Generalized Predictive Control tuning by controller matching

Quang N. Tran, Ryvo Octaviano, Leyla Özkan and A.C.P.M. Backx

Department of Electrical Engineering
Eindhoven University of Technology, Eindhoven, The Netherlands
Email: N.Q.Tran@tue.nl, R.Octaviano@student.tue.nl, L.Ozkan@tue.nl and A.C.P.M.Backx@tue.nl

Abstract—The tuning of state-space model predictive control (MPC) based on reverse engineering has been investigated in literature using the inverse optimality problem ([1] and [2]). The aim of the inverse optimality is to find the tuning parameters of MPC to obtain the same behavior as an arbitrary linear-time-invariant (LTI) controller (favorite controller). This requires equal control horizon and prediction horizon, and loop-shifting is often used to handle non-strictly-proper favorite controllers. This paper presents a reverse-engineering tuning method for MPC based on transfer function formulation, also known as generalized predictive control (GPC). The feasibility conditions of the matching of a GPC with a favorite controller are investigated. This approach uses a control horizon equal to one and does not require any loop-shifting techniques to deal with non-strictly-proper favorite controllers. The method is applied to a binary distillation column example.

I. INTRODUCTION

Model predictive control (MPC) is a popular advanced process control technology due to its ability to handle system constraints explicitly. Apart from the obvious advantage of handling constraints, interpreting the available degrees of freedom in the MPC cost function while the constraints are inactive is not straightforward ([3]). Among various ways of selecting the cost function (the tuning parameters) of MPC in literature ([4]), the tuning methods which enable MPC to inherit the characteristics of an arbitrary LTI controller are of particular interest. When MPC operates closely to the constraints and active constraints occur frequently, the system will take advantage of the traditional ability of MPC. When MPC operates away from the constraints (e.g. at commissioning), the system can inherit the characteristics of an LTI controller, e.g. its robustness.

The matching of MPC with an LTI controller when MPC is formulated in the state space has been investigated by several authors ([5], [6], [7], [3] and [8]). In that case, the unconstrained solution of MPC can be written as a state feedback control law and the aim of the matching is to minimize the error between the state feedback gain of the favorite controller and that of MPC. The foundation of this approach is the inverse problem of linear optimal control, laid by [1] and [2]. The inverse optimality problem is extended to a more general cost function in [9] with a cross-product term between the state and the control input. In [7], a matching method based on formulating an optimization problem with linear matrix inequality (LMI) or bilinear matrix inequality (BMI) constraints is proposed. The cost function of the optimization problem is the error between the control action of the MPC and the favorite controller. The matching methods based on the inverse problem of linear optimal control usually consider the case in which the MPC is equivalent to a linear-quadratic regulator (LQR) and the states of the system are available.

In many applications, the states of the system are not measurable and the use of a state observer is required. In [5], the observer is designed with the loop-shaping procedure introduced in [10] and the tuning parameters of MPC are found by investigating the inverse problem of the normalised left co-prime factorization (NLCF) optimal control. In [6], separate designs of the robust observer and state feedback gain are used for the matching purpose, and non-convex optimization techniques are employed to perform the matching when the terminal weight is not used.

In [11], it is shown that robustness is not guaranteed even when one attempts to design a “good” observer and a state feedback gain. Based on this observation, [3] makes use of the observer realization techniques described in [12] to divide a favorite controller into the observer part and state feedback part before performing the matching. A major drawback of this approach is that if a favorite output feedback controller contains a feed-through term from the outputs to the control inputs (i.e. a non-strictly-proper controller), loop-shifting techniques must be used to “transfer” the feed-through term to the dynamics of the plant so that the matching is feasible. Introducing some assumptions, [8] has proposed a solution to the problem by considering the feed-through term in the framework of reference tracking.

