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Maximizing biogas production from the anaerobic digestion

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ABSTRACT

This paper presents an optimal control law policy for maximizing biogas production of anaerobic digesters. In particular, using a simple model of the anaerobic digestion process, we derive a control law to maximize the biogas production over a period T using the dilution rate as the control variable. Depending on initial conditions and constraints on the actuator (the dilution rate $D(\cdot)$), the search for a solution to the optimal control problem reveals very different levels of difficulty. In the present paper, we consider that there are no severe constraints on the actuator. In particular, the interval in which the input flow rate lives includes the value which allows the biogas to be maximized at equilibrium. For this case, we solve the optimal control problem using classical tools of differential equations analysis. Numerical simulations illustrate the robustness of the control law with respect to several parameters, notably with respect to initial conditions. We use these results to show that the heuristic control law proposed by Steyer et al., 1999 [20] is optimal in a certain sense. The optimal trajectories are then compared with those given by a purely numerical optimal control solver (i.e. the "BOCOP" toolkit) which is an open-source toolbox for solving optimal control problems. When the exact analytical solution to the optimal control problem cannot be found, we suggest that such numerical tool can be used to intuiter optimal solutions.

1. Introduction

Anaerobic digestion or methanization is a biological process in which organic compounds are transformed into carbon dioxide and methane (biogas) by micro organisms. These processes represent a promising technology for treating liquid and solid waste while producing valuable energy and limiting the greenhouse [14]. The operation of such process poses however a number of practical problems since anaerobic digestion is a complex nonlinear system which is known to be unstable: an organic overload can destabilize the biological process and its restart needs long delays (over months). It is thus necessary to develop automatic systems to optimally manage such a process when dealing with disturbances or to optimize important steps as its operation during the starting period.

Schematically, there are two families of automatic controllers developed for such purpose: model- and knowledge-based approaches. The first refer to the synthesis and the application of automatic control laws when a model of the system is available. Most of such controllers have been proposed by people from the automatic control community. They include approaches based on both linear or nonlinear techniques. Their main advantage lie in their theoretical properties they are suppose to guarantee such as performance or stability robustness with respect to uncertainty or disturbances. For instance, the controllers proposed by [1] are part of this family. The second class of approaches – called here knowledge-based – include approaches – not only but rather – developed by experts of the anaerobic digestion (biotechnologists, chemical engineers) who proposed control methods based on the detailed practical knowledge they have about bioprocess dynamics. They are most often validated on real processes than model-based controllers and are usually based on easily accessible measurements usually available in an industrial context such as pH, gas flow rates, H2 concentration, partial or total alkalinity... Approaches by [10], [15] or [20] can be classified in this family. The counterpart of the fact they are easily applicable on real processes is that no

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theoretical guarantee with respect to performance can be given since no model is necessary to synthesize the controller.

Steyer et al., 1999 [20] proposed the 'Disturbances Monitoring' principle as a way to control highly loaded anaerobic processes. This strategy is based on the following idea: a known overload is first applied voluntary to the process. The analysis of the system's response allows one to decide whether the system is able to deal with an increase in the pollutant load or not. If it is the case, the feeding flow undergoes a step while it remains at its actual value or is decreased otherwise. Once the new equilibrium has been reached, a new load test is applied and so on. In their paper, the authors claim that 'the control law allows to reach automatically the maximum treatment ability of the anaerobic process whatever the input concentration in organic matter is' without being able to prove it because their control law is completely heuristic. If we define the maximum treatment ability of an anaerobic system as the maximum biogas flow rate it can deliver over a given period of time, and if we consider a model of the process, we face an optimal control problem that can be posed from a mathematical viewpoint. To do so, we need a model of the anaerobic digestion process. The anaerobic process involves thousands of microorganisms interacting together through a complex metabolic network which is, actually, only partially known. On the one hand, even if several synthetic functional models have recently been proposed, including high dimensional ones like the ADM1 (cf. [9]), but also more simplified ones like the AM2 (cf. [3]), it is to be noticed that the nonlinear character of biological models and their relatively high dimension (the AM2 is of dimension 4 in its simplest form) render their use inappropriate for the application of optimal control theory. On the other hand, it has been shown that under some circumstances, very simple models were able to adequately capture the main dynamical behavior of the anaerobic model [8].

