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# SCHEDULING QUASI-MIN-MAX MODEL PREDICTIVE CONTROL ALGORITHM FOR NONLINEAR SYSTEMS

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## Abstract

In this paper, a model predictive control algorithm, scheduling quasi-min-max MPC algorithm, is designed for nonlinear systems. Combination of a linear model with a linear parameter varying model approximates the nonlinear behavior. The linear model expresses the current nonlinear dynamics, and the linear parameter varying model covers the future nonlinear behavior. In the algorithm, a "quasi worst case" value of infinite horizon objective function is minimized. Closed-loop stability is guaranteed when the algorithm is implemented in a receding horizon fashion by including a Lyapunov constraint in the formulation. The proposed approach is applied to control a jacketed styrene polymerization reactor

## 1 Introduction

In recent years research on nonlinear model predictive control has attracted significant attention. In industry, model predictive controllers based on linear models are often used to control nonlinear systems. However when the operating conditions undergo significant changes, the performance of linear MPC can deteriorate drastically. Under such conditions nonlinear models should be considered.

An optimization problem involving nonlinear models is usually computational demanding. In order to alleviate this difficulty, [7] suggests a switching dual-mode horizon controller. A local linear feedback control law is applied once the states enter an invariant terminal region, and a finite horizon nonlinear predictive controller is applied outside this terminal region. In [9] a contractive constraint is imposed on the optimization problem. Closed-loop stability is guaranteed by the feasibility of the algorithm. In [3] the infinite horizon MPC cost function is bounded by a finite horizon stage cost with a terminal penalty term. This term is calculated off-line by using a local state feedback law. Local stability is proven by the existence of a feasible solution to the optimization problem. It is found that this quasi-infinite horizon MPC approach reduces the computational burden. However, when the initial condition is far from the desired operating point and the terminal region is too small, the algorithm requires long horizons and becomes computationally demanding since on-line optimization uses the nonlinear dynamic model.

Another approach to handle nonlinear dynamics is to use approximate models. A contractive MPC algorithm based on local linearization is given in [4]. Linear approximations of the plant at each time step are utilized in order to predict future outputs. A scheduling MPC controller based on linear parameter varying models is developed in [1]. A family of linear models around different operating regimes of the nonlinear system is first obtained, and then a global linear parameter varying model is constructed to approximate the nonlinear behavior. This algorithm however has been found conservative regarding input constraints. In this paper, we show that a combination of linear and linear parameter varying models reduces the conservatism and stability of the resulting control algorithm can be guaranteed when the associated optimization problem has a feasible solution.

The rest of the paper is structured as follows. Section 2 discusses the approximation of the nonlinear systems with "current linear model + linear parameter varying model". Section 3 presents the formulation of the scheduling quasi-min-max MPC algorithm. Section 4 demonstrates the applications of the scheduling quasi-min-max MPC algorithm to a jacketed styrene polymerization reactor. Finally, section 5 draws some conclusions.

## 2 Nonlinear System Approximation

It is assumed that the nonlinear first principle model is known, and that it can be expressed as follows:

$$\begin{aligned} \dot{\hat{x}} &= f(\hat{x}, \hat{u}) \\ \hat{y} &= C\hat{x} \end{aligned} \tag{1}$$

where $\hat{x}$ is the state variable, $\hat{u}$ is the control variable, and $\hat{y}$ is the output variable.

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The first step of the approximation is to obtain a current linear model to approximate the nonlinear dynamics. At the current sampling time $k$, a Taylor series expansion around the current point $k$ is used to linearize the nonlinear plant:

$$\begin{aligned}\dot{\hat{x}} &= f(\hat{x}(k|k), \hat{u}(k-1|k-1)) \\ &+\frac{\partial f}{\partial x}|_{\hat{x}(k|k),\hat{u}(k-1|k-1)}(\hat{x}-\hat{x}(k|k)) \\ &+\frac{\partial f}{\partial u}|_{\hat{x}(k|k),\hat{u}(k-1|k-1)}(\hat{u}-\hat{u}(k-1|k-1)) \\ &+\pi_1(k) \end{aligned} \tag{2}$$

