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State and Input Estimation of an Anaerobic Digestion Reactor using a Continuous-discrete Unknown Input Observer ⋆

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Abstract: The objective of this paper is to address the problem of state estimation in an Anaerobic Digestion Reactor (ADR) with unknown inputs - typically some influent concentrations, and to compare two different state and input estimation schemes. The first one is the classical Extended Kalman Filter (EKF) based on an augmented system that considers a slowly varying input (approach that has been already applied to this system and reported in the literature), whereas the second one is a recently proposed Unknown Input Observer (UIO), formulated in the spirit of a Kalman Filter, for continuous estimation with discrete measurements. The two filters are evaluated in simulation, demonstrating the superiority of the UIO.

Keywords: State estimation; Input estimation; Robust estimation; Biotechnology.

1. INTRODUCTION

Anaerobic digestion (AD) of organic waste and wastewater is increasingly applied as it is an important source of renewable energy in the form of biogas (a mixture of mostly carbon dioxide and methane), and can be used combined to other process units in biorefineries. However, the AD process has complex dynamics, is quite sensitive to input fluctuations, and requires tight control. Unfortunately, the development of efficient controllers is hampered by the lack of on-line measurements of some key component concentrations. The missing information has therefore to be reconstructed by means of state estimation schemes, the so-called software sensors, which blend the information of a process model and of some available on-line probes. The state estimation problem has usually to be formulated in the presence of unknown inputs, i.e. unknown component concentrations in the process influent.

The problem of state estimation in AD process has usually been dealt with in two ways [1]: (a) the asymptotic observer which allows to reconstruct the process state despite the lack of knowledge of the kinetics - however, the asymptotic observer is very sensitive to unknown process inputs, (b) interval observers, which allows to predict intervals of variations for the state variables based on intervals for the process parameters and inputs - however these intervals can be delicate to exploit for control.

In this study, attention is focused on the design of unknown input observers for monitoring the AD process. Unknown Input Observers (UIO) are dynamical systems that estimate the state variables of a system robustly with respect to the disturbances or unknown inputs that affect the system. For example, in a recent paper [9], the authors have proposed the design of an UIO consisting of three parts, i.e., two supertwisting observers and an asymptotic observer for estimating two biomass and two inlet substrate concentrations in a AD process described by a two-step reaction model.

In the present study, attention is focused on filters, optimal in a minimum-variance unbiased sense. On the one hand, we implement the classical Extended Kalman Filter (EKF) applied to a two-step reaction model supplemented by an exosystem assuming that the unknown input concentration varies slowly. This approach is similar to the proposal of [5], where an Unscented Kalman Filter (UKF) is designed instead. This latter study shows satisfactory results for some of the state variables, with the exception of the biomass concentrations which cannot be measured and therefore do not allow a full validation of the estimation approach. This observation motivates the use of alternative techniques, and we consider an UIO filter proposed in [3], and extended to nonlinear continuous-time models associated to discrete-time (and often rare) measurements in [8].

This paper is organized as follows. The next section presents the AD process model under consideration and the state estimation problem. A global observability assessment is given in section

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3 in accordance with the available measurements. In section 4, some background material about state and input estimation is discussed, while the main results about the evaluation of the performance of the two filters are presented in section 5. Finally, some conclusions are drawn and future work commented in section 6.

2. ANAEROBIC DIGESTION MODEL

Several two-step reaction models have been proposed in the last decades, including the model of Hill [6], and the nowadays very popular AM2 model developed in [2].

In the present study, inspired by the work of Haugen, et al. [4] where the model of Hill is prefered, we also adopt the latter. This model consists of four mass balance ordinary differential equations

$$\begin{aligned}\dot{S}_{bvs} &= \left(S_{bvs_{in}} - S_{bvs}\right)\frac{F_{feed}}{V} - \mu\left(S_{bvs}\right)k_1 X_{acid}\\ \dot{S}_{vfa} &= \left(S_{vfa_{in}} - S_{vfa}\right)\frac{F_{feed}}{V} + \mu\left(S_{bvs}\right)k_2 X_{acid} - \\ &\quad -\mu_c\left(S_{vfa}\right)k_3 X_{meth}\\ \dot{X}_{acid} &= \left(\mu\left(S_{bvs}\right) - K_d - \frac{F_{feed}/b}{V}\right)X_{acid}\\ \dot{X}_{meth} &= \left(\mu_c\left(S_{vfa}\right) - K_{dc} - \frac{F_{feed}/b}{V}\right)X_{meth}\end{aligned} \tag{1}$$

where S_{bvs} is the concentration of organic substrate (biodegradable volatile solids) in $[gBVS/L]$, S_{vfa} is the concentration of volatile fatty acids in $[gVFA/L]$, X_{acid} represents the acidogenic bacteria in $[g\ acidogens/L]$, and X_{meth} the methanogenic bacteria in $[g\ methanogens/L]$. The factor $\frac{F_{feed}}{V}$ represents the dilution rate in $[(LCH_4/d)/L]$, and k_1, k_2, k_3 are the stoichiometric coefficients.

