Computer simulation of control strategies for optimal anaerobic digestion

S. Strömberg, M. O. Possfelt and J. Liu

ABSTRACT

Three previously published control strategies for anaerobic digestion were implemented in Simulink/Matlab using Anaerobic Digestion Model No. 1 (ADM1) to model the biological process. The controllers’ performance were then simulated and evaluated based on their responses from five different types of process scenarios i.e. start-up and steady state performance as well as disturbances from concentration, pH and ammonia in the inflow. Of the three evaluated control strategies, the extremum-seeking variable gain controller gave the best overall performance. However, a proportional feedback controller based on the pH-level, used as a reference case in the evaluation, proved to give as good results as the extremum-seeking variable gain controller but with a lower wear on the pump. It was therefore concluded that a fast proportional control of the reactor pH is a key element for optimally controlling a low-buffering anaerobic digestion process.

Key words | anaerobic digestion (AD) control, ADM1, anaerobic digestion, biogas, computer simulation

NOMENCLATURE

**Extremum-seeking variable gain controller**

- $Q$ Inflow
- $Q_0$ Inflow at set point
- $K_{pH}$ Proportional gain for pH
- $K_{CF}$ Proportional gain for gas flow
- $pH$ pH level
- $pH_{sp}$ pH set point
- $pH_{sp,o}$ pH set point at set point
- $GF$ Total gas flow
- $GF_{sp}$ Total gas flow set point
- $GF_{sp,old}$ Previous total gas flow set point
- $GF_{step}$ Change in gas flow set point
- $D$ Difference between $GF$ and $GF_{sp}$
- $D_{old}$ Previous value of $D$
- $D_{min}$ Lower boundary for $D$
- $D_{max}$ Upper boundary for $D$
- $\Delta D$ Change in dilution rate
- $D_{old}$ Previous dilution rate
- $k$ Proportional gain
- $f_{CH_4}$ Factor based on CH$_4$ productivity
- $f_{H_2}$ Factor based on H$_2$ concentration
- $\alpha$ Sensitivity parameter for $f_{CH_4}$
- $GF_{CH_4}$ Methane productivity
- $GF_{CH_4,sp}$ Methane productivity set point
- $H_2$ Hydrogen concentration in gas
- $H_{2,sp}$ Hydrogen concentration set point
- $n$ Sensitivity parameter for $f_{H_2}$ at high $H_2$
- $m$ Sensitivity parameter for $f_{H_2}$ at low $H_2$

**Disturbance monitoring controller**

- $\Delta Q$ Change in inflow
- $Q_{old}$ Previous inflow
- $EGV$ Gas volume from pulse
- $EGV_{exp}$ Expected $EGV$
- $\alpha$ Increase in flow rate in pulse
- $\delta t$ Time for pulse
- $GF_{av}$ Average gas flow
- $R$ Ratio of EGV and $EGV_{exp}$
- $R_{min}$ Lower boundary for R
- $R_{max}$ Upper boundary for R
- $f_{max}$ Maximal change in inflow

**Hydrogen variable gain controller**

- $\gamma$ Sensitivity parameter for $f_{H_2}$ at low $H_2$

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INTRODUCTION

Anaerobic digestion is a complex and versatile biological process that needs constant monitoring in order to achieve its optimal performance. In case of a digester failure, the process could take up to several months to recover, leading to big losses in revenues (Bernard et al. 2005). Due to this, to be on the safe side, many operators prefer to operate the biogas plant far below the maximum capacity. A way to overcome this insecurity whilst still maintaining a stable process with a higher gas productivity is to implement a control strategy that can push the process to an optimum and at the same time have the capacity to react fast on disturbances and unstable process conditions (Steyer et al. 1999; Liu et al. 2006; Rodríguez et al. 2006).

Over the past decades, several control strategies have been developed for the control of anaerobic digestion. In many of these cases, the controller was able to improve the process significantly, either by maximizing the gas production and/or by disturbance rejection. However, so far, little focus has been directed toward comparing and evaluating these control strategies, much due to the extensive workload of such studies. A way to overcome this problem is to utilize dynamic computer simulations (Rosen et al. 2004). Model implementations using Anaerobic Digestion Model No. 1 (ADM1) has proved to be a good tool for evaluating control performance in an anaerobic digestion process (Batstone & Steyer 2007; Zhou et al. 2012). As an example, the Benchmark Simulation Model No. 1 (BSM1, Copp et al. 2002), a benchmark platform for evaluation of control strategies and operation of wastewater treatment plants, has been developed for this purpose and has had great success with over 300 publications worldwide (Nopens et al. 2010). With inspiration from BSM1, this study aimed at evaluating three previously published control strategies by putting them through a number of critical process situations with the help of computer simulations.

