Critical remarks on monitoring and control of technical scale biogas plants

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Abstract Energy production from sewage sludge, solid wastes and energy crops by anaerobic digestion is a widely used practice. However, due to the risk of process-overload, technical scale plants are often operated underloaded. To increase the biogas production and simultaneously avoid an overload of the plant, an enhanced control of the anaerobic digestion process is needed. Many different approaches for such control tools exist, including models based control tools as Neuronal Networks or Fuzzy Logic based tools. We have developed and tested different tools based on these technologies. The test phase in the lab-scale reactors show that the control tools are operative. But a lot of different problems occurred trying to implement the tools in technical scale plants. This paper is summarising our experiences during the AMONCO and the CROPGEN project. Furthermore, some recommendations for the implementation of control tools in practice will be discussed.
Keywords Anaerobic digestion; model; neural network; fuel scale experiences; fuzzy logic;

Introduction

The biological degradation of biomass, solid wastes and sewage sludge without oxygen (anaerobic digestion) results in an useful product (biogas). The formed biogas is converted into electric energy by gas engines and fuel cells. The anaerobic digestion (AD) process itself is a very complex biochemical process, which can be divided in several steps: (i) the disintegration of complex particulates and the following hydrolysis to monosaccharides, amino acids and long chain fatty acids (LCFA); (ii) the subsequent degradation of sugars and amino acids to volatile fatty acids (VFAs), hydrogen and carbon dioxide by acidogens; (iii) the acetogenesis from LCFAs and VFAs to acetate and (iv) the methanogenesis from acetate and hydrogen to methane. Due to the variety of reactions occurring, observation and monitoring of the AD process is very difficult and costly (Emmanoulides and Petrou, 1997). Plant operators fear a process-overload, thus technical scale plants are often operated underloaded (Holubar *et al.*, 2002). An advanced monitoring and control can lead to increased methane content (MC), augmented biogas yields, higher loading rates, smaller reactor volume and can avoid reactor overload. Typically parameters for monitoring full scale plants are alkalinity, gas production (GP), biogas composition, dissolved hydrogen, VFAs, pH and volatile suspended solid (VSS). This improved control can be accomplished by modelling the process. Due to the complexity of the process, the construction of a describing model is difficult (Wilcox *et al.*, 1995). This is normally not possible without any assumptions and simplifications. Therefore a good alternative are black box models, for example neuronal networks (NN) or expert systems, such as fuzzy logic and hybrid systems - Neuro-fuzzy combinations.

A Model based predictive control uses different kinds of models to forecast the future development of the process (Pannochia, 2003), considering threshold values and stability of the process .

NNs consist of an assemblage of simple processing elements (neurones) combined in a network by a set of weights. NNs are especially applicable for modelling non-linear systems (Strik, 2004b). The NN is defined by the structure of the network, the value of the weights and the mode of operation (Strik *et al.*, 2004a). A neurone takes input values, weights them, sums them up and adds a bias which finally results in the argument of an output function, the so-called transfer function. In the most common networks the neurones are arranged in layers, with an input layer, several hidden layers and an output layer (Strik, 2004b). If the number of layers is too low the ability for modelling the process is limited, whereas on the contrary, too much layer would result in too much freedom for the weights to adjust (Linko *et al.*, 1997). The advantage provided by the NNs is that less know-how and expert knowledge compared to Fuzzy Logic (FL) based control tools is necessary. However, a big disadvantage is that a lot of data are needed for training the models.

FL was originally developed from Lofti Zadeh (Sproule *et al.*, 2002). FL uses "Fuzzy" numbers, not crisp numbers, in form of membership functions (representing degrees of truthfulness). This technique is based on control rules, mostly in form of descriptive terms. Thus, the evaluation of the stability of the tool is difficult (Zani, 2001). Normally, a FL based control consists of the fuzzyfication of an input, the application of the interference rules and the subsequent defuzzyfication of the output. As an expert system, this control tool needs process specific experience. Compared to the model based control tools, however, a reduced amount of measured data is necessary.

Neuro-Fuzzy tools are combined systems of NN and FL. At the Institute of Applied Microbiology (IAM) different control tools were developed, based on NNs, FL or Neural-Fuzzy technique (Holubar *et al*, 2003). All these tools are able to predict parameters for the next day, for instance the biogas production and methane content (MC) (Holubar *et al.*, 2000). Hence, by employing a decision support tool (DST) based on these parameters, the organic loading rate (OLR) for the next day (Holubar *et al.*, 2002) can be calculated. It also was reported that control tools without an implemented model, such as FL based tools, show very good results (Domnanovich *et al.*, 2004).

