The design of the MISO Model Predictive Controller for Bioreactor

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Abstract

Bioprocesses have the inherent characteristics of high nonlinearity, parameter uncertainty and information imperfection. These specific natures may cause some difficulties in control. Jacobian linearization method was used in this paper to linearize the bioreactor model firstly, and then a Multiple-input and single output (MISO) model predictive controller was designed for the reactor. PID controller and fuzzy-PID controller were also introduced to compare with the MPC controller. Simulation results prove that the model predictive control has several advantages over the other controls for bioreactors.

Keywords: bioreactor, linearization, model predictive control, rolling optimization

1. Introduction

As a high and new technology of life sciences, biotechnology is one of the fastest growing technologies. The application and development of biotechnology has opened up broad prospects for medical, pharmaceutical, food, environmental and some other industries. Due to the needs of high production meeting product quality, process safety and environmental regulation, control systems play a key role in chemical and biochemical plants operation [1]. Monitoring and control of biological processes is becoming more and more important [2-3].

Bioprocesses have complicated dynamics, they also are inherently concerned with nonlinearity and non-stationarity, which make modeling and parameter estimation particularly difficult, therefore their control is a challenging and delicate task [4-5]. Moreover, the scarcity of on-line measurements of the component concentrations makes this task more sophisticated [6]. Hence, conventional control methods do not succeed in such task [7].

It is well known that the design of high-performance model-based control algorithms for biotechnological processes is hampered by two major problems which call for adequate engineering solutions. First, the process kinetics is most often poorly understood nonlinear functions, while the corresponding parameters are in general time-varying. Second, up till now there has been a lack of reliable sensors suited to real-time monitoring of the process variables which are needed in advanced control algorithms. The control of biotechnological processes has been an important problem attracting wide attention [8]. The main engineering motivation in applying control methods to such processes is to improve operational stability and production efficiency [9-10].

Model predictive control (MPC) is an optimization strategy for the control of constrained dynamic systems [11-12]. MPC uses multi-step prediction, rolling optimization and feedback correction control strategies [13], so it can not only give a good control effect and strong robustness, but also have an advantage of less demand on the accuracy of the model. MPC can handle the uncertainty, non-linearity and parallel nature effectively, and can make it easy to deal with the various kinds constraints existing in process controlled variables and manipulated variables. It is an effective method to solve complex industrial process control [14-15]. Good progress has recently been made in simplifying the implementation of MPC [16]. MPC technology can now be found in a wide

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variety of application areas including chemicals, petroleum, metallurgy, food processing, aerospace, machinery, wastewater treatment and some other industrial sectors [17].

Model predictive control is used in this paper to a continuous bioreactor with uncertainty. Jacobian matrix linearization method is applied to linearize the nonlinear biochemical reactor model and get a reduced linearization system model which is suitable for controller designing. Furthermore, model predictive controller is designed and is simulated in the MATLAB/Simulink simulation environment.

2. Model of bioreactor

The biochemical reactor is an essential unit operation in a wide variety of biotechnological processes. Biochemical reactors are used to produce a large number of intermediate and final products, including medical products, food, beverages, and industrial solvents [18]. A biotechnological process with growth of a single microbial population on a single growth rate limiting substrate is described as [19]:

\[
\begin{align*}
\frac{dY_x}{dt} &= \mu(Y_x)Y_x - DY_x \\
\frac{dY_s}{dt} &= -\frac{1}{Y_{ds}}\mu(Y_x)Y_x + D(Y_{sin} - Y_s)
\end{align*}
\]

where

\[
\mu(Y_x) = \frac{\mu_{max}Y_x}{K_s + Y_s + Y_s^2/K_s}
\]

And \(Y_x\) is biomass concentration, \(Y_s\) is substrate concentration, \(Y_{sin}\) is the inlet substrate concentration, \(D\) is dilution factor, \(\mu_{max}\) is the maximum specific growth rate, \(K_s\), \(K_i\) and \(Y_{x,s}\) are inhibition constant, saturation constant and yield coefficient for cells based on substrate consumed. The nominal values of the model parameters used in the process simulation are given in Table. 1.