METHODS

Evaluated control strategies

In order to find the most suitable controllers to evaluate, a literature study was carried out. It was required that the controllers would be unique, reject disturbances and maximize the biogas or methane production. Especially the maximizing criteria greatly limited the number of candidates, and in the end three strategies where chosen (Table 1).

Below is a short summary of the control algorithms evaluated in this work. For a more detailed description and explanation of the symbols please see the respective reference (Table 1).

Extremum-seeking variable gain controller (ES)

This control strategy uses a cascade structure with an additional rule-based expert system where the lower level controller (also called the slave controller) operates on the pH-level and the top level controller (also called the master controller) manipulates the set point of total gas flow while the expert system pushes the gas production.

\[
Q = K_{\text{pH}} \cdot (pH - pH_{\text{sp}}) + Q_o \tag{1}
\]

\[
pH_{sp} = K_{GF} \cdot (GF - GF_{sp}) + pH_{sp,D} \tag{2}
\]

If \( D \geq D_{\text{max}} \) then \( GF_{sp} = GF_{sp,old} + GF_{step} \tag{3} \)

If \( D_{\text{min}} \leq D < D_{\text{max}} \) then \( GF_{sp} = GF_{sp,old} + 0.5GF_{step} \tag{4} \)

If \( D < D_{\text{min}} \& D_{old} \geq D_{\text{max}} \) then \( GF_{sp} = GF_{sp,old} \tag{5} \)

If \( D < D_{\text{min}} \& D_{old} < D_{\text{max}} \) then \( GF_{sp} = GF_{sp,old} - GF_{step} \tag{6} \)

Table 1 | Summary of evaluated controllers

<table>
<thead>
<tr>
<th>Controller</th>
<th>Reference</th>
<th>Input</th>
<th>Output</th>
<th>Acronym</th>
</tr>
</thead>
<tbody>
<tr>
<td>Open loop reference controller</td>
<td>–</td>
<td>–</td>
<td>Flow rate</td>
<td>OR</td>
</tr>
<tr>
<td>Proportional reference controller</td>
<td>–</td>
<td>pH</td>
<td>Flow rate</td>
<td>PR</td>
</tr>
<tr>
<td>Hydrogen-based variable gain controller</td>
<td>Rodríguez et al. (2006)</td>
<td>H₂ &amp; CH₄ prod.</td>
<td>Flow rate</td>
<td>HVG</td>
</tr>
</tbody>
</table>
The lower level controller regulates the inflow according to Equation (1), in which the gain constant ($K_{pH}$) is determined by a gain scheduling state function with eight different process states (Liu et al. 2006). The objective of the top level controller is to make sure that the gas flow, set by the supervisory logic from the expert system, is maintained. This objective is achieved by manipulating the set point of the lower level controller according to Equation (2). The supervisory logic is achieved by a simple set of rules that can be seen in Equations (3)–(6), where $D_{\text{max}}$ and $D_{\text{min}}$ are constants and $D$ is the gas flow ($GF$) subtracted by the gas flow set point ($GF_{\text{sp}}$). In Equations (1)–(6) the subscript old refers to the previous value of the parameter and step refers to the change that is added to the parameter. In the numerical implementation the following sample times were used: 2.5 min for lower level controller, 30 min for upper level controller and 60 min for the rule-based expert system.

**Disturbance monitoring controller (DM)**

The basic concept of the disturbance monitoring controller is to introduce a disturbance on purpose to the process and then, based on the response, determine if the process is operating at maximum capacity, or is above/below maximum (Velut et al. 2007). The disturbance is applied as a short pulse of increased inflow and the change in gas production is used as the response variable. The size of the pulse is calculated as a factor ($\alpha$) multiplied with the current inflow and duration of the pulse ($\delta t$). Based on the response from the pulse, the change in inflow is adjusted according to a number of equations (Equations (7)–(11)). At first, the expected gas production increase ($EGV_{\text{exp}}$) is calculated by taking into account the pulse size and the average gas production just before the pulse (Equation (7)). In order to determine the state of the process, a ratio of the expected and the actual gas production is calculated (Equation (8)) which is then used to determine the change in inflow according to Equations (9)–(11). The controller also has an emergency pH stop which prevents further pulses if the pH falls below a critical level. In the numerical implementation, a 1 hour pulse was generated at an interval of 0.4 days.