Due to the nature of the inverse optimality problem ([1], [2] and [9]), the controller matching is often studied with a state-feedback MPC law and an observer design. Nevertheless, MPC can also be formulated by transfer functions and this formulation is also well adopted by several MPC providers in process industry ([13]). The MPC based on transfer function models (GPC) was introduced in [14], [15] and further developed in [16]. Although there is certain equivalence between the GPC and the state-feedback MPC, there are differences in formulating the cost function and computing the solution. Hence, the matching of GPC with a favorite controller is investigated to overcome the limitations of the matching problem in state space. [17] and [18] proposed a tuning method for the GPC such that the poles and zeros of the closed-loop
system approximates certain desired ones. [19] makes use of optimization techniques to find an output feedback gain that minimizes the difference between the closed-loop behavior of the GPC and the desired behavior in the frequency domain. In that work, the tuning parameters are found by solving a convex optimization problem with LMI constraints. The approach is limited to the case where the control horizon is 1.

The focus of this paper is to match a GPC with a favorite controller when the constraints are inactive instead of using optimization techniques, we solve a set of linear equations to find the output feedback gain of GPC. This is done in the backward shift of the system. To this end, the rank conditions of coefficient matrices are investigated. Once the rank conditions are fulfilled, a feedback gain is computed that guarantees the matching can always be found. Then, a convex optimization problem with LMI constraints similar to [7] is used to find the tuning parameters which provide the considered system is strictly proper, let

\[
D(z) = I + D_1 z^{-1} + D_2 z^{-2} + \ldots + D_{n+1} z^{-n-1}
\]

and

\[
N(z) = N_1 z^{-1} + N_2 z^{-2} + \ldots + N_n z^{-n}
\]

Let \( H_p \) denote the prediction horizon, the prediction model of the system is constructed as follows (with the assumption that the best prediction of \( v_k \) is zero):

\[
\begin{align*}
\tilde{y}_{k+1} + D_1 \tilde{y}_{k+1} + \ldots + D_{n+1} \tilde{y}_{k-n} &= N_1 \Delta \tilde{u}_{k+1} + \ldots + N_n \Delta \tilde{u}_{k-n+1} \\
\tilde{y}_{k+2} + D_1 \tilde{y}_{k+2} + \ldots + D_{n+1} \tilde{y}_{k-n+1} &= N_1 \Delta \tilde{u}_{k+2} + \ldots + N_n \Delta \tilde{u}_{k-n+2} \\
&\vdots \\
\tilde{y}_{k+H_p} + D_1 \tilde{y}_{k+H_p} + \ldots + D_{n+1} \tilde{y}_{k-H_p-1} &= N_1 \Delta \tilde{u}_{k+H_p} + \ldots + N_n \Delta \tilde{u}_{k-H_p+n}
\end{align*}
\]

When a control horizon \( H_c < H_p \) is considered, the inputs become constant from time instant \( k \) + \( H_c \) if the prediction is made at time instant \( k \): \( \Delta \tilde{u}_{k+H_c+1} = 0 \) for \( l \geq 0 \). In this work, a control horizon of 1 is considered. The extension to the case where \( H_c > 1 \) is inspired by [7] and has also been investigated but it is not presented here. It should be noted that although \( \Delta \tilde{u}_{k+H_c+1} = 0 \) for \( l \geq 0 \), it does not necessarily lead to \( \Delta \tilde{u}_{k+H_c+1} = 0 \) for \( l \geq 0 \) due to the filtering effect of \( T^{-1}(z) \). Therefore, a so-called filter horizon \( H_f \) is defined such that \( \Delta \tilde{u}_{k+H_f+1} \approx 0 \) for \( l \geq 0 \). Hence:

\[
\begin{align*}
\begin{bmatrix}
\tilde{y}_{k+1} \\
\tilde{y}_{k+2} \\
\vdots \\
\tilde{y}_{k+H_p}
\end{bmatrix} &= -H_D \\
\begin{bmatrix}
\tilde{y}_{k} \\
\tilde{y}_{k-1} \\
\vdots \\
\tilde{y}_{k-n}
\end{bmatrix} + C_D \begin{bmatrix}
\Delta \tilde{u}_{k} \\
\Delta \tilde{u}_{k+1} \\
\vdots \\
\Delta \tilde{u}_{k+H_f}
\end{bmatrix} + C_{zN} \begin{bmatrix}
\Delta \tilde{u}_{k-1} \\
\Delta \tilde{u}_{k-2} \\
\vdots \\
\Delta \tilde{u}_{k-n}
\end{bmatrix} \\
\tilde{y}_{k+H_f} &= -H_{zN} \begin{bmatrix}
\Delta \tilde{u}_{k-1} \\
\Delta \tilde{u}_{k-2} \\
\vdots \\
\Delta \tilde{u}_{k-n}
\end{bmatrix}
\end{align*}
\]

