Discrete-Time Nonlinear Control of Processes with Actuator Saturation

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Introduction

Analytical model-based control of nonlinear processes with actuator saturation nonlinearities has received considerable attention in recent years (Åström and Rundqwist, 1989; Zheng et al., 1994; Coulibaly et al., 1995; Oliveira et al., 1995; Kurtz and Henson, 1997; Kendi and Doyle, 1997; Valluri and Soroush, 1998; Kapoor and Daoutidis, 1998). Analytical controllers are those whose implementation does not require solving an optimization problem on-line. Examples include proportional-integral-derivative (PID) controllers, model state feedback controllers, internal model controllers, and input–output linearizing controllers.

While in analytical model-based control, the closed-loop performance may be poor in the presence of input constraints, in model-predictive control (MPC) the constraints are explicitly accounted for, and the controller action is solution to a constrained optimization problem and thus is optimal. Furthermore, in MPC tunable parameters such as prediction and control horizons can be adjusted to achieve a desirable closed-loop response in the presence of constraints.

This note presents discrete-time nonlinear model-based control laws for multivariable processes with actuator saturation. This work is a continuation of the nonlinear controller synthesis results for unconstrained processes already published in this same journal (Soroush and Kravaris, 1996). The control laws presented in this note are input–output linearizing in the absence of input constraints, can provide significant improvement in control quality in the presence of active input constraints, and are model-predictive in the sense that they are exact solutions to a moving-horizon optimization problem. The connections between the derived control laws and (a) model state feedback control (Coulibaly et al., 1995) and (b) modified internal model control (IMC) (Zheng et al., 1994) are explained briefly.

This note begins with a description of the scope of the work. Dynamic control laws are derived first for processes with full state measurements and then for processes with incomplete state measurements. The application and performance of one of the nonlinear control laws are demonstrated by a chemical reactor example.

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Scope

The focus of this study is on nonlinear multivariable processes described by a mathematical model of the form

$$\begin{cases} x(k+1) = \Phi[x(k), u(k)], & x(0) = 0 \\ y(k) = h[x(k)], \end{cases} \tag{1}$$

with

$$u_{l_\ell} \le u_\ell(k) \le u_{h_\ell}, \qquad \ell = 1, \ldots, m$$

where $x = [x_1 \cdots x_n]^T$, $u = [u_1 \cdots u_m]^T$, and $y = [y_1 \cdots y_m]^T$ denote the vectors of state variables, manipulated inputs, and controlled outputs, respectively, all in the form of deviation variables; $(x_{ss}, u_{ss}) = (0,0)$ is the nominal equilibrium pair; and $\Phi(x,u)$ and $h(x)$ are smooth-vector functions. It is assumed that the "delay-free part" of the process is minimum-phase. The vector of measured controlled outputs, denoted by $\bar{y}$, is related to the vector of measured state variables, represented by $\bar{x}$, according to

$$\bar{y} = h(\bar{x}) + d, \tag{2}$$

where d is the vector of unmeasurable constant disturbances.

For a process of the form of Eq. 1, the relative order of an output y_i with respect to the vector of manipulated inputs is denoted by r_i (a definition of the relative order can be found in Soroush and Kravaris (1996)), and the characteristic matrix of the process by

$$\mathcal{C}(x,u) \triangleq \begin{bmatrix} \dfrac{\partial}{\partial u} h_1^{r_1}(x,u) \\ \vdots \\ \dfrac{\partial}{\partial u} h_m^{r_m}(x,u) \end{bmatrix},$$

where

$$h_i^0(x) \triangleq h_i(x)$$

$$h_i^l(x) \triangleq h_i^{l-1}[\Phi(x,u)], \qquad l = 1, \cdots, r_i - 1.$$

$$h_i^{r_i}(x,u) \triangleq h_i^{r_i-1}[\Phi(x,u)]$$

Throughout this note, it will be assumed that all the relative orders $r_1, \cdots, r_m$ are finite, and the characteristic matrix $\mathcal{C}(x,u)$ is nonsingular in a neighborhood of nominal operating conditions.

