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On Interfacing Model Predictive Controllers with Low-Level Loops

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Abstract Two options arising during implementation of an advanced model-based control system on a process with low-level loops are discussed. Strengths and deficiencies of the options are examined and methods to overcome the deficiencies are proposed. Simulation results of a CSTR and distillation column are presented to demonstrate the performance improvements.

Keywords : Low-Level PID Loops, Model Predictive Control, Inferential Control, Stochastic System Identification

1. Introduction

Traditionally, industrial processes have relied on regulatory PID loops (e.g., flow loops, pressure loops, temperature loops, level loops, etc.) to maintain stable plant operation. These days, however, advanced model based control systems (such as model predictive controllers) are introduced to more and more processes, to move the process variables dynamically for improved productivity, economic benefits and quality control. In implementing an advanced control system on a process with PID loops, one is faced with the following two options:

Option A Break the PID loops and have the model based controller manipulate the control valves directly.

Option B Leave the existing loops and have the model-based controller manipulate the setpoints to these loops, resulting in a cascade control structure.

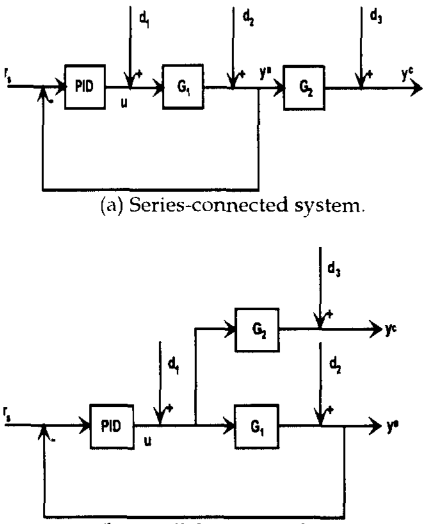
There are pros and cons associated with both options.

In Option A, since the manipulated variables for the model-based controller are the control valves, valve limits can be entered directly into the model predictive control (MPC) algorithm as input constraints. However, without a special provision, the efficient local disturbance rejection property afforded by the low-level loops may be lost, i.e., disturbances have to propagate through the process to affect the feedback variables for MPC before any control action is taken. Furthermore, identification can be unsafe and time-consuming with these loops taken out, especially when the process has unstable or excessively slow dynamics [3]. Examples of such are the integrating dynamics found in many level loops. In Option B, because the PID loops are retained, disturbances that occur inside these loops are quickly rejected before they ever affect other parts of the process. In addition, identification can be made easier since unstable or excessively slow dynamics can be stabilized or made faster by these loops. This arrangement also endows the process with some integrity in the case that the advanced control system shuts down. A drawback of the approach is that the valve limits cannot be handled as input constraints within the MPC algorithm. Translating the valve constraints into input constraints (i.e., constraints on the setpoints of the low-level loops) present some difficulties, as their relationships are usually dynamic and time-varying (for example, see Ricker and Lee [5] who discuss such a problem in the context of the Tennessee-Eastman problem). Other drawbacks of this approach include: (1) valve movements becoming overy sensitive to local disturbances which may not have much impact on the ultimate controlled variables, (2) inability to fully exploit the dynamic correlations present among the outputs of different loops, and (3) the process dynamics changing when the low-level loops are retuned by the operator.

In this paper, recognizing that both options have merits and a proper choice depends on other practical considerations, we study them with the aim of removing their deficiencies without losing the attractive features. We make use of the state estimation and corresponding MPC algorithm. Model development and identification issues are considered in detail. Numerical examples (involving a CSTR and a distillation column) are provided to demonstrate the performance improvements.

2. Problem Definition

A candidate process for model-based control can be represented through the block diagram shown in Figure 1.



(a) Series-connected system.

(b) Parallel-connected system.

Figure 1. Block diagram of process with low level loops.

In the diagram, we refer to the controlled variables of intended model-based control (like the production rate, product compositions, etc.) as the *primary variables*. The process variables that are controlled by the low-level loops are referred to as the *secondary variables*. In terms of how the primary variables and secondary variables are connected to each other, two different arrangements are possible. In the *series connection*, secondary variables act as inputs to the process. Implementing a model-based controller on top of these loops result in the conventional cascade control structure. In the *parallel connection*, the secondary variables as well as the primary variables are the outputs of the process. They may exhibit high-level correlations due to manipulated inputs and disturbances (d_2 and d_3 are often correlated through process dynamics). A model-based controller implemented on top of these low-level loops leads to the so called *parallel cascade control* structure.

