Chemosphere 140 (2015) 159–166

Contents lists available at ScienceDirect

Chemosphere

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

Regression based state space adaptive model of two-phase anaerobic reactor

Antonius Yudi Sendjaja [a], Youming Tan [a,b,*], Santosh Pathak [a], Yan Zhou [a], Maszenan bin Abdul Majid [c], Jian Lin Liu [d], Wun Jern Ng [a,c,e,*]

[a] Advanced Environmental Biotechnology Center, Nanyang Environment and Water Research Institute, Nanyang Technological University, Singapore
[b] School of Public Health, Shanghai Jiaotong University, Shanghai, PR China
[c] Nanyang Environment and Water Research Institute, Nanyang Technological University, Singapore
[d] Sembcorp Industries Ltd., Jurong Island, Singapore
[e] School of Civil and Environmental Engineering, Nanyang Technological University, Singapore

HIGHLIGHTS

- The discrete state space correlation among parameters in anaerobic reactor.
- The relation is updated at every time point, giving it an adaptive feature.
- The proposed algorithm to estimate methane generation from industrial waste.

ARTICLE INFO

Article history:
Received 21 January 2014
Received in revised form 3 November 2014
Accepted 9 November 2014
Available online 23 December 2014

Keywords:
Adaptive model
Anaerobic reactor
Process control
Biogas
Volatile fatty acids (VFAs)

ABSTRACT

In this paper, a linear state space model for the two-phase anaerobic reactor system was developed based on historical data. Subsequently, the model was used to predict its future behavior. The state space model developed involved correlation analysis and model development. The model would be updated at every time point when a new data set became available, giving it an "adaptive" feature. The model was then applied to monitor two-phase anaerobic co-digestion of a feed comprising 2 industrial secondary sludges and 2 industrial wastewaters. The case study showed the proposed model was able to provide good predictions of various process parameters. In addition, it also predicted impending process failure and this would have allowed the operator to take necessary measures to prevent or reduce impact of such failure during plant operation.

1. Introduction

The anaerobic process converts organic carbon into methane gas and is attractive as it has the potential to address two main issues simultaneously, organic wastes treatment and energy recovery via the biogas generated. Various types of organic wastes, such as industrial and municipal wastes, livestock manure, and food wastes, can be utilized as organic carbon sources (Gunaseelan, 1997; Van Starkenburg, 1997; Molino et al., 2012).

The anaerobic process can be divided into two parts: acidogenesis, which converts complex organic substrates into acetic acid, mediated by the Eubacteria consortium, and methanogenesis, which generates methane gas from acetic acid or from carbon dioxide and hydrogen by the methanogens (Gujer and Zehnder, 1983). Acidogenesis and methanogenesis can be performed either in a single reactor or in separate reactors. They are usually referred to then as the single stage and two-phase anaerobic process, respectively. As compared to the single stage process, the two-phase anaerobic process allows optimization of each individual process with the intention to increase conversion (Azbar and Speece, 2001). Moreover, as later shown in this work, the first phase can act as an early warning of a failing process.

In order to gain better understanding and control of the anaerobic process, mathematical models of the anaerobic reaction have been developed. These models were typically developed from empirical equations involving several constants. These constants were subsequently sought using experimental data and statistical analysis. One of the most commonly used empirical model is anaerobic digestion model number 1 (ADM1) (Batstone et al.,

* Corresponding authors at: Advanced Environmental Biotechnology Center, Nanyang Environment and Water Research Institute, Nanyang Technological University, Singapore. Tel.: +65 6592 1833 (Y. Tan), +65 6790 6813 (W.J. Ng).
E-mail addresses: youmingtan@ntu.edu.sg (Y. Tan), wjng@ntu.edu.sg (W.J. Ng).

http://dx.doi.org/10.1016/j.chemosphere.2014.11.027
0045-6535/

Nomenclature

SCOD	soluble chemical oxygen demand	I	influent
TCOD	total chemical oxygen demand	AR	acidogenic reactor
VFA	volatile fatty acid	MR	methanogenic reactor
TDS	total dissolved solids	R	Pearson's correlation coefficients
TOC	total organic carbon	N	number of candidate state variables
TS	total solids	u	input variable
TSS	total suspended solids	x	state variable
VSS	volatile suspended solids	y	output variable
TN	total nitrogen		
CH_4	methane flow rate		

2002). A MATLAB/Simulink code of this model, which can simulate the concentration of various substrates and biomass over time, had been previously developed (Rosen et al., 2006). Simpler mass balance models assumes all VFAs are directly converted into methane gas (Bello-Mendoza and Sharratt, 1998) or using state variables which later can be used to facilitate control system design of an anaerobic digester (Bernard et al., 2001; Sbarciog et al., 2011). However, the anaerobic process is sensitive to variation in process operating conditions (Fripiat et al., 1984; Simeonov and Diop, 2010) such as variations in organic load (Skogestad and Poslethwaite, 2005) which makes its stable operation difficult.