Nonlinear Controller Synthesis

We seek nonlinear controllers that

1. In the absence of constraints can induce a desirable, offset-free, linear, input–output, closed-loop behavior (set point-to-output relation) of the form

$$\begin{bmatrix} \bar{y}_1(k+r_1) \\ \vdots \\ \bar{y}_m(k+r_m) \end{bmatrix} + \sum_{i=1}^{m} \sum_{l=1}^{r_i} \gamma_{i\ell} \bar{y}_i(k+r_i-l) = Qy_{sp}(k), \quad (3)$$

where $y_{sp} = [y_{sp_1} \cdots y_{sp_m}]^T$ is the vector of output set points,

$$Q = I_m + \left[\left(\sum_{\ell=1}^{r_1} \gamma_{1\ell} \right) \cdots \left(\sum_{\ell=1}^{r_m} \gamma_{m\ell} \right) \right],$$

and $\gamma_{i\ell} = [\gamma_{i\ell}^1 \cdots \gamma_{i\ell}^m]^T$, $\ell = 1, \cdots, r_i$, $i = 1, \cdots m$, are m-vectors of constant parameters with $det[Q] \neq 0$.

2. Represent the solution to the constrained m-dimensional minimization problem:

$$\min_{u(k)} \left\{ \sum_{j=1}^{m} \left[y_{d_j}(k+r_j) - \hat{y}_j(k+r_j) \right]^2 \right\},$$

subject to the input constraints (4)

$$u_{l_\ell} \leq u_\ell(k) \leq u_{h_\ell}, \qquad \ell = 1, \cdots, m,$$

where the reference trajectories $y_{d_1}, \cdots, y_{d_m}$ are given by

$$\begin{bmatrix} y_{d_1}(k+r_1) \\ \vdots \\ y_{d_m}(k+r_m) \end{bmatrix} = Qy_{sp}(k) - \sum_{i=1}^{m} \sum_{\ell=1}^{r_i} \gamma_{i\ell} \hat{y}_i(k+r_i-\ell) \quad (5)$$

and each predicted output $\hat{y}_i$ is given by

$$\hat{y}_i(k+\ell) \triangleq \bar{y}_i(k) + h_i^\ell[x(k)] - h_i[x(k)], \qquad \ell = 1, \cdots, r_i - 1$$

$$\hat{y}_i(k+r_i) \triangleq \bar{y}_i(k) + h_i^{r_i-1}\{\Phi[x(k), u(k)]\} - h_i[x(k)]. \quad (6)$$

When measurements of the state variables are available in the preceding prediction equations, we set $x = \bar{x}$. Otherwise, the values of the state variables have to be estimated, for example, via on-line simulation of the process model (use of an open-loop observer).

The following notation will be used in the theoretical results given in the rest of this article:

- $u(k) = \Psi[x(k), v(k)]$ will denote the solution to the constrained m-dimensional minimization problem:

$$\min_{u(k)} \| \phi[x(k), u(k)] - Qv(k) \|^2$$

subject to the input constraints (7)

$$u_{l_\ell} \leq u_\ell(k) \leq u_{h_\ell}, \qquad \ell = 1, \cdots, m,$$

where $\| \cdot \|$ is the Euclidean norm and

$$\phi[x(k), u(k)] \triangleq \begin{bmatrix} h_1^{r_1}[x(k), u(k)] \\ \vdots \\ h_m^{r_m}[x(k), u(k)] \end{bmatrix} + \sum_{i=1}^{m} \sum_{\ell=1}^{r_i} \gamma_{i\ell} h_i^{r_i-\ell}[x(k)]. \quad (8)$$

- The linear system

$$\eta(k+1) = A_c \eta(k) + B_c Q y_{sp}(k)$$

$$y(k) = C_c \eta(k) \quad (9)$$

will represent a minimal-order state-space realization of the desirable linear response of Eq. 3, where $\eta \in \mathbb{R}^{r_1 + \cdots + r_m}$, and A_c, B_c, and C_c are constant matrices (see supplementary material).

The following two theorems describe two nonlinear controllers that have the following properties: the controllers possess integral action, do not exhibit integral windup (see Valluri et al. (1998) for several definitions of windup), are input–output linearizing in the absence of actuator saturation, and are model predictive in the sense that they are solutions to the moving-horizon optimization problem of Eq. 4.

Theorem 1. For a process of the form of Eq. 1 with complete state measurements ($\bar{x}$), finite relative orders, $r_1, \cdots, r_m$, and a locally nonsingular characteristic matrix $\mathcal{C}(x,u)$, the dynamic mixed error- and state-feedback control law:

$$\begin{cases} \eta(k+1) = A_c \eta(k) + B_c \phi[\bar{x}(k), u(k)], & \eta(0) = 0 \\ u(k) = \Psi\{\bar{x}(k), C_c \eta(k) + e(k)\}, \end{cases} \quad (10)$$

where $e = y_{sp} - \bar{y}$

(a) Is the solution to the minimization problem of Eq. 4 when all the state variables are measurable.