Description of the used Control Tools

Following the objectives of the AMONCO-Project (Advanced Prediction, Monitoring and Control of Anaerobic Digestion Process Behaviour towards Biogas Usage in Fuel Cells) control tools for the AD process were developed (see below) and tested on lab-scale fermenters (Strik *et al.*, 2004). These control tools were supposed to be implemented on technical biogas plants.

Strategy 1 (Neuronal Networks)

For the NN control tools Feed-Forward-Back-Propagation (FFBP) NNs were used. FFBP NNs are supervised networks, typically trained by comparing the errors between the actual output and the purposed output (Zupan and Gasteiger, 1999). In this case the weights are moved along the negative of the gradient of the transfer function (Strik, 2004). The NN were validated with data set not used during training of the model. Figure 1 shows the schema of the used NN.

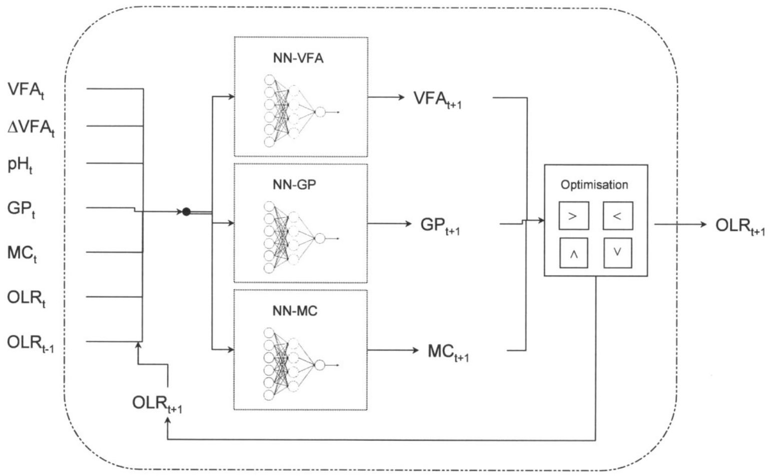

Figure 1: Schema of the used Neuronal Network; the VFA, ΔVFA, pH, GP, MC and OLR from the actual day and also the OLR from the day before were used to predict the OLR of the next day.

Strategy 2 (Fuzzy Logic Tools)

Two different FL based control tools were developed. The first FL control tool was based on the pH. This control tool was used to achieve an enhanced biogas production and a higher methane yield by predicting the OLR for the next day. For this tool the following set of parameters was used: The OLR, the methane content, the biogas production, the pH, and the difference between the pH of the actual day and the day before. The second tool was based on VFA concentration. Otherwise the observed inputs were the same as in the first FL tool. In Figure 2 the structure of the second FL tool is shown.

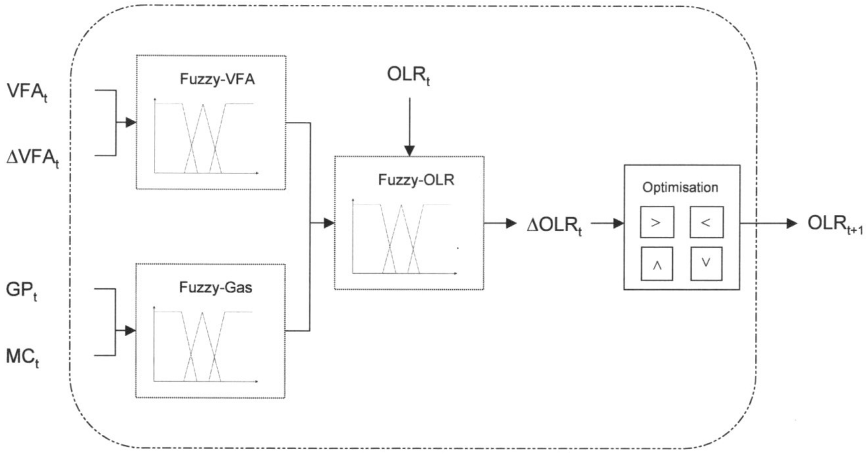

Figure 2: Construction of the used FL Tools; as input for the control tool VFA, ΔVFA, GP and MC from the actual day were used to predict the OLR of the next day.

