Increasing profit of a co-digestion plant utilizing real time process data

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Abstract

There is a potential for improvement of the management of a co-digestion plant, which would make the installation more economic sustainable. Profit of a co-digestion plant can be increased by making use of temporal variation in input efficiency of the influent. Current decision support systems do not account for this variation. Suitable models for on-line estimation of the efficiency are dynamic linear models (DLM), a Bayesian approach to time series analysis. An integrated system for decision support using DLM was developed. The model was pre-tested on data of co-digestion of organic biomass with animal manure in four laboratory-scale biogas plants, with different starch contents in the mixture. In the anaerobic digestion process multiple bacteria are involved. This makes co-digestion a complex and dynamic system which is hard to understand, interpret and optimize. To maximize profit from a full scale co-digestion plant the challenge is to optimize continuously the daily input and its composition. In our study we use real time process data to estimate the effect of daily input on gas production of the plant. Additionally, we will give a method to calculate the optimal settings of input allocation such that the economic returns minus input costs could be maximized in future. The application was developed and tested on four laboratory-scale biogas plants. New optimal settings for daily input were calculated and implemented twice a week. The results show different response curves for different mixtures of manure and starch. For 100% pig manure the optimal retention time can at least be lower than 15 days in this feeding schedule. This research indicated that the optimal retention time is higher for mixtures with higher amount of starch.

Keywords: response curve, dynamic linear model, co-digestion

Introduction

In anaerobic digestion the reduction in volatile organic solid material is frequently far from complete. The results depend on the substrate, but incomplete conversion is typical of systems in which water is the sole plasticizing agent and hydrolytic pretreatment is not often employed (Sharma *et al.,* 1988). The possibility of co-digestion of different types of energy crops and industrial by-products with manure is evaluated in several studies (Ahring *et al.,* 1992; Angelidaki and Ahring, 1997; Kaparaju *et al.,* 2002). These studies show a high potential of many products as potential co-substrates.
However, the disadvantage of co-digestion without any information is digestion failure caused by three types of overload; organic, hydraulic and toxic. This can result in a short disruption of gas production, but sometimes it causes serious problems and a long period of lower production of the energy plants.
The common practice to monitor the success of digestion is to do intensive chemical analysis of the biomass in the plant. This type of information is mainly useful to investigate whether the chemical process is close to a danger zone of digestion failure, but is based on general knowledge of digestion in general. The disadvantage of this information is that it does a direct and clear relationship with daily input.

For some co-digestions plants with constant difficulties to find cheap and useful co-products it might therefore informative to know more about digestion of mixtures with a high percentage of manure. The influence of retention time on gas production efficiency for different C:N-ratio's of the mixture is not always clear.

Individual database of co-digestion plants contain a treasury of information about the efficiency and performance of historical feeded mixtures, but up to now methods that effectively estimate actual response from real time process data are lacking

In our general research a dynamic linear model, developed by West and Harrison (1997), is used for on line estimation of parameters that describe efficiency of gas production from co-digestion (mixture) intake. This method is a Bayesian approach of adaptive modeling with sequential learning techniques to investigate the time-specific relationship between amount of input and output.

Additionally, using the daily parameter estimates and actual prices of gas and co-digestion products in the mixture provides the opportunity for a continuous adjustment of mixture intake such that maximum economic profit is obtained (Duinkerken *et al.,* 2003). We will give a brief introduction to concept of automatic adjustment of mixture intake for economic purposes.

In this specific research we use the dynamic linear model to investigate the influence of retention time (by changing the amount of input) on gas production efficiency in small experimental digestion plants with each a different C:N ratio of the mixture.

Material and methods

The test was sponsored by the Dutch Product Board for Livestock and Meat and was carried out at the facilities of LeAF in Wageningen, the Netherlands. The four biogas plants where relatively small (8 l) and continuously mixed and kept on a constant temperature of 35-37 °C. The plants were fed every Monday morning and Thursday afternoon. Gas production was measured by using big bags at the time before feeding. Also just before feeding, the plants were opened and the planned volume of digestate was first removed.

Testing of the dynamic approach on small laboratory plants with different mixtures of input

A prototype of the dynamic approach was tested on four experimental co-digestion plants in the summer period of 2008. As these co-digestion plants were relatively small laboratory plants, there was a non-automatic feeding system, which means that plant had to be opened twice a week for feeding the mixture input. The gas production from the last time period was measured just before the new feeding. Therefore the implementation of the optimal setting of mixture intake was delayed to the next feeding time.