(b) In the absence of constraints, induces the linear input–output closed-loop response of Eq. 3.

(c) Has integral action (in the presence of constant disturbances and model errors, induces an offset-free closed-loop response), but does not exhibit integral windup (because it is a model-predictive controller).

The proof is given in the Supplementary Material.

The block diagram of the controller of Eq. 10 is depicted in Figure 1a. In this controller, $C_c \eta$ simply represents the vector of the estimated values of "disturbance-free" controlled outputs, obtained via on-line simulation of the nominal linear input–output closed-loop response (i.e., the system of Eq. 3). Since $C_c \eta + e = y_{sp} - d$, the preceding controller

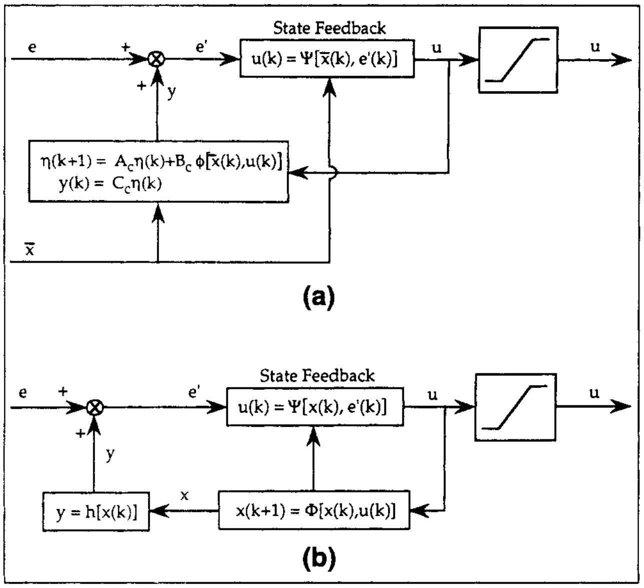

Figure 1. (a) Mixed error- and state-feedback control structure; (b) error-feedback control structure.

can be interpreted as a nonlinear model state feedback (modified internal model) controller for processes with complete state measurements. In the continuous-time setting, these connections have been established in Valluri et al. (1988).

Theorem 2. For a process of the form of Eq. 1 with incomplete state measurements, finite relative orders, $r_1, \cdots, r_m$, and a locally nonsingular characteristic matrix $\mathcal{C}(x,u)$, the dynamic error-feedback control law:

$$\begin{cases} x(k+1) = \Phi[x(k), u(k)], & x(0)=0 \\ u(k) = \Psi\{x(k), h[x(k)] + e(k)\} \end{cases} \tag{11}$$

(a) Is the solution to the minimization problem of Eq. 4.

(b) In the absence of constraints, induces the linear input-output closed-loop response of Eq. 3.

(c) Has integral action (in the presence of constant disturbances and model errors, induces an offset-free closed-loop response), but does not exhibit integral windup (because it is a model-predictive controller).

The proof is given in the Supplementary Material.

The block diagram of the controller of Eq. 11 is depicted in Figure 1b. When the nonlinear controller of Eq. 11 is applied to linear systems, the resulting linear system will be a discrete-time model state feedback controller (a minimal-order state-space realization of a discrete-time linear internal model controller (a) that does not exhibit windup, and (b) whose action is optimal (minimizes the performance index of Eq. 4)).

In the preceding controller, the estimated values of the disturbance-free controlled outputs are obtained via on-line simulation of the process model, while in the controller of Theorem 2, these estimated values are obtained via on-line simulation of the nominal linear input-output closed-loop response. Since $h(x)+e = y_{sp} - d$, the preceding controller can be interpreted as a nonlinear model state feedback (modified internal model) controller for processes with incomplete state measurements.

Note that the integral action added to the controllers of Theorems 1 and 2 ensures offset-free closed-loop responses provided that (1) the closed-loop control system is asymptotically stable and (2) the process is subjected to "rejectable" constant disturbances and "feasible" set point step changes (rejectable and feasible in the sense that always $u_{l_i} \le u_{i_{ss}} \le u_{h_i}$, $i = 1, \ldots, m$).

