

Model Predictive Control Examples Sheet

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Reading: Kouvaritakis & Cannon, Sections 2.1–2.6 and 3.1–3.3
or Maciejowski Chapters 2, 3, 6, 8

Prediction equations

1. A system with model

$$x_{k+1} = Ax_k + Bu_k, \quad y_k = Cx_k$$

$$A = \begin{bmatrix} 1 & 0.1 \\ 0 & 2 \end{bmatrix}, \quad B = \begin{bmatrix} 0 \\ 0.5 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

is to be controlled using an unconstrained predictive control law that minimizes the predicted performance cost

$$J_k = \sum_{i=0}^{N-1} (y_{i|k}^2 + \lambda u_{i|k}^2) + y_{N|k}^2, \quad \lambda = 1.$$

(a). Show that the state predictions can be written in the form

$$\mathbf{x}_k = \mathcal{M}x_k + \mathcal{C}\mathbf{u}_k, \quad \mathbf{u}_k = \begin{bmatrix} u_{0|k} & u_{1|k} & \cdots & u_{N-1|k} \end{bmatrix}^\top$$

and evaluate \mathcal{C} and \mathcal{M} for a horizon of $N = 3$.

(b). For $N = 3$, determine the matrices H , F and G in

$$J_k = \mathbf{u}_k^\top H \mathbf{u}_k + 2x_k^\top F^\top \mathbf{u}_k + x_k^\top G x_k.$$

(c). Give expressions for the derivatives $\partial J / \partial u_{i|k}$ for $i = 0, 1, 2$. Hence verify that the gradient of J is $\nabla_{\mathbf{u}} J = 2H\mathbf{u} + 2F^\top x$.

2. (a). For the plant model and cost given in Question 1, show that the unconstrained predictive control law for $N = 3$ is linear feedback:

$$u_k = Lx_k, \quad L = -\begin{bmatrix} 0.1948 & 0.1168 \end{bmatrix}.$$

Hence show that the closed-loop system is unstable.

(b). Write some Matlab code to evaluate \mathcal{C}_i for $i = 1, \dots, N$, and to determine H and F for any given horizon length N . Show that the predictive control law does not stabilize the system if $N < 6$.

Infinite horizon cost and constraints

3. (a). Explain why the predictive control law of Question 1 necessarily stabilizes the system if the cost is minimized subject to $x_{N|k} = 0$. (Hint: what is the infinite horizon cost when this constraint is used?)

(b). How would you modify the cost of Question 1 in order to achieve closed loop stability without including the constraint $x_{N|k} = 0$? Why would this be preferable?

4. A predictive controller minimizes the predicted performance index:

$$J_k = \sum_{i=0}^{\infty} (y_{i|k}^2 + u_{i|k}^2)$$

at each time-step k subject to input constraints: $-1 \leq u_{i|k} \leq 2$ for all $i \geq 0$. The system output y is related to the control input u via

$$x_{k+1} = Ax_k + Bu_k, \quad y_k = Cx_k$$

$$A = \begin{bmatrix} -2 & 1 \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 1 \end{bmatrix}.$$

(a). Why is the MPC optimization performed repeatedly, at $k = 0, 1, 2, \dots$, instead of just once, at $k = 0$?

(b). If the mode 2 feedback law is $u_k = \begin{bmatrix} 2 & -1 \end{bmatrix} x_k$, show that

$$J_k = \sum_{i=0}^{N-1} (y_{i|k}^2 + u_{i|k}^2) + x_{N|k}^\top \begin{bmatrix} 13 & -1 \\ -1 & 2 \end{bmatrix} x_{N|k}$$

where N is the length of the mode 1 prediction horizon.

- (c). Show that the constraints

$$-1 \leq u_{i|k} \leq 2, \quad i = 0, 1, \dots, N+1$$

ensure that the predictions satisfy $-1 \leq u_{i|k} \leq 2$ for all $i \geq 0$.

- (d). Derive a bound on $J_{k+1}^* - J_k^*$, where J_k^* is the optimal value of J_k . Hence show that $\sum_{k=0}^{\infty} (y_k^2 + u_k^2) \leq J_0^*$ along trajectories of the closed loop system.
- (e). Is the closed loop system stable? Explain your answer.

5. (a). Explain the function of terminal constraints in a model predictive control strategy for a system with input or state constraints. Define two principal properties that must be satisfied by a terminal constraint set.

