Real-Time Substrate Feed Optimization of Anaerobic Co-Digestion Plants

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Chapter 6

State of the Art of Biogas Plant Feed Control

The anaerobic digestion process is used for a wide range of applications (Olsson et al., 2007). Depending on the application the main objectives for process control vary. Whereas the goal of agricultural biogas plants (ABP) is renewable energy production, anaerobic wastewater treatment aims for minimization of the pollution (measured as COD) in the effluent while maximizing the throughput. Therefore, control objectives and properties of potential feed control algorithms must be adapted to match the needs of the application. Although the primary goal of ABP is energy production a control also needs to assure safe and stable process conditions. At the same time profit has to be maximized and ecological criteria have to be met. But, most control methods proposed so far are only capable of satisfying one or two of these criteria at the same time. The most often encountered ones are:

- maximization or set-point tracking of methane production rate (economical criteria)
- minimization or set-point tracking of COD in the digester effluent (ecological criteria)
- control of stability criteria, such as VFA, VFA/TA, propionate or dissolved hydrogen

An important difference between ABP and anaerobic waste treatment plants is that in the latter application the operator often cannot choose between different feeds, because there often is only one mixed feedstream available, e.g. wastewater. Given a limited storage capacity for the input, the scope of feed control is restricted. This is in contrast to ABP, where a range of different feeds is used. These are all separately stored and solely used for energy production.

To investigate whether control methods exist, which optimally control either an ABP or a waste treatment process, respectively, a definition of optimal control for both applications is necessary. This definition is given in Definitions 6.1 and 6.2.

Definition 6.1: A substrate feed control for an ABP is said to be optimal if it is a robustly stable setpoint control for the produced volumetric flow rate of methane, while maximizing the economical benefit, minimizing the ecological footprint and maximizing process stability.

Definition 6.2: A substrate feed control for an anaerobic waste treatment process is said to be optimal if it is a robustly stable setpoint control for effluent COD, while maximizing the throughput as well as economical benefit, minimizing the ecological footprint and maximizing process stability. Instead of a COD setpoint control, minimizing the effluent COD is possible as well.

Most of the published control methods are applied to anaerobic wastewater treatment systems, only very few are focused on controlling dry (total solids content TS $>$ 20 $\%_{\mathrm{FM}}$) or semi-dry (8 $\%_{\mathrm{FM}}$ $<$ TS $<$ 15 $\%_{\mathrm{FM}}$) digestion processes. Due to that most controls are only capable to control the feed of one substrate, mostly the wastewater. Therefore, the dilution rate of the feed is very often used as the manipulated variable. Depending on the application control variables such as methane flow rate or COD in the effluent as well as stability parameters such as VFA/TA, bicarbonate (Rozzi et al., 1985), propionate or dissolved hydrogen are used (see also Molina et al. (2009), Boe et al. (2010)). In low-buffered systems pH can also be an indicator for process stability (Björnsson et al., 2000).

The following extensive review of control methods proposed for biogas plant control is presented to give an overview of the state of the art of AD control. The review includes 146 publications focusing on the development of algorithms for substrate feed control for anaerobic digestion processes. Only those anaerobic digestion processes are included, that produce biogas, thus excluding dark fermentation and processes producing acids only. The control methods range from simple on/off and PID controllers over fuzzy and neural network control up to linearizing and other advanced approaches such as adaptive, robust and model-based control methods.

Excellent reviews on monitoring and control of anaerobic digesters can be found in Olsson et al. (2007) and Pind et al. (2003). The experience of 15 years in instrumentation, control and automation in anaerobic digesters is summarized in Steyer et al. (2006). In Batstone and Steyer (2007) and Strömberg et al. (2012) comparisons of different control approaches are performed in simulation studies using the Anaerobic Digestion Model No. 1 (ADM1) (see Section 7.1, Batstone et al. (2002a)). They are two of the very few objective control comparisons of three, respectively four control methods. However, a broad comparison of the high number of existing control methods has not yet been performed. Thus, the need for further objective performance evaluation and comparison of control strategies at full-scale AD plants is high.

6.1 Classical Control

To classical control methods belong the well known PID controllers and on/off control. Applications of these control methodologies are listed in the Tables 6.1, 6.2 and 6.3. For the convenience of the user all tables are shifted to the end of this chapter, see Section 6.7.

In the 70s the first control methods were proposed (Table 6.1), which are mainly on/off controls, that set the manipulated variable to a binary value depending on predefined threshold values. They were followed by PID controls including P, PI, and PID cascade controls, which are listed in Tables 6.2 and 6.3. PID cascade controls are a simple but effective approach for feed control such that they are nowadays still developed and published with good results. Their advantages are that two possibly conflictive setpoints can be simultaneously controlled while the setpoint of the master loop can be set by an expert system. As previously noted, most approaches are dedicated to control anaerobic wastewater treatment processes, such that almost all listed methods use the dilution rate as the manipulated variable.