where

\[
C_D = \begin{bmatrix}
I \\
D_1 I \\
\vdots \\
D_{n+1} I
\end{bmatrix}, H_D = \begin{bmatrix}
D_1 \\
D_2 \\
\vdots \\
D_{n+1}
\end{bmatrix},
\quad C_{zN} = \begin{bmatrix}
N_1 \\
N_2 \\
\vdots \\
N_{n-n}
\end{bmatrix}, H_{zN} = \begin{bmatrix}
N_1 \\
N_2 \\
\vdots \\
N_{n+n}
\end{bmatrix}
\]

The predicted output is then given by:

\[
\tilde{y}_{k+H_f} = \tilde{y}_{k+H_f} + C_D \begin{bmatrix}
\Delta \tilde{u}_{k} \\
\Delta \tilde{u}_{k+1} \\
\vdots \\
\Delta \tilde{u}_{k+H_f}
\end{bmatrix} + C_{zN} \begin{bmatrix}
\Delta \tilde{u}_{k-1} \\
\Delta \tilde{u}_{k-2} \\
\vdots \\
\Delta \tilde{u}_{k-n}
\end{bmatrix}
\]

The predicted output is then given by:

\[
\tilde{y}_{k+H_f} = \tilde{y}_{k+H_f} + C_D \begin{bmatrix}
\Delta \tilde{u}_{k} \\
\Delta \tilde{u}_{k+1} \\
\vdots \\
\Delta \tilde{u}_{k+H_f}
\end{bmatrix} + C_{zN} \begin{bmatrix}
\Delta \tilde{u}_{k-1} \\
\Delta \tilde{u}_{k-2} \\
\vdots \\
\Delta \tilde{u}_{k-n}
\end{bmatrix}
\]
\[
\dot{\hat{y}}_k = H \Delta \hat{u}_{k-1} + P \Delta \hat{\hat{u}}_{k-1} + Q \hat{\hat{y}}_k
\]

where \(H = C_D^{-1}C_zN\), \(P = C_D^{-1}H_zN\) and \(Q = -C_D^{-1}H_D\). To compute the solution of the MPC, a prediction model based on \(y_k\) and \(\Delta \hat{u}_{k-1}\) is needed. Define \(T(z) = I + T_1 z^{-1} + T_2 z^{-2} + \ldots + T_{n+1} z^{-n-1}\) where \(T_i = t_i I_n\), \(t_i \in \mathbb{R}\) and \(t_{n+1} \neq 0\). It implies that:

\[
\begin{bmatrix}
    I & 0 & \cdots & 0 \\
    \vdots & I & \ddots & \vdots \\
    0 & \cdots & \cdots & I \\
\end{bmatrix}
\begin{bmatrix}
    \hat{y}_k \\
    \hat{u}_k \\
    \Delta \hat{u}_{k-1} \\
\end{bmatrix}
= \begin{bmatrix}
    T_1 & \cdots & T_{n+1} \\
    \vdots & \ddots & \vdots \\
    0 & \cdots & 0 \\
\end{bmatrix}
\begin{bmatrix}
    y_k \\
    u_k \\
    \Delta y_{k-1} \\
\end{bmatrix}
+ \begin{bmatrix}
    0 \\
    \vdots \\
    0 \\
\end{bmatrix}
\]

