

Lessons learnt from 15 years of ICA in anaerobic digesters

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Abstract Anaerobic digestion plants are highly efficient wastewater treatment processes with inherent energy production. Despite these advantages, many industries are still reluctant to use them because of their instability confronted with changes in operating conditions. There is therefore great potential for application of instrumentation, control and automation (ICA) in the field of anaerobic digestion. This paper will discuss the requirements (in terms of on-line sensors needed, modelling efforts and mathematical complexity) but also the advantages and drawbacks of different control strategies that have been applied to AD high rate processes over the last 15 years.

Keywords Anaerobic digestion; automation; control; diagnosis; instrumentation; modelling

Introduction

Anaerobic digestion (AD) is a multistep process in which complex organic material is converted to simpler compounds without an external electron acceptor such as oxygen or nitrate. AD is naturally present in many natural and cultivated ecosystems where it is actively involved in biogeochemical cycles of organic material. In parallel, AD can be considered as one of the oldest technologies for waste and wastewater treatment. It has been indeed applied since the end of the 19th century for the treatment of household waste(water)s in septic tanks, of slurries in digesters and of sewage sludge in municipal treatment plants. It is also probably the major biological process involved in stabilisation of landfill waste. Several advantages are recognised to AD processes when used as WWTPs: high capacity to treat slowly degradable substrates at high concentrations, very low sludge production (5 to 10 times less than in aerobic processes), potential for valuable intermediate metabolites production, low energy requirements (no aeration is required), reduction of odours in a closed system, pathogens reduction and possibility for energy recovery through methane combustion or even hydrogen production. However, AD processes also have drawbacks.

- The low sludge production is closely linked to the slow growth of micro-organisms. As a consequence, the start-up phase is often tedious and some time is required (e.g. 2–4 months or longer in UASB reactors) before steady state conditions are obtained.
- AD micro-organisms are highly sensitive to overloads of the process and disturbances of several causes. For example, methanogenic microbes are inhibited by high concentrations of its own substrate (i.e. volatile fatty acids). In manure digesters, the most common cause of instability is free ammonia inhibition, which stops aceticlastic methanogenesis. In primary and activated sludge digesters, it may be overloading,

ammonia, or long chain fatty acid inhibition. In high-rate digesters, the cause may be pH or organic acid inhibition.

- AD is a complex process involving many different micro-organisms (about 140 species are involved in AD stepwise reactions) which is still not completely understood. In addition, despite recent studies, the spatial distribution of individual organisms in flocs, granules and biofilms is not completely understood even though it has a strong influence on the overall process performance. Nevertheless, use of full-scale anaerobic granular sludge or biofilm reactors is widespread.

Despite these drawbacks, it is interesting to notice that it has been reported about 5.7 million AD processes used at the family scale in China for producing local energy (Qian, 1997). The aforementioned drawbacks explain probably that AD processes are not more widely used at the industrial scale. In the past, the lack of knowledge concerning AD processes led indeed to breakdowns, ranging from minor to catastrophic, mainly due to organic overloads of various origins. They created some kind of suspicion towards this process and delayed its development at the industrial scale. This is why actual research aims not only to extend the potentialities of anaerobic digestion, but also to optimise anaerobic processes and increase their robustness towards perturbations (van Lier *et al.*, 2001). Thus, the importance of implementing appropriate, carefully designed and efficient ICA strategies for AD processes is of no doubt.

Control objectives

The most common objective of AD is complete digestion to carbon dioxide and methane, but partial digesters are also used in specific applications. Some examples, with different control objectives, are listed here.