Approaches such as Liu et al. (2004a), Alferes et al. (2008), Alferes and Irizar (2010) are dedicated to control biogas production at a setpoint, or to operate the digester at high organic load, respectively. Therefore they try to maximize the economical benefit of the digester, whereas the setpoint is set accordingly to not overload the digester. But they do not use direct measurements such as VFA, COD, dissolved hydrogen or bicarbonate which are able to signalize whether the digester is currently overloaded. This is done by Zhou et al. (2012), where the methane flow rate setpoint is set based on measurements of VFA and VFA/TA.

Another approach is to minimize COD in the effluent or the VFA content inside the digester as is e.g. done by Alvarez-Ramirez et al. (2002), Batstone and Steyer (2007), Mu et al. (2007). Their goal is to stabilize the digester and maximize the degradation of COD. In contrast to them the approach in García-Diéguez et al. (2011) is able to maximize the methane flow rate, while tracking a setpoint for VFA in the digester effluent. However, as the setpoint for methane depends on the VFA concentration in the digester, this control is not suited to control agricultural biogas plants, which are in need of a user-defined methane setpoint. Together with Boe and Angelidaki (2012) it is the only approach that was applied at pilot-scale, the others were applied at lab-scale, none was applied at full-scale.

6.2 Expert Systems

Expert systems are rule-based systems (Table 6.4), fuzzy systems (Table 6.5) and systems extended with a surrogate model such as an artificial neural network (Table

6.6). As biogas plants are nonlinear processes, applying nonlinear control methods comes quite natural. Such expert systems are quite popular for controlling anaerobic digesters because of their intuitive design based on rules and their non-linearity coping with the non-linearity of the plant. The first approach is performed by rule-based systems such as the well-known fuzzy controls and the latter one by the use of neural networks. Furthermore, expert systems can incorporate all measured variables easily and are easily extensible if an additional process value is measured in the future.
Because of their non-linearity their disadvantage is that it can not be proofed whether the closed-loop control is stable. Furthermore, surrogate models need proper data to train them otherwise these models can be very bad representatives of the real process. Especially for full-scale plants obtaining data representing the full range of operation very often is not possible, such that those models actually only will work on lab- and pilot-scale where a dynamic operation is more easily.
Approaches not listed in the tables, because not really fitting but related to this topic are Flores et al. (2000a) and Kottas et al. (2006).

6.3 Linearizing Control

Conventional linear controls have a disadvantage controlling a nonlinear process because the closed loop is nonlinear (see Figure 6.1). Linearizing controls are designed so that the closed loop is linear. Linear means, that the time t dependent dynamics of the control error signal $e(t)$ can be described by the first order differential equation $\frac{\mathrm{d}}{\mathrm{d}t}e(t) + C(t) \cdot e(t) = 0$, with the damping factor $C(t) > 0$, assuming $\frac{\mathrm{d}}{\mathrm{d}t}C(t) \approx 0$. As a consequence the control error converges exponentially to zero with increasing time t: $e(t) = \exp(-C(t)) \cdot e(0)$. As a result linearizing controls can be highly nonlinear, which means that they are not per default robust against uncertainties such as noise or model mismatch. Using interval observers, they can be made robust against uncertainties in the process input and initial states. Furthermore, model parameters can be properly estimated using adaptive schemes. Linearizing controls can have different kind of properties from model-based, adaptive to robust, which is why there are many different philosophies and approaches on how to develop linearizing controls. Linearizing controls are popular for a stabilizing feed control of anaerobic digestion processes and the dilution rate is mostly used as manipulated variable. The approaches found in the literature are listed in the Tables 6.7 and 6.8.

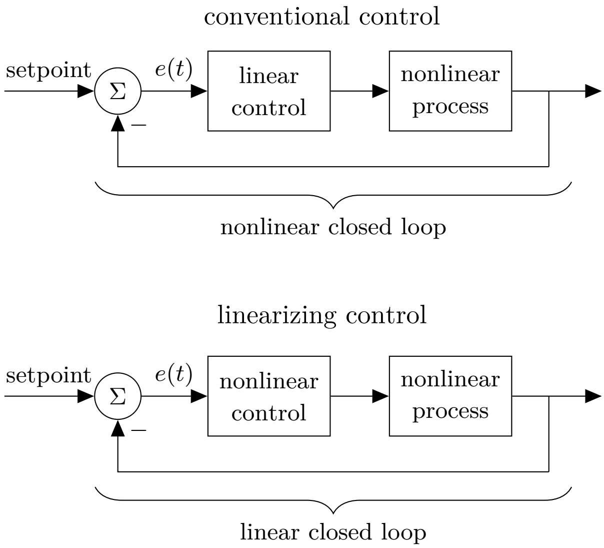


Figure 6.1: Comparison between conventional and linearizing control (cf. Bastin and Dochain (1990)).

6.4 Discontinuous Control

Discontinuous controls come from optimal control theory solving Pontryagin's maximum principle (see Table 6.9). As they switch from a minimal to a maximal dilution rate in one instant they have a bang-bang behavior. This behavior does not seem to be practical for full-scale ABP, because, although theoretically impossible, such a huge instantaneous change in the dilution rate might lead to process imbalances.

