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Study of advanced control of ethanol production through continuous fermentation

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Maximum productivity

Abstract This paper investigates the control of an experimentally validated model of production of bioethanol. The analysis of the open loop system revealed that the maximum productivity occurred at a periodic point. A robust control was needed to avoid instabilities that may occur when disturbances are injected into the process that may drive it toward or through the unstable points. A nonlinear model predictive controller (NLMPC) was used to control the process. Simulation tests were carried out using three controlled variables: the ethanol concentration, the productivity and the inverse of the productivity. In the third configuration, the controller was required to seek the maximum operating point through the optimization capability built in the NLMPC algorithm. Simulation tests presented overall satisfactory closed-loop performance for both nominal servo and regulatory control problems as well as in the presence of modeling errors. The third control configuration managed to steer the process toward the existing maximum productivity even when the process operation or its parameters changed. For comparison purposes, a standard PI controller was also designed for the same control objectives. The PI controller yielded satisfactory performance when the ethanol concentration was chosen as the controlled variable. When, on the other hand, the productivity was chosen as the controlled output, the PI controller did not work properly and needed to be adjusted using gain scheduling. In all cases, it was observed that the closed-loop response suffered from slow dynamics, and any attempt to speed up the feedback response via tuning may result in an unstable behavior.

1. Introduction

Research on using ethanol as an alternative fuel is gaining tremendous attention all over the world. One of the promising routes for ethanol production is the continuous fermentation of sugars. The microorganism, *Zymomonas mobilis*, has long been known to be a promising medium for industrial production of ethanol (Astudillo and Alzate, 2011). However, the continuous culture is known to exhibit undesired sustained oscillations over a wide range of operating conditions

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Nomenclature

A	matrix of linear constraints in NLMPC
B	vector of constraints values for NLMPC
D	disturbance estimates in NLMPC
D	dilution rate (1/h)
F	flow rate (l/h)
K	sampling instant
K_1, K_2	saturation constants (g/l)
k_c, k_i	PI controller settings, i.e. gain and gain divided by integral time
k_{c0}	initial value for controller gain
k_p, k_{p0}	process gain, initial process gain
m_p	maintenance factor of ethanol (1/h)
m_s	maintenance factor for substrate (1/h)
M	control horizon in NLMPC
P	ethanol concentration (g/l) also prediction horizon in NLMPC
P_c	limiting ethanol concentration for viable cells (g/l)
P_c'	limiting ethanol concentration for non-viable cells (g/l)
P_r	productivity of ethanol (g/l hr)
r, R	set point, vector of set points
S, S_0	substrate, feed concentration (g/l)
V	reactor volume (l)
t	time
x	state vector
X_v	viable cell concentration (g/l)
X_{nv}	non-viable cell concentration (g/l)
X_d	dead cells concentration (g/l)
Y	process output
y_p	measured plant output
$Y_{x/p}$	yield coefficient for conversion from biomass to ethanol (–)
$Y_{x/s}$	yield coefficient for conversion from biomass to substrate (–)
μ_d	growth rate of dead cells (1/h)
μ_{max}	maximum growth rate of viable cells (1/h)
μ'_{max}	maximum growth rate of non-viable cells (1/h)
μ_{nv}	growth rate of non-viable cells (1/h)
μ_V	growth rate of dead cells (1/h)
Δu, ΔU	change in manipulated variable, vector of change in manipulated variable
Λ	matrix of weights on manipulated variables
Γ	matrix of weights on controlled variables
σ	tuning parameter for Kalman Filtering

(Borzani, 2001; Garhyan et al., 2003; Garhyan and Elnashaie, 2004a,b). This leads to a decrease in ethanol productivity and less efficient use of available substrate.

Adequate control is one of the best ways to maintain the process performance. However, the development of an efficient control for bioreactive systems is not straight forward owing to a number of reasons. These include the lack of accurate models describing cell growth and product formation, the non-linear nature of the model, if available, which makes parameter estimation particularly difficult, the slow process response and the scarcity of on-line measurements of the component concentrations (Astudillo and Alzate, 2011; Schurgel, 2001; Alford, 2006).

A variety of open loop as well as closed loop control strategies can be found in the literature. Open loop strategies are still frequently encountered (Gregory and Turner, 1993). The common difficulty in these techniques, however, is that no compensation is made for modeling mismatch or random disturbances during the process operation. Classical PID controllers, on the other hand, can fail to stabilize the process if the tuning parameters are not carefully selected (Chen and Chang, 1984). Therefore, in recent years, several advanced control strategies have been proposed. Robust adaptive controllers, for instance, were designed to track the product trajectory in a fermenter in which the kinetics are complex and most of the state variables are difficult to measure (Frahm et al., 2002; Johnston et al., 2002; Whiffin et al., 2004; Smets et al., 2002). For most bioprocesses in which there is a deficiency in reliable on-line sensors, an extended Kalman filter can be used to estimate unmeasured states and parameters (Frahm et al., 2002; Johnston et al., 2002; Whiffin et al., 2004; Smets et al., 2002). Recently, Kawohl et al. (2007) presented a survey of the application of model based estimation, optimization, and control methods for bioprocesses. Chung et al. (2006) studied the implementation of a robust control strategy for a bioprocess. The overall control structure included an optimal feedforward controller and a multiloop feedback controller. Model predictive control was also used for the control and optimization of a number of bioprocesses (Ramaswamy et al., 2005; Renard and Wouwer, 2008; Ashoori et al., 2009).

As for control studies on bioethanol, Hodge and Karim (2002) developed an unstructured kinetic model incorporating the effect of product, substrate, and pH inhibition on the kinetic rates of ethanol fermentation by recombinant *Z. mobilis*. The model was used in a nonlinear model predictive control (NMPC) algorithm to control the product concentration during fermentation to offset the inhibitory effects of product. Arpornwichanop and Shomchoam (2009), on the other hand, proposed a hybrid neural network and an on-line optimal control strategy for the control of a bioreactor for ethanol fermentation. Simulation results showed that the neural network provided a good estimate of unmeasured variables. The on-line optimal control with the neural network estimator gave a better control performance in terms of the amount of the desired ethanol product, compared with a conventional off-line optimal control method. Other researchers have also studied the challenging issue of controlling variables at the peak value where conventional controllers cannot handle (Kishore and Patwardhan, 2002; Shah et al., 1999; Reddy and Chidambaram, 1995).

The objectives of this paper are the study of the open loop behavior of a validated model for ethanol fermentation using *Z. mobilis*, then the implementation of a model predictive control strategy using different controlled configurations. A comparison between simple PI controllers with the model predictive controller, and a study of the effect of control on fermentation are also carried out. The numerical investigation is based on an experimentally validated model of fermentation