- Partial fermenters which produce a specific product. These may produce organic acids for enhanced biological phosphorus removal, ethanol, hydrogen, or specific acids for industrial use. Control objective is here maximum product yield.
- Primary and activated sludge digesters in municipal wastewater treatment plants (WWTPs) for sludge destruction. Control objectives are normally stable operation and minimisation of the effect on the activated sludge plant of disturbances caused by the recycle of nutrients (nitrogen and phosphorus) via the treated sludge reject water stream. Maximisation of energy production (via the biogas) can also result in important operating cost reductions for the entire WWTP.
- Solids digesters in which a solid or semi solid stream is converted to methane for renewable energy production and solids destruction. Control objectives are stable operation and maximum energy production.
- High-rate digesters treating industrial streams with mostly soluble organics, to minimise downstream treatment charges and avoid environmental pollution. Control objectives are stable operation and to avoid damage to, or inhibition of the reactor sludge.

The main control objective in methanogenic treatment plants is thus stability, normally as measured by biogas production rate, effluent soluble COD or volatile fatty acids concentrations. However, from a control prospective, it is to be noticed that the nature of influent to be treated (i.e. liquid wastewater or solid waste) and the reactor configuration will largely influence the process dynamics and the achievable performances in terms of organic loading rate.

Smart on-line instrumentation for closed loop control

It is out of the scope of the present paper to review in details the specific aspects related to instrumentation when applied to AD processes. To this end, the reader can refer for example to Vanrolleghem (1995) and Liu (2003) and related references. For sake of

clarity, we will focus in the following on two main pilot scale processes that we operated over the last ten years: a 150 litre fluidised bed reactor (Dochain *et al.*, 2000) and a 1 m³ fixed bed reactor (Steyer *et al.*, 2002a). The same wastewaters (i.e. raw industrial distillery wastewaters) were used in both processes to have a basis for comparison. Being a real waste stream, they have changing characteristics according to the wineries they are taken from. The main applied change was by diluting the raw influent with tap water during the experiments (dilution factor between 1 and 4). The two processes had standard on-line instrumentation, including liquid flow rates, temperature and pH in the reactor, and biogas flow rate and composition (i.e. CO₂, CH₄ and H₂ content in the biogas). In addition, the following sensors were installed over the years: a TOC analyser, a titrimetric sensor, a UV spectrometer and a FT-IR spectrometer. From the end of 1998, this instrumentation has provided us with the following on-line measurements in the liquid phase: soluble chemical oxygen demand (COD), total organic carbon (TOC), total volatile fatty acids (VFA), acetate (Ac), dissolved CO₂ (CO_{2d}), and bicarbonate concentrations and total and partial alkalinity. Some of these are measured twice or even three times by multiple instruments (see Table 1). Of course, not all these sensors are needed to apply the control strategies presented below but it has allowed us to compare – in the long term – the respective benefits of each of these sensors when used in an on-line context. From a control point-of-view, one important lesson is that some sensor technologies are more useful than other ones. Indeed, if all on-line sensors provide numerical values of the measured variables, some (e.g. a titrimetric sensor or an infrared spectrometer – *cf.* Figure 1) also provide information on how the measurements have been obtained. This information can then be used as a confidence index on the measurement and is of great help to decide – in an on-line context – if a control law can rely or not on the obtained measurements. In order to guarantee a safe operation of the plant, the controller can indeed be turned off in case of sensor fouling or any other dysfunctioning which will appear on the titration curves or on the multi-wavelength spectra.

Control laws were largely implemented through feed flow manipulation. However, this degree of freedom is not always available, as it is generally determined by the upstream factory discharge. There is therefore a lack of actuators to manipulate in anaerobic digestion, even though other options could include change in recycle flow, either directly from the reactor, or to a preacidification and CO₂ stripping mixed reactor.

On the model complexity needed for model based control

Various models have been developed over the years for anaerobic digestion processes. Early models included a single microbial population, and were proposed in the 60s and 70s. This representation of the process was later improved by considering three stages

Table 1 The different variables measured on-line on the pilot scale fixed bed reactor

	From classical measurements (pH, T, Q _{gas} , %CO ₂ , P)	TOC analyser	Titrimetric Sensor	UV Spectrometer	FT-IR Spectrometer
Partial alkalinity			✓		✓
Total alkalinity			✓		✓
Bicarbonate	✓		✓		✓
Dissolved CO ₂	✓				✓
TOC		✓		✓	✓
Soluble COD				✓	✓
Total VFAs			✓	✓	✓
Acetate				✓	✓
Other (e.g. N, P)				✓	✓