When the dilution rate \(D\) and the influent substrate concentration \(Y_{sin}\) are chosen as the control variables and the output are chosen as substrate concentration \(Y_s\) and the biomass concentration \(Y_x\), the output curves can be simulated by the upper described model and are shown in Figure 1.

3. Linearizing Bioreactor Model

Biological processes involve living organisms. The bioprocess advancement is determined by the living cells capabilities and characteristics, the bioreactor performance as well as by the cultivation media composition and the main parameters evolution. The high metabolic network complexity inside the cells often determine very sophisticated, non-linear growth and product formation kinetics, with further consequences on the bioprocess behavior, but at the same time on the product quality and yield.

The high nonlinearity and parameter uncertainty exist in system models make it rather difficult to design a control scheme using the non-linear model directly[20-21]. In order to make the controller designing easy, the nonlinear model should be linearized to get a linearization model.

Considering the non-linear system described as the following form

\[
\begin{align*}
\dot{x} &= f(x,u,t) \\
y &= g(x,u,t)
\end{align*}
\]

where \(x(t) \in \mathbb{R}^n\) is the state vector, and \(u(t) \in \mathbb{R}^m\) is the control vector. Thus, in the case of the initial value of \(x\), \(u\) and the input time are determined, the following equation is obtained:
\[
\begin{align*}
\delta \dot{x} &= A \delta x + B \delta u \\
\delta y &= C \delta x + D \delta u
\end{align*}
\] (4)

<table>
<thead>
<tr>
<th>State/Parameters</th>
<th>Range</th>
<th>Nominal values</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \gamma ), g l(^{-1})</td>
<td>0.1-2</td>
<td>-</td>
</tr>
<tr>
<td>( D ), h(^{-1})</td>
<td>0.2-2.75</td>
<td>-</td>
</tr>
<tr>
<td>( \gamma ), g l(^{-1})</td>
<td>0.1-19</td>
<td>-</td>
</tr>
<tr>
<td>( \mu_{\text{max}} ), h(^{-1})</td>
<td>0.24-0.36</td>
<td>0.31</td>
</tr>
<tr>
<td>( Y_{\text{max}} ), g g(^{-1})</td>
<td>0.4-0.6</td>
<td>0.5</td>
</tr>
<tr>
<td>( K_{a} ), g l(^{-1})</td>
<td>0.08-0.12</td>
<td>0.1</td>
</tr>
<tr>
<td>( K_{r} ), g l(^{-1})</td>
<td>40-60</td>
<td>40</td>
</tr>
<tr>
<td>( \gamma_{\text{sin}} ), g l(^{-1})</td>
<td>10-30</td>
<td>20</td>
</tr>
</tbody>
</table>

Figure 1. Curves of the model

Figure 2. Comparison of linearized model and the non-linearized model

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In which, the coefficient matrix $A$, $B$, $C$, $D$ can be obtained by using Jacobian linearization method:

$$
A = \frac{\partial}{\partial x} f'(x,u,t), \quad B = \frac{\partial}{\partial u} f'(x,u,t) \\
C = \frac{\partial}{\partial x} g'(x,u,t), \quad D = \frac{\partial}{\partial u} g'(x,u,t)
$$

(5)

For the actual bioreactor system, both dilution rate and influent substrate concentration have great impacts on the output (substrate concentration). From the practical point of view, the influent substrate concentration should and could become a control variable. A controller with dual inputs often can get better outputs than that with single input. So, a dual input MPC controller is used to control the reactor in this paper.

For the biochemical reactor model described in equation (1), if the start point of the linear system is chosen as follows: the dilution rate is $D = 0.2\text{h}^{-1}$, the biomass concentration is $x_0 = 5\text{g l}^{-1}$, the substrate concentration is $s_0 = 0.202\text{g l}^{-1}$, and the dilution factor $D$ and the inlet substrate concentration $s_{in}$ are chosen as the control variables, and the substrate concentration is chosen as the output, the linearized point is chosen at steady state, then the linearized state space equation can be described as

$$
\dot{x} = Ax + Bu
$$

(6)

where

$$
A = \begin{bmatrix}
-1.327 \times 10^{-5} & 1.617 \\
-0.4 & -3.434
\end{bmatrix}, \quad B = \begin{bmatrix}
-5 & 0 \\
14.8 & 0.2
\end{bmatrix}
$$

(7)

The linearization model and the non-linearization model are compared in Figure 2. As the curve shows, the linearization model can give a valid description of the real system. Thus the linear model can be used to replace the original nonlinear model approximately.

