Computers and Chemical Engineering 75 (2015) 49–59

Contents lists available at ScienceDirect

Computers and Chemical Engineering

journal homepage: www.elsevier.com/locate/compchemeng

On the dynamic optimization of methane production in anaerobic digestion via extremum-seeking control approach

Gerardo Lara-Cisneros[a,*], Ricardo Aguilar-López[b], Ricardo Femat[a]

[a] División de Matemáticas Aplicadas, IPICYT, Camino a la Presa San José 2055, C.P. 78216, San Luis Potosí, S. L. P., Mexico
[b] Departamento de Biotecnología y Bioingeniería, CINVESTAV-IPN. Av. Instituto Politécnico Nacional, No. 2508, San Pedro Zacatenco, D.F., Mexico

ARTICLE INFO

Article history:
Received 27 May 2014
Received in revised form 23 October 2014
Accepted 21 January 2015
Available online 30 January 2015

Keywords:
Anaerobic digestion process
Extremum-seeking control
Sliding mode
Robust variable-structure control

ABSTRACT

This paper proposes an extremum-seeking control approach based on sliding mode to achieve the dynamic optimization of methane outflow rate in anaerobic digestion processes. Open-loop analysis for a two-population model shown that the system becomes unstable due at the accumulation of volatile fatty acids (VFA). Then the controller is designed to achieve the regulation of VFA concentration close to the optimal set-point while maximizing the methane production. The control law is based on a variable-structure feedback to iteratively extremize the methane outflow rate and converges to the neighborhood of the optimum with sliding mode motions. In contrast with previous works on extremum-seeking control with sliding mode, the control scheme includes an observer-based uncertain estimator which computes the unknown terms related to the growth kinetics and the inlet composition. Practical stabilizability for the closed-loop system around to unknown optimal set-point is analyzed. Numerical experiments illustrate the effectiveness of the proposed approach.

1. Introduction

Anaerobic digestion (AD) has gained considerable importance lately as a wastewater treatment technology to reduce organic matter in agro-food industries and municipal effluents. At the same time AD produces biogas, consisting firstly on methane and carbon dioxide and is widely suggested as source of renewable energy. Nevertheless, its widespread application has been limited because of the difficulties involved in achieving stable operation of the AD process (Hess and Bernard, 2008; Méndez-Acosta et al., 2008; Smith and Waltman, 1995). From the power generation viewpoint, the optimization of methane outflow rate is one of the key issues in the operation of anaerobic processes (Sbarciog et al. 2011). However, the optimal operation of AD process is complicated to reach, mainly due to: their highly nonlinear and unstable nature, inhibition by substrates or products and by the substantial unmodeled dynamics (Hess and Bernard, 2008; Sbarciog et al., 2010; Serhani et al., 2011; Shen et al., 2007). Additionally, the optimal operating conditions of the AD process can be riskier; i.e., the effect of the external perturbations or small changes in the AD environment can lead towards undesirable operating conditions (Sbarciog et al., 2010; Shen et al., 2007). In fact, it is well known that the inhibition of the methanogenic bacteria growth by accumulation of volatile fatty acids (VFA) provokes the acidification of the anaerobic process (Hess and Bernard, 2008; Méndez-Acosta et al., 2005; Shen et al., 2007). Hence, AD process is a suitable candidate for optimal and robust stabilization schemes.

The feedback control schemes can be found in literature, they are mostly focused on the regulation of the organic pollution level, measurable as chemical oxygen demand (COD), or in to tracking reference trajectories for some operational variables which are readily available on-line (Álvarez-Ramírez et al., 2002; Bastin and Dochain, 1990; Flores-Estrella et al., 2013; Méndez-Acosta et al., 2005, 2008). The most popular ones are: linear PID-like controllers (Álvarez-Ramírez et al., 2002), robust output linearizing control schemes (see, e.g. Méndez-Acosta et al., 2008) and adaptive controllers (Mailleret et al., 2004). However, in many biotechnological applications the control objective is to optimize a cost criterion that is a function of unknown parameters in order to keep a performance variable at its optimal value (Dochain, 2008; Dochain et al., 2011). Also, it is well known that the explicit form of the performance function in biotechnological processes is highly uncertain (e.g., the growth rate or the specific metabolites production). The performance function in bio-processes also can be subject to bounded time-varying disturbances due to the effect of variation in environmental variables as dissolved oxygen, temperature, or pH (Dochain,