Results and Discussion

The developed tools were tested at three different technical scale biogas plants (Plant A - C). Our experiences, made during this implementations, are described in the case studies 1 - 3

Case Study 1

Plant A consisted of two storage tanks, two 440 m³-continuous stirred tank reactors (CSTR) connected in parallel and a residue tank. The used substrate consisted of cattle manure, slaughterhouse waste, food- and fish waste. The waste was diluted with slurry to make it pumpable. The fermenters were working at 50°C (thermophile) and the organic waste had an average retention time of 14 days. No extra hygenisation is applied. Around 800.000 m³ of biogas are produced per year. In average the produced biogas contained 65 % methane and 35 % carbon dioxide. Electrical energy and heat is produced from the formed biogas.

Table 1: Measured Parameter at Plant A

Parameter	Frequency
OLR_{OV}	Continuously
$pH_{DIGESTER\ 1}$	Daily
$pH_{DIGESTER\ 2}$	Daily
GP_{OV}	Continuously
MC_{OV}	Continuously
COD_{FEED}	1/week resp. daily*
$COD_{EFFLUENT}$	1/week resp. daily*
Total $VFA_{EFFLUENT}$	1/week resp. daily*
DM	1/week resp. daily*
VSS	1/week resp. daily*
$NH_{4\ FEED}$	1/week resp. daily*
$NH_{4\ EFFLUENT}$	1/week resp. daily*
Dissolved Fe_{FEED}	1/week resp. daily*
Total N_{FEED}	1/week resp. daily*
$SO_4^{2-}{}_{FEED}$	1/week resp. daily*
NH_3	1/week resp. daily*
H_2S	half-hourly

*over a test period of 2 - 3 months

Parameters with a major importance to the control tool were measured at the plant including the overall organic loading rate (OLR_{ov}) for both reactors and the volume of feed, the pH of each reactor and the overall biogas production, the methane content for both reactors and the hydrogen sulphate content in the biogas. Moreover, the total VFA in the effluent of both reactors, the COD of the feed and the effluent, the dry matter and the volatile suspended solids were measured over a certain test period (Table 1). Due to the lack of some necessary data, assumptions had to be made, as for example that the OLR, the biogas production and the methane content were exact 50 % for each reactor. This account, though, does not seem to be totally correct as the pH in the two CSTRs' was rather different.

It was initially tried to implement a model based control tool at Plant A (Strategy 1). However, this model could not be sufficiently trained, as the required parameters were not measured often enough, nor on a regularly basis and besides, the measured data displayed a too small range of variation (Figure 3).

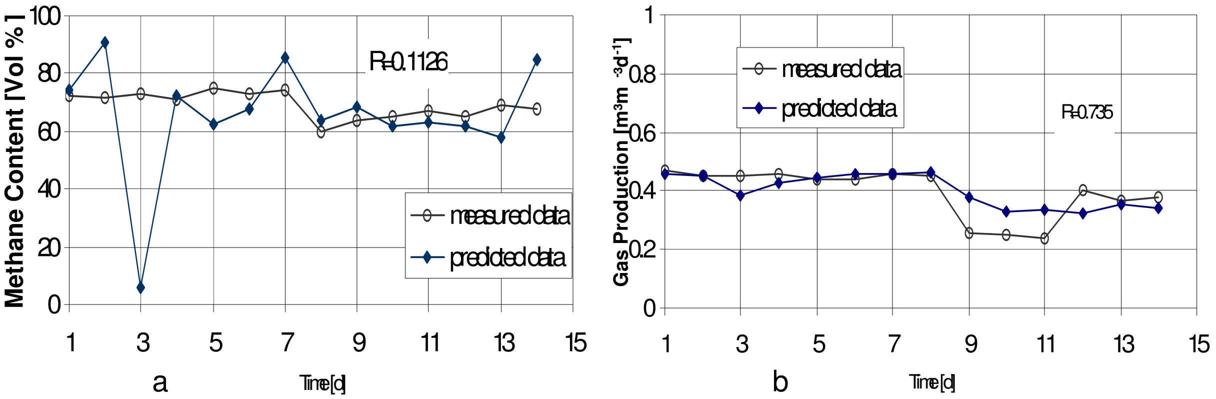

Figure 3: Results of modelling Plant A with NN: a) MC in the biogas; b) GP; it can be seen that the model cannot follow the fluctuations of the measured data.

