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An Approach towards Multivariable Control of Anaerobic Digestion using the EPSAC Predictive Control Strategy

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Abstract: Energy from biomass and waste is regarded as one of the most dominant future renewable energy sources to comply with a continuous power demand. In this context, anaerobic digestion (AD) is emerging in control engineering applications at a spectacular pace. The necessity for advanced control of AD systems is motivated by the challenges of the process in terms of instability problems, especially when applying high influent loads with variable composition. Intrinsic process advantages, such as efficiency in pollutant removal or energy production, can also be part of global process optimization through advanced control. The aim of this paper is to analyse the application of Extended Prediction Self-Adaptive Control (EPSAC), a model based predictive control strategy, to AD processes. The widely adopted Anaerobic Digestion Model No.1 (ADM1) is used to simulate the AD process and to extract simplified models for prediction over a future time interval. The general control strategy objective is to manipulate the inputs within the operation limits such that maximum methane production is ensured.

Keywords: ADM1, BSM1, anaerobic digestion, biogas, multivariable control, predictive control,

INTRODUCTION

Anaerobic Digestion (AD) is a complex biological process carried out in the absence of oxygen that involves hundreds of different types of microbes, which break down biodegradable organic matter [1,2]. The process is characterized by the formation of biogas, which consists mainly in carbon dioxide (CO_2) and methane (CH_4). Anaerobic digestion processes have been applied for over hundred years, but there is still much room for advanced control methodologies to widen the competitive and complex scope of this process [3,4]. More specifically, one aims at improving the process performance in terms of the applied loading rate and the biogas quality and quantity, while ensuring process stability. Hitherto, only classic control strategies have been applied mainly based on heuristic rules (i.e. fuzzy) [5] and basic proportional-integral-derivative (PID) control [6]. These strategies worked well for single-input single-output cases, however AD processes can be viewed as multivariable systems, thus it might be useful to investigate more advanced control strategies. As such, model-based predictive control (MPC) strategies are good candidates to control the AD process, since they can inherently tackle multivariable dynamics, coupling effects, non-minimum phase behaviour, variable delays and multi-objective optimization [7-9]. A general objective of MPC schemes is to maintain the controlled variables close to their reference values while respecting process operating constraints. The MPC consists in a family of control methods that make use of an explicit process model when determining, by prediction over a future horizon, the control signal to be applied.

BENCHMARK APPLICATION

The EPSAC control strategy [9] is applied to the anaerobic digestion of sludge produced in a wastewater treatment plant (WWTP). The latter has been simulated using the Benchmark Simulation Model no. 2 (BSM2) (Figure 1). The BSM2, describes the treatment of settled wastewater through a predenitrifying activated sludge system (i.e. 2 anoxic reactors followed by 3 aerobic reactors) followed by a secondary clarifier. Primary and thickened secondary sludge is treated through anaerobic digestion and subsequently dewatered. Plant performance evaluation is based on a one-year simulation, using influent data from [10]. Within BSM2, the anaerobic digestion process is described through the widespread and generally accepted Anaerobic Digestion Model No.1 (ADM1) [2]. The choice of the control structure for the anaerobic digestion process is important, since pairing correctly the inputs/outputs can have a significant effect on the performance that can be expected in closed loop operation. Moreover, operating constraints and the nonlinear behaviour of the process make the process control problem very attractive for performing multivariable algorithms such as MPC-EPSAC. An overview of inputs and outputs chosen for the multivariable control of the AD process is given in figure 2. Within the context of multivariable control, the standard input-output from figure 1 has been adapted to the one from figure 2 by adding buffers with manipulating valves. In this way we were able to manipulate the flow of the primary clarifier and the thickener flow.

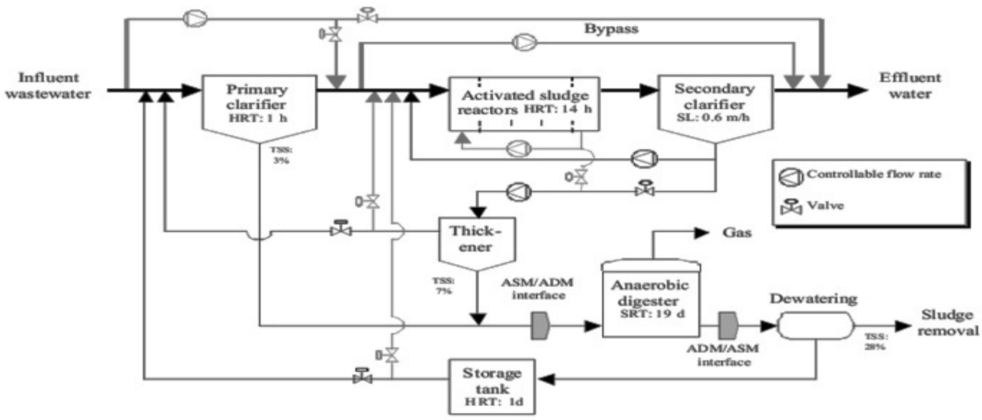

Figure 1. General overview of BSM2 wastewater treatment plant, including anaerobic digestion Jeppsson et al., (2006).