6.5 Other Advanced Controls

Other advanced control approaches are not further subdivided into different groups and contain model-based, robust, adaptive and other approaches. They are listed in Tables 6.10, 6.11 and 6.12.

6.6 Summary and Discussion

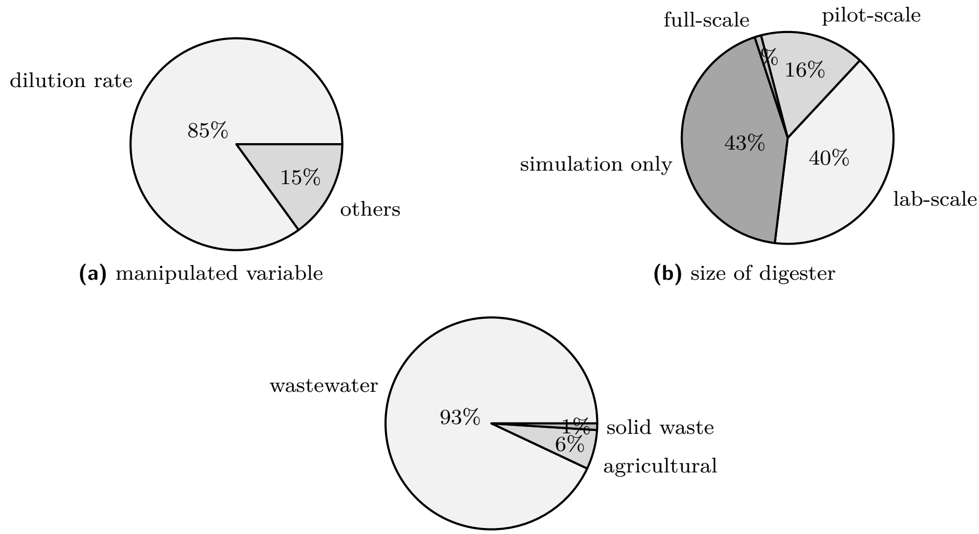
In this chapter an extensive review on feed control of the anaerobic digestion process is given. Despite the vast amount of publications in this field, none was found focusing on dynamic real-time feed optimization of co-digestion plants. The two key features of dynamic RTO are an arbitrary optimization criterion to be defined by the user and a dynamic model that is used for prediction. In most proposed control algorithms the optimization criterion is restricted to be either to maximize or control methane production or to minimize or control the COD concentration in the effluent. Furthermore, no model based feed control was found that uses the Anaerobic Digestion

Model No. 1 as prediction model. As a result, this review revealed a lack in research on dynamic real-time feed optimization whereas this thesis is trying to make a contribution to this field.
In the following paragraphs the main results of the review are examined.

Manipulated Variable By far the most developed controls use the dilution rate as manipulated variable (see Figure 6.2a). Examples for other manipulated variables are recirculation rates and the addition of bases to stabilize the process. In case of a co-digestion plant only one substrate or a constant substrate mix can be controlled using the dilution rate as manipulated variable. The other substrates then must be calculated based on boundary conditions such as hydraulic retention time, organic loading rate or restrictions defined by funding schemes (Zhou et al., 2012). For German ABP some funding schemes are linked to a required minimal amount of manure and a maximal allowable amount of maize in the feed (BMU, 2012a).

Scale of the Digester Looking at the scale of the digesters where the control methods were applied to, it can be observed that most of the evaluations were performed at lab-scale or pilot-scale plants (Figure 6.2b). However, a clear distinction between lab and pilot-scale is difficult. Therefore, digesters with a volume from 500 l to 10 m^3 are considered to be pilot-scale, while smaller digesters are lab-scale and larger ones full-scale. The largest part of all proposed controllers are applied to simulation models only. If controls are evaluated at simulation models, nowadays complex models (such as Batstone et al. (2002b), Siegrist et al. (2002)) should be used to make the evaluation as realistic as possible. As stability of controls can only be proved for simple models exhaustive simulations can show the performance and stability of the control empirically. Figure 6.2b clearly shows, that feed control of the anaerobic digestion process has not yet reached full-scale application. The main reasons are a lack of measurement devices and missing advanced diagnosis schemes, that are needed for process monitoring (Batstone et al., 2004, Alcaraz-González et al., 2012). Whereas control approaches for waste treatment processes, which come very close to the optimal control defined in Definition 6.2, do exist (e.g. García-Diéguez et al. (2011), Dimitrova and Krastanov (2009)), an optimal control for agricultural biogas plants as defined in Definition 6.1 has not yet been developed. Although robustly stable methane setpoint controls are available (e.g. Hilgert et al. (2000)), wrongly chosen setpoints might easily lead to process imbalances that strongly affect process stability. Therefore, the key is to set the setpoint properly, so that the process is stable at all times.

Substrates Looking at the substrates it can be observed, that the vast majority of controls are applied to wastewater treating plants (see Figure 6.2c). Wastewater



(a) manipulated variable

(b) size of digester

(c) substrates

Figure 6.2: Percentage distribution of manipulated variable (121 publications), size of digester (134 publications) and substrates (109 publications) of the reviewed publications.

includes different streams from municipal treatment plants and industry. Agricultural substrates are energy crops, grass and manure. Solid waste is the organic fraction of municipal solid waste as well as biowaste. For the latter two substrates only a very few feed controls were developed in the past. Treating wastewater in high-rate reactors offers the opportunity to operate with very low hydraulic retention times requiring a control with a low sampling rate.