III. PROBLEM FORMULATION

Let a favorite proper (but not necessarily strictly proper) controller be given by:

\[
(I + A_1 z^{-1} + A_2 z^{-2} + \ldots + A_p z^{-p}) u_k
= \left(\hat{B}_0 + B_1 z^{-1} + \ldots + B_p z^{-p}\right) y_k
\]

(20)

Hence:

\[
(I + A_1 z^{-1} + \ldots + A_p z^{-p}) \Delta u_k
= \left(\hat{B}_0 + B_1 z^{-1} + \ldots + B_p z^{-p}\right) (1 - z^{-1}) y_k
\]

(21)

\[
\Rightarrow A(z) \Delta u_k = -B(z) y_k
\]

(22)

where \(A(z) = I + A_1 z^{-1} + \ldots + A_p z^{-p}\) and \(B(z) = \hat{B}_0 + B_1 z^{-1} + \ldots + B_p z^{-p}-1\).

To investigate the matching problem, two subproblems are studied:

- Matching transfer matrices: Find the controller gain \(\hat{K}_{MPC}\) in (14) such that \(\hat{N}_k(z) = B(z)\) and \(\hat{D}_k(z) = A(z)\).

- Finding the tuning parameters: Find cost function (12) such that \(\left(\hat{H}^T Q \hat{H} + R\right)^{-1} \hat{H}^T Q = \hat{K}_{MPC}\)

IV. MATCHING TRANSFER MATRICES

The aim of the matching is to equate \(B(z)\) with \(\hat{N}_k(z)\) and \(A(z)\) with \(\hat{D}_k(z)\), while the order of \(B(z)\) is \(p+1\), \(\hat{N}_k(z)\) is \(n\), \(A(z)\) is \(p\) and \(\hat{D}_k(z)\) is \(n+1\). Due to the orders of the transfer matrices, the prediction model must be over-parameterized if \(n < p + 1\) and the controller must be over-parameterized if \(n > p + 1\). The simplest over-parametrization technique is adding zero coefficients to high order terms of the transfer functions. Assume that \(n = p + 1\), the target of the matching is to find \(\hat{K}_{MPC}\) such that:

\[
\hat{K}_{MPC} = \begin{bmatrix} A_1 & \ldots & A_p & 0 & 0 \\ \vdots & \ldots & \vdots & 1 & 0 \\ \vdots & \ldots & \vdots & \vdots & \vdots \\ B_0 & \ldots & B_{p+1} \end{bmatrix}
\]

(23)

The problem above is feasible for arbitrary \([A_1 A_2 \ldots A_p]\) and \([B_0 B_1 \ldots B_{p+1}]\) if both following conditions hold:

- Matrix \([\hat{P} \hat{Q}]\) is full rank.
- Matrix \([\hat{P} \hat{Q}]\) is square or skinny.

As the number of rows of \([\hat{P} \hat{Q}]\) is \(H_z n_d\) and the number of columns is \(2(n+1)n_d\), which is typically the case since \(H_p\) is usually chosen long enough to cover the main dynamics of the system. Given \(\hat{P}\) and \(\hat{Q}\) as:

\[
\hat{P} = C_T y P - C_T y H C_T^{-1} H_T u \\
\hat{Q} = C_T y P C_T^{-1} H z N - C_T y C_T^{-1} C_z N C_T^{-1} H_T u
\]

(24)

we investigate the rank of \([\hat{P} \hat{Q}]\). Since \(C_T y\) and \(C_D\) are square and full-rank, it follows that:

\[
\text{rank}(\hat{P}) = \text{rank}(H_z N - C_z N C_T^{-1} H_T u) \\
\text{rank}(\hat{Q}) = \text{rank}(C_D C_T^{-1} H_T y - H_D)
\]

(26)

(27)
Theorem 1. Given model (1) and matrices $\hat{P}, \hat{Q}$ in (11), \(\text{rank}([\hat{P} \ \hat{Q}]) \leq (2n+1)n_d\) if $H_f = 1$ or $H_p - H_f < n + 1$.