$$EGV_{\text{exp}} = \alpha \cdot \delta t \cdot GF_{\text{av}}$$  \hspace{1cm} (7)

$$R = \frac{EGV}{EGV_{\text{exp}}}$$  \hspace{1cm} (8)

If $R \geq R_{\text{max}}$ then $\Delta Q = Q_{\text{old}} \cdot f_{\text{max}} \cdot \left(\frac{R - R_{\text{max}}}{1 - R_{\text{max}}}\right)$ \hspace{1cm} (9)

If $R_{\text{min}} \leq R < R_{\text{max}}$ then $\Delta Q = 0$ \hspace{1cm} (10)

If $R < R_{\text{min}}$ then $\Delta Q = Q_{\text{old}} \cdot f_{\text{max}} \cdot \left(\frac{R - R_{\text{min}}}{R_{\text{min}}}\right)$ \hspace{1cm} (11)

**Hydrogen-based variable gain controller (HVG)**

This control strategy uses hydrogen concentration from the reactor headspace and methane productivity to manipulate the inlet flow rate. The change in dilution rate (Equation (12)) is a function of the old dilution rate ($D_{\text{old}}$), a gain constant ($K$) and two empirical functions; one based on the methane productivity ($f_{\text{CH}_4}$, Equation (13)) and one based on the hydrogen concentration ($f_{\text{H}_2}$, Equations (14)–(15)).

$$\Delta D = D_{\text{old}} \cdot K \cdot f_{\text{H}_2} \cdot f_{\text{CH}_4} \cdot \Delta t$$ \hspace{1cm} (12)

$$f_{\text{CH}_4} = \frac{\alpha \cdot GF_{\text{CH}_4,\text{sp}}}{Q_{\text{CH}_4} + \alpha \cdot GF_{\text{CH}_4,\text{sp}}} \in [0, 1]$$ \hspace{1cm} (13)

If $H_2 > H_{2,\text{sp}}$ then $f_{\text{H}_2} = \left(\frac{H_{2,\text{sp}}}{H_2}\right)^n - 1 \in [-1, 0]$ \hspace{1cm} (14)

If $H_2 \leq H_{2,\text{sp}}$ then $f_{\text{H}_2} = \left(1 - \frac{H_2}{H_{2,\text{sp}}}\right)^m \in [1, 0]$ \hspace{1cm} (15)

The main objective of $f_{\text{CH}_4}$ is to determine the size of the change in inflow whereas $f_{\text{H}_2}$, besides determining the size of the inflow, also decides the direction of the change in inflow (increase or decrease). The controller was implemented in a pseudo-continuous mode, i.e. $\Delta t$ in Equation (12) was varied according to the time step in the numerical solver.

**Evaluated process situations**

The controllers were evaluated based on their responses to five different types of process scenarios. These were chosen to simulate known critical situations that can occur in the operation of an anaerobic reactor and are all presented below.
Start-up

Evaluates how fast and stable the controllers can accomplish a start-up of an anaerobic process. This was interesting to study since the start-up of a reactor is a very time consuming and sensitive process that differs from the steady state conditions of an ongoing process (Zhao et al. 2010).

Steady state performance

Evaluates how far the controllers can push the process at steady state when the inlet concentration is constant.

Concentration disturbances

Evaluates how well the controllers can handle big changes in the inlet concentrations and was implemented as a random gain on all the inlet concentration states, i.e. changing every second day within a span of 0.1 to 2.

pH disturbances

Evaluates how well the controllers can handle big changes in the inlet pH. Two types of disturbance were tested: (1) pulses of low pH that grew bigger with time to see the controllers' response to quick changes in pH and (2) a negative pH gradient to see how far the controller can sustain a working process.

Ammonia disturbances

Evaluates how well the controllers can handle big changes in the inlet ammonia concentration. This was interesting to study due to the different inhibition properties of ammonia, where inhibition occurs at high pH levels and mainly on the methanogenic bacteria. The ammonia disturbances were added in the same way as the pH disturbances, i.e. as growing pulses and as a positive gradient.