Concluding Remarks Substrate feed control for anaerobic wastewater treatment has come very far in the last decades. Control algorithms yielding a good performance are available and ready to be used in practice. But, feed controllers for ABP and solid waste digesting plants are still lacking. The key difficulty with ABP is a lack of a methane setpoint control which offers an economically profitable operation and at the same time guaranteeing stable operation. Before such a control can be applied, robust measurement devices must be installed or soft sensor approaches should be used to estimate key process values. In solid waste digestion the main problem seems to lie in the lack of sufficiently, mechanically robust measurement devices. Because of the solids content such measurement devices are under very high mechanical stress, which makes them more expensive than those developed for wastewater treatment plants. High solid contents also lead to bad miscibility inside the digester. It is astonishing how few full-scale applications are published in the literature. And the question remains

how well advanced control methods applied to small-scale plants or simulation models do perform in the real world at full-scale biogas plants.
To get a better overview over the vast amount of feed controllers the author thinks that more objective comparisons of different controls should be published. Today it is not that difficult to compare them at hand of advanced simulation models such as the ADM1 (see Section 7.1) (Batstone et al., 2002a). For anaerobic wastewater treatment the benchmark model BSM2 (Jeppsson et al., 2007) can be used, but to the author's knowledge no benchmark model for agricultural biogas plants exists.

6.7 Tables

In the following all tables created in this review are listed.
They are:

- Classical Control of Biogas Plants
  - Table 6.1: on/off controls
  - Table 6.2: PID controls
  - Table 6.3: adaptive PID and PID cascade controls
- Expert Systems Control of Biogas Plants
  - Table 6.4: expert systems
  - Table 6.5: fuzzy controls
  - Table 6.6: neural networks and special fuzzy systems
- Linearizing Control of Biogas Plants
  - Table 6.7: Part I
  - Table 6.8: Part II
- Discontinuous Control of Biogas Plants
  - Table 6.9
- Other Advanced Controls for Biogas Plants
  - Table 6.10: Part I
  - Table 6.11: Part II
  - Table 6.12: Part III

Table 6.1: Classical Control of Biogas Plants: on/off controls

Control type	Author	Description	Manipulated variable	Control variable
on/off	Podruzny and van den Berg (1984)	"on" time proportional-integral to reference error measured biogas flow rate Q_{gas} application: lab-scale AFB, synthetic wastewater	dilution rate	biogas flow rate
on/off	Denac et al. (1988)	"off" time proportional to surplus above threshold application: lab-scale FBR, wastewater	dilution rate	effluent VFA
on/off	Rozzi (1984)	proposal of three controllers (1, 2, 3) purpose of stabilization application: simulation only	alkaline solution	1) pH 2) bicarbonate 3) pH, pCO_2
on/off	Whitmore and Lloyd (1986)	membrane inlet mass spectrometry measures dissolved H_2 application: lab-scale CSTR, wastewater, thermophilic	dilution rate	dissolved H_2
on/off	Whitmore et al. (1987)	as in Whitmore and Lloyd (1986), except: mesophilic	dilution rate	dissolved H_2
on/off	Andrews (1974)	application: CSTR, simulation only, wastewater	recirculation	CH_4 flow rate
on/off	Pretorius (1994)	pH is measured in an unbuffered region based on biogas stripping application: lab-scale UASB, synthetic wastewater, mesophilic	dilution rate	pH
on/off	Romli et al. (1994)	2-stage (CSTR, FBR), recirculation is changed to find optimum: min. addition of caustic soda/max. biogas flow rate application: lab-scale CSTR, wastewater, mesophilic	caustic soda	pH
on/off + P	Graef (1972), Graef and Andrews (1974)	proposal of three controllers: 1, 2) on/off, 3) P in 1) the scrubbed gas (CO_2) is recirculated to the digester application: CSTR, simulation only	1) gas scrubbing 2) base addition 3) sludge recycle	1, 2) pH 3) CH_4 flow rate