Proof: If $H_f = 1$,

$$C_{sN} = \begin{bmatrix} N_1 \\ \vdots \\ N_n \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

(28)

It implies that

$$H_{sN} - C_{sN}C_{T_0}^{-1}H_{T_u} = \begin{bmatrix} N_2 & \cdots & N_n & 0 & 0 \\ \vdots & \ddots & \vdots & \vdots & \vdots \\ N_n & \ddots & \vdots & \vdots & \vdots \\ 0 & \cdots & 0 & 0 & 0 \end{bmatrix} - \begin{bmatrix} N_1 \\ \vdots \\ N_n \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

(29)

$$\Rightarrow \text{rank}(\hat{P}) \leq n_d$$

(30)

$$\Rightarrow \text{rank}([\hat{P} \ \hat{Q}]) \leq (2n + 1)n_d$$

(31)

The rest of the proof shows that $\text{rank}([\hat{P} \ \hat{Q}]) \leq (2n + 1)n_d$ if $H_p - H_f < n + 1$. For simplicity, assume $n = 1$, $H_f = 3$ and $H_p = 4$,

$$\text{rank}([\hat{P} \ \hat{Q}]) = \text{rank}([H_{sN} - C_{sN}C_{T_0}^{-1}H_{T_u} C_{D}C_{T_0}^{-1}H_{T_y} - H_D])$$

(33)

Note that $C_{T_y}^{-1} = \begin{bmatrix} I \\ -T_1 \\ -T_2 + T_1^2 \\ -T_1 \\ I \\ -T_2 + T_1^2 \\ -T_1 \\ I \end{bmatrix}$

matrix $V := C_{D}C_{T_0}^{-1}H_{T_y} - H_D$ is:

$$\begin{bmatrix} \tau_1 - d_1 \\ \vdots \\ \tau_1 - d_1 \end{bmatrix} = \begin{bmatrix} \tau_2 - d_2 \\ \vdots \\ \tau_2 - d_2 \end{bmatrix}$$

The calculation of $H_{sN} - C_{sN}C_{T_0}^{-1}H_{T_u}$ also shows identical linear dependency. Hence, $\text{rank}([\hat{P} \ \hat{Q}]) \leq 3n_d$ while size([\hat{P} \ \hat{Q}]) = 4n_d.

Theorem 1 shows that $H_f$ and $H_p$ must satisfy $1 < H_f$ and $H_p - H_f \geq n + 1$ so that matrix $[\hat{P} \ \hat{Q}]$ is full rank.

Corollary 1. Assume $H_f > 1$, $H_p - H_f \geq n + 1$ and matrix $[\hat{P} \ \hat{Q}]$ is full rank. If $H_p = 2n + 2$, a solution $K_{MPC}$ to (23) is unique. If $H_p > 2n + 2$, there are infinite number of solutions $K_{MPC}$ since matrix $[\hat{P} \ \hat{Q}]$ has more rows than columns.

Proposition 1. $H_f$ is chosen based on the settling time of $T^{-1}(z)$ and $H_p \geq \max(2(n + 1); H_f + n + 1)$ so that matrix $[\hat{P} \ \hat{Q}]$ is full rank and to obtain a decent prediction model.

V. FINDING THE TUNING PARAMETERS

Section IV explains how to match $K_{MPC}$ to favorite controller (20). This section describes how to find the tuning parameters after finding $K_{MPC}$. When cost function (12) is used, the problem of finding the tuning parameters can be formulated as a convex optimization problem with LMI constraints as shown in [7], [17], [18] and [19]. The problem is given by:

$$\min_{Q, \hat{R}} \| (\hat{H}^T Q \hat{H} + \hat{R}) K_{MPC} - \hat{H}^T Q \|_2$$

(34)

s.t. $Q \succeq 0$ and $\hat{R} \succeq 0$. In [7], raising the prediction horizon is a method to increase the degrees of freedom in the LMI to obtain a lower error when matching the state feedback gain. Nevertheless, this work as well as [17], [18] and [19] solve the matching of the output feedback gain $K_{MPC}$, whose size depends on the prediction horizon. This is a fundamental difference that limits the benefit gained by increasing the prediction horizon to obtain more degrees of freedom. As shown in Corollary 1, when $H_p > 2n + 2$, there are infinite number of $K_{MPC}$ that satisfies (23). Let $M$ be the set of all $K_{MPC}$’s that satisfy (23). One method to increase the degrees of freedom is to use $K_{MPC}$ as an optimization variable in the optimization problem, subject to $K_{MPC} \in M$. However, this approach will lead to a bilinear optimization problem, which is difficult to solve and not considered in this work.