where $\hat{x}(k|k)$ is the measured current state variable, $\hat{u}(k-1|k-1)$ is the control action calculated from the previous point, and $\pi_1(k)$ is a tuning parameter to cover linearization error. If the state matrices are defined as:

$$\begin{aligned}A^c(k|k) &= \frac{\partial f}{\partial x}|_{\hat{x}(k|k),\hat{u}(k-1|k-1)} \\ B^c(k|k) &= \frac{\partial f}{\partial u}|_{\hat{x}(k|k),\hat{u}(k-1|k-1)} \end{aligned} \tag{3}$$

and the deviation variables are defined around the desired operation point of $\{\hat{x}_d, \hat{u}_d, \hat{y}_d\}$:

$$x = \hat{x} - \hat{x}_d \quad u = \hat{u} - \hat{u}_d \quad y = \hat{y} - \hat{y}_d \tag{4}$$

equation (2) becomes:

$$\begin{aligned}\dot{\hat{x}} - \dot{\hat{x}}_d &= A^c(k|k)(\hat{x}-\hat{x}_d) + B^c(k|k)(\hat{u}-\hat{u}_d) \\ &+f(\hat{x}(k|k), \hat{u}(k-1|k-1)) \\ &+A^c(k|k)(\hat{x}_d - \hat{x}(k|k)) \\ &+B^c(k|k)(\hat{u}_d - \hat{u}(k-1|k-1)) \\ &+\pi_1(k) \end{aligned} \tag{5}$$

and

$$\hat{y} - \hat{y}_d = C(\hat{x} - \hat{x}_d) \tag{6}$$

Since $\dot{\hat{x}}_d = 0$, $\dot{\hat{u}}_d = 0$, and if we define

$$\begin{aligned}\pi(k|k) &= f(\hat{x}(k|k), \hat{u}(k-1|k-1)) \\ &+A^c(k|k)(\hat{x}_d - \hat{x}(k|k)) \\ &+B^c(k|k)(\hat{u}_d - u(k-1|k-1)) \\ &+\pi_1(k) \end{aligned} \tag{7}$$

then we have

$$\begin{aligned}\dot{x} &= A^c(k|k)x + B^c(k|k)u + \pi(k|k) \\ y &= Cx \end{aligned} \tag{8}$$

The discrete state space model can be obtained with the sampling time $\Delta t$

$$\begin{aligned}x(k+1|k) &= A(k|k)x(k|k) + B(k|k)u(k|k) + \theta(k|k) \\ y(k|k) &= Cx(k|k) \end{aligned} \tag{9}$$

where

$$\begin{aligned}A(k|k) &= e^{A^c(k|k)\Delta t} \\ B(k|k) &= A^c(k|k)^{-1}(e^{A^c(k|k)\Delta t} - I)B^c(k|k) \end{aligned} \tag{10}$$

and

$$\theta(k|k) = -A^c(k|k)^{-1}(I - e^{A^c(k|k)\Delta t})\pi(k|k) \tag{11}$$

The next step of the approximation is to approximate the future nonlinear behavior. It is assumed that the future nonlinearities can be covered by a family of linear models that can be expressed in linear parameter varying (LPV) form:

$$\begin{aligned}x(k+i+1|k) &= A(\rho(k+i|k))x(k+i|k) \\ &+B(\rho(k+i|k))u(k+i|k) \\ y(k+i|k) &= Cx(k+i|k) \quad i \geq 1 \end{aligned} \tag{12}$$

where

$$\begin{aligned}A(\rho(k+i|k)) &= \sum_{j=1}^{N} \rho_j(k+i|k)A_j \\ B(\rho(k+i|k)) &= \sum_{j=1}^{N} \rho_j(k+i|k)B_j \end{aligned} \tag{13}$$

$[A_j, B_j]$ are local models that can be obtained around different operating points (e.g. see [5] and [2]). Here $N$ is the number of the local models included in the LPV model, and $\rho_j(k+i|k)$ is the scheduling parameter reflecting the validity of the local linear models. When the scheduling parameters satisfy

$$\sum_{j=1}^{N} \rho_j(k+i|k) = 1, \quad 0 \leq \rho_j(k+i|k) \leq 1, j = 1, 2, \cdots, N \tag{14}$$

it is easy to show that the state matrices of $[A(\rho(k+i|k)), B(\rho(k+i|k))]$ belong to a polytope $\Omega$ constructed by the convex hull of the different local models:

$$\Omega = C_o\{[A_1, B_1], [A_2, B_2], \cdots, [A_N, B_N]\} \tag{15}$$

In summary, a linear model (9) is obtained to express the current nonlinear dynamics, and the future nonlinear behavior is assumed to vary within a region constructed by a linear parameter varying model (12). In the next section, we give the formulations of the scheduling quasi-min-max MPC algorithm based on these models.