3. Removing the Deficiencies of Option A

In Option A, one removes the existing loops and designs a model-based controller that manipulates the valves directly. In this section, we present methods to remove the deficiencies we elaborated in the previous section.

3.1 Improving Disturbance Rejection

In the case that the process G_2 contains significant delays or other nonminimum-phase characteristics, loss of the low-level loops can worsen the disturbance rejection significantly. To improve the disturbance rejection in such cases, one must utilize the measurements of the secondary variables in the prediction of the primary variables (as in *inferential control*). Hence, the model developed for MPC should include both the primary and secondary variables as outputs and contain *correlations* among these variables. With such a model, one can build an observer that uses the secondary measurements to improve the long-range prediction of the controlled variables. The end result is quicker action taken by the model predictive controller in response to disturbances. The idea is similar to feedforward control, but the measurements do not have to made directly at the disturbance sources. The overall approach is illustrated in Figure 2.

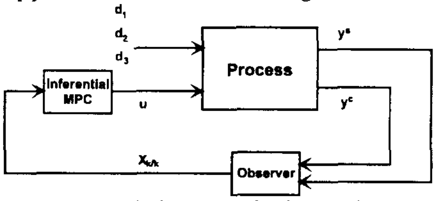


Figure 2. Block diagram of inferential MPC

The procedure for designing a controller can be summarized as below:

1. Obtain a model in the form of

$$x_{k+1} = \Phi x_k + \Gamma \Delta u_k + w_k$$

$$\begin{bmatrix} y^c \\ y^s \end{bmatrix} = H x_k + \nu_k \qquad (1)$$

In the above Δu_k is the change in the valve position, and w_k and ν_k are white noise sequences. As mentioned, it is particularly important that the above model captures the dynamic correlations that exist between y^s and y^c. Without proper correlations embedded into the model, the secondary measurements cannot be used to improve the long-range prediction of the primary variables.

2. Build an observer on the basis of the above model. A linear observer takes the form of

$$x_{k/k} = \Phi x_{k-1/k-1} + \Gamma_u \Delta u_{k-1} + K(y_k - H(\Phi x_{k-1/k-1} + \Gamma_u \Delta u_{k-1})) \qquad (2)$$

Kalman filter can be used if the covariances of w_k and ν_k are specified.

3. Valve movements can be computed in real time by solving the optimization

$$\min_{\Delta u_k, \cdots, \Delta u_{k+m-1}} \sum_{i=1}^{p} \left\| (y^c_{k+i/k} - r^c_{k+i/k} \right\|_Q + \sum_{i=1}^{m} \left\| \Delta u_{k+i-1} \right\|_R \qquad (3)$$

with the prediction equation constraint

$$\begin{bmatrix} y^c_{k+1|k} \\ y^c_{k+2|k} \\ \vdots \\ y^c_{k+p|k} \end{bmatrix} = \begin{bmatrix} H_c\Phi \\ H_c\Phi^2 \\ \vdots \\ H_c\Phi^p \end{bmatrix} X_{k|k} + \begin{bmatrix} H_c\Gamma_u & 0 & \cdots & 0 \\ H_c\Phi\Gamma_u & H_c\Gamma_u & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ H_c\Phi^{p-1}\Gamma_u & H_c\Phi^{p-2}\Gamma_u & \cdots & H_c\Phi^{p-m}\Gamma_u \end{bmatrix} \begin{bmatrix} \Delta u_k \\ \Delta u_{k+1} \\ \vdots \\ \Delta u_{k+m-1} \end{bmatrix} \qquad (4)$$

plus other inequality constraints expressing valve limits and constraints on the associated variables. Change the valve positions by Δu_k^* which denotes the optimal value for Δu_k in the above optimization. The most important and demanding step in the above procedure is the model identification step. There are several ways to obtain a model of the form (1) that captures the dynamic correlations among the outputs. Here we discuss a few options:

- One approach to obtaining the required model is to construct models for individual blocks and then put them together into one model. For instance, in the case of a series-connected system, suppose the models for G_1 and G_2 are identified as

$$\hat{x}_{k+1} = \hat{A}\hat{x}_k + \hat{B}u_k \qquad (5)$$
$$y_k^s = \hat{C}\hat{x}_k$$

and

$$\bar{x}_{k+1} = \bar{A}\bar{x}_k + \bar{B}y_k^s \qquad (6)$$
$$y_k^c = \bar{C}\hat{x}_k$$

respectively. In addition, disturbances d_1, d_2 and d_3 may be described through the stochastic processes (driven by white noises)