Run protocol

In order to evaluate the performance of the control strategies as objectively as possible a run protocol, specifying different phases in the simulation runs, was designed (Table 2).

<table>
<thead>
<tr>
<th>Time span (d)</th>
<th>Purpose</th>
<th>Disturbances</th>
</tr>
</thead>
<tbody>
<tr>
<td>Start-up and concentration disturbances</td>
<td>0–100</td>
<td>Time for start-up as well as for reaching steady state</td>
</tr>
<tr>
<td>100–282</td>
<td>Time for the controller to adapt to the disturbances</td>
<td>Yes</td>
</tr>
<tr>
<td>282–646</td>
<td>Evaluation period</td>
<td>Yes</td>
</tr>
<tr>
<td>Steady state performance and pH and ammonia disturbances</td>
<td>0–63</td>
<td>Time for reaching steady state</td>
</tr>
<tr>
<td>63–427</td>
<td>Evaluation period</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Evaluation criteria

The control systems were evaluated based on the results from four process parameters which are presented and described in Table 3.

The actuator wear was calculated according to Equation (16) where $t_{\text{start}}$ and $t_{\text{stop}}$ are the start and stop time for the evaluation, $\frac{\partial Q}{\partial t}$ is the derivative of the inflow (controller output) and $n$ is the number of simulation time steps within the evaluation period.

$$A.W. = \frac{\sum_{t_{\text{start}}+1}^{t_{\text{stop}}} \frac{\partial Q}{\partial t}}{n}$$

Anaerobic digestion model

ADM1 (Batstone et al. 2002) was used to model the biological and physio-chemical processes in the reactor. This model has been widely used and on several occasions.
occasions proved to provide an accurate representation of the process (Parker 2005; Batstone et al. 2006). However, in order to achieve a more realistic start-up process, variable growth rates of the bacterial groups were added to the model. These were implemented as a time-varying growth rate factor that was multiplied with the growth rate (Zhao et al. 2010). In order to make it as simple as possible, the same growth rate factor was used for all bacterial groups and was designed as an exponential curve going from zero to one during the first 30 days.

**Equalization tank**

An equalization tank previous to the digester was included in order to give the controller a realistic amount of substrate to work with. It was implemented as a simple mixing model where the derivatives were a function of the inputs and outputs of each component.

**Measurement noise and filters**

To increase the realism of the simulated process and to avoid giving different control strategies unrealistic advantages, measurement noise and filtering were added to the input signals. Measurement noise was added as a 2.5% random error of the original signal (Rieger et al. 2005). The signals were filtered using a backward discretized low-pass filter with a step size of 0.1 min and a filter time constant of 10 min. Also, a negative drift of the pH sensors was included as a gradual decrease of 0.1 pH unit/month compared to the real pH-value. This drift phenomena was then reset every second month when the sensor was assumed to be recalibrated.

**Substrate**

The substrate characteristics were the same as presented in (Rosen & Jeppsson 2006), with a low buffering capacity and the main biodegradable material in the form of carbohydrates, proteins and lipids.

**Controller tuning**

The tuning of the control parameters was primarily focused on maximizing the methane production in the simulations where concentration disturbances were applied. In the procedure, a high average methane productivity and disturbance rejection capability were prioritized compared to a more stable and low producing process. Since all evaluated control algorithms were structured differently, no uniform tuning method could be derived. Instead, a large number of simulations were implemented for familiarization with the controller performances and, when sufficient experience had been gained, the parameters were tuned manually to fulfil the requirements mentioned above. This simple method was chosen to reduce the otherwise extensive complexity of the calibration procedure. If the controllers are to be evaluated for a more specific target process, the calibration should be matched to the conditions of that process in order to reach the optimal performance of the controllers.

**Numerical implementation**

The simulations were carried out in Simulink/Matlab using ode45 as the numerical solver. ADM1 was implemented in C-code of the DAE2 version (s-functions were provided by Dr Ulf Jeppsson, Department of Industrial Electrical Engineering and Automation, Lund University) for maximal simulation speed (Rosen & Jeppsson 2006).

**RESULTS**

Below is a short summary of the results from the simulations of the five different presented process scenarios. Due to a lack of space, most of the visualization of the results had to be excluded from this paper.

**Start-up**

Only ES and PR (proportional reference controller) were able to complete the start-up within the designated time frame (Table 4). These results indicate that a simple proportional controller should be able to handle a start-up process fairly well. The large values for DM and HVG indicate that these controllers are too slow to fully optimize a start-up process.