Every plants was fed with a plant-specific mixture of (the same batch of) pig manure and starch (in solution). As four plants, there where four mixtures in total: 0%, 2%, 4% and 6% of starch solution in the mixture.

Response curve estimation

In a period of seven weeks there was a regular adjustment of the amount of mixture intake. After each day of new measurements the response curve was re-evaluated with the dynamic linear model (DLM) based on a Bayesian approach for on-line estimation and analysis of time series. The outcome of the model resulted in an adjustment of feeding strategy of the amount of mixture intake after each time point, where input and output was recorded. Disturbance of the process, such as outliers, are automatically detected.

The general univariate dynamic linear model is written as:

Observation Equation: $Y_t = F_t'q_t + v_t$, $v_t \sim N(0, V_t)$
System Equation: $\theta_t = G_t\theta_{t-1} + \omega_t$, $\omega_t \sim N(0, W_t)$

In this notation F_t is the regression vector and G_t is a matrix of known coefficients that defines the systematic evolution of the state vector θ_t across time.
We assumed that the gas production per period (GP) is a quadratic response to mixture input per period (M):

$$GP = c_0 + c_1M + c_2M^2$$

With individual dynamic parameters:
c_0 intercept or base-level (m^3/period)
c_1 linear effect of mixture intake (m^3/kg/period)
c_2 quadratic effect of concentrate intake (m^3/kg^2/period)

This type of relationship was implemented in the regression vector of the DLM and therefore the parameters $c_{0,}$ c_1 and c_2 can change in time.

Outline: future financial optimization for the optimum input of co-products on farms
The objective is to maximize the daily financial balance, given a constant input of manure, gas returns minus co-product intake costs. Gas returns depend on the gas price (α_G) which is effected by the electricity price and gas constitution. Co-products costs depend on the pricing of the mixture of co-products (α_M) which is affected by the price of co-digestion products in the mixture. The optimum mixture allocation (C_{Opt}) is given by:

$$C_{Opt} = \frac{\alpha_M - \alpha_G c_1}{2c_2\alpha_G}$$

Results and discussion

The adaptive model describes the relationship between input and output of the co-digestion process. The model for the relation between the input and output variable is given in the equations. Real time process data used are gas production and mixture intake per period of approximately 3.5 days. These data are used to estimate the individual dynamic parameters to predict responses gas production to (changes in) mixture intake.

Outline of the parameter estimation
The parameters can potentially be estimated on-line from real time process data using linear models (DLM) based on a Bayesian procedure for on-line estimation and analysis of time series. At the start of each series initial parameter settings are set. Subsequently the parameters are sequentially updated, based on historical process data.
Also disturbance of the process, such as outliers, where automatically detected. However, after a short period of adaptation to the data, there was a good forecast of gas production (Figure 1).
As we can see in Figure 2, it turned out that each co-digestion plant with its own mixture type had its own typical response to mixture intake. It turned out that the optimal amount of mixture intake becomes lower as the mixture contains a relatively higher amount of starch. This can be explained by the fact that some processes in the early stage of the hydraulic residence time (such as a decreasing pH shortly after feeding) can result in a short disruption of gas production.

