



## 151-0310-00 Problem Set 4

Topic: Unconstrained Linear MPC

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In today's exercise you will implement an unconstrained linear model predictive controller for the engine air-path control task. For a given prediction horizon and control horizon, your task is to find the optimal control trajectory  $\Delta u(\cdot|k)^*$ , which minimizes the cost function

$$J(\Delta \boldsymbol{u}(\cdot|k)) = \|\boldsymbol{r}(\cdot|k) - \boldsymbol{y}(\cdot|k)\|_{\boldsymbol{Q}}^{2} + \|\Delta \boldsymbol{u}(\cdot|k)\|_{\boldsymbol{R}}^{2},$$

$$= (\boldsymbol{r}(\cdot|k) - \boldsymbol{y}(\cdot|k))^{T} \boldsymbol{Q}(\boldsymbol{r}(\cdot|k) - \boldsymbol{y}(\cdot|k)) + \Delta \boldsymbol{u}(\cdot|k)^{T} \boldsymbol{R} \Delta \boldsymbol{u}(\cdot|k). \quad (1)$$

As shown in the lecture, the optimal input rate trajectory  $\Delta u(k|k)^*$  for a linear model and an optimal control problem without constraints is

$$\Delta u(k|k)^* = K_{\text{MPC}} e(\cdot|k) . \tag{2}$$

In the following exercises, you will derive the constant control law  $K_{\text{MPC}}$  and all the matrices required to calculate the free control error  $e(\cdot|k)$ , implement them in Simulink, and use them to control the plant.

## Exercise 1 (System Response Trajectory Matrices)

In order to find the optimal input rate  $\Delta u(k|k)^*$  trajectory, we set the derivative of  $J(\Delta u(\cdot|k))$  to zero. Therefore, we have to calculate the system response trajectory  $y(\cdot|k)$  for a given prediction horizon and control horizon.

For a discrete-time linear system of the form

$$\boldsymbol{x}(k+1) = \boldsymbol{A} \boldsymbol{x}(k) + \boldsymbol{B} \boldsymbol{u}(k-1) + \boldsymbol{B} \boldsymbol{\Delta} \boldsymbol{u}(k|k) \qquad \boldsymbol{x} \in \mathbb{R}^n ; \qquad \boldsymbol{u} \in \mathbb{R}^l$$
 (3)

$$\mathbf{y}(k) = \mathbf{C} \mathbf{x}(k)$$
  $\mathbf{y} \in \mathbb{R}^m,$  (4)

the system response trajectory was derived in the lecture and is given by

$$\boldsymbol{y}(\cdot|k) = \boldsymbol{\Gamma} \boldsymbol{x}(\cdot|k) = \boldsymbol{\Gamma} \left( \boldsymbol{\Psi} \boldsymbol{x}(k) + \boldsymbol{\Upsilon} \boldsymbol{u}(k-1) + \boldsymbol{\Theta} \boldsymbol{\Delta} \boldsymbol{u}(\cdot|k) \right) \qquad \boldsymbol{y}(\cdot|k) \in \mathbb{R}^{m \cdot (N_2 - N_1 + 1) \times 1}.$$
 (5)

It depends on the initial conditions  $\boldsymbol{x}(k)$ , the initial input  $\boldsymbol{u}(k-1)$  and the input rate trajectory  $\Delta \boldsymbol{u}(\cdot|k)$ . The matrices  $\Gamma$ ,  $\Psi$ ,  $\Upsilon$ , and  $\Theta$  are defined as

$$\Gamma = \begin{bmatrix} C & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & C \end{bmatrix} \in \mathbb{R}^{m \cdot (N_2 - N_1 + 1) \times n \cdot (N_2 - N_1 + 1)}$$

$$(6)$$

$$\Psi = \begin{bmatrix} \mathbf{A}^{N_1} \\ \vdots \\ \mathbf{A}^{N_2} \end{bmatrix} \in \mathbb{R}^{n \cdot (N_2 - N_1 + 1) \times n}$$
(7)

$$\Upsilon = \begin{bmatrix}
\sum_{i=0}^{N_1-1} \mathbf{A}^i \mathbf{B} \\
\vdots \\
\sum_{i=0}^{N_2-1} \mathbf{A}^i \mathbf{B}
\end{bmatrix} \in \mathbb{R}^{n \cdot (N_2-N_1+1) \times l}$$
(8)