- (b). A discrete time system has the state space model

$$x_{k+1} = Ax_k + Bu_k, \quad A = \begin{bmatrix} 0.3 & -0.9 \\ -0.4 & -2.1 \end{bmatrix}, \quad B = \begin{bmatrix} 0.5 \\ 1 \end{bmatrix}$$

and constraints

$$|[x]_1 + [x]_2| \leq 1, \quad |[x]_1 - [x]_2| \leq 1, \quad x = \begin{bmatrix} [x]_1 \\ [x]_2 \end{bmatrix}$$

- (i). If the terminal feedback law is $u_k = Kx_k$, $K = \begin{bmatrix} 0.4 & 1.8 \end{bmatrix}$, show that the following set is a valid terminal constraint set

$$\{x : |[x]_1 + [x]_2| \leq 1, \quad |[x]_1 - [x]_2| \leq 1\}.$$

- (ii). Describe a procedure for determining the largest terminal constraint set for the case of a general feedback gain K .
- (c). What are the main considerations that govern the choice of the prediction horizon N ?

Integral action and disturbances

6. The vertical position y of a machine tool positioning platform is controlled by a motor which applies a vertical force F to the platform (Figure 1). The platform has mass M and carries a variable load of mass m ; the unloaded weight of the platform is balanced by a counter-weight. The force F is proportional to the voltage V applied to the motor, so that $F = K_V V$ where K_V is a fixed gain.

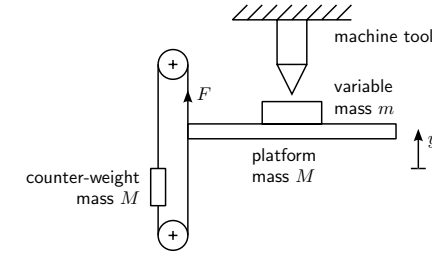


Figure 1. Machine tool and positioning platform

Assuming m is small enough that $M + m \approx M$, the unknown load constitutes a (constant) disturbance in the discrete-time model of the system for sampling interval T :

$$x_{k+1} = Ax_k + Bu_k + Dw, \quad e_k = Cx_k$$

$$A = \begin{bmatrix} 1 & T \\ 0 & 1 \end{bmatrix}, \quad B = \frac{K_V}{2M} \begin{bmatrix} T^2/2 \\ T \end{bmatrix}, \quad D = -\frac{g}{2M} \begin{bmatrix} T^2/2 \\ T \end{bmatrix}, \quad C = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

where e is the error in y relative to a desired steady-state height y^0 , and

$$x_k = \begin{bmatrix} y(kT) - y^0 \\ \dot{y}(kT) \end{bmatrix}, \quad u_k = v(kT), \quad w = m.$$

- (a). For the model parameters $M = 10 \text{ kg}$, $K_V = 7 \text{ N V}^{-1}$, $T = 0.1 \text{ s}$, the LQ-optimal feedback law with respect to the cost

$$J_k = \sum_{i=0}^{\infty} (e_{k+i}^2 + \lambda u_{k+i}^2), \quad \lambda = 10^{-4}$$

is $u_k = Kx_k$, $K = \begin{bmatrix} -66.0 & -19.4 \end{bmatrix}$. Determine the maximum steady state error $y - y^0$ with this controller if the mass of the load is limited to the range:

$$m \leq 0.5 \text{ kg.}$$

- (b). Explain how to modify the cost and model dynamics in order to obtain a stabilizing LQ-optimal controller giving zero steady-state error.
- (c). The motor input voltage is subject to the constraints

$$-1 \leq V \leq 1$$

A predictive controller is to be designed based on the predicted cost:

$$J_k = \sum_{i=0}^{\infty} (e_{i|k}^2 + v_{i|k}^2 + \lambda u_{i|k}^2), \quad \lambda = 10^{-4}$$

where $v_{i+1|k} = v_{i|k} + e_{i|k}$ is the prediction of the integrated error.

- (i). For a predicted input sequence with N degrees of freedom, show that J_k can be re-written as

$$J_k = \sum_{i=0}^{N-1} (e_{i|k}^2 + v_{i|k}^2 + \lambda u_{i|k}^2) + \|\xi_{N|k}^\top\|_P^2$$

and define ξ and P . What is the implied mode 2 feedback law?

- (ii). Briefly explain how the constraints on V can be incorporated in a robust MPC strategy for this system (i.e. for all values of m in the range $m \leq 0.5 \text{ kg}$).

7. Assume that, for the given initial condition $x(0)$, the optimization of J subject to the robust constraints determined in Question 6 is initially feasible. Will the online optimization remain feasible at all future sampling times? What can be said about the steady-state value of y ? Will the optimal value of the cost necessarily decrease monotonically, and what can be concluded about the convergence of the state x_k to zero in closed-loop operation?