Other anaerobic reaction models were derived from past experimental data through statistical or regression analysis. Typically, these aim at estimating a particular parameter given a set of historical observed data. Such approach had been used to estimate biogas volume (Govatsmark and Skogestad, 2005), methane production rate (Schievano et al., 2012), sludge volume index (Ng et al., 2000) and effluent solids, and residual chemical oxygen demand (Avella et al., 2011). Another approach includes implementation of artificial neural network structures to predict various parameters within the anaerobic process, see e.g. (Ozkaya et al., 2007; Qdais et al., 2010). In addition, instead of looking at the current value of parameters, some models were developed based on rate of change, which gives them predictive ability, (Azbar and Speece, 2001; Sbarciog et al., 2011). Recently, an extensive review on modeling of the anaerobic process was done (Donoso-Bravo et al., 2011) which informed on the various stepwise model developments available in the literature.

In this work, an "adaptive" discrete state space model for the anaerobic process is developed. This model is a modification of statistical based method, where historical data are used to estimate future behavior of anaerobic process. The main difference between the proposed model and conventional statistical based model is that in the proposed model coefficient and shape are updated at every time step, which provides its adaptive ability in the presence of changing condition. Instead of data fitting, the model aims to estimate future values of various parameters. The adaptive feature comes from the continuous update of model parameters, as experimental data used to develop the model shifted over time. A continuous update enabled the model to keep pace with recent changes in process behavior as well as changing input conditions which would occur in real life situations. The main advantage of the proposed model is that it is updated continuously with time, to account for changing operational condition. As compared to other model, such as ADM1, which have same model over time, the proposed model keeps on self-updating over time, such that it would not have same model at present and in future. Other advantages of the proposed model as compared to mathematical models are:

i. ADM1 and most models require assumptions, as not all parameters are measurable. Our model parameters are all measurable, and can be chosen. We have the option to use or not use the parameter, if it is not measurable or difficult to measure, we do not use it. The flexibility is not in other models, when all parameters have to be there.
ii. Unlike ADM1, it is designed specifically for a particular process, where ADM1 and others were generic.

Model development was made in two steps. In the first step, the parameters available for consideration were screened and analyzed based on their respective importance to the anaerobic process. In the second step, the parameters were used as state variables to estimate the behavior of various parameters in the anaerobic process. Subsequently, the model was verified by implementing it in a two-phase anaerobic reaction process.

A benefit of discrete state space model implementation is its predictive capability. Based on past data, the model provides one step prediction of the future state. As described in Section 2.2, by doing recursive calculation on the model, it can predict future states, given the inputs are known where the adaptive feature is still maintained.

2. Model development

A discrete state space model between outputs $\boldsymbol{y}$, inputs $\boldsymbol{u}$, and states $\boldsymbol{x}$ can be written as:[1]

$$\boldsymbol{x}(t+1) = \boldsymbol{A}\,\boldsymbol{x}(t) + \boldsymbol{B}\,\boldsymbol{u}(t) \quad (1)$$

$$\boldsymbol{y}(t) = \boldsymbol{C}\,\boldsymbol{x}(t) + \boldsymbol{D}\,\boldsymbol{u}(t) \quad (2)$$

The step by step procedures for model development are indicated below

2.1. Parameter screening and selection

The model was built for the two-phase anaerobic process. Model development for single stage anaerobic process can be carried out in similar fashion by ignoring all parameters in the second reactor. Based on the biochemical reaction in each reactor, the first and second reactors are referred as acidogenic reactor and methanogenic reactor, respectively. All recorded parameters during the experiment are considered to be state or output candidates, while all manipulated parameters are considered to be input candidates. These parameters are listed in Table 1.

[1] Notations: Throughout this paper, a bold capital letter indicates an *nxn* matrix, a bold small letter indicates an *nx1* vector, a number or symbol *t* in brackets indicates time, $\boldsymbol{A}^T$ denotes transpose of $\boldsymbol{A}$, and $\boldsymbol{A}^{-1}$ indicates inverse of $\boldsymbol{A}$.