Subsequently, FL based control tools (Strategy 2) were developed. This tools were tested in 20 l lab-scale CSTRs, operating in mesophilic temperature range (35°C). The reactor set-up was similar to the one described by Holubar *et al.* (2003). Synthetic maize silage was used as substrate. The required parameters were measured either on-line or off-line. Tool A raises the OLR until a threshold level, to subsequently reduce the organic loading rate again. Tool B reacts comparable to Tool A. As result an increased biogas production could be reached and higher OLRs were possible. Common disadvantages of the tools included a reduced cleaning efficiency, (due to a decreased COD degradation), an increased VFA concentration and a decreased pH with time, with the latter being less problematic as the reactor acclimatised to this effects. A further description of these tools and the results of the test phase are reported by Domnanovich *et al.* (2004). Tool A was then implemented at Plant A (Figure 4).

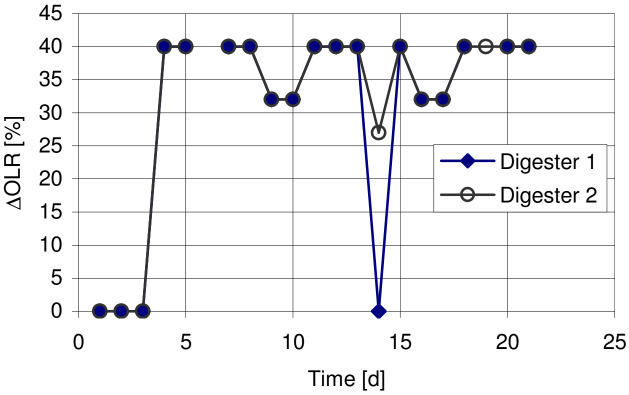

Figure 4: Theoretical control of Plant A; the OLR could have been increased nearly every day up to 40 %.

Following problems occurred during the implementation:

- As it turned out to be the plant design was in fact almost inadequate for the implementation of any control tool, nevertheless the used tool itself showed acceptable results. The substrate supply from the two storage tanks is not fairly separated from each other, which makes a control of feed difficult.

Further drawbacks were:

- The measurements of the data was too infrequent and irregular. Complete data sets were very rare, as the net training needs complete data sets.
- The unreadiness of the users, to take over a control tool, which was understandable thinking of the risks of a new tool. Figure 4 shows the theoretical results of the control tool, the maximal increase of the OLR (ΔOLR) was set to 40 %. As a result of the scepticism of the plant operator to use the control tool properly the reactor was habitually underloaded. The OLR could have been increased every day in the test phase.
- Also the inflexibility in changing measurement schemas (more and regularly measurements). Limited personnel costs showed to be very important.
- Finally oversized reactors and therefore underloaded reactor causes the impossibility of a feed control.

Case Study 2

Plant B consisted of a tank for hygenisation, a hydrolysis tank, two digester tanks (each 9,2 m³) and two residual tanks. The capacity of the plant was approximately 180 ta^{-1}. The substrate consisted of slaughterhouse waste mainly. The Volume of the feed (V_{FEED}), the dry matter and the biogas production were measured continuously. The volatile fatty acids, pH, and the H_2S, CH_4, CO content and the COD in the effluent ($COD_{EFFLUENT}$) and the COD in the added substrate (COD_{FEED}) were measured on a regularly basis (Table 2).

Table 2: Measured Parameter at Plant B

Parameter	Frequency
V_{Feed}	Continuously
DM	1 - 3/week
GP	Continuously
Total VFA	1 - 3/week
PH	1 - 3/week
$NH_{4\ EFFlUENT}$	1 - 3/week
H_2S	1 - 3/week
CH_4	1 - 3/week
CO_2	1 - 3/week
$COD_{EFFLUENT}$	1 - 3/week
COD_{FEED}	1 - 3/week
TOC_{FEED}	1/month
$SO_4^{2-}{}_{FEED}$	1 - 3/week

Due to the fact that a higher amount of data was available, in this case also Strategy 1 was tried first (Figure 5). The prerequisites in Plant B were better than in Plant A for implementing such a technique, however this plant had some deficiencies too, for instance:

- The implementation of a model based control tool was difficult, as the data had a very small range of variation.
- The measurements were very irregularly and infrequent, and besides, not done on the same day. Therefore, the amount of complete and usable data sets was low.
- Additionally, due to an incident at the plant, the data-set of the last month was unusable.
- An overdimensioned reactor caused the same problems as mentioned above.

Thus it was tried to implement a Neural-Fuzzy based control tool, due to the fact that the amount of data would have been sufficient. However, after the incident at the plant the range of data was completely changed. In the beginning the total VFA concentration, OLR and MC was very high, but also relative constant. The Neural-Fuzzy control tool showed complete confuse results. Therefore the control was changed to strategy 2. Even though an implementation of such a control in Plant B would have been more reasonable, compared to Plant A, this tool could not be tested in practice due to the end of the project,.