## 3 Scheduling Quasi-Min-Max Algorithm

The methodology of the scheduling quasi-min-max MPC algorithm is first developed in [6] strictly for LPV models. Here it is applied to models (9) and (12) developed for nonlinear processes. In the scheduling quasi-min-max MPC algorithm, infinite prediction and control horizon are used, and the optimization is expressed as:

$$\min_{U_0^\infty} J_0^\infty = \sum_{i=0}^{\infty} x(k+i|k)^T Q x(k+i|k) + u(k+i|k)^T R u(k+i|k) \tag{16}$$



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where $Q$ and $R$ are the appropriate weights with:

$$Q > 0 \qquad R \geq 0 \tag{17}$$

Here $U_0^\infty$ stands for all the control actions from the current time to the infinity.

$$U_0^\infty = \{u(k+i|k), i = 0, 1, 2, \cdots\} \tag{18}$$

The principle idea behind the quasi-min-max algorithm is to divide the infinite horizon objective function into two parts:

$$\begin{aligned} J_0^\infty(k) &= x(k|k)^T Q x(k|k) + u(k|k)^T R u(k|k) \\ &\quad + \sum_{i=1}^{\infty} x(k+i|k)^T Q x(k+i|k) \\ &\quad + u(k+i|k)^T R u(k+i|k) \\ &= J_0^1(k) + J_1^\infty(k) \end{aligned} \tag{19}$$

The upper bound of $J_1^\infty(k)$, based on the worst case scenario for all the possible state matrices in the prescribed polytope $\Omega$ (15), is found by following the approach in [6].

$$\max_{[A(\rho(k+i|k)), B(\rho(k+i|k))] \in \Omega, i \geq 1} J_1^\infty(k) \leq V(x(k+1|k)) \tag{20}$$

where $V(x(k+1|k))$ is a quadratic function of $x(k+1|k)$, and it is required to satisfy

$$\begin{aligned} & V(x(k+i+1|k)) - V(x(k+i|k)) \\ \leq\ & -x(k+i|k)^T Q x(k+i|k) \\ & -u(k+i|k)^T R u(k+i|k) \end{aligned} \tag{21}$$

for all $i \geq 1$. The first stage cost plus the upper bound of $J_1^\infty(k)$ is minimized:

$$\begin{aligned} \min_{U_0^\infty} \Phi(k) &= x(k|k)^T Q x(k|k) + u(k|k)^T R u(k|k) \\ &\quad + V(x(k+1|k)) \end{aligned} \tag{22}$$

The objective function of quasi-min-max $\Phi(k)$ is forced to decrease monotonically by including the following constraint in the optimization:

$$\Phi(k) < \Phi(k-1) \tag{23}$$

The current control action $u(k|k)$ is separated from the rest $U_1^\infty = \{u(k+i|k)|_{i=1}^\infty\}$, and a feedback control law is applied to the future inputs $U_1^\infty$:

$$u(k+i|k) = F(k) x(k+i|k), \qquad i \geq 1 \tag{24}$$

When there are input constraints, only the control action that will be implemented to the plant $u(k|k)$ is constrained. Similarly only the resulting output $y(k+1|k)$ is constrained when output constraints are included in the problem formulation:

$$\begin{aligned} & u^{min}(k) \leq u(k|k) \leq u^{max}(k) \\ & y^{min}(k+1) \leq y(k+1|k) \leq y^{max}(k+1) \end{aligned} \tag{25}$$

The optimization (22) is solved subject to the constraints (21), (25) and (23) based on the linear models (9) and (12). The optimization can be solved by converting all the constraints into the form of Linear Matrix Inequalities (LMIs). The interested reader is referred to [6] for similar derivations.