In the absence of constraints, model errors, and disturbances, the closed loop under the controllers of Theorems 1 and 2 will be asymptotically stable, if the following conditions are satisfied. The closed-loop systems will be input-output stable if the m-vector parameters $\gamma_{i\ell}$, $i =, \cdots, m$, $\ell = 1, \cdots, r_i$ are chosen such that all the roots of the characteristic equation

$$\det\left\{\operatorname{diag}\{z^{r_i}\} + \left[\left(\sum_{\ell=1}^{r_1} \gamma_{1\ell} z^{r_1-\ell}\right) \cdots \left(\sum_{\ell=1}^{r_m} \gamma_{m\ell} z^{r_m-\ell}\right)\right]\right\} = 0 \tag{12}$$

lie inside the unit circle. For an input-output stable closed-loop system, the internal stability will be ensured [a] under the controller of Theorem 1, if the process is hyperbolically minimum-phase (Soroush and Kravaris, 1996); [b] under the controller of Theorem 2, if the process is hyperbolically minimum-phase, and the process is asymptotically open-loop stable.

Remark 1. In the case that the vector function $\phi(x,u)$ in affine-in-u [i.e., $\phi(x,u) = f(x) + \mathcal{C}(x)u$, where $f(x) \in \mathbb{R}^{n\times 1}$], and the characteristic matrix, $\mathcal{C}(x)$, is diagonal, the minimization problem of Eq. 4 will have an analytical solution, and thus there is no need for on-line optimization. The explicit analytical forms of the control laws of Theorems 1 and 2, respectively, are:

$$\begin{cases} \eta(k+1) = A_c\eta(k) + B_c\{f[\bar{x}(k)] + \mathcal{C}[\bar{x}(k)]u(k)\}, & \eta(0)=0 \\ u_i(k) = \operatorname{sat}_i\left\{\dfrac{1}{\mathcal{C}_{ii}}\left(Q_i\{C_c\eta(k)+e(k)\} - f_i[\bar{x}(k)]\right)\right\}, & i = 1, \ldots, m \end{cases} \tag{13}$$

and

$$\begin{cases} x(k+1) = \Phi[x(k), u(k)], & x(0)=0 \\ u_i(k) = \operatorname{sat}_i\left\{\dfrac{1}{\mathcal{C}_{ii}}\left(Q_i\{h[x(k)]+e(k)\} - f_i[x(k)]\right)\right\}, & i = 1, \cdots, m, \end{cases} \tag{14}$$

where $\mathcal{C}_{ii}$ is the iith entry of the characteristic matrix, Q_i is the ith row of the matrix and

$$\mathrm{sat}_i(\theta) \triangleq \begin{cases} u_{l_i}, & \theta \le u_{l_i} \\ \theta, & u_{l_i} \le \theta \le u_{h_i} \quad i=1, \cdots, m. \\ u_{h_i} & u_{h_i} \le \theta \end{cases}$$

Thus, in this case the optimal controller action is obtained exactly by "clipping" the unconstrained controller output.

Remark 2. The feedback controllers of Theorems 1 and 2 can be simplified by requesting a desirable closed-loop response (see Soroush and Kravaris, 1996). For example, when process is delay-free (relative orders $r_1 = \cdots = r_m = 1$) and a completely decoupled input-output response, that is,

$$y_i(k+1) + \gamma_{i1}^i y_i(k) = [1+\gamma_{i1}^i] y_{sp_i}(k), \qquad i=1, \cdots, m \quad (15)$$

is desirable, the controllers of Theorems 1 and 2, respectively, take the following simple forms:

$$\begin{cases} \eta(k+1) = \mathrm{diag}\{\gamma_{i1}^i\}[h(\bar{x}(k)) \\ -\eta(k)] + h(\Phi[\bar{x}(k), u(k)]), \qquad \eta(0)=0 \\ u(k) = \Psi\{\bar{x}(k), \eta(k)+e(k)\} \end{cases} \quad (16)$$

$$\begin{cases} x(k+1) = \Phi[x(k), u(k)], \qquad x(0)=0. \\ u(k) = \Psi\{x(k), h[x(k)] + e(k)\} \end{cases} \quad (17)$$

Note that in this case,

$$\phi[\bar{x}(k), u(k)] = h(\Phi[\bar{x}(k), u(k)]) + \mathrm{diag}\{\gamma_{i1}^i\} h[\bar{x}(k)].$$