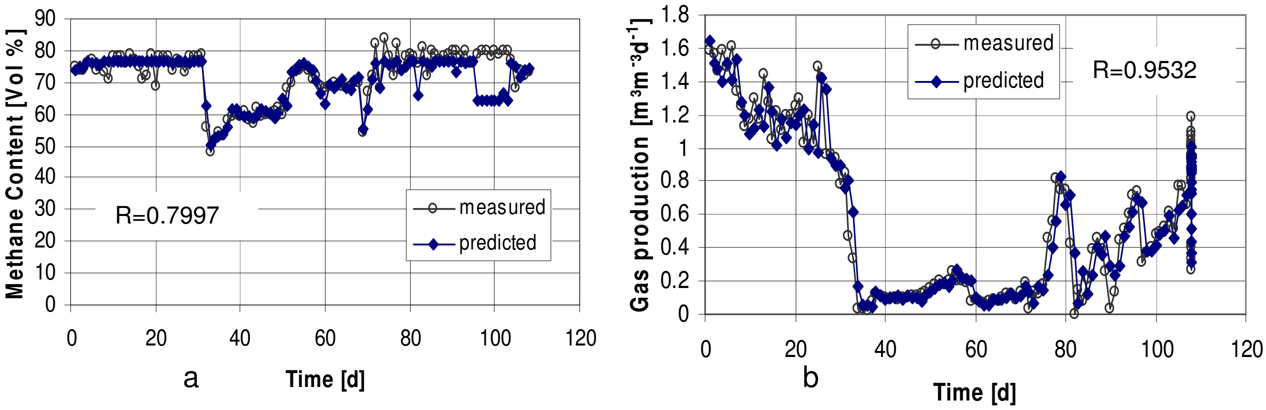

Figure 5: Modelling results of Plant B: a) MC in the biogas b) GP; the predicted data follows the measured data very precise, due to the fact that same data set were used for training and validation of the model, as result of the low amount of usable data sets.

Case Study 3

The third Case Study was engaged in the implementation of the control tools in a one-stage biogas plant (Plant C), operating in the mesophilic temperature range (35- 38 °C). Plant C consists of two storage tanks with a capacity of 24000 t respectively 36000 t, whereas the second storage tank is also the mixing tank. Further two hygenisation tanks with a capacity of 30 m³ was installed. The hygenisation was carried out at 70 °C within one hour. The reactor itself had a volume of 4000 m³. The digestions time was about 20-22 days. The plant had a capacity of approximately 60000 ta^{-1}. As substrates cattle manure (60 %) and other organic wastes were used. The plant had a 500 m³ gas storage with a following gas cleaning (active coal filters). The methane content was about 65%. The produced biogas was converted to electrical energy in two gas engines. Here the organic loading rate, the temperature in the reactor and gas production were monitored continuously. The pH, dry matter and methane content, carbon dioxide content and hydrogen sulphate were measured manually (Table 3).

Table 3: Measured Parameter at Plant C

Parameter	Frequency
OLR_{Feed}	daily*
DM	Daily
VSS	Daily
GP	Continuously
Total $VFA_{FEED\ \&\ EFFLUENT}$	2/week+
$Acetat_{FEED\ \&\ EFFLUENT}$	2/week+
$Propionat_{FEED\ \&\ EFFLUENT}$	2/week+
pH	2/week+
H_2S	daily (working days)
CH_4	daily (working days)
Siloxane	1/month

*calculated, not measured
+over test period of 3 month

As in Plant A and B first a model based control tool (Strategy 1) was tested on Plant C (Figure 6). As in case study 1, soon it become clear that, due to the later showed problems and deficiencies of the plant, Plant C is absolutely inapplicable for the implementation of a control tool neither model based nor FL based (Strategy 2):

- Most important data, as pH or VFA were measured infrequent and only for a short period. Therefore practically no complete data sets were available. The data had also a very small margin of variation.

- Sampling at the plant was complicated and difficult.
- Like in many other biogas plants the reactor had vast proportions, so that a feed control was neither necessary nor accomplishable.