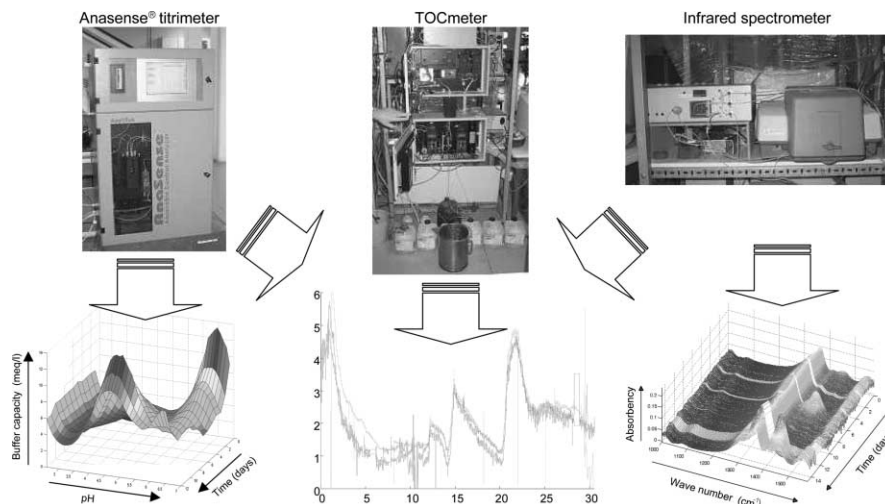


Figure 1 On-line sensors should also provide a confidence index of their measurements to guarantee safe closed-loop control of the plant (titrimeter and spectrometer do it in the form of buffer capacity curve and multi-wavelength spectra whereas the TOCmeter does not)

with solubilization of organic compounds, acidogenesis and methanogenesis or even a multiple-population model with two acidogenesis reactions and two-methanization reactions. Thereafter, these models have been improved and detailed by other authors in order to get closer to the complexity of the process. Lately, the AD specialist group of IWA proposed a general model for anaerobic digestion called the ADM1 (see [Batstone et al., 2002](#) and related references) that is very useful for benchmarking.

However, the resulting models include several bacterial populations and various substrates so that the number of parameters may become very large (e.g. up to 26 dynamic state concentration variables and 19 biochemical kinetic processes in ADM1). The problem is that it is then difficult, not to say impossible, to use these models for on-line control purposes since they are hard to fully calibrate and to validate. Moreover, their mathematical behaviour can be complex and derivation of an automatic controller becomes a very tedious task. Simpler models should thus be chosen in a model-based controller architecture. Such models lump assumptions and correlated processes, and circumvent difficulties related to poor reliability in bacterial growth modelling by locating the biological variability in dedicated terms. An example of such a model can be found in [Bernard et al. \(2001a\)](#) and this model has been used in all the non linear model based control approaches described in the following sections.

Experimental comparison of control laws

In the literature, little attention has been paid over the years to the comparison of control approaches when applied to AD processes. One of the first and very interesting surveys was done in the early nineties by [Heinzle et al. \(1993\)](#). However, at that time, they referenced only 15 control applications on AD processes, out of which 6 were done in simulations (i.e. without any experimental validation). Moreover, except two studies, all the other ones were using either basic on-off or PI/PID controllers. Since then, research work and applications have been developed for controlling more and more efficiently AD processes. Despite this increase of interest for AD processes, it is interesting to notice that very often, these studies were concerned with process operation, which basically deals with static optimisation and thus, they rarely consider dynamic plant optimisation. Nevertheless, because of the increasing availability of reliable on-line sensors and increasing

knowledge of biological phenomena involved in AD process, there is a general trend of more complex control approaches with higher efficiency and more practical applicability. It is out of the scope of the present paper to review in details all these approaches from a mathematical point-of-view. We will focus on few experimental validations performed on high rate processes. For more details about control of AD processes, see for example Premier (2003) or Liu (2003) and related references. Table 2 summarises the different advantages and drawbacks of the control laws that have been implemented on our processes. Clearly, the use of a specific control approach is closely linked to the data/knowledge/model availability. Moreover, it demonstrates that three issues are key aspects in AD monitoring: efficient disturbance rejection, handling of non linearities and explicit uncertainty management.