Table 6.2: Classical Control of Biogas Plants: PID controls

Control type	Author	Description	Manipulated variable	Control variable
P	Cord-Ruwisch et al. (1997)	setpoint control; purpose: high OLR and stability application: lab-scale CSTR, wastewater, mesophilic	dilution rate	dissolved H_2
P	Andrews (1974)	application: CSTR, simulation only, wastewater	base addition	pH
P	Franke et al. (2008)	as in Cord-Ruwisch et al. (1997) application: lab-scale CSTR, agricultural, mesophilic	dilution rate	dissolved H_2
P deadband	Denac et al. (1990)	based on alkaline consumption application: lab-scale FBR, wastewater	- dilution rate - alkali addition	- effluent VFA - pH
I deadband	Feitkenhauer et al. (2002)	application to an acidic phase reactor, goal: max. VFA application: lab-scale CSTR, wastewater	dilution rate	VFA
PI	von Sachs et al. (2003)	application: two-phase AD system, lab-scale FBR (2nd phase), wastewater, mesophilic expert system overrules control in special user-defined cases	dilution rate	biogas flow rate
PI	Batstone and Steyer (2007)	proposal of two controls (1, 2) application: simulation only (ADM1), wastewater	dilution rate	1) VFA 2) alkalinity
PI	Mu et al. (2007)	decision system switches between both manipulated variables application: simulation only, lab-scale UASB (ADM1d), wastewater	- recirculation-to-influent ratio - dilution rate	effluent COD
PI + PID	Ryhiner et al. (1993), Heinzle et al. (1993)	proposal of four controllers (1 PI, 2 PID, 3 PI, 4 PID) application: lab-scale FBR, whey, mesophilic	dilution rate	1),2) pH 3) dissolved H_2 4) organic acids
PI + PID	Simeonov (1994)	four different gas setpoints according to a performance index application: simulation only; taken from Pind et al. (2003)	dilution rate	biogas flow rate
PID	Marsili-Libelli and Beni (1996)	purpose: stabilization application: simulation only	bicarbonate addition	bicarbonate alkalinity

Table 6.3: Classical Control of Biogas Plants: adaptive PID and PID cascade control

Control type	Author	Description	Manipulated variable	Control variable
adaptive PI	Perrier and Dochain (1993)	proposal of three controllers (1, 2, 3) application: simulation only	dilution rate	1) effluent COD 2) dissolved H_2 3) propionate
adaptive PID	Zhou et al. (2012)	CH_4 setpoint set by VFA and VFA/TA application: simulation only (ADM1), CSTR, manure and corn	dilution rate	CH_4 flow rate
cascade P	Liu et al. (2004a,b)	inner loop: pH; outer loop: gas flow rate setpoint of outer loop given by rule-based supervisory system lab-scale AFB reactor, wastewater, mesophilic	dilution rate	OLR
cascade P	Boe and Angelidaki (2012)	inner loop: VFA; outer loop: gas flow rate rule-based system as in Liu et al. (2004a) application: pilot-scale CSTR, manure, thermophilic	dilution rate	CH_4 flow rate
cascade P	Liu et al. (2006)	same as Liu et al. (2004a) inner loop pH control is rule-based variable-gain P control with rules defined by state machine lab-scale AFB reactor, wastewater, mesophilic	dilution rate	OLR
cascade P	Alferes et al. (2008)	same as Liu et al. (2004a) includes fill level of an upstream equalization tank application: simulation only (ADM1), UASB-AF, wastewater	dilution rate	- OLR - fill level
cascade P	Alferes and Irizar (2010)	same as Alferes et al. (2008) rule-based supervisory system implemented by a fuzzy module application: simulation only (ADM1), UASB-AF, wastewater	dilution rate	- OLR - fill level
cascade PI	Alvarez-Ramirez et al. (2002)	inner loop: VFA; outer loop: COD application: lab-scale UASB, wastewater	dilution rate	effluent COD
cascade PID	García-Diéguez et al. (2011)	inner loop: methane flow rate; outer loop: VFA application: pilot-scale UASB-AF, wastewater, mesophilic	dilution rate	- CH_4 flow rate - effluent VFA

Table 6.4: Expert Systems Control of Biogas Plants: expert systems

Control type	Author	Description	Manipulated variable	Control variable
expert system	Boe (2006), Boe et al. (2008)	if propionate ..., then in-/decrease feed high fluctuations in biogas flow rate, because propionate is too persistent application: lab-scale CSTR, cow manure, thermophilic	dilution rate	propionate
expert system	Barnett and Andrews (1992)	rules implemented with fuzzy logic inputs: a lot; output: a few next to dilution rate application: simulation only	dilution rate	normal operation
expert system	Chynoweth et al. (1994)	rules based on CH_4 flow rate, its derivative, dilution rate and its derivative able to distinguish between overloading, underloading and inhibition application: lab-scale CSTR, wastewater, mesophilic	dilution rate	CH_4 flow rate
expert system	Moletta et al. (1994)	inputs: pH, biogas flow rate, H_2 content of biogas application: lab- and pilot-scale FBR, wastewater, mesophilic	dilution rate	normal operation
expert system	Ehlinger et al. (1994)	decision tree: pH, gas and H_2 flow rate application: lab-scale FBR, mesophilic, wastewater	dilution rate	normal operation
expert system	Flores et al. (2000b)	application: start-up of pilot-scale UASB-AF reactor, wastewater	dilution rate	normal operation
expert system	Pullammanappallil et al. (1991, 1998)	bumpless switch between four different control strategies based on a t-test: 1) set-point control, 2) constant yield control 3) batch operation, 4) constant dilution rate application: lab-scale CSTR, wastewater, mesophilic	dilution rate	CH_4 flow rate
expert fuzzy system	Müller et al. (1997)	H_2 and CH_4 flow rate; uses Fuzzy C-Means Clustering of Marsili-Libelli and Müller (1996) application: lab-scale FBR, wastewater, mesophilic	- bypass - storage - dilution	normal, overload, inhibition, toxicity
expert fuzzy system	Puñal et al. (2001, 2002), Carrasco (2002)	many input variables application: pilot-scale UASB-AF, wastewater	flow rates	over-, underload recovery