**Steady state performance**

In the steady state performance evaluation ES and DM were able to give fairly good results compared with the open loop reference, OR (Table 4). All the controllers had a typical trend of a decrease in COD reduction with an increase in gas productivity and vice versa. PR, ES and DM gave similar results in methane productivity and COD reduction whereas the actuator wear differed significantly.
Concentration disturbances

In the concentration disturbance evaluation, ES had the highest methane productivity (1.44 Nm$^3$/m$^3$/d) of the evaluated controllers (Table 4). One interesting point discovered was that the methane productivity for ES was at the same level as in the steady state performance evaluation, indicating that it can handle varying inlet concentration very well. In contrast, DM and HVG both had lower methane productivities compared to the open-loop case, demonstrating that these controllers experienced difficulties with the disturbances.

As with the steady state case, ES experienced higher actuator wear compared to the other controllers and this can be clearly seen when comparing the volumetric inflow from ES (c) and PR (d) in Figure 1. A more oscillating trend from ES can also be seen when comparing the methane productivity (e and f) while the two controllers had a more similar profile with regards to the methanogenic biomass concentration (sum of acetogenic and hydrogenotrophic groups in ADM1) (g and h). A comparison of the pH-level trend (i and j) indicates that PR maintained a slightly lower pH level but with a similar trend as ES.

Table 4 | Summary of most important results from simulations of start-up, steady state and concentration disturbances

<table>
<thead>
<tr>
<th>Controller</th>
<th>Start-up time (days)</th>
<th>Average $Q_{CH4}$ (Nm$^3$/m$^3$/d)</th>
<th>Average COD red (%)</th>
<th>Average A.w. (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td>OR</td>
<td>--</td>
<td>1.29</td>
<td>38.4</td>
<td>0</td>
</tr>
<tr>
<td>PR</td>
<td>64</td>
<td>1.44</td>
<td>33.3</td>
<td>1,770</td>
</tr>
<tr>
<td>ES</td>
<td>60</td>
<td>1.43</td>
<td>34.6</td>
<td>7,090</td>
</tr>
<tr>
<td>DM</td>
<td>100</td>
<td>1.45</td>
<td>33.4</td>
<td>793</td>
</tr>
<tr>
<td>HVG</td>
<td>100</td>
<td>1.26</td>
<td>38.9</td>
<td>1.09</td>
</tr>
</tbody>
</table>

Ammonia disturbances

Similar to the pH disturbances, the results from the ammonia disturbances also show low methane productivities for all controllers (Table 5). The difference was that the results were more evenly distributed among the controllers, but in many of the previous cases, ES had the highest methane productivity. The controller that deviated the most was HVG which had a lower methane productivity compared to OR.

DISCUSSION

Since this work has been carried out strictly in silico, without any form of experimental data, there are several limitations and uncertainties that should be considered when evaluating the results. Three of the most important ones are: (1) even though ADM1 is a very advanced model, it is still far from describing the full complexity and unpredictability of a real-life anaerobic digestion process; (2) the same type of substrate characteristics is used in all simulations, giving very uniform responses; (3) the tuning of the control parameters was performed manually, with a rather simple methodology, which compromises the validity when comparing the control strategies. Therefore, to better verify the results, an improved strategy for tuning the control parameters needs to be designed and implemented. However, this should be considered a difficult task as most controllers for anaerobic digestion are non-linear and differ greatly in both structure and type.

ES was found to give the best overall performance of the evaluated control strategies. However, ES also had the highest actuator wear. Interestingly, PR gave the best results of all controllers but, as ES, experienced high values for the actuator wear. The similar results from ES and PR are probably due to the fact that
Figure 1 | Examples of some results from the simulations of concentration disturbances with inlet COD concentrations for ES (a) and PR (b), inflow for ES (c) and PR (d), methane productivity for ES (e) and PR (f), methanogenic biomass for ES (g) and PR (h) and pH for ES (i) and PR (j).
both have a fast feedback loop acting on the pH-level. The high actuator wears for both these controllers show that they were affected by the measurement noise and/or experienced instability around the set point which most likely could be reduced by using longer sampling intervals, better filters and differently tuned parameters. Nevertheless, the good performance from these two controllers indicates that a reasonable parameter for both disturbance rejection and gas maximization is the pH-level, provided that on-line pH monitoring can be properly implemented. However, this conclusion is limited to the specific feedstock and conditions used in this study. pH as a process indicator has on many occasions been proven to be an unreliable parameter due to different buffering capacities of the feedstock and if a high buffering feedstock would have been investigated, the outcome might have been different (Strik et al. 2006). Therefore, to evaluate the controllers’ performance on a more general level, several similar studies, using different types of feedstock, should be carried out.