**Theorem** When the scheduling quasi-min-max MPC algorithm is implemented in a receding horizon fashion to the nonlinear system, feasibility guarantees stability.

Proof:
Define $\Phi(x(k|k)$ as a candidate Lyapunov function and check Lyapunov stability. First establish that $\Phi(x(k)) = x(k|k)^T Q x(k|k) + u(k|k)^T R u(k|k) + x(k+1|k)^T P(k) x(k+1|k) \geq 0$ and $\Phi(x(k)) = 0$ if only if $x(k) = x(k|k) = 0$.

Since $Q$, $R$ and $P(k)$ are positive definite, it is true that $\Phi(x(k)) > 0$ for all $x(k) \neq 0$. If $x(k) = 0$, since the minimum value the objective function $\Phi(k)$ can take is zero, the optimal solution of input is $u(k|k) = 0$. This results in $x(k+1|k) = 0$ and $\Phi(k) = 0$. On the other hand, when $\Phi(x(k)) = 0$, the terms $x(k|k)^T Q x(k|k)$, $u(k|k)^T R u(k|k)$, and $x(k+1|k)^T P(k) x(k+1|k)$ must be all zero. Therefore, we know $x(k) = 0$ since $Q > 0$.

Secondly, it is known that $\Phi(k) < \Phi(k-1)$ for $k \geq 1$ holds whenever the optimization is feasible.

Based on the above two conditions, $\Phi(k)$ is a Lyapunov function and based on Lyapunov Stability Theory, the controller is known asymptotically stabilizing.

## 4 Examples and Simulations

Consider a jacketed continuous stirred tank styrene polymerization reactor. The first principle nonlinear model in dimensionless form can be found in [8]. The jacketed styrene polymerization reactor exhibits multiplicity behavior as shown in figure 1. In the simulations, we choose three operating conditions.

$$u^1 = u^2 = u^3 = 0.5$$

$$x^1 = \begin{bmatrix} 0.0077 \\ 0.3857 \\ -0.2847 \\ -0.7911 \\ 0.0000 \\ 0.0143 \end{bmatrix} \quad x^2 = \begin{bmatrix} 0.0067 \\ 0.2876 \\ 0.5498 \\ -0.4488 \\ 0.0006 \\ 0.1124 \end{bmatrix} \quad x^3 = \begin{bmatrix} 0.0002 \\ 0.0907 \\ 2.2235 \\ 0.2377 \\ 0.0045 \\ 0.3093 \end{bmatrix}$$

Different discrete linear models can be obtained around these three operating points. Model one $[A_1, B_1]$ is open-loop stable with eigenvalues of $0.3679,\ 0.3679,\ 0.6361,\ 0.1939,\ 0.3481,\ 0.3661$. Model two $[A_2, B_2]$ is open-loop unstable with eigenvalues of $0.3679,\ 0.3679,\ 4.5348,\ 0.4169 \pm 0.1275i,\ 0.3320$. Model three $[A_3, B_3]$ is open-loop stable with eigenvalues of $0.3679,\ 0.3679,\ 0.6052,\ -0.0056 \pm 0.1058i,\ 0$. In the simulations, we study the transitions among these three operating conditions. The features of the scheduling quasi-min-max algorithm are studied in the control of the transition processes. In all the simulations, it is assumed that all the state variables can be measured, and there is no mismatch between the plant and model.



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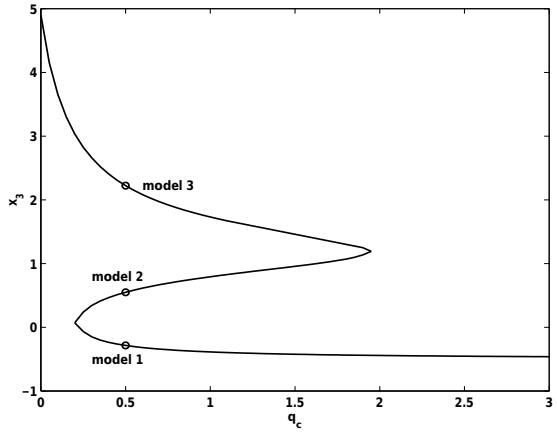