Table 6.5: Expert Systems Control of Biogas Plants: fuzzy controls

Control type	Author	Description	Manipulated variable	Control variable
fuzzy P	Bernard et al. (2001b)	inputs: TA, VFA/TA application: pilot-scale FBR, wastewater	dilution rate	VFA/TA
fuzzy P	Scherer et al. (2008, 2009)	inputs: pH value, CH_4 content and specific gas flow rate application: lab-/pilot-scale CSTR, agricultural, meso-/thermophilic	dilution rate	OLR
fuzzy I	Boscolo et al. (1993)	inputs: nine variables application: pilot-scale CSTR, OFMSW, thermophilic	- feed rate - TS of feed - recycling rates	normal operation
fuzzy P + PI	Murnleitner (2001), Murnleitner et al. (2002), Grepmeier (2002)	inputs: H_2, CH_4, biogas flow rate, pH, filling level application: lab-scale FBR, two-stage, wastewater, mesophilic	- different flows (PI) - pH (P) - temperature (P)	overload avoidance
fuzzy PI	Estaben et al. (1997)	inputs: error to setpoints of gas flow rate and pH value and the derivatives of the errors; output: change of feed rate application: lab-scale FBR, wastewater	dilution rate	- gas flow rate - pH value
fuzzy PI	Puñal et al. (2003)	inputs: error of VFA to its setpoint and its derivative output: change of feed rate application: pilot-scale AFB, wastewater	dilution rate	effluent VFA
fuzzy PI	Garcia et al. (2007)	inputs: CH_4 flow rate; H_2 content of gas; VFA/TA output: change of feed rate application: ADM1, lab-scale UASB-AF, wastewater	dilution rate	OLR
fuzzy PI	Wolfsberger (2008)	eight different fuzzy controls application: lab-scale, agricultural, meso-/thermophilic	dilution rate	OLR
fuzzy PI cascade	Martinez-Sibaja et al. (2007)	- inner loop (conventional PI): pH - outer loop (fuzzy PI): gas flow rate application: simulation only	dilution rate	- gas flow rate - pH value

Table 6.6: Expert Systems Control of Biogas Plants: neural networks and special fuzzy systems

Control type	Author	Description	Manipulated variable	Control variable
hierarchical fuzzy	Steyer et al. (1997)	inputs: control error of pH, T and biogas flow rate for a small rule-set a hierarchical fuzzy structure is chosen application: lab-scale FBR, wastewater, mesophilic	dilution rate	VFA
neural network	Holubar et al. (2002, 2003)	ANN models for: pH, VFA, biogas production and composition optimal COD loading rate is solution of max. CH_4 flow rate and COD degradation; application: lab-scale CSTR, primary sludge	COD loading rate	CH_4 flow rate
neural	Wilcox et al. (1995), Guwy et al. (1997)	ANN model for bicarbonate alkalinity (BA) out of past BA values application: lab-scale FBR, ice-cream and baker's yeast WW	BA dosing pump	bicarbonate alkalinity
neural network	Emmanouilides and Petrou (1996)	adaptive on-line trained neural networks application: simulation only	dilution rate	- CH_4 flow rate - effluent COD
neural-fuzzy	Yordanova et al. (2004)	fuzzy PI, fuzzy tuning control application: simulation only, wastewater	dilution rate	biogas flow rate
neural-fuzzy	Waewsak et al. (2010)	ANN models for: pH, TA and VFA, predicted out of past values application: lab-scale UASB-AF, synthetic WW, mesophilic	dilution rate	- high performance - stability
fuzzy supervision	Carlos-Hernandez et al. (2007)	Takagi-Sugeno supervisor switches between: 1) open loop, 2) base addition (fuzzy PI), 3) dilution rate (fuzzy PI) application: FBR, wastewater, simulation only	- base addition - dilution rate	high performance
fuzzy supervision	Carlos-Hernandez et al. (2010a)	as in Carlos-Hernandez et al. (2007) PCA and Takagi-Sugeno estimate biomass and substrate application: CSTR, wastewater, simulation only	- base addition - dilution rate	CH_4 flow rate
fuzzy supervision	Gurubel et al. (2013)	as in Carlos-Hernandez et al. (2010a), additional using PSO to improve setpoint tracking	- base addition - dilution rate	CH_4 flow rate
neural-fuzzy	Carlos-Hernandez et al. (2010b)	as in Carlos-Hernandez et al. (2007) neural observer trained by EKF estimates methanogenic biomass application: FBR, abattoir wastewater, simulation only	- base addition - dilution rate	high performance