$$\hat{\Xi}_{k+1} = \hat{A}_d\hat{\Xi}_k + \hat{B}_d\hat{w}_k$$
$$(d_1)_k = \hat{C}_d\hat{\Xi}_k + \hat{D}_d\hat{w}_k \qquad (7)$$
$$\bar{\Xi}_{k+1} = \bar{A}_d\bar{\Xi}_k + \bar{B}_d\bar{w}_k$$
$$(d_2)_k = \bar{C}_d\bar{\Xi}_k + \bar{D}_d\bar{w}_k \qquad (8)$$

and

$$\tilde{\Xi}_{k+1} = \tilde{A}_d\tilde{\Xi}_k + \tilde{B}_d\tilde{w}_k$$
$$(d_3)_k = \tilde{C}_d\tilde{\Xi}_k + \tilde{D}_d\tilde{w}_k \qquad (9)$$

respectively, where $\hat{w}_k, \overline{w}_k$ and $\widetilde{w}_k$ are white noise sequences. Then, the overall model can be written as

$$\begin{bmatrix} \hat{x}_{k+1} \\ \bar{x}_{k+1} \\ \hat{\Xi}_{k+1} \\ \bar{\Xi}_{k+1} \\ \tilde{\Xi}_{k+1} \end{bmatrix} = \begin{bmatrix} \hat{A} & 0 & \hat{B}\hat{C}_d & 0 & 0 \\ \bar{B}\hat{C} & \hat{A} & 0 & 0 & 0 \\ 0 & 0 & \hat{A}_d & 0 & 0 \\ 0 & 0 & 0 & \bar{A}_d & 0 \\ 0 & 0 & 0 & 0 & \tilde{A}_d \end{bmatrix} \begin{bmatrix} \hat{x}_k \\ \bar{x}_k \\ \hat{\Xi}_k \\ \bar{\Xi}_k \\ \tilde{\Xi}_k \end{bmatrix} + \begin{bmatrix} B \\ 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} u_k + \begin{bmatrix} \hat{B}\hat{D}_d & 0 & 0 \\ 0 & 0 & 0 \\ \hat{B}_d & 0 & 0 \\ 0 & \bar{B}_d & 0 \\ 0 & 0 & \tilde{B}_d \end{bmatrix} \begin{bmatrix} \hat{w}_k \\ \bar{w}_k \\ \tilde{w}_k \end{bmatrix} \qquad (10)$$

$$\begin{bmatrix} y_k^s \\ y_k^c \end{bmatrix} = \begin{bmatrix} \hat{C} & 0 & 0 & \bar{C}_d & 0 \\ 0 & C & 0 & 0 & \tilde{C}_d \end{bmatrix} \begin{bmatrix} \hat{x}_k \\ x_k \\ \hat{\Xi}_k \\ \Xi_k \\ \tilde{\Xi}_k \end{bmatrix} + \begin{bmatrix} 0 & \bar{D}_d & 0 \\ 0 & 0 & \tilde{D}_d \end{bmatrix} \begin{bmatrix} \hat{w}_k \\ w_k \\ \tilde{w}_k \end{bmatrix} \qquad (11)$$

which is in the standard form of (1).

Models for the parallel connected case can be constructed in a similar manner. However, in this case, it is desirable to capture the correlations between d_2 and d_3 so that their effects on y^p can be rejected on the basis of y^s. Such a correlation model, however, will be difficult to construct on the basis of intuition alone. If d_3 is significant and is strongly correlated with d_2, the subsequently introduced data-based methods will be useful.

- An alternative is the subspace identification. A subspace identification method called N4SID[4], for instance, enables one to construct from input-output data a state-space model of the form

$$\hat{x}_{k+1} = A\hat{x}_k + Bu_k + K\varepsilon_k$$
$$\begin{bmatrix} y^c \\ y^s \end{bmatrix}_k = C\hat{x}_k + \varepsilon_k \qquad (12)$$

where ε_k is a white noise sequence. The method involves only linear algebra operations and has nice proven properties (asymptotic unbiasedness, etc.). One noteworthy point is that the standard N4SID algorithm assumes the stochastic part of the system to be stationary, while disturbances for many processes have integrating characteristics and are better described through nonstationary processes (e.g., integrated white noises). Simple differencing of the input output data before applying the algorithm can remove the integrating characteristics of the output data. The resulting model will be in the form of

$$\hat{x}_{k+1} = A\hat{x}_k + B\Delta u_k + K\varepsilon_k$$
$$\begin{bmatrix} \Delta y^c \\ \Delta y^s \end{bmatrix}_k = C\hat{x}_k + \varepsilon_k \qquad (13)$$