* Corresponding author. Tel.: +52 444 834 20 00; fax: +52 444 175 24 04.
E-mail address: laracis@hotmail.com (G. Lara-Cisneros).

http://dx.doi.org/10.1016/j.compchemeng.2015.01.018
0098-1354/

2008; Wang et al., 1999). Complementarily, self-optimizing control and extremum-seeking control are two techniques to handle these kinds of dynamic optimization problems (Ariyur and Krstic, 2003; Dochain et al., 2011; Lara-Cisneros et al. 2014, Simeonov et al. 2007). The goal of extremum seeking schemes is to find the operating set-points, a priori unknown, such that a performance function reaches their extremum value (Guay et al., 2004). Dynamical optimization via extremum-seeking algorithms has been extensively used in the last decades in, for example: the adjustment of radio telescope antennas in order to maximize the received signal; blade adjustment in water turbines or wind mills to maximize the generated power, and in anti-lock braking system (ABS) control to lead the maximal value of the tire/road friction force to be reached during emergency braking (Ariyur and Krstic, 2003; Drakunov et al., 1995; Utkin, 1992). An intensive research activity has been developed by Dochain et al. (see, e.g. Dochain et al., 2011) in to design adaptive extremum seeking control schemes applied to biotechnological processes. The adaptive extremum schemes are based on parameter learning laws for unknown parameters estimation, and a dither signal to ensure the convergence to a neighborhood of its optimal value (Dochain, 2008; Wang et al., 1999). However, the model-based adaptive extremum seeking algorithms require prior information about: (a) the models for the population's growth rates (as for example Haldane, Monod, or Cointois model) and (b) bounds of the parameters which, in most biochemical processes, may be hard to obtain from available data (Dimitrova and Krastanov, 2011; Dochain et al., 2011; Wang et al., 1999). On the other hand, the extremum-seeking control problem has been studied in the sliding mode control framework (see, e.g. Drakunov et al., 1995; Haskara et al., 2000). In such contributions, the main idea is to ensure that the desired output (or performance function) follow an increasing time signal as close as possible to its extremal value via discontinuous controls and sliding mode motions (Drakunov et al., 1995; Haskara et al., 2000; Pan et al., 2003; Utkin, 1992). Nevertheless, as far as we know, there is no extreme-seeking schemes based on sliding mode techniques for the dynamic optimization of AD process.

In this paper, we propose an extremum-seeking control scheme with sliding mode to achieve the dynamic optimization of methane outflow rate in anaerobic processes. Open-loop analysis for a two-population mathematical model, in terms of methanogenic and acidogenic bacteria, shown that the system becomes unstable by effect of the accumulation of VFA's in the digester. Then the controller is designed to regulate the VFA concentration close to the optimal value while maximizing the methane production. The VFA concentration and methane outflow rate are considered available for on-line measurement, and the dilution rate was taken as the control input. First, an "ideal" optimum seeking controller is designed which is found from the extremum-seeking control with sliding mode techniques (Haskara et al., 2000; Pan et al., 2003). The ideal control allows us to reach at extremum of the methane outflow rate and converges to the neighborhood of the optimal VFA concentration with sliding mode motions. In the second step, an observer-based uncertainty estimator is used to approach the unknown terms in the ideal control law. Thus, the stabilization at the neighborhood (practical stabilizability) of the unknown optimal set-point is ensured when the estimator scheme and controller are coupled. Unlike previous extremum-seeking schemes for online optimization of bio-processes, the proposed control approach is based upon sliding mode techniques without using gradient, and comprises a dynamic estimation algorithm to compute the unknown terms and provides robustness at the control law. The rest of the paper is organized as follows: In Section 2 the dynamic model for AD process is presented and some issues related with operational stability at the optimal conditions are discussed, also the control problem is formulated. Section 3 contain the design of the extremum-seeking controller and the stability analysis of the closed-loop system is analyzed. Numerical experiments that illustrate the performance and robustness of the proposed control approach are shown in Section 4. Some concluding remarks are discussed in Section 5.