Table 6.7: Linearizing Control of Biogas Plants: Part I

Control type	Author	Description	Manipulated variable	Control variable
linearizing	Alvarez-Ramirez et al. (1996), Monroy et al. (1996)	adaptive, no need for measuring biogas flow rate application: lab-scale UASB, wastewater, mesophilic	dilution rate	effluent COD
linearizing	Petre et al. (2007)	adaptive, asymptotic state observer application: simulation only	dilution rate	effluent COD
feedback linearization	Angulo et al. (2007)	derivation using AM1 (Bernard et al., 2001a), model-based application: simulation only, AFB reactor, wastewater	dilution rate	effluent VFA
external linearization	Renard et al. (1988)	adaptive control, influent COD needs to be measured application: lab-scale CSTR, WW (citric acid), mesophilic	dilution rate	effluent COD
external linearization	Johnson et al. (1995)	Renard et al. (1988) approach used application: lab-scale AFB, wastewater, mesophilic	dilution rate	effluent COD
external linearization	Renard et al. (1991)	adaptive control, influent COD needs to be measured application: lab-scale CSTR, WW (citric acid), mesophilic	dilution rate	propionate
linearizing	Dochain and Perrier (1993)	direct adaptive linearizing application: CSTR, simulation only	dilution rate	propionate
linearizing	Dochain et al. (1991)	nonlinear adaptive, model-based application: CSTR, simulation only	dilution rate	dissolved H_2
linearizing	Bernard et al. (2001b)	adaptive control, influent COD estimated by soft sensor application: pilot-scale FBR, wastewater	- dilution rate - alkalinity	VFA/TA
linearizing	Rincon et al. (2009)	adaptive control, normal form of fold bifurcation application: simulation only, wastewater	dilution rate	effluent VFA
linearizing	Simeonov and Queinnec (2006)	model-based, organic wastes and acetate application: simulation only, CSTR, mesophilic	acetate addition	biogas flow rate

Table 6.8: Linearizing Control of Biogas Plants: Part II

Control type	Author	Description	Manipulated variable	Control variable
robust linearizing	Rapaport and Harmand (2002)	interval observer application: simulation only, CSTR	dilution rate	effluent COD
geometric	Méndez-Acosta et al. (2003, 2004, 2005)	to avoid overshooting fuzzy-based gain-scheduling and anti-windup scheme are used, high-gain observer application: simulation only, AFB, wastewater	dilution rate	effluent COD
geometric robust	Méndez-Acosta et al. (2007a, 2008)	model-based: extended Luenberger observer application: pilot-scale AFB, wastewater	dilution rate	effluent VFA
geometric robust	Méndez-Acosta et al. (2007b)	model-based: extended Luenberger observer; proposal of two controls (1, 2); TOC: total organic carbon application: pilot-scale AFB, wastewater, mesophilic	dilution rate	1) VFA 2) TOC
geometric robust	Méndez-Acosta et al. (2010)	model-based: extended Luenberger observer, antiwindup structure application: simulation only, wastewater	- dilution rate - alkali solution	- VFA - TA
linearizing	Dochain and Bastin (1985)	nonlinear adaptive application: CSTR, simulation only	dilution rate	effluent VFA
Generic Model Control	Costello et al. (1989)	improvement of Dochain and Bastin (1985) application: CSTR, simulation only, wastewater	dilution rate	effluent COD
linearizing	Petre et al. (2013)	three controls: 1) adaptive (asymptotic observer), 2) robust, 3) robust-adaptive (interval observer, both) application: CSTR, simulation only, wastewater	dilution rate	effluent COD
VSM	Tartakovsky et al. (2002, 2005)	variable structure model (VSM) containing three linear submodels, for each submodel one linearizing control application: lab-scale UASB, synthetic wastewater, mesophilic	influent COD	effluent COD
decoupled linearizing	Aguilar-Garnica et al. (2007, 2009)	two-phase AD system, modeled by PDE, observer-based estimator application: simulation only, two AFBs, wastewater	recycle flow rates	- effluent VFA - effluent COD

Table 6.9: Discontinuous Control of Biogas Plants

Control type	Author	Description	Manipulated variable	Control variable
singular control	Stamatelatou et al. (1997)	optimal is model-based (bang-bang), suboptimal is P control application: CSTR, simulation only	dilution rate	CH_4 flow rate
switching control policy	Sbarciog et al. (2011, 2012a), Sbarciog and Vande Wouwer (2012)	bang-bang control maximizes CH_4 flow rate application: CSTR, simulation only, wastewater	dilution rate	CH_4 flow rate
switching control policy	Sbarciog et al. (2012b)	as Sbarciog et al. (2011) and others, but biogas measured only application: CSTR, simulation only, wastewater	dilution rate	CH_4 flow rate
piecewise continuous	Chamroo et al. (2008)	two controls (1, 2) application: simulation only	dilution rate	1) effluent COD 2) CH_4 flow rate
sliding mode	Tabrizi et al. (2010)	application: AFB, simulation only, wastewater	dilution rate	effluent COD
sliding mode	Kravaris and Savoglidis (2012)	application: CSTR, simulation only	dilution rate	CH_4 flow rate