The above can be put into the following standard form through simple algebraic manipulation:

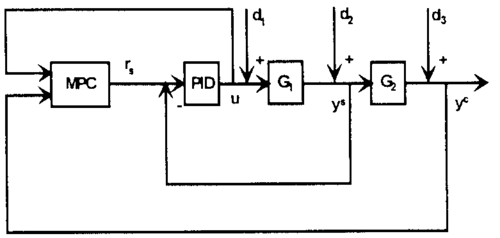
$$\underbrace{\begin{bmatrix} x_{k+1} \\ \eta_{k+1} \\ y_{k+1} \end{bmatrix}}_{x_{k+1}} = \underbrace{\begin{bmatrix} A & K & 0 \\ 0 & 0 & 0 \\ CA & CK & I \end{bmatrix}}_{\Phi} \underbrace{\begin{bmatrix} x_k \\ \varepsilon_k \\ y_k \end{bmatrix}}_{x_k} + \underbrace{\begin{bmatrix} B \\ 0 \\ CB \end{bmatrix}}_{\Gamma} \Delta u_k + \underbrace{\begin{bmatrix} 0 \\ I \\ I \end{bmatrix}}_{w_k} \varepsilon_{k+1}$$
$$y_k = \begin{bmatrix} 0 & 0 & I \end{bmatrix} x_k \qquad (14)$$

where $y_k = \begin{bmatrix} y^c \\ y^s \end{bmatrix}_k$.

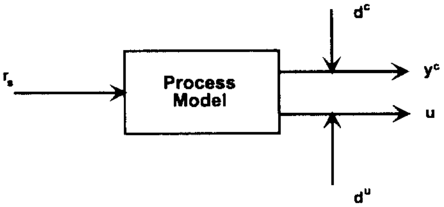
4 Option B: Retaining the Low-Level Loops

4.1 Improved Handling of the Valve Constraints

For Option B, one of the problems is the handling of the valve constraints. A conceptually simple way to incorporate the valve limits directly into the MPC algorithm is to include the valve position in the output of the model. Then the valve limits can be entered into the algorithm as output constraints. The net result is a dynamic, time-varying constraint on the setpoint r_s. The strategy is illustrated in Figure 3.



(a) Block Diagram



(b) model used for MPC design

Figure 3. Block diagram of Option B with valve constraint handling feature (shown here for series-connected system)

Since disturbances and nonlinear / time-varying nature of the valve characteristics change the relation between the setpoint r_s and the valve position u, the valve position need to be monitored continuously and the information should be fed back to the MPC algorithm. It is also important that the model used by MPC allows updating of the valve position based on its feedback. The procedure for controller design is as follows:

1. Identify a model for relating the valve position u and the primary variables y^c to the setpoint signal r_s.

The form of the model needed is displayed in Figure 3(b). Note that d^u is needed to cover the nonlinearity and time-varying characteristics of the valve. Without such a disturbance signal included in the model, the valve position will not be predicted on the basis of the valve position feedback.

Put the model in the form of

$$x_{k+1} = \Phi x_k + \Gamma \Delta r_k^s + w_k$$
$$\begin{bmatrix} y^c \\ u \end{bmatrix} = H x_k + v_k \qquad (15)$$

where w_k and v_k are white noise sequences.

2. Build an observer (e.g., the Kalman filter) on the basis of the model:

$$x_{k/k} = \Phi x_{k-1/k-1} + \Gamma \Delta r_{k-1}^s + K\left(\begin{bmatrix} y^c \\ u \end{bmatrix} - H(\Phi x_{k-1/k-1} + \Gamma \Delta r_{k-1}^s)\right) \qquad (16)$$

Optimal setpoint movements at $t = k$ can be computed by solving the optimization

$$\min_{\Delta r_k^s, \ldots, \Delta r_{k+m-1}^s} \sum_{i=1}^{p} \left\| (y_{k+i/k}^c - r_{k+i/k}^c \right\|_Q + \sum_{i=1}^{m} \left\| \Delta r_{k+i-1/k}^s \right\|_R \qquad (17)$$