As in [4], it is considered that

$$\begin{aligned}S_{bvs_{in}} &= B_0 S_{vs_{in}}\\ S_{vfa_{in}} &= A_f S_{bvs_{in}} = A_f B_0 S_{vs_{in}}\end{aligned}$$

The first equation defines the portion of the raw waste which can serve as substrate (biodegradable part) and the second one defines the portion of that biodegradable material which is initially in the acid form. Parameters B_0 and A_f are considered in the original Hill model [6] and obtained from laboratory test in [4]. In this way, both concentration inputs depend on $S_{vs_{in}}$, which is then considered as the unknown input.

The measurable output is the methane gas flow rate (gas production) in $[LCH_4/d]$ given by

$$F_{meth} = V\mu_c\left(S_{vfa}\right)k_5 X_{meth} \tag{2}$$

The reaction rate functions are of Monod type

$$\begin{aligned}\mu\left(S_{bvs}\right) &= \mu_m \frac{S_{bvs}}{K_s + S_{bvs}}\\ \mu_c\left(S_{vfa}\right) &= \mu_{mc}\frac{S_{vfa}}{K_{sc} + S_{vfa}}\end{aligned} \tag{3}$$

The maximum reaction rates μ_m, μ_{mc} are functions of the reactor temperature as in the original Hill model [6]

$$\mu_m\left(T_{reac}\right) = \mu_{mc}\left(T_{reac}\right) = 0.013T_{reac} - 0.129 \tag{4}$$

for $20[°C] < T_{reac} < 60[°C]$.

The considered values of the model parameters are the same as in [4], and correspond to a real-life pilot plant.

A_f	=	0.69	$[(gVFA/L)/(gBVS/L)]$
B_0	=	0.25	$[(gBVS/L)/(gVS/L)]$
b	=	2.90	$[d/d]$
k_1	=	3.89	$[gBVS/(g\ acidogens/L)]$
k_2	=	1.76	$[gVFA/(g\ acidogens/L)]$
k_3	=	31.7	$[gVFA/(g\ methanogens/L)]$
k_5	=	26.3	$[L/g\ methanogens]$
K_d	=	0.02	$[d^{-1}]$
K_{dc}	=	0.02	$[d^{-1}]$
K_s	=	15.5	$[gBVS/L]$
K_{sc}	=	3	$[gVFA/L]$
V	=	250	$[L]$
T_{reac}	=	35	$[°C]$

3. OBSERVABILITY ANALYSIS

In the classical observability concept, all inputs are assumed to be known. When some inputs are unknown, a stricter property must be proved, that is a robust observability or observability with unknown inputs. Such a property can be tested using the method described in [7], which is based on the analysis of solutions of an error dynamics. This method can also be understood as an analysis of distinguishability of states under the assumption that the output y and the control inputs u are perfectly known.

In this case, one can define a copy of system (1) that renames the state vector $s = [S_{bvs}, S_{vfa}, X_{acid}, X_{meth}]$, the unknown input $w = S_{vs_{in}}$ and the output $y = F_{meth}$ as $x = [x_1, x_2, x_3, x_4]$, $\bar{w}$ and y_x, respectively. That is

$$\begin{aligned}\dot{x}_1 &= \left(B_0\bar{w} - x_1\right)u - \mu\left(x_1\right)k_1 x_3\\ \dot{x}_2 &= \left(A_f B_0 \bar{w} - x_2\right)u + \mu\left(x_1\right)k_2 x_3 - \mu_c\left(x_2\right)k_3 x_4\\ \dot{x}_3 &= \left(\mu\left(x_1\right) - K_d - \frac{u}{b}\right)x_3\\ \dot{x}_4 &= \left(\mu_c\left(x_2\right) - K_{dc} - \frac{u}{b}\right)x_4\\ y_x &= V\mu_c\left(x_2\right)k_5 x_4\end{aligned} \tag{5}$$

where $u = D = \frac{F_{feed}}{V}$.

An error between the states of the original system and those of the copy can be defined as $\epsilon = x - s$. Then the state error dynamics with the same known input $u = \frac{F_{feed}}{V}$ is

$$\begin{aligned}\dot{\epsilon}_1 &= B_0 u\left(w - \bar{w}\right) - u\epsilon_1 - \mu_m k_1 \phi_1\left(x_1, x_3, \epsilon_1, \epsilon_3\right)\\ \dot{\epsilon}_2 &= A_f B_0 u\left(w - \bar{w}\right) - u\epsilon_2 - \mu_m k_2 \phi_1\left(x_1, x_3, \epsilon_1, \epsilon_3\right) - \\ &\quad -\mu_{mc} k_3 \phi_2\left(x_2, x_4, \epsilon_2, \epsilon_4\right)\\ \dot{\epsilon}_3 &= -\left(K_d + \frac{u}{b}\right)\epsilon_3 - \mu_m \phi_1\left(x_1, x_3, \epsilon_1, \epsilon_3\right)\\ \dot{\epsilon}_4 &= -\left(K_{dc} + \frac{u}{b}\right)\epsilon_4 + \mu_{mc}\phi_2\left(x_2, x_4, \epsilon_2, \epsilon_4\right)\end{aligned}$$

where