4. Controller Design

The main idea of MPC algorithms is to solve an optimization problem in order to find the control vector trajectory that optimizes the cost function over a future prediction horizon [22]. Different from the traditional optimal control strategy, the model predictive control uses the non-parametric model based on impulse response as its internal model. By finding the optimal solution of the performance indicator according to the historical information and the future input, the future control action can be decided and the future output can be predicted [23-25]. The performance indicator can be described as

$$
J(k) = \sum_{j=1}^{N} \|y(k+j) - r(k+j)\|^2 + \lambda \|u(k+j-1)\|^2
$$

(8)

MPC state space matrix can be expressed as a general form as follow:

$$
x_m(k+1) = A_m x_m(k) + B_m u(k) \\
y(k) = C_m x_m(k)
$$

(9)

where
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\[ x_m(k+1) = \begin{bmatrix} \Delta x_m(k+1) \\ y(k+1) \end{bmatrix}, \quad A_m = \begin{bmatrix} A & O^T \\ CA & 1 \end{bmatrix}, \quad B_m = \begin{bmatrix} B \\ CB \end{bmatrix}, \quad C = [O \ 1] \]  

(10)

For the bioreactor model described above, if the predictive length is chosen as \( N_p = 10 \), the control length is \( N_c = 8 \), and the Robustness and Rapidity is chosen as \( r_w = 0.8 \), then MPC matrix of the state space and correlation matrix can be obtained as follows

\[
A_m = \begin{bmatrix}
0.9971 & 0.1367 & 0 \\
-0.0338 & 0.7068 & 0 \\
-0.0338 & 0.7068 & 1
\end{bmatrix}, \quad B_m = \begin{bmatrix}
-0.3925 & 0.0014 \\
1.2602 & 0.0169 \\
1.2602 & 0.0169
\end{bmatrix}
\]

(11)

\[ C_m = [0 \ 0 \ 1] \]

(12)

The output matrix of this system is

\[ Y = FX + \phi \Delta U \]

(13)

where \((\phi^T \phi)^{-1} \phi^T R_s\) corresponds to the set-point change, while \(-(\phi^T \phi)^{-1} \phi^T F\) corresponds to the state feedback control within the framework of predictive control, and

\[
\phi = \begin{bmatrix}
C_m B_m \\
C_m A_m B_m \\
C_m A_m^2 B_m \\
\vdots \\
C_m A_m^{19} B_m
\end{bmatrix}
\]

(14)

5. Simulation and Results Analysis

To examine and certify the control effect of the proposed approach, simulation of the bio-reactor using model predictive control is carried out. In the simulation process, the set point output is 1, the rate weight is 0.1, the output weight is 1.2, the input constraints \( u_1 \in [0, 0.275] \) and \( u_2 \in [10, 30] \). The Simulink simulation model of the MPC control and fuzzy-PID control based on the linear model of the bioreactor is shown in Figure 3.

The running curves of substrate concentration and dilution rate are shown in Figure 4. When the PID controller is used, the three parameters are: \( K_P = 10, K_I = 3.5 \), \( K_D = 0.01 \). The output under MPC is very different from which under Fuzzy-PID control and PID control. From the comparison of the output curves, the model predictive control is proved to have better robustness such as stability and performance of closed-loop system in the whole domain and could deal with the constraints over time.
Figure 3. MPC and fuzzy-PID controller of the bioreactor

Figure 4. Substrate concentration and dilution rate
It can be seen from Figure 4 that the designed model predictive control scheme can handle multivariable control problems effectively and meet the demands for both precise and fast tracking.

6. Conclusions

Appropriate model linearization method can facilitate the designing of the model predictive controller. By using MPC controller to the bio-reactor, the system can not only have fast response characteristic, but also have good steady-state behavior and strong robustness.

Acknowledgements

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References