Figure 1: Steady state curve

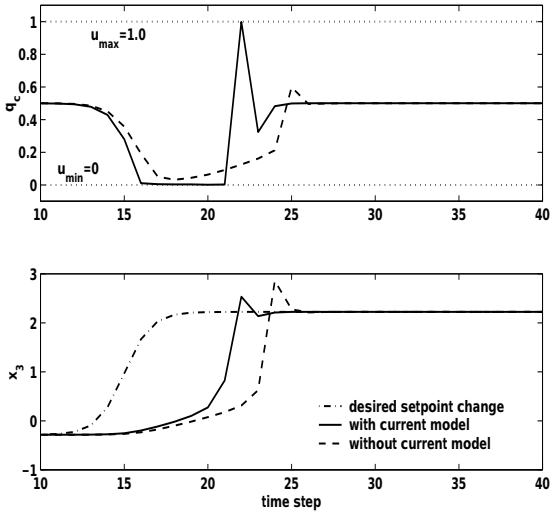



Figure 2: Control comparison with current model and without current model on transition from point 1 to point 3

### 4.1 Current model vs. no current model

The most important feature of the scheduling quasi-min-max MPC algorithm is that a current linear model is obtained on-line, in addition to the linear parameter varying model. By contrast, in the algorithm developed in [1], the nonlinear behavior is assumed varying within the range constructed by multiple linear models, and no current linear model is used to approximate the current nonlinear dynamics.

We consider the transition from operating point 1 to operating point 3. The input variable is constrained by $0 \leq u \leq 1$. Two local models $[A_1, B_1]$ and $[A_3, B_3]$ are chosen to construct the polytope. It is found that the scheduling quasi-min-max algorithm and the algorithm in [1] can both find feasible solutions. The control performances are shown in figure 2. From the plots of the state variable in figure 2, we can observe that the scheduling quasi-min-max algorithm has better performance as it attains the desired operating condition faster. From the plots of the input variables, we can see that the control actions calculated from the scheduling quasi-min-max algorithm reach their saturation points while the saturation points are not attained with the algorithm in [1] indicating conservatism. Constraints concerning input and output variables in the algorithm developed by [1] are satisfied for all the local models, and the input and output are over-bounded since the nonlinear behavior only takes one possible trajectory. However, in the scheduling quasi-min-max algorithm, the first control action $u(k|k)$ is separated and the constraints on input and output are not connected with the local models, therefore, there is no conservatism concerning input/output constraints.

### 4.2 Polytope construction

In the scheduling quasi-min-max MPC algorithm, the current linear model describes the current nonlinear dynamics, and a polytope is constructed by a family of linear models to cover the future nonlinear behavior. In this section, we will discuss how the operating conditions are chosen to construct the polytope. The following four different approaches will be studied.

- Approach One: Polytope is constructed by linear models obtained around some chosen conditions. The number of the local models to construct the polytope, $N$, equals the number of the chosen points.

$$\Omega_1 = C_o\{[A_1, B_1], [A_2, B_3], \cdots, [A_N, B_N]\} \quad (26)$$

- Approach Two: Polytope is constructed by the initial and the final conditions and $N = 2$:

$$\Omega_2 = C_o\{[A_i, B_i], [A_f, B_f]\} \quad (27)$$

- Approach Three: Polytope is constructed by the single current model and $N = 1$:

$$\Omega_3 = C_o\{[A(k|k), B(k|k)]\} \quad (28)$$

- Approach Four: Polytope is constructed by the current condition and the final condition, $N = 2$

$$\Omega_4 = C_o\{[A(k|k), B(k|k)], [A_f, B_f]\} \quad (29)$$

In Approach three and four, $[A(k|k), B(k|k)]$ is being updated in real-time; consequently, the polytopes $\Omega_3$ and $\Omega_4$ are also updated on-line.

**Comparison between $\Omega_1$ and $\Omega_2$**

Consider the transition from point 3 to point 2 with the input constraint $0 \leq u \leq 1.7$. $\Omega_2$ is constructed by the two local models $[A_3, B_3]$ and $[A_2, B_2]$. The closed-loop trajectory of the scheduling quasi-min-max with $\Omega_2$ is shown in figure 3.