Alternatively, the use of a cross term $S \in \mathbb{R}^{H_{p}n_d \times H_{n_d}}$ in the cost function is proposed to gain more degrees of freedom in the optimization. The cost function of the MPC is then given by:

$$J_k = y_k^T Q y_k + \Delta u_k^T \hat{R} \Delta u_{k-1} + y_k^T S \Delta u_{k-1} + \Delta u_{k-1}^T S^T y_k$$

(35)

The unconstrained control law is given by:

$$\Delta u_k = -K_{MPC} \left( \hat{P} \Delta \hat{y}_{k-1} + \hat{Q} \hat{y}_{k-1} \right)$$

(36)

where

$$K_{MPC} = \left( \hat{H}^T Q \hat{H} + \hat{R} + \hat{H}^T S + S^T \hat{H} \right)^{-1} \left( \hat{H}^T Q + S^T \right)$$

(37)

The optimization problem with LMI constraints is then given by:

$$\min_{Q, S, \hat{R}} \| (\hat{H}^T Q \hat{H} + \hat{R} + \hat{H}^T S + S^T \hat{H}) K_{MPC} - (\hat{H}^T Q + S^T) \|_2$$

(38)

s.t. $[Q \ S \ \hat{S}^T \ \hat{R}] > 0$. When the resulting error is not sufficiently small, the constraint can also be relaxed by forcing
only the Hessian matrix \( H^T Q H + R + H^T S + S^T H \) to be positive definite as shown in [6]. However, the interpretation of a non-positive-definite \( \begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} \) is still under investigation.

VI. EXAMPLE

The controller matching approach is applied to a binary distillation column model. A detailed description of the model is provided in [21]. The considered distillation column consists of 110 trays and the feed to the column is located at tray 39. The relative volatility and the liquid holdup are assumed to be constant at \( \alpha = 1.35 \) and \( M = 30 \) Kmol, respectively. The column operates at a feed flow of \( F = 219 \) Kmol/min with a light component composition of \( x_p = 0.65 \). The model has 2 control variables (top \( y_{top} \)) and bottom (\( y_{bot} \)) purity) and 2 manipulated variables (liquid \( LF \) and vapor \( VF \) flow rates). The objective of the controller is to keep the bottom purity constant at 0.9506 [mole fraction] for the top composition is changed to 0.9606 [mole fraction] and that of the top composition is 0.015 [mole fraction]. The model has 22 manipulated variables (liquid \( LF \) and vapor \( VF \) flow rates). The objective of the controller is to keep the bottom composition to change more slowly than the feed rate. At sample 500, the setpoint of the bottom composition is changed to 0.0429 [mole fraction] and that of the top composition is changed to 0.9606 [mole fraction].

In this example, \( T(z) = t(z)I_2 \) with \( t(z) = (1 - 0.7z^{-1})^5 \). Since the order of the model is 2 and that of the \( H_{\infty} \) controller is 3, the prediction model is over-parameterized with zero coefficients in high-order terms so that \( n = p + 1 = 4 \).