Illustrative Example: Application to a Chemical Reactor

To illustrate the application and performance of the derived control laws, we consider the same continuous stirred-tank reactor used in (Soroush and Kravaris, 1996). The correct values of the preexponential factors of the reactions are given below:

$$Z_1 = 7.8120 \times 10^{-1}\ \mathrm{s}^{-1}$$
$$Z_{-1} = 1.8000 \times 10^{2}\ \mathrm{s}^{-1}$$
$$Z_2 = 7.8120 \times 10^{-1}\ \mathrm{m}^6 \cdot \mathrm{kmol}^{-2} \cdot \mathrm{s}^{-1}$$
$$Z_3 = 1.9980 \times 10^{10}\ \mathrm{m}^6 \cdot \mathrm{kmol}^{-2} \cdot \mathrm{s}^{-1}$$
$$Z_4 = 1.9980 \times 10^{10}\ \mathrm{s}^{-1}$$
$$Z_d = 4.9986 \times 10^{5}\ \mathrm{m}^3 \cdot \mathrm{kmol}^{-1} \cdot \mathrm{s}^{-1}.$$

The following bounds on the manipulated inputs are assumed: $0.0 \le u_1(k) \le 7.0\ \mathrm{kmol \cdot m^{-3}}$ and $-20.0 \le u_2(k) \le 20.0\ \mathrm{kJ \cdot s^{-1}}$. For this process, the relative orders $r_1 = 1$ and $r_2 = 1$, $\mathcal{C}(x,u) = \mathrm{diag}[\Delta t/\tau \ \ \Delta t/(\rho c_p V)]$, and $\phi(x,u)$ is affine-in-u:

$$\phi_1[C_A(k), C_{U_1}(k), T(k), u_1(k)] = [\gamma_{11}^1 + 1] C_A(k) + f_1[C_A(k), C_{U_1}(k), T(k)]\Delta t + \frac{\Delta t}{\tau} u_1(k)$$

$$\phi_2[C_A(k), C_{U_1}(k), T(k), u_2(k)] = [\gamma_{21}^2 + 1] T(k) + f_3[C_A(k), C_{U_1}(k), T(k)]\Delta t + \frac{\Delta t}{\rho c_p V} u_2(k).$$

Thus, Remarks 1 and 2 are applicable to this example, in which the control law of Eq. 13 with $\gamma_{11}^1 = \gamma_{21}^2 = 0$, takes the following form:

$$\eta_1^{(1)}(k+1) = -\gamma_{11}^1 \eta_1^{(1)}(k) + \phi_1\left[\bar{C}_A(k), \bar{C}_{U_1}(k), \bar{T}(k), u_1(k)\right], \qquad \eta_1^{(1)}(0) = \bar{C}_A(0)$$

$$\eta_2^{(1)}(k+1) = -\gamma_{21}^2 \eta_2^{(1)}(k) + \phi_2\left[\bar{C}_A(k), \bar{C}_{U_1}(k), \bar{T}(k), u_2(k)\right], \qquad \eta_2^{(1)}(0) = \bar{T}(0)$$

$$u_1(k) = \mathrm{sat}_1\left\{\left\{(1+\gamma_{11}^1)[e_1(k) + \eta_1^{(1)}(k) - \bar{C}_A(k)] - f_1\left[\bar{C}_A(k), \bar{C}_{U_1}(k), \bar{T}(k)\right]\Delta t\right\} \frac{\tau}{\Delta t}\right\}$$

$$u_2(k) = \mathrm{sat}_2\left\{\left\{(1+\gamma_{21}^2)[e_2(k) + \eta_2^{(1)}(k) - \bar{T}(k)] - f_3\left[\bar{C}_A(k), \bar{C}_{U_1}(k), \bar{T}(k)\right]\Delta t\right\} \frac{\rho c_p V}{\Delta t}\right\}. \quad (18)$$

Application of the control law of Theorem 2 of (Soroush and Kravaris, 1996) leads to the following controller:

$$\eta_1^{(1)}(k+1) = -\gamma_{11}^1 \eta_1^{(1)}(k) + (1+\gamma_{11}^1) e_1(k), \qquad \eta_1^{(1)}(0) = \bar{C}_A(0)$$

$$\eta_2^{(1)}(k+1) = -\gamma_{21}^2 \eta_2^{(1)}(k) + (1+\gamma_{21}) e_2(k), \qquad \eta_2^{(1)}(0) = \bar{T}(0)$$

$$u_1(k) = \mathrm{sat}_1\left\{\left\{(1+\gamma_{11}^1)[e_1(k) + \eta_1^{(1)}(k) - \bar{C}_A(k)] - f_1\left[\bar{C}_A(k), \bar{C}_{U_1}(k), \bar{T}(k)\right]\Delta t\right\} \frac{\tau}{\Delta t}\right\}$$

$$u_2(k) = \mathrm{sat}_2\left\{\left\{(1+\gamma_{21}^2)[e_2(k) + \eta_2^{(1)}(k) - \bar{T}(k)] - f_3\left[\bar{C}_A(k), C_{U_1}(k), \bar{T}(k)\right]\Delta t\right\} \frac{\rho c_p V}{\Delta t}\right\} \quad (19)$$