8. A production planning problem involves optimizing the quantity u of stock manufactured in each week. The quantity x of stock that remains unsold at the start of week $k+1$ is given by

$$x_{k+1} = x_k + u_k - w_k, \quad k = 0, 1, \dots$$

where the quantity w_k that is sold in each week is unknown in advance but is expected to be equal to a known constant \hat{w} . Limits on storage and manufacturing capacities imply that x and u can only take values in the intervals

$$0 \leq x_k \leq X, \quad 0 \leq u_k \leq U.$$

The desired level of stock in storage is x^* , and the planned values $u_{0|k}, u_{1|k}, \dots$ are to be optimized at time k given a measurement of the value of x_k by minimizing a cost

$$J_k = \sum_{i=0}^{\infty} e_{i|k}^2, \quad e_{i|k} = x_{i|k} - x^*.$$

- (a). What are the advantages of using a receding horizon control strategy in this application instead of an open-loop control sequence computed at $k = 0$?

- (b). Assume that $w_k = \hat{w}$ for all $k = 0, 1, \dots$

- (i). Show that the unconstrained optimal control law is $u_k = \hat{w} - e_k$.

- (ii). Show that, for a mode 1 horizon of N , the infinite horizon cost can be expressed

$$J_k = \sum_{i=0}^N e_{i|k}^2,$$

and state the corresponding mode 2 feedback law.

- (iii). Show that constraints are satisfied over an infinite horizon if $0 \leq x_{i|k} \leq X$ and $0 \leq u_{i|k} \leq U$ for $0 \leq i \leq N-1$, and

$$\max\{0, \hat{w} + x^* - U\} \leq x_{N|k} \leq \min\{X, \hat{w} + x^*\}.$$

What assumptions on \hat{w} , x^* , U and X are needed?

- (c). Assume now that the future value of w is unknown and may take any value in an interval: $0 \leq w_k \leq W$. Suggest how to express the planned sequence $u_{0|k}, u_{1|k}, u_{2|k}$ in terms of the free variables in the receding horizon optimization problem, and justify your answer by determining the predictions $e_{1|k}, e_{2|k}, e_{3|k}$.

Some answers

1. (a). $C = \begin{bmatrix} 0.15 & 0.05 & 0 \\ 2 & 1 & 0.5 \end{bmatrix}$
 (b). $H = \begin{bmatrix} 1.025 & 0.0075 & 0 \\ 0.0075 & 1.0025 & 0 \\ 0 & 0 & 1 \end{bmatrix}$, $F = \begin{bmatrix} 0.2 & 0.12 \\ 0.05 & 0.035 \\ 0 & 0 \end{bmatrix}$, $G = \begin{bmatrix} 4 & 1.1 \\ 1.1 & 0.59 \end{bmatrix}$
2. (a). Closed loop poles for $N = 3$: $\text{eig}(A + BL) = 1.01, 1.93$
 (b).

N	4	5	6	7
$\text{eig}(A + BL)$	1.03, 1.69	$1.11 \pm 0.15i$	$0.86 \pm 0.10i$	0.95, 0.58
3. (b). In J_k , replace $y_{N|k}^2$ with $\|x_{N|k}\|_P^2$, $P = \begin{bmatrix} 22.46 & 4.098 \\ 4.098 & 12.79 \end{bmatrix}$
4. (d). $J_{k+1}^* - J_k^* \leq -(y_k^2 + u_k^2)$
 (e). $x = 0$ is locally asymptotically stable
6. (a). $|y - y^0| \leq 0.0106$ m in steady state
 (c). ξ : augmented predicted state, $\xi = \begin{bmatrix} x & v \end{bmatrix}^\top$, P : the solution of

$$P - \left(\begin{bmatrix} A & 0 \\ C & I \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} K_\xi \right)^\top P \left(\begin{bmatrix} A & 0 \\ C & I \end{bmatrix} + \begin{bmatrix} B \\ 0 \end{bmatrix} K_\xi \right) = \begin{bmatrix} C^\top C & 0 \\ 0 & 1 \end{bmatrix} + \lambda K_\xi^\top K_\xi,$$
 Mode 2 feedback law: $u = K_\xi x$, e.g. LQ-optimal $K_\xi = - \begin{bmatrix} 201.4 & 29.6 & 48.2 \end{bmatrix}$
8. (c). $u_{i|k} = \hat{w} - e_{i|k} + c_{i|k}$, where $c_{i|k}$ = for $i = 0, \dots, N-1$ are decision variables, and $c_{i|k} = 0$ for $i \geq N$