Table 6.10: Other Advanced Controls for Biogas Plants: Part I

Control type	Author	Description	Manipulated variable	Control variable
disturbance monitoring	Steyer et al. (1999)	increased biogas yield caused by an impulse in feed is compared with expected. Overloading/inhibition reflected by an unsatisfactory gas yield. application: lab-scale FBR, wastewater, mesophilic	dilution rate	biogas flow rate
disturbance accommodating	Harmand et al. (2000)	ARMAX model with bias estimation application: lab-scale FBR, wastewater	dilution rate	biogas flow rate
nonlinear adaptive	Polihronakis et al. (1993)	proposal of three controls: 1), 2) and combination of both combination switches between both control objectives application: full-scale, wastewater	dilution rate	1) effluent COD 2) CH_4 flow rate
adaptive robust	Hilgert et al. (2000)	ARMAX model with uncertain part, estimated by kernel estimator application: lab-scale FBR, wastewater, mesophilic	dilution rate	biogas flow rate
adaptive	Harmon et al. (1993)	taken from Pind et al. (2003) application: lab-scale CSTR, glucose	temperature	CH_4 flow rate
nonlinear	Harmon et al. (1990)	constant reactor yield control application: lab-scale CSTR, synthetic WW, thermophilic	dilution rate	CH_4 flow rate
sampled delayed control	García-Sandoval et al. (2007)	nonlinear, robust, delayed measurements application: simulation only, wastewater	dilution rate	effluent COD
sampled delayed control	Méndez-Acosta et al. (2011)	same as in García-Sandoval et al. (2007), COD measured daily application: lab-scale AFB, wastewater, mesophilic	dilution rate	effluent COD
robust output feedback	Antonelli et al. (2002, 2003)	nonlinear; only measured variable: CH_4 flow rate application: pilot-scale AFB, wastewater, mesophilic	dilution rate	CH_4 flow rate
robust output feedback	Mailleret and Bernard (2001), Mailleret et al. (2003)	CH_4 flow rate and input COD needed application: pilot-scale AFB, wastewater	dilution rate	effluent COD

Table 6.11: Other Advanced Controls for Biogas Plants: Part II

Control type	Author	Description	Manipulated variable	Control variable
nonlinear adaptive	Mailleret et al. (2004)	CH_4 flow rate needed application: pilot-scale AFB, wastewater	dilution rate	effluent COD
nonlinear adaptive	Dimitrova and Krastanov (2009)	extremum seeking algorithm to maximize CH_4 production application: simulation only	dilution rate	- effluent COD - CH_4 flow rate
adaptive	Seok (2003)	recursive system identification, convex optimization problem application: lab-scale FBR, wastewater, mesophilic	dilution rate	propionate
extremum seeking	Marcos et al. (2004a,b)	adaptive; substrate concentration kept at setpoint application: CSTR, AFB, simulation only	dilution rate	CH_4 flow rate
extremum seeking	Simeonov et al. (2007), Simeonov and Stoyanov (2011)	application: CSTR, simulation only, mesophilic	dilution rate	CH_4 flow rate
LQT	Mu et al. (2008)	linear quadratic tracking (LQT) and error integral action application: simulation only, lab-scale UASB, distributed model, wastewater	- recirculation-to-feed ratio - bypass-to-feed ratio	effluent COD
NMPC	Aceves-Lara et al. (2010)	asymptotic observer estimates influent, effluent and some product concentrations; dark fermentation application: lab-scale CSTR, diluted molasses, mesophilic	dilution rate	H_2 flow rate
EPSAC-MPC	Ordace et al. (2012)	Extended Prediction Self-Adaptive Control (EPSAC) application: simulation only (ADM1), wastewater sludge	feed flow rates	CH_4 flow rate

Table 6.12: Other Advanced Controls for Biogas Plants: Part III

Control type	Author	Description	Manipulated variable	Control variable
variable-gain	Rodríguez et al. (2006)	indirect COD control by controlling H_2 in gas phase application: pilot-scale UASB-AF, wastewater	dilution rate	effluent COD
composed	Wang et al. (2011, 2013)	algebraic differential estimator, adaptive (Wang et al., 2011); model-free (Wang et al., 2013) application: CSTR, simulation only, agricultural, mesophilic	dilution rate	CH_4 flow rate
adaptive optimization	Ryhiner et al. (1992)	steepest descent finds optimal operating point application: FBR, wastewater	dilution rate	- CH_4 flow rate - VFA
saturated proportional	Grognard and Bernard (2006)	no input COD measurement needed; attracts to a region application: simulation only, wastewater	dilution rate	effluent COD
H_∞	Flores-Estrella et al. (2013)	application: simulation only, wastewater	dilution rate	effluent COD
dynamic compensator	Simeonov and Stoyanov (2003)	linear model with interval parameters; proposes two controls (1, 2) application: simulation only	dilution rate	1) biogas flow rate 2) effluent COD
robust adaptive	Rincón et al. (2012)	Lyapunov-like function application: simulation only, wastewater	dilution rate	effluent VFA
robust set-valued	Alcaraz-González et al. (2000)	interval observers, nonlinear application: simulation only, AFB, wastewater	dilution rate	- effluent VFA - effluent COD
robust interval	Alcaraz-González et al. (2001, 2005)	interval observers application: pilot-scale AFB, wastewater	dilution rate	effluent COD