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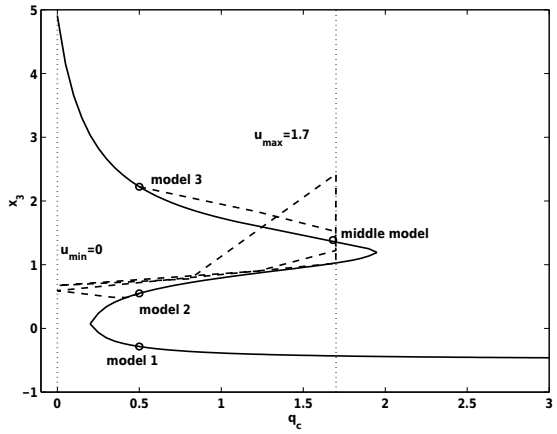



Figure 3: Trajectory of the scheduling quasi-min-max for the transition from point 3 to point 2 with $\Omega_2$

One middle operating point is chosen around the closed-loop trajectory which is also close to the steady state curve:

$$u = 1.6815$$
$$x = [0.0035;\ 0.1891;\ 1.3867;\ -0.1055;\ 0.0026;\ 0.2109]$$

and a model $[A_{mid}, B_{mid}]$ is obtained with open-loop eigenvalues of $0.3679,\ 0.3679,\ 467.8079,\ 0.8246,\ 0.2162,\ 0.1280$. Then $\Omega_1$ is constructed by three local models, $[A_3, B_3]$, $[A_2, B_2]$ and $[A_{mid}, B_{mid}]$. The control performance comparison between $\Omega_1$ and $\Omega_2$ is shown in figure 4. It is obvious that

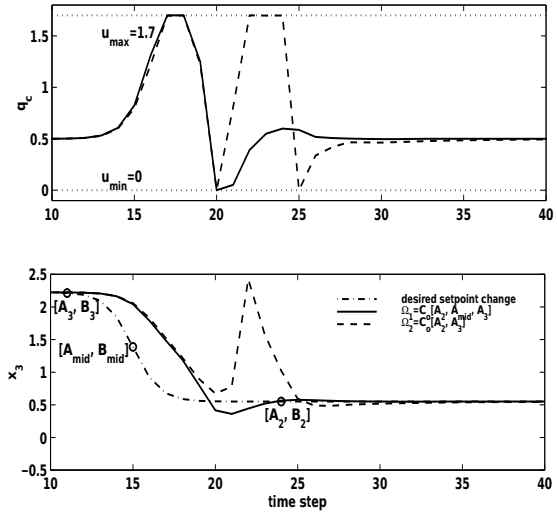



Figure 4: Control comparison with $\Omega_1$ and $\Omega_2$ on transition from point 3 to point 2

the control performance is better by using polytope $\Omega_1$ than by using polytope $\Omega_2$. When more "proper" operating conditions are chosen and included in the polytope, the nonlinear behavior can be approximated more accurately, and the control performance is better.

When the middle operating points are not "properly" chosen, including the middle operating points may not improve the control performance. We consider the transition from point 1 to point 3. Polytope $\Omega_2$ is constructed by two local models $[A_1, B_1]$ and $[A_3, B_3]$, and the scheduling quasi-min-max MPC finds a feasible solution. The closed-loop trajectory is shown in figure 5. If polytope $\Omega_1$ is constructed by including the model around point 2, it is found that the scheduling quasi-min-max cannot find a feasible solution even with input constraint and Lyapunov stability constraint relaxed.

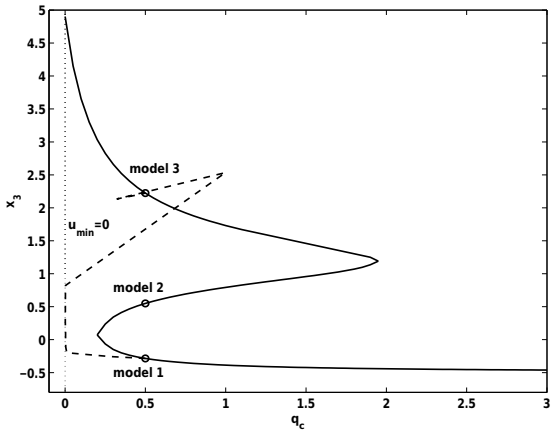



Figure 5: Trajectory of the scheduling quasi-min-max for the transition from point 1 to point 3 with $\Omega_2$

The infeasibility of the scheduling quasi-min-max MPC algorithm with $\Omega_1$ is due to model $[A_2, B_2]$ in the polytope. As shown in figure 5, the operating point 2 is not on the closed-loop trajectory. Model $[A_2, B_2]$ does not improve the approximation of the nonlinear transition from point 1 to point 3. Under this condition, including model 2 in the polytope makes the algorithm more conservative.