Advanced instrumentation or advanced control law ?

In order to answer this question, a fuzzy logic controller, and model-based adaptive controller are compared using alkalinity as input. It is considered that for safe operation of AD processes, the alkalinity should be maintained in the following range: $IA/TA \leq 0.3$ and $TA \geq 3$ g/l where TA stands for the total alkalinity and IA the intermediate alkalinity (i.e. the difference between partial and total alkalinity, $IA = TA - PA$). The control objective can then be translated in the regulation of the ratio IA/TA at a setpoint lower than 0.3 (e.g. 0.2) through the manipulation of the input liquid flow rate. The main consideration is that if there is no direct measurement of alkalinity, indirect measurements should be combined with a mathematical model to estimate alkalinity. A possible structure is an adaptive controller described in Figure 2a and the obtained results are presented in Figure 3 from $t = 5$ to $t = 30$ h.

Compared to this, if a reliable alkalinity sensor is available and provides an on-line measurement, it can be directly controlled using a fuzzy logic controller. The controller structure is depicted in Figure 2b and comparative results between the adaptive controller and the fuzzy one are shown in Figure 3 from 47 to 80 hours (recall that the adaptive controller does not use the alkalinity measurements). As it can be seen, both controllers achieve the same performances of (i) an increase of the loading rate compared to the open loop operation of the plant, (ii) a regulation of the ratio IA/TA to the setpoint and (iii) reactor remains in safe operating conditions while avoiding *VFA* accumulation.

A summary of the requirements of these 2 control approaches is provided in Table 3. The main idea is that a model can efficiently replace expensive sensors (here an alkalinity sensor) in an on-line control framework and it is up to the plant manager to decide to use either advanced instrumentation or advanced calculations. But another question remains: what if a reliable model of the process and a reliable on-line sensor are available at the same time? Will better performances be achieved? Is it worth the effort and money? The answer is clearly *yes* since it will allow us to face the great challenge of handling changing operating conditions, of explicitly managing the non linearities inherent to the biological activity while optimising the control actions through the prediction of process dynamics when facing disturbances.

Diagnosis and decision support systems

It is important to note that all these control laws will meet and only meet the specific objectives they have been designed for. As a consequence, a control law cannot manage a technical problem (e.g. a clogging of a pipe) if its goal is to control COD in the output of the reactor. In addition – and since there does not exist any “universal” control law that could manage all the disturbances occurring on a process – it is mandatory to couple control laws with advanced diagnosis scheme. We believe this is the only possible way

Table 2 Summary of the different control approaches possible to monitor AD processes