with the prediction equation constraint

$$\begin{bmatrix} \begin{bmatrix} y_{k+1/k}^c \\ u_{k+1/k} \end{bmatrix} \\ \begin{bmatrix} y_{k+2/k}^c \\ u_{k+2/k} \end{bmatrix} \\ \vdots \\ \begin{bmatrix} y_{k+p/k}^c \\ u_{k+p/k} \end{bmatrix} \end{bmatrix} = \begin{bmatrix} H\Phi \\ H\Phi^2 \\ \vdots \\ H\Phi^p \end{bmatrix} X_{k/k} + \begin{bmatrix} H\Gamma & 0 & \cdots & 0 \\ H\Phi\Gamma & H\Gamma & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ H\Phi^{p-1}\Gamma & H\Phi^{p-2}\Gamma & \cdots & H\Phi^{p-m}\Gamma \end{bmatrix} \begin{bmatrix} \Delta r_k^s \\ \Delta r_{k+1}^s \\ \vdots \\ \Delta r_{k+m-1}^s \end{bmatrix} \qquad (18)$$

the valve constraints

$$u_{\min} \le u_{k+i/k} \le u_{\max} \qquad (19)$$
$$\Delta u_{\min} \le u_{k+i/k} - u_{k+i-1/k} \le \Delta u_{\max}$$

plus other inequality constraints expressing the constraints on the associated variables.

Change the setpoint r^s by $(\Delta r_k^s)^*$ which denotes the optimal value for Δr_k^s in the above optimization.

The model (21) can be obtained using any of the methods we discussed in the previous section. In this case, however, it is not necessary to capture correlations between d^u and d^c. Hence, it is probably the simplest to identify G_1 and G_2 separately and put them together along with some assumed stochastic models (e.g., integrated white noise models) for d^u and d^c. however, capturing correlations through MIMO identification can improve the performance.

5. Numerical Examples

The proposed ways for the deficiencies are tested on CSTR and distillation column. A subspace identification technique called N4SID to construct state-space models that correlates process outputs (including valve position in the first approach and secondary measurement in the second approach) and process inputs including unmeasured disturbance.

5.1 CSTR

When the classical cascade control structure is removed and MPC structure is applied to the CSTR, aim of this work is choosing the best MPC structure. We consider four kind of the structure. (1) option A, (2) option A with local disturbance rejection approach (3) option B, (4) option B with handling valve constraints in inner-loop. Figure 4 shows the responses by disturbances are different severely. Handling of valve constraints is so important is shown in Figure 4.

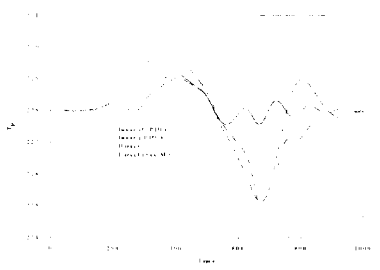


Figure 3. Disturbance rejection responses for CSTR

Note that responses by structure 2, 4 are very similar.

5.2 Distillation Column

Let us consider the distillation column with an binary feed, a total condenser and a thermosyphon reboiler. The column model used is "Column A" studied in several papers by Skogestad and Morari. The aim of this work is choosing the best MPC structure. We consider four kind of the structure. (1) option A, (2) option A with local disturbance rejection approach (3) option B, (4) option B with handling valve constraints in inner-loop. Figures 4.a and b show the responses by increasing disturbances are different severely. Handling of valve constraints is so important is also shown in Figure 4.

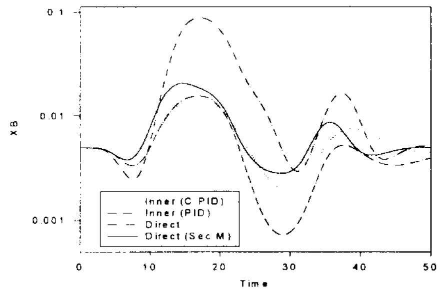


Figure 4.a Disturbance rejection responses in top composition.

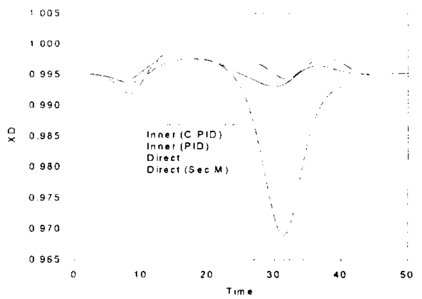


Figure 4.b Disturbance rejection responses in bottom composition.

6. Conclusions

In this paper, two options exist when model predictive controller is implemented to process with low-level loops, were described. The deficiencies for the options were discussed. The deficiencies in the option A, were to lose effect local disturbance rejection and difficulty of identification. To remove the deficiencies, the way using secondary measurements were presented. The deficiencies in the option B, was difficulty of handling valve constraints in inner-loop. The way using valve position as secondary measurement was presented. Superiority for the solving ways were illustrated by simulation results of CSTR and distillation column.

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