Both the disturbance monitoring controller (DM) and the hydrogen-based variable gain controller (HVG) had problems handling the different disturbance scenarios and also experienced long start-up times. One of the major reasons for this was likely a poor tuning of the control parameters. HVG in particular was complicated to tune since its parallel controller structure made it difficult to foresee the sensitivity and effects of each parameter. For DM, the much longer sampling interval (only 2.5 pulses per day) was probably one of the major reasons for the poor results. Another concern with DM is that the probing pulses themselves might lead to reactor imbalance. A way to reduce this risk could be to include negative pulses (Velut et al. 2007).

An aspect that was not fully covered in this study is the stability. Since all controllers except PR have variable set points it was difficult to evaluate this in detail. Nevertheless, when they were tested with step disturbances almost no fluctuations were observed even though some overshooting occurred. The controllers were also able to handle measurement noise without failing even if this introduced fluctuations in the controller output. The actuator wear gives an indication of the controller’s sensitivity to noise and other disturbances, and controllers with high actuator wears should therefore be used with caution if implemented in a real-case application. However, when it comes to the stability of the anaerobic digestion (AD) process, the controllers that experienced high actuator wears (i.e. ES and PR) were also able to reject disturbances better and thus maintain a more stable process.

A problem that needs to be further addressed is how to evaluate the performance of a control system. An important factor is the objective of the process, that is, whether it is to maximize the gas production or reduce a waste stream as much as possible. On many occasions these two objectives contradict each other. When the process is pushed to generate as much gas as possible, less material will have the chance to be fully degraded and accumulation of VFA (volatile fatty acids) will occur (Ahring et al. 1995). This will in turn leave high amounts of easy degradable material in the effluent which is undesired if the feedstock is to be degraded as much as possible. Therefore, if the aim is maximal degradation, pH could be less interesting to use, since this parameter has been shown to give small changes in stable and less stressed processes (Björnsson et al. 2000; Boe et al. 2010).

### Table 5

<table>
<thead>
<tr>
<th>Controller</th>
<th>Average $O_{2\text{out}}$ (Nm$^3$/m$^3$/day)</th>
<th>Average COD$_{red}$ (%)</th>
<th>Average A.w. (-)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>pH pulse</td>
<td>NH$_3$ pulse</td>
<td>pH grad.</td>
</tr>
<tr>
<td>OR</td>
<td>0.04</td>
<td>0.09</td>
<td>0.41</td>
</tr>
<tr>
<td>PR</td>
<td>0.94</td>
<td>0.44</td>
<td>0.51</td>
</tr>
<tr>
<td>ES</td>
<td>0.92</td>
<td>0.45</td>
<td>0.52</td>
</tr>
<tr>
<td>DM</td>
<td>0.04</td>
<td>0.02</td>
<td>0.47</td>
</tr>
<tr>
<td>HVG</td>
<td>0.04</td>
<td>0.34</td>
<td>0.28</td>
</tr>
</tbody>
</table>

### CONCLUSIONS

A fast control strategy based on pH was found to give the best overall performance in an evaluation based on simulations using ADM1. In the simulations, the control systems were tested with severe disturbances in the
incoming feedstock. The conclusion was that, besides the good process indications from pH, a short sampling time of the control loop was especially important to handle the disturbances. Another point that was found to be important for the performance is how the control strategy is structured. In fact, in theory most control systems should be able to handle disturbances rather well. However, in order to do this, every control parameter has to be carefully tuned which requires expert knowledge and understanding of the control mechanisms. Such knowledge and understanding is much easier to gain when the structure of the controller is simple and clear. This fact had a significant impact on the outcome of this study, where the most successful control strategies had a more well-defined structure which made their tuning more efficient.

Using computer simulations to evaluate control strategies for the control of anaerobic digestion has proved to be a promising approach as long as the user is aware of the limitations of such studies. However, to reach its full potential, the simulations platform needs to be developed further to include more features such as new types of feedstock, generic performance indicators and a better defined tuning strategy.

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