**Comparison between $\Omega_3$ and $\Omega_2$**

In this section, we compare the different performances with $\Omega_2$ and $\Omega_3$. If the scheduling quasi-min-max MPC algorithm is based on $\Omega_3$, it is assumed that the future nonlinear behavior is described by the single current linear model. Figure 6 shows the control performance comparison of the scheduling quasi-min-max MPC algorithm with $\Omega_3$ and $\Omega_2$ on the transition from point 3 to point 2 with input constraint $0 \leq u \leq 1.7$.

Figure 6 illustrates that the operation with $\Omega_3$ gives a large offset. This is because the single current linear model cannot cover the nonlinear behavior and the approximation of nonlinear system is poor. This stimulation also verifies that MPC algorithm based on a single linear model cannot handle transition for a strong nonlinear system.



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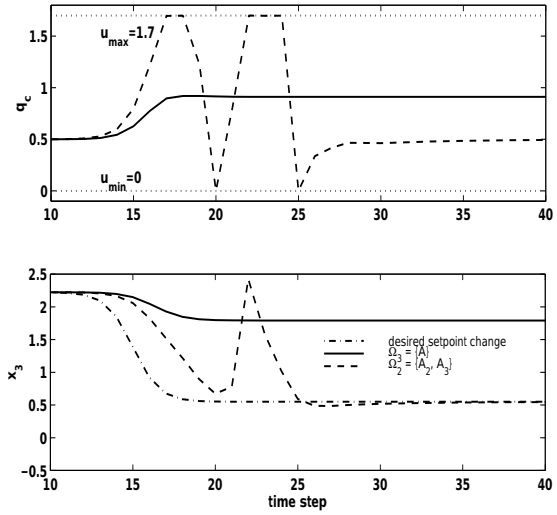



Figure 6: Control comparison with $\Omega_2$ and $\Omega_3$ on transition from point 3 to point 2

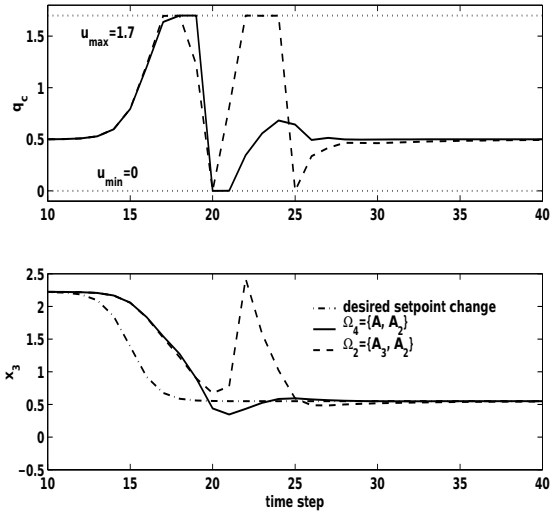



Figure 7: Control comparison of $\Omega_4$ with $\Omega_2$ on transition from point 3 to point 2

**Comparison between $\Omega_4$ with $\Omega_2$**

Polytope $\Omega_4$ is constructed by the current linear model $[A(k|k), B(k|k)]$ and the model around the desired operating point $[A_f, B_f]$. The range that $\Omega_4$ covers decreases as the operation goes to the desired condition since the current linear model is updated on-line and approaches to the model around the desired operating condition. When $\Omega_4$ still covers the future nonlinear behaviors. we can observe that the control performance is improved as it is shown in figure 7.

## 5 Conclusion

In this paper, a scheduling quasi-min-max MPC algorithm is developed for nonlinear processes with input and output constraints. A current local linear model is obtained by on-line linearization around the trajectory to approximate the local dynamics, and the future state space models are assumed to belong to a polytope. Different approaches to construct the polytope are studied on the simulation example of a jacket styrene polymerization reactor.

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