The use of such a simplified model is not new and several authors have already proposed to use it for optimal control design of anaerobic digesters (cf. for instance [19]). From the seminal work by D'Ans et al. [4] who established the bang–bang character of a simple optimal-time control problem of the chemostat, the optimal control of bioprocesses in general, and of the anaerobic digestion in particular, has been studied over a quite long time. More particularly, an optimal control policy to avoid the failure in the digester operation and restore its normal operation or lead it to a new optimal steady state was proposed by Stamatelatou et al. [19]. It has been designed using a simplified model of anaerobic digestion to determine the optimal dilution rate as a function of time, in response to entry of inhibitors or sudden changes in the feed substrate concentration. The authors shown that there is a proportional relationship between the dilution rate and the methane production. A simpler and implementable suboptimal control law was derived by Dimitrova and Krastanov to stabilize in real time a dynamic model towards the maximum methane flow rate [7]. Their approach is however not model-based: the algorithm is presented in the form of a block-scheme to iteratively adjust the dilution rate to drive the process dynamics towards a set point, where an optimal value of the output is achieved. The main limitation in applying this approach is that the dynamics should be open-loop stable. Otherwise, a locally stabilizing controller is necessary to stabilize the equilibrium points around the optimal operating point [7]. Other extensions were derived by the same authors [5,6]. Sbarciog et al. [16,17] have proposed a control strategy for maximizing biogas production of an anaerobic digestion system modeled by a 2-order system. The control law was synthesized by solving two optimization problems: firstly, a static optimization problem to determine the optimal operating point and, secondly, a transient optimization problem using the maximum principle of Pontryagin to find the control which will drive the system from an initial condition towards the optimal operating point while maximizing the gas flowrate. Recently, considering other sets of measurements, Sbarciog et al. [18] proposed a simple switching strategy for optimizing anaerobic digestion process. In [19], the problem of maximizing the biogas production over a given period of time has been investigated considering different possible disturbances (presence of an inhibitor or over/under-loads). The singular arcs were calculated using the Maximum Principle of Pontryagin. However, the optimal control synthesis was not given explicitly and no controllability analysis was performed.

In the present work, considering (i) a simple model of a chemostat (see Eq. (1) below), (ii) a restricted set of initial conditions (see Hypothesis 2 below), (iii) assuming the biogas produced is a linear function of the activity defined as $k\mu(s)x$ as proposed in [2] (see Section 2), we solve the problem of maximizing the biogas production over a given period of time $\max_{D(t)} \int_{t=0}^{t=T} \mu(s)x dt$ for a large class of kinetics functions (including both Monod and Haldane growth rates). These results are then used to better understand the knowledge-based controller proposed by Steyer et al. [20].

This paper is organized as follows. In Section 2 we present the class of problems we are interested in. In the next section, we establish the main results of the paper about the maximization of the output gas flow rate for the chemostat model. In Section 4, we compare the control law we establish in Section 3 with that one proposed by Steyer et al., 1999 [20]. In Section 5, we propose to use a direct approach to intuiter the optimal trajectories for a more general class of initial conditions than those considered in previous sections before some conclusions and perspectives are drawn.

2. Model description and control problem

In the present work, we consider a single-step model for the anaerobic digestion process based on one biological reaction, where the organic substrate denoted by s is degraded into methane biogas (CH_4) by a bacterial population x. We assume that the methane flow rate, Q_{CH_4}, is proportional to the microbial activity as proposed in [2]. The mass balance model of the classical chemostat model is given by the following nonlinear system of ordinary differential equations:

$$\begin{cases} \dot{x} = (\mu(s) - D)x \\ \dot{s} = D(s_{in} - s) - \mu(s)x \end{cases} \tag{1}$$

where x and s denote biomass and substrate concentrations, respectively, s_{in} is the concentration of the influent substrate s, while $\mu(s)$ is the specific growth rate of biomass. $D \in [D_{min}, D_{max}]$ is the dilution rate which is considered hereafter as the control variable, μ is the specific growth rate of microorganisms. Notice that the yield coefficient Y which usually appears in the chemostat model, does not appear in the equations since it is straightforward to show that the change of variable $x = X/Y$ allows us to reduce the system to (1). In the sequel, we will consider that the kinetic μ, satisfies the very general property:

Hypothesis 1. $\mu(0) = 0$ and $\mu(s) > 0$ for all $s > 0$. The function $\mu(\cdot)$ is either increasing, or there exists $\bar{s}$ such that $\mu(s)$ is increasing for $0 < s < \bar{s}$ and decreasing for $s > \bar{s}$.

In this paper, we seek to maximize the biogas production over a given time interval. The total methane production over the interval $[0, T]$ can be expressed as:

$$J(x(\cdot), s(\cdot), D(\cdot)) = \int_0^T k\mu(s(t))x(t)dt \tag{2}$$

where $(x(\cdot), s(\cdot), D(\cdot))$ satisfy (1). Since k is constant, without loss of generality, we will consider $k = 1$ in the following.