For both controllers of Eqs. 18 and 19, we set $\gamma_{11}^1 = -0.90$ and $\gamma_{21}^2 = -0.96$, as in Soroush and Kravaris (1996). Thus, in the absence of the constraints, the two preceding controllers induce the same completely decoupled linear input–output closed-loop response of Eq. 15, with $i = 2$.

Simulation Results

Figure 2 depicts the responses of the controlled outputs and manipulated inputs under the controllers of Eqs. 18 and 19. The solid, dashed, and dotted lines, respectively, repre-

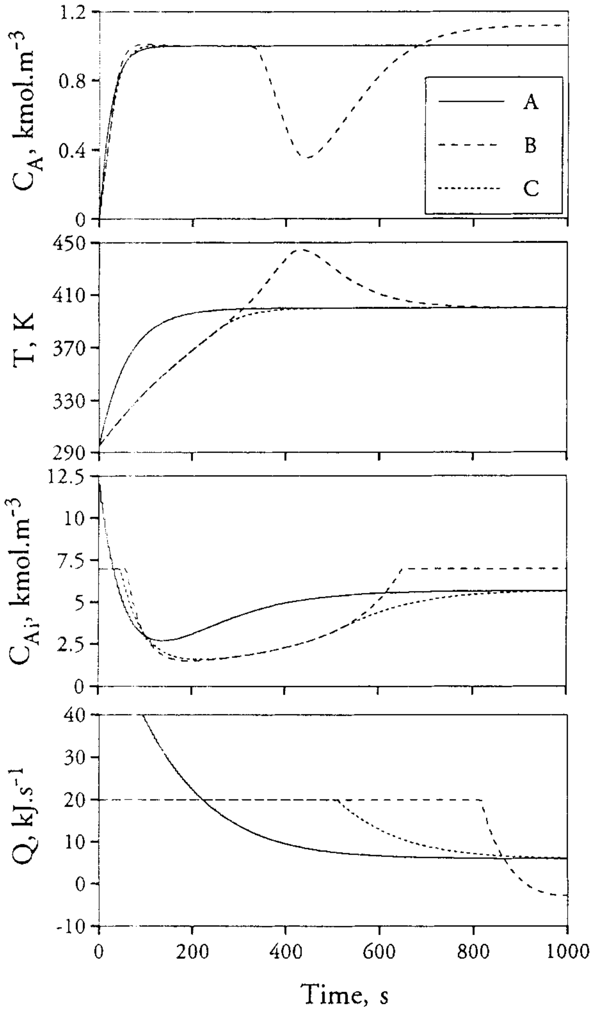

Figure 2. Startup profiles of the controlled outputs and manipulated inputs.

sent the responses in the following cases: (1) under the two controllers and in the absence of the input constraints, (2) under the controller of Eq. 19 and in the presence of the input constraints, and (3) under the controller of Eq. 18 and in the presence of the input constraints. As expected, in the absence of the input constraints the closed-loop controlled output responses under the two controllers are identical. In the presence of the input constraints, however, these responses are substantially different; while under the controller of Eq. 19 the process outputs exhibit a large overshoot, a large undershoot, and long response times, under the controller of Eq. 18 the process responses do not have overshoot or undershoot and have short response times. Indeed, the controller of Eq. 19 cannot operate (stabilize) the process at the desirable steady state, as there is a nonzero steady-state error between the reactant concentration and its set point. The instability, the excessive overshoot and undershoot, and the long response times are all indications of the presence of integral windup in the controller of Eq. 19. Under the controller of Eq. 19, both manipulated inputs stay at their upper limits much longer; the inlet reactant concentration indeed never leaves its upper limit, leading to the offset in the reactant concentration. Under the controller of Eq. 19 and in the presence of the constraints, although the controlled outputs are bounded, one of the state variables of the controller, $\eta_1^{(1)}$ increases with time indefinitely (becomes unbounded). Indeed, it is this very high value of $\eta_1^{(1)}$ that prevents the inlet reactant concentration from leaving its upper limit. Overall, the simulation results show that considerable improvement in control quality can be obtained by implementing the derived

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