$$\boldsymbol{\Theta} = \begin{bmatrix}
\boldsymbol{\Lambda}(N_1) & \boldsymbol{\Lambda}(N_1-1) & \dots & \boldsymbol{\Lambda}(N_1-N_{\mathrm{u}}+1) \\
\boldsymbol{\Lambda}(N_1+1) & \boldsymbol{\Lambda}(N_1) & \dots & \boldsymbol{\Lambda}(N_1-N_{\mathrm{u}}+2) \\
\vdots & \vdots & \ddots & \vdots \\
\boldsymbol{\Lambda}(N_2) & \boldsymbol{\Lambda}(N_2-1) & \dots & \boldsymbol{\Lambda}(N_2-N_{\mathrm{u}}+1)
\end{bmatrix} \in \mathbb{R}^{n \cdot (N_2-N_1+1) \times l \cdot N_{\mathrm{u}}}$$

$$(9)$$

$$\boldsymbol{\Lambda}(i) = \begin{cases}
\sum_{j=0}^{i-1} \boldsymbol{A}^j \boldsymbol{B} & , i \ge 1 \\
\sum_{j=0}^{i-1} \boldsymbol{A}^j \boldsymbol{B} & , i \ge 1
\end{cases} \in \mathbb{R}^{n \times l}.$$

$$\mathbf{\Lambda}(i) = \begin{cases} \sum_{j=0}^{i-1} \mathbf{A}^j \mathbf{B} &, i \ge 1 \\ \mathbf{0} &, i < 1 \end{cases} \in \mathbb{R}^{n \times l}.$$

$$(10)$$

As a simplification, we introduce the horizon N, which defines both the prediction horizon and the control horizon. Neglect any influence of a system delay and set  $N_1 = 1$ . As a result use

$$N = N_2 - N_1 + 1 = N_2 = N_{\rm u} \,. \tag{11}$$

- Complete the provided function template **a**) [Gamma, Psi, Upsilon, Theta] = setupPredictionMatrices(A, B, C, N) to calculate the four matrices  $\Gamma$ ,  $\Psi$ ,  $\Upsilon$ , and  $\Theta$  for a generic discrete-time linear system with steate-space matrices A, B, and C and for a given horizon N. As a starting point, the implementation of  $\Gamma$  and  $\Psi$  are provided in the function template.
- b) Use the provided function [sysC, linearizationPt] = getLinearModel(u\_vtg, u\_egr) to derive a continuous-time linearized model of the ROM at  $[u_{\text{vtg}}; u_{\text{egr}}] = [0.5; 0.5]$ . Name the resulting linearized model sysC and the resulting operating point linearizationPt.
- **c**) Discretize the continuous-time model with a sampling time  $T_s = 0.05$  s in order to derive the discrete system sysD with state-space matrices A, B, and C. Use the Matlab function c2d() with the 'zoh' method.
- d) Use the derived discrete-time state-space matrices and a horizon N=50 to calculate the prediction matrices with the function from Exercise 1 a). Make sure the dimensions of your matrices are correct. Hint: For debugging, you can use generic, simple, low-dimensional state-space matrices and a small horizon, e.g., N = 3.

### Exercise 2 (MPC Control Law)

In this exercise, you derive the optimal control law  $K_{\rm MPC}$ . In order to calculate the optimal control rate trajectory  $\Delta u(k|k)^*$ , we insert Eq. (5) into Eq. (1), calculate its derivative with respect to  $\Delta u(k|k)$ , and set it to zero. Solving the resulting equation for  $\Delta u(k|k)$  gives the optimal control rate trajectory

$$\Delta u(\cdot|k)^* = (\Theta^T \Gamma^T Q \Gamma \Theta + R)^{-1} \Theta^T \Gamma^T Q e(\cdot|k) , \qquad (12)$$

$$e(\cdot|k) = r(\cdot|k) - \Gamma(\Psi x(k) + \Upsilon u(k-1)).$$
(13)