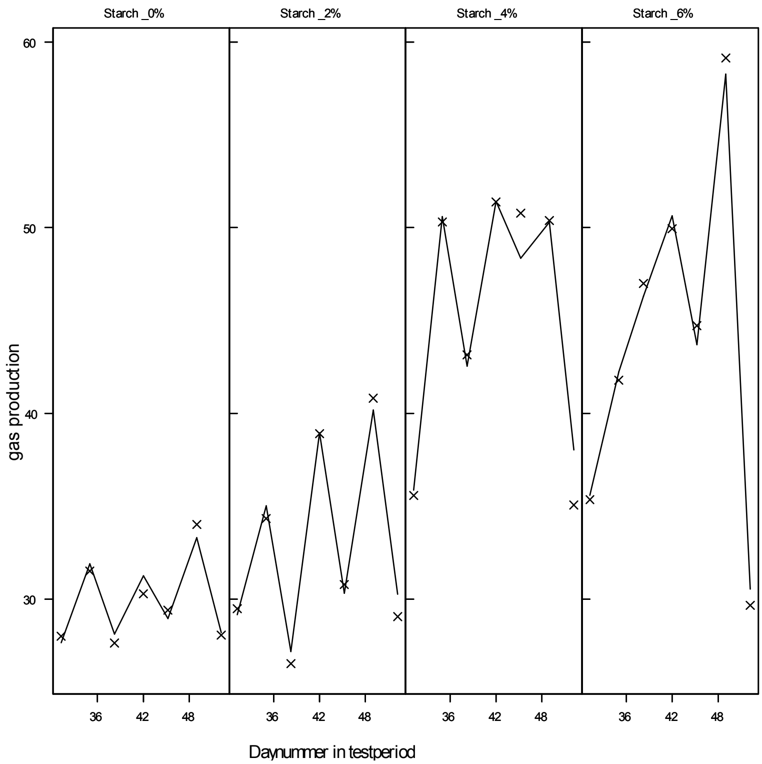

Figure 1. Gas production in the final (steady) stage of the test period, including forecast of the model.

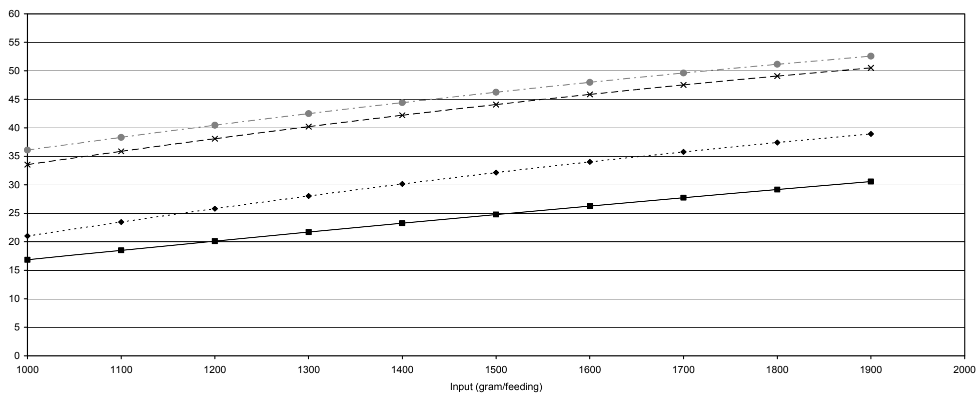

Figure 2. Estimated response curve right after the final period.

With a closer look, as we can see in Figure 3, it appeared that the high starch mixtures show very good efficiencies at the relatively low input levels. However the low starch mixtures (mainly pig manure) showed a very constant efficiency. This indicates that digestion of manure can be done with a fairly low retention time of less than 15 days.

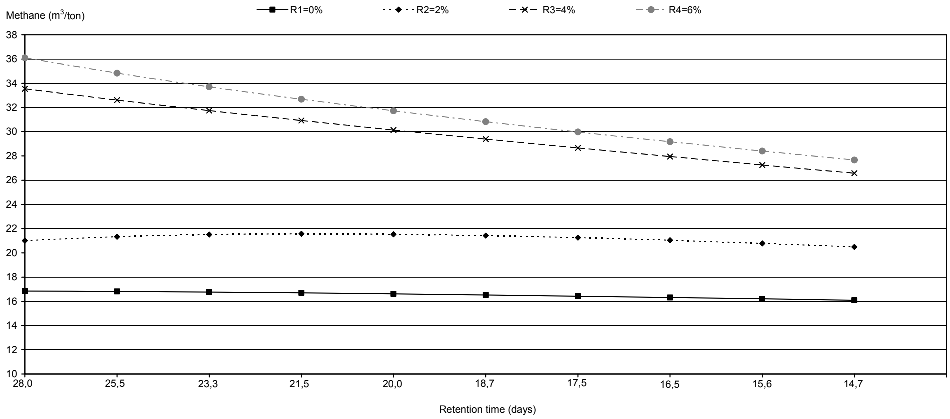

Figure 3. Estimated response curve after transformation into efficiency figures (input figures were transformed into retention time).

Conclusion

Dynamic optimal settings of mixture allocation in co-digestion plants can be successfully estimated form real time process data with a dynamic linear model, which appears to be a flexible estimation procedure. Application of optimal settings can result in an increase in financial profit and an early warning system for disruptions.
In this experiment it turned out that digestion of pig manure can be done with a low retention time of less then 15 days. The addition of starch in the mixture does effect the optimal retention time.

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