2. Model description and problem statement

Throughout this paper the reduced version of the AD model developed by Bernard et al. (2001), is used in to design of the proposed control scheme. The underlying model assumes two main bacterial populations, the first one, called acidogenic bacterial X_1, consumes organic substrate S_1 (total soluble Chemical Oxygen Demand COD except Volatile Fatty Acids VFA) and produces VFA, that is considered as secondary substrate S_2 through an acidogenesis stage. The second population, known as methanogenic bacteria X_2, uses VFA as substrate in a methanogenesis stage for growth and produces methane and carbon dioxide. Thus, the global anaerobic process can be written as the reduced biochemical reaction network

$$k_1 S_1 \overset{\mu_1(\cdot)X_1}{\looparrowright} X_1 + k_2 S_2 \tag{1}$$

$$k_3 S_2 \overset{\mu_2(\cdot)X_2}{\looparrowright} X_2 + k_4 CH_4 \tag{2}$$

The growth rates are denoted by $\mu_i(\cdot)X_i$, for $i = 1, 2$, where each $\mu_i : \mathbb{R}_+ \to \mathbb{R}$, is a smooth function of the respective substrate, and the symbol $\looparrowright$ denotes the corresponding bacterial population X_i is an autocatalyst; *i.e.*, the microorganisms are at the same time products and catalysts. From a mass balance in an ideal Continuous Stirred Tank Reactor (CSTR), the system dynamics described by the reaction network (1 and 2) is given by the four-dimensional dynamical system

$$\dot{S}_1 = D(S_{1f} - S_1) - k_1\mu_1(S_1)X_1 \tag{3}$$

$$\dot{X}_1 = \mu_1(S_1)X_1 - aDX_1 \tag{4}$$

$$\dot{S}_2 = D(S_{2f} - S_2) + k_2\mu_1(S_1)X_1 - k_3\mu_2(S_2)X_2 \tag{5}$$

$$\dot{X}_2 = \mu_2(S_2)X_2 - aDX_2 \tag{6}$$

The state vector is defined as $\xi = [S_1 X_1 S_2 X_2]' \in \mathbb{R}_+^4$, S_{1f} and S_{2f} denotes the inlet concentration of the primary organic substrate and VFA, respectively. The dilution rate D, is defined as the ratio between the feeding flow F with respect to the digester volume V, while k_1, k_2, k_3 are constant yield coefficients. The parameter $a \in [0, 1]$ represents the proportion of the bacterial population that are affected by the digester dilution; so, $a = 0$ and $a = 1$ correspond to an ideal fixed bed reactor and to an ideal CSTR, respectively (Bernard et al., 2001; Méndez-Acosta et al., 2005). Because of the very low solubility of methane in the liquid phase, the concentration of dissolved methane is neglected, and the produced methane is assumed to go directly out of the digester, with the outflow rate of methane gas Q proportional to the reaction rate of the methanogenesis stage (see, Bernard et al., 2001)

$$Q(\xi) = k_4\mu_2(S_2)X_2 \tag{7}$$

where k_4 is the yield coefficient for the methane production. With respect to the specific growth rates for the acidogenic and methanogenic populations, in Bernard et al. (2001) are assumed to be described by the Monod and Haldane expressions, respectively, i.e.,

$$\mu_1(S_1) = \frac{\mu_{1,\max} S_1}{K_{S1} + S_1} \tag{8}$$

$$\mu_2(S_2) = \frac{\mu_{2,\max} S_2}{K_{S2} + S_2 + S_2^2/K_{I2}} \tag{9}$$