Type of controller	When should it be used ?	Notes
<i>Model free controllers</i>		
PI/PID	When a low amount of data is available When little knowledge about the plant behaviour is available When no model is valid	Good but not excellent results can be obtained. Moreover, applications are usually limited to single input single output control strategies and to linear cases.
Control through a "dialogue with bacteria" (Steyer <i>et al.</i> , 1999)	When it is possible to apply small disturbances (e.g. on the feed flow) without affecting the process	This strategy does not need any advanced sensors (i.e. only gas flow and pH). It is applicable if the answers to the applied disturbances are faster than the main disturbances that can affect the process. It is also very useful to start-up AD processes.
Artificial neural networks (Steyer <i>et al.</i> , 2000)	When a large amount of data is available When little knowledge about the plant behaviour is available When no mechanistic model is valid	Excellent results can be obtained but be careful about the way adaptive learning is performed (the neural controller remains a black box).
Fuzzy logic (Estaben <i>et al.</i> , 1997)	When a low amount of data is available When good knowledge about the plant behaviour is available When no explicit model is valid	It is able to handle process non linearities and multiple inputs multiple outputs control scheme can be developed while being easily handle by human operators and accounting for their expertise.
<i>Linear model based controllers</i>		
Disturbance accommodating control (Harmand <i>et al.</i> , 2000)	When a linear model is valid	It should be used when disturbances are likely to occur on sensors and/or actuators and when it is important to follow their evolutions.
Non parametric adaptive control (Hilgert <i>et al.</i> , 2000)	When a linear model is partially known.	It should be used when robustness is important around an equilibrium point.
Non linear control with constraints handling (Antonelli <i>et al.</i> , 2003)	When a low amount of data is available When little knowledge about the plant behaviour is present	It is able to handle actuators constraints and provides soft control actions while handling some process non linearities.
<i>Non linear model based controllers</i>		
Adaptive control (Bernard <i>et al.</i> , 2001b)	When a non linear model is valid but model parameters do not need to be very well known. When the inputs of the process are known (or at least their variations are slow).	It is a very efficient control strategy. It takes advantage of what is well known about the dynamics (reaction pathways and mass balances) while accounting for model uncertainty (mainly the kinetics). It also provides on-line estimation of some unknown variables (e.g. concentration of pollutant) and parameters (e.g. reaction rates).
Interval based non linear control (Acaraz-Gonzalez <i>et al.</i> , 2005)	When a non linear model is valid but model parameters do not need to be very well known. The inputs of the process can be roughly known (<i>min</i> and <i>max</i> values are required).	Here, the control objective is not an exact regulation at the setpoint but to keep the controlled variable in a "pipe" around the setpoint. Changing operating conditions can be handled in a way similar to adaptive control. However, less effort is required for knowledge of the process input concentrations.
Robust non linear control (Mailleret <i>et al.</i> , 2004)	When the structure of a non linear model is valid and the yield coefficients correctly identified. The inputs of the process do not need to be measured on-line but only once in a while.	This approach is interesting since it allows one to get very efficient regulation while being naturally robust (in case of problem, the control action goes automatically to safe conditions), non linear (it thus covers a broad range of situations) and uses simple sensors (the methane flow rate is the main sensor required).

for achieving successful optimisation of AD processes at *industrial* scale. In the past, we tackled diagnosis objectives using quantitative (Aubrun *et al.*, 2000) and qualitative (Genovesi *et al.*, 2000) model based approaches, sometimes combining them together (Steyer *et al.*, 2002b) or with process history based methods (Steyer *et al.*, 1997). From

