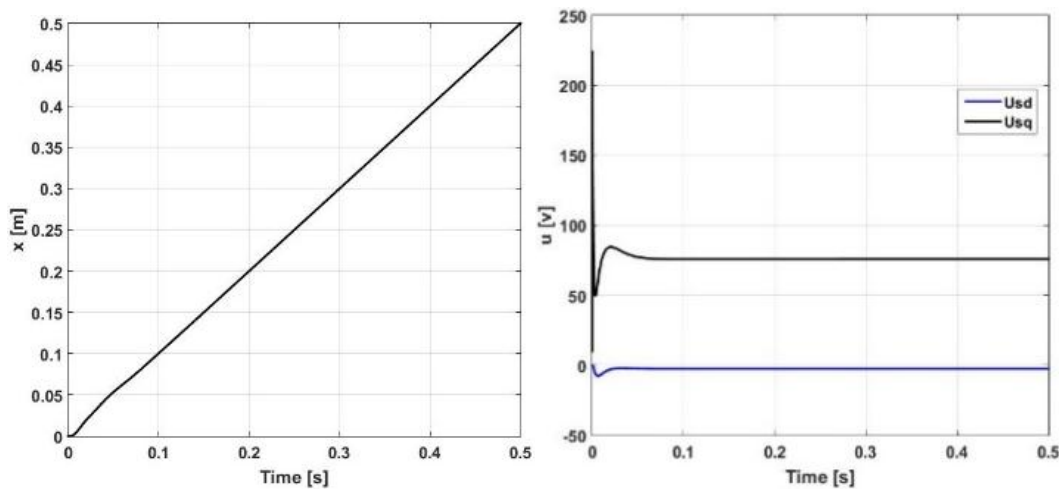


Figure 1. Actual trajectory and control signal with unconstrained MPC

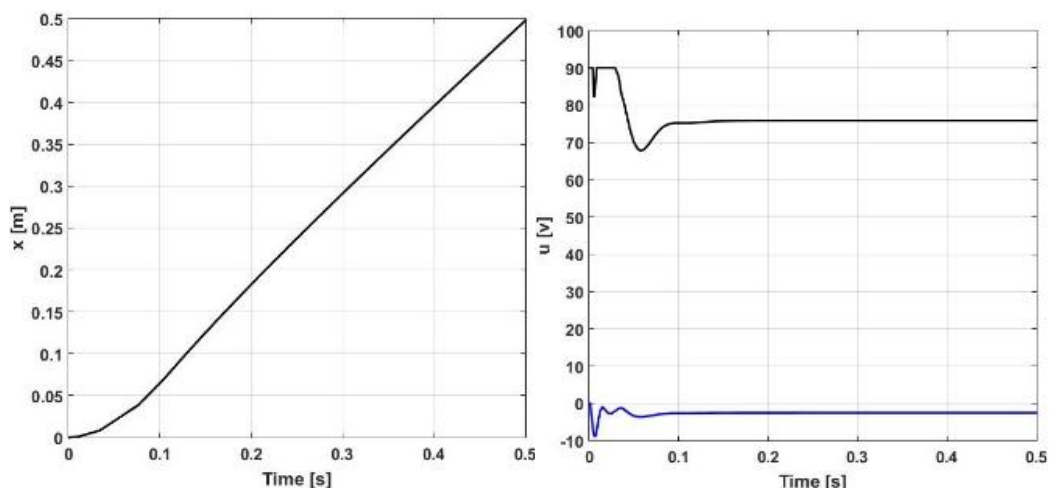


Figure 2. Actual trajectory and control signal with constrained MPC

5. CONCLUSION

In this work, we apply cascade control strategy for polysolenoid linear motor to separate the motor into outer and inner loop. The offline MPC controller based on MPP method was proposed for inner loop to make motor current to follow the reference signal from the outer controller. Optimization problem in the MPC controller was modified by using a Laguerre Model approach to reduce the number of optimal variables. The major advantage of our MPC controller lies in the ability to solve constraints problem and reducing amount of calculation because the optimal problem is offline solved. The outer controller was designed based on nonlinear damping method to guarantee the error between real and reference velocity converge to arbitrary small value.

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