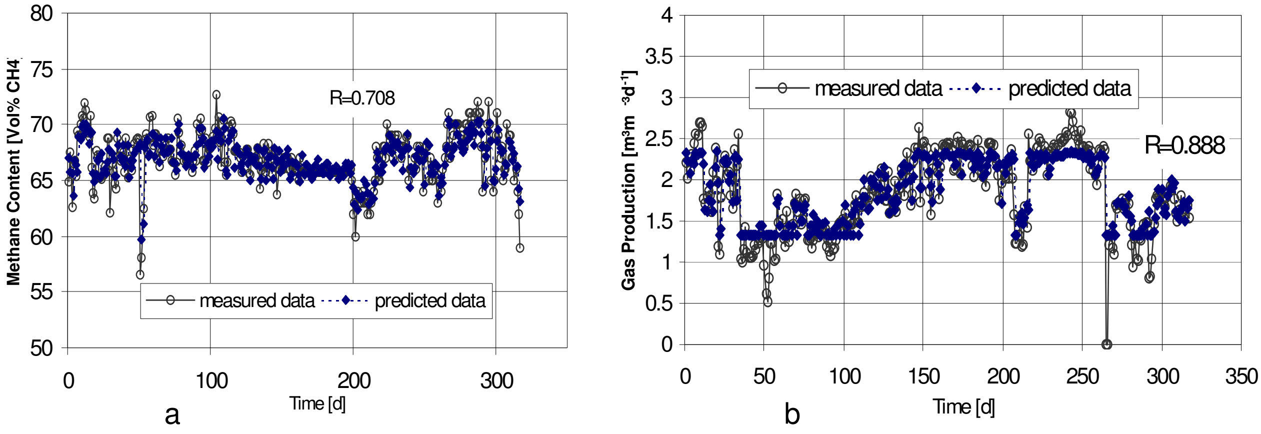

Figure 6: Modelling Results of Plant C: a: MC in the biogas b: GP; the correlation between the predict and the measured data is good, but due to the fact that the most important data as pH or VFA were not measured the implementation of a control tool was impossible.

Conclusion and Recommendation

Different control tools were developed for the implementation in technical scale plants. First tested in our lab-scale CSTRs, all control tools, NN and FL, showed acceptable and adequate results. But it can be seen from the aforementioned examples that an implementation of a control tool in technical scale plants is often very awkward, particularly due to the lack of measuring devices. As in Plant A and Plant C, it was not possible to implement a fully functional control tool, due to the minimised amount of known parameters. In plant B, an implementation of such a control tool would have been more applicable, but the practical test failed, which founds its reason also in the ending of the AMONCO project. Therefore, it was not possible, during the project time of AMONCO, to show an effective, successful and sustainable demonstration of the different control tools in practice. Nevertheless, the efforts of the AMONCO-Project will be continued in the CROPGEN-Project (Renewable energy from crops and agrowastes). Due to the experiences during the project the following recommendations can be given:

- The technical design of the biogas plant is for sure very important. An implementation of such a control tool will be very complicated for existing biogas plants, as most of them do neither have improved measurement equipment nor the feasibility for sampling, or the possibility for a later installation.
- The type of management system and the company's work philosophy has also great influence on the successfulness of such implementation. (Top down strategy).
- The effort and cost for the data needed for the control tool has to be as low as possible. It should be feasible to implement the sampling and analysis in the daily working routine. The analysis should be fast and simple. For example, test kits could be used. In order to save manpower, on-line sensors should find favour for such control tools. The sensor should have a long life time and be easy to calibrate. So that this operations can be accomplished by plant operators. Control tools using exclusively on-line data are absolutely possible.
- The economic benefit of an advanced control in the biogas plants has to be clearly shown.

- A successful implementation needs better promotion work, to really convince plant operators from the advantages provided by such control tools.
- A national or European training and support programme should be established for plant operators, who are willing to improve the measurement equipment at their plants.
- Due to an existing financial risk, especially for smaller plants, a central server control tool would be optimal. This would also lead to a larger pool of operation experiences.
- Existing biogas plants, pilot plants could serve as demonstration units. This would minimise the financial risk during the testing phase of a control tool. Therefore, also a funding and support system should be established.

To sum up, the ideal case for the implementation of a control tool would be:

- A possible implementation and the type of control tool is already be in mind during the planning phase of the biogas plant.
- Adequate measurement equipment and the will to also use them regularly are existing. Sample taking should be possible on several point in the biogas plant.
- The substrate should be characterised in detail. And it should be possible to really control the feed.
- The management is backing the use of the control tool all the way.

Acknowledgement

The project AMONCO is funded by the European Commission on the project number: NNE5-2001-00067 and the project CROPGEN (Renewable energy from crops and agrowastes) is funded by the European Commission on the project number: SES6-CT-2004-502824

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