The first step of the matching is to find \( \hat{K}_{MPC} \) such that the numerator and denominator of the MPC match those of the \( H_{\infty} \) controller. Since matrix \( [ \hat{P} \ \hat{Q} ] \) is full rank, the command \( \backslash \) of MATLAB\textsuperscript{\textregistered} is used to solve the set of equations given in (23) to obtain \( \hat{K}_{MPC} \), which is a 2 x 20 matrix. With this \( \hat{K}_{MPC} \), the convex optimization problem (38) is solved subject to \( \hat{H}^T Q \hat{H} + \hat{R} + \hat{H}^T S + S^T \hat{H} > 0 \). The resulting weighting matrices are not shown here due to limited space. The 2-norm of the error between \( \hat{K}_{MPC} \) and

\[
\begin{align*}
\begin{bmatrix} Q & S \\ S^T & R \end{bmatrix} &= \begin{bmatrix} 1.1614 & 0 \\
0 & 0.5 \end{bmatrix}, \quad \begin{bmatrix} 0 & 0 \\
0 & 0 \end{bmatrix} = \begin{bmatrix} w_u(z) & 0 \\
0 & w_u(z) \end{bmatrix} \quad \begin{bmatrix} 0 & 0 \\
0 & w_u(z) \end{bmatrix} \end{align*}
\]

The sensitivity functions \( S(z) \) and \( K(z)S(z) \) together with their templates are given in Fig. 1. It is shown that the functions are below their upper bound with an \( H_{\infty} \) cost of \( \gamma = 1.1614 \).

<table>
<thead>
<tr>
<th>Weights</th>
<th>Low-frequency gain</th>
<th>Crossover frequency [rad/min]</th>
<th>High-frequency gain</th>
</tr>
</thead>
<tbody>
<tr>
<td>( w_u(z) )</td>
<td>( 10^{-3} )</td>
<td>0.628</td>
<td>1.0005</td>
</tr>
<tr>
<td>( w_u(z) )</td>
<td>( 10^{0.5} )</td>
<td>0.015</td>
<td>0.3</td>
</tr>
</tbody>
</table>

TABLE I: Input and output weights of the \( H_{\infty} \) controller.
when the constraints are inactive. The use of $T(z)$ and over-parametrization helps to fulfill the rank conditions while $T(z)^{-1}$ remains a low-pass filter. Two main steps are followed in the matching. The first step is to find a gain $\hat{K}_{\text{MPC}}$ that matches the transfer function given. The second step is to find the tuning parameters by formulating a convex optimization problem with LMI constraints.

The use of $T(z)$ helps to satisfy the rank condition of the coefficient matrices. Moreover, $T(z)^{-1}$ is usually a low-pass filter whose bandwidth is preferred to be higher than that of the model. In this work, $T(z)$ is selected based on engineering rules in [16]. It should be noted that $H_f$ also affects the quality of the prediction. A high $H_f$ is needed for a slow $T(z)$ but leads to rank deficiency in $[\hat{P} \quad \hat{Q}]$ as shown in Theorem 1, which makes the matching infeasible. A fast $T(z)$ will allow a low $H_f$ but may cause numerical issues since the coefficients of $T(z)$ will become small. Therefore, a more analytical approach to the computation of $T(z)$ should be considered in future work.

For all the tuning parameters, the convex optimization problem is easy to solve and some constraints on the weighting matrices must be removed to obtain a low error. Unlike the matching of the state feedback gain in [7], the impact of increasing the prediction horizon on the degrees of freedom is not clear. One solution to this problem is to consider the gain $\hat{K}_{\text{MPC}}$ as a decision variable as well, based on the results of Corollary 1. Nevertheless, this will lead to an optimization problem with bilinear constraints, which is more difficult to solve.

Since feed-forward terms are often considered in the prediction model of MPC when measurable disturbances are present, the inclusion of feed-forward terms in the controller matching will also be investigated in future work. Scaling the gain $\hat{K}_{\text{MPC}}$ will also be considered when optimization problem (38) is solved in order to satisfy the definite positiveness of

$$
\begin{bmatrix}
Q & S \\
S^T & R
\end{bmatrix}
$$

The case of a control horizon higher than 1 will also be investigated based on the approach presented in [7].

**Fig. 2:** The response of top and bottom compositions to $H_{\text{DC}}$ and MPC controller.

**ACKNOWLEDGMENT**

The research leading to these results has received funding from the European Union’s Seventh Framework Programme (FP7/2007-2013) under grant agreement n° 257059, the ‘Autoprofit’ project (www.fp7-autoprofit.eu).

**REFERENCES**