The free control error trajectory  $e(\cdot|k)$  represents the predicted control error for  $\Delta u(\cdot|k) = 0$ . The extended error weighting matrix Q and the extended control weighting matrix R are defined

$$Q = \begin{bmatrix} Q_{N_1} & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & Q_{N_2} \end{bmatrix} \in \mathbb{R}^{m \cdot (N_2 - N_1 + 1) \times m \cdot (N_2 - N_1 + 1)}$$

$$R = \begin{bmatrix} R_0 & \mathbf{0} \\ & \ddots & \\ \mathbf{0} & R_{N-1} \end{bmatrix} \in \mathbb{R}^{l \cdot N_{\mathrm{u}} \times l \cdot N_{\mathrm{u}}}.$$

$$(14)$$

$$\mathbf{R} = \begin{bmatrix} \mathbf{R}_0 & \mathbf{0} \\ & \ddots \\ \mathbf{0} & \mathbf{R}_{N_{\mathrm{u}}-1} \end{bmatrix} \in \mathbb{R}^{l \cdot N_{\mathrm{u}} \times l \cdot N_{\mathrm{u}}}.$$
 (15)

For the controller, we only need the first value of the optimal control rate trajectory. By comparing Eqs. (2) and (12) we get

$$\boldsymbol{K}_{\text{MPC}} = [\boldsymbol{I} \ \boldsymbol{0} \ \dots \boldsymbol{0}] \left(\boldsymbol{\Theta}^T \boldsymbol{\Gamma}^T \boldsymbol{Q} \boldsymbol{\Gamma} \boldsymbol{\Theta} + \boldsymbol{R}\right)^{-1} \boldsymbol{\Theta}^T \boldsymbol{\Gamma}^T \boldsymbol{Q}, \tag{16}$$

where I is the identity matrix

$$I \in \mathbb{R}^{l \times l} \,. \tag{17}$$

### Exercise Tasks:

a) For given weighting matrices  $Q_i$  and  $R_i$  calculate the extended weighting matrices Q and R, required for the calculation of  $K_{\mathrm{MPC}}$ .

$$\mathbf{Q}_{i} = \begin{bmatrix} 10^{-10} & 0 \\ 0 & 10 \end{bmatrix} \forall i \in [N_{1}, N_{2}] \qquad \mathbf{R}_{i} = \begin{bmatrix} 10 & 0 \\ 0 & 10 \end{bmatrix} \forall i \in [0, N_{u} - 1]$$
 (18)

Hint: Instead of for-loops, you can use the Matlab command R = kron(eye(...), R\_i);

b) Calculate  $K_{\mathrm{MPC}}$ .

# Exercise 3 (MPC Implementation in Simulink)

Now we are ready to implement the derived matrices in Simulink and use them in a model predictive controller. The control output u(k) to the engine model is given by

$$\boldsymbol{u}(k)^* = \boldsymbol{u}(k-1) + \boldsymbol{K}_{\text{MPC}} \boldsymbol{e}(\cdot|k) = \boldsymbol{u}(k-1) + \boldsymbol{K}_{\text{MPC}} \left( \boldsymbol{r}(\cdot|k) - \boldsymbol{\Gamma} (\boldsymbol{\Psi} \boldsymbol{x}(k) + \boldsymbol{\Upsilon} \boldsymbol{u}(k-1)) \right). \tag{19}$$

The reference trajectory  $r(\cdot|k)$  is kept constant over the prediction horizon, i.e.,

$$\boldsymbol{r}(\cdot|k) = \begin{bmatrix} \boldsymbol{r}(k,k) \\ \vdots \\ \boldsymbol{r}(k,k) \end{bmatrix} \in \mathbb{R}^{m \cdot (N_2 - N_1 + 1) \times 1}.$$
(20)

#### **Exercise Tasks:**

- a) Open the Simulink template file ps04\_ex3\_LinearModel.slx. It contains the continuous-time linearized model sysC derived in Exercise 1 with full state feedback. Implement Eq. (19) in the subsystem Linear Unconstrained MPC. Hints:
  - In order to generate the reference trajectory  $r(\cdot|k)$  you can use the Simulink block MATLAB Function and the command repmat.
  - To do matrix multiplications with the standard Gain block in Simulink, change its multiplication setting from Element-wise to Matrix(K\*u)
  - To check whether your implementation contains syntax errors or to see signal dimensions and visualize sampling times, you can use the Update Diagram command by pressing Ctrl+D.
- b) Copy the subsystem Linear Unconstrained MPC into the Simulink file ps04\_ex3\_ROM.slx. This model contains the nonlinear ROM with full state feedback. Run both models using the Matlab script ps04\_run\_ex3.m and compare the results. Explain why the simulation with the ROM model has a steady-state error.