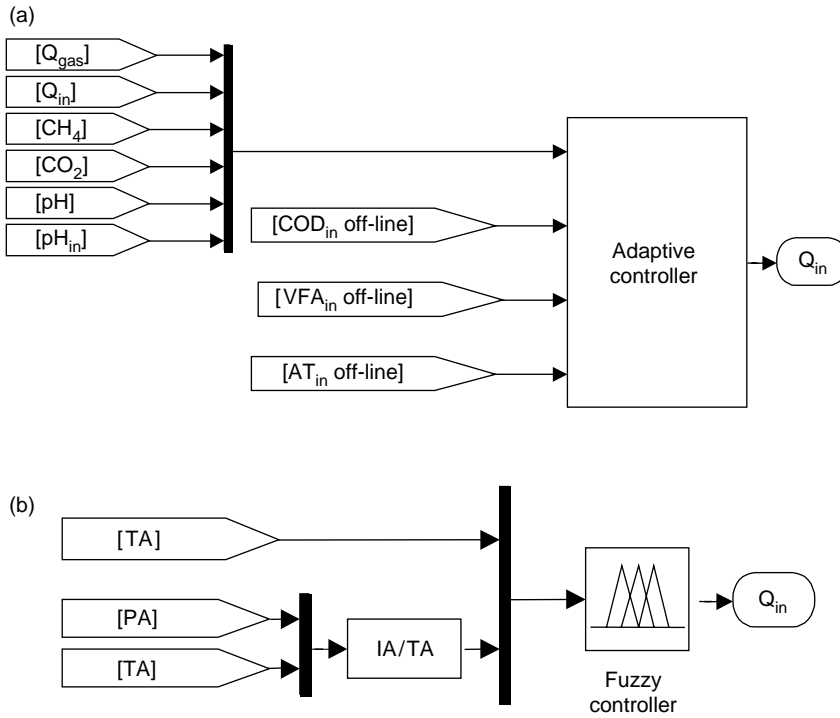


Figure 2 Overall structure of (a) a model based adaptive controller and (b) a model free fuzzy controller used for the regulation of the ratio of the intermediate alkalinity over the total alkalinity

these experiences, it is our strong belief that a unified approach based on evidence theory could be of great help for overall optimisation of AD processes (Lardon *et al.*, 2004) and for management of sensors network (Steyer *et al.*, 2004). Evidence theory gathers many advantages: modularity, robustness, novelty identifiability, adaptability, low modelling requirements and multiple fault identifiability. Additionally, it allows an easy integration of software sensors, an automatic activation and tuning of control loops and a validation

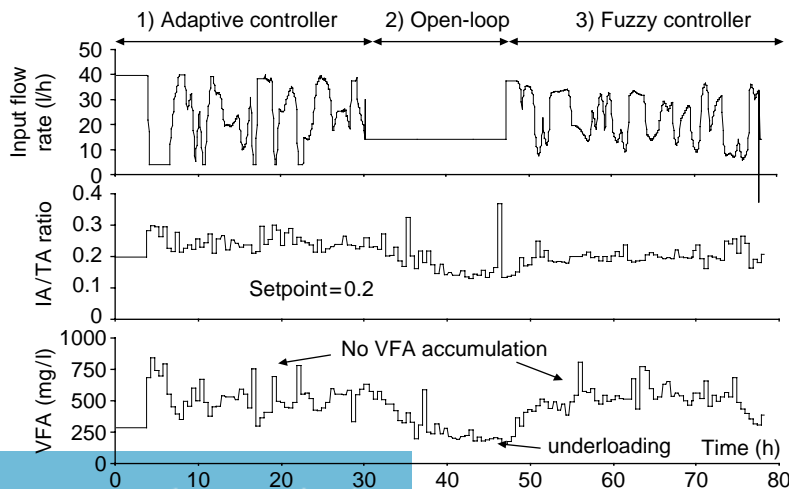


Figure 3 Comparison between adaptive and fuzzy controllers for the regulation of the IA/TA ratio

Table 3 Comparison of the requirements for model based and model free controllers

<i>Model based controller (e.g. adaptive controller)</i>	<i>Model free controller (e.g. fuzzy controller)</i>
⊗ Simple sensors	⊗ Advanced sensor
⊗ Need of a simple model	⊗ No need of a model
⊗ Knowledge of the input concentrations	⊗ No knowledge of the input concentrations
⊗ Advanced mathematical calculations	⊗ Simple calculations

of different simple models developed to handle specific situations, these aspects being of great help for remote monitoring purposes (Bernard *et al.*, 2005).

Conclusion

Anaerobic digestion has classically been regarded as a process difficult to manage because of slow dynamics, limitations in available inputs for manipulation and a lack of understanding of the process. There is still a lack of control handles, but the other two problems have been alleviated by technological advances. In particular, there are now robust on-line sensors available on the market. Advances allow implementation of very efficient decision support systems which can lead to successful optimisation of digesters and opens large perspectives for industrial development. Our work has shown that an advanced sensor with simple control can perform comparably with simple sensors and an advanced controller. Combination of multiple sensors allows fault detection, and advanced early warning systems. However, ICA of AD processes is still emerging. For example, there is a lack of applications in solids/manure and municipal digesters. We are confident this will improve in the future, and advanced control of AD processes has the potential to widen their competitive scope, and make application in low COD systems (e.g. municipal wastewater treatment) a realistic option.

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