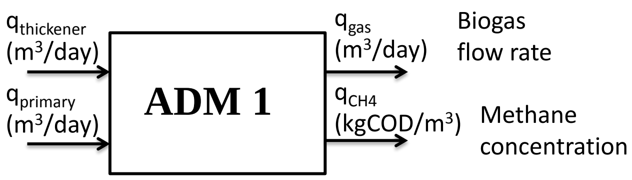

Figure 2: Input-Output overview of the AD process

EPSAC (Extended-Prediction Self-Adaptive Control) APPROACH TO MPC

The MPC principle is based on the calculation of the predicted values of the process output over a time horizon called the *prediction horizon* by means of the available dynamic model. The forecast depends not only on past measured outputs and applied inputs, but also on the intended future control actions subject to the constraints and the desired reference trajectory. For the AD process the reference is given by the nominal operating point which gives the highest efficiency in terms of methane production, and the prediction model is identified from input-output data [9]. In the EPSAC strategy, a multistep prediction problem is solved using filtering techniques [8,9]. Therefore, within the generic model of a process, as shown in figure 3, the process output is considered to be the effect of the process inputs (i.e. past real inputs and outputs from the plant) on one hand and of the disturbances one the other hand. Notice that the term “disturbance” refers to everything which is not captured by the process model (i.e. modelling errors and noise).

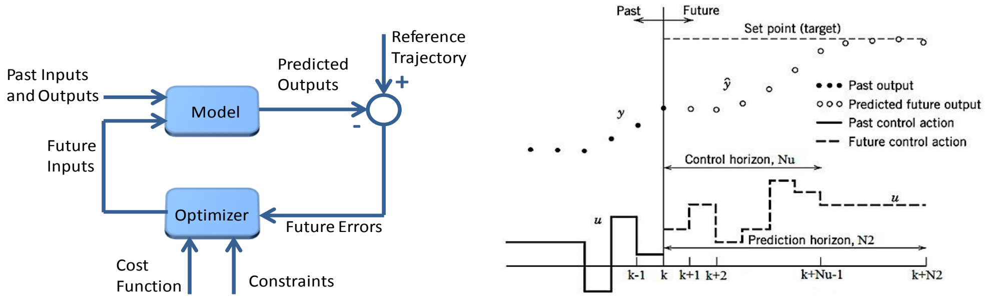

Figure 3. Schematic of the MPC strategy and of the principles of output prediction

To better understand the MPC principle (figure 3 left) we will explain it by using figure 3 right. The process output $y(t+k)$ is predicted over a time horizon $k = 1 \ldots . N2$ at each ‘current’ moment t. The predicted values are indicated by $y(t+k)/t$ and the value $N2$ is called the prediction horizon. The prediction will be done by means of a model of the process [9].

In the MPC-EPSAC approach, the MIMO control objective can be either selfish or solidary. In the selfish approach, each output is optimized with respect to its direct input and taking into effect the interaction coming from the other inputs. In the solidary approach, each output is optimized with respect to all inputs and outputs, leading to a global optimization of the multivariable process. In our initial efforts to investigate the feasibility of the MIMO EPSAC control applied to AD, it turned out that the solidary control outperforms the selfish control (as expected) [8]. Another issue which can be tackled by EPSAC-MPC are the constraints. The control engineer has the choice of clipping (i.e. here the constraints are not taken into account during the optimization algorithm and if any manipulated variable is outside its limits, then saturation is applied), or constrained control (i.e. here the constraints are taken into account during the optimization algorithm). We showed that constrained control is obviously better in terms of minimizing variability on the controlled variable, as depicted in figure 4. As the methane production cannot be measured directly, the effectively controlled variables are the biogas flow rate and the methane concentration, their product representing the methane mass flow rate.

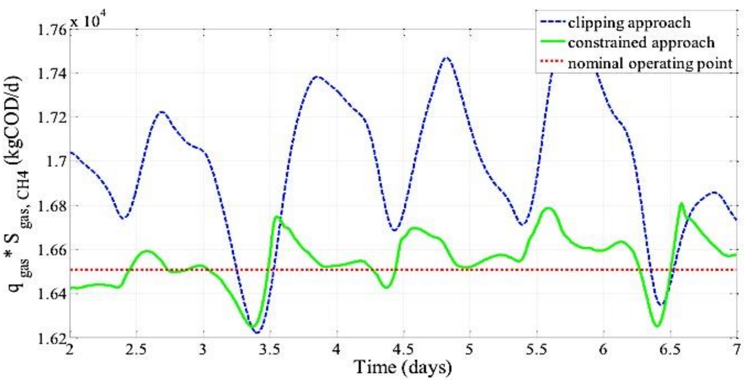

Figure 4: a detail of a simulation comparison between clipping and constrained control. This shows the obvious advantage of MPC over classical control which cannot handle constraints (e.g. PID).

Further on, based on a dynamic data set over a 609 days period, the solidary control strategy was implemented taking into account constraints. The Total Methane Production (TMP) evaluated on the entire period of 609 days of simulations is statistically significantly higher in solidary control than in selfish control, with a reduction in the variability of the controlled variable with about 40%. A detailed report on this makes the scope of another publication.

CONCLUSIONS

In this paper, the concept of multivariable predictive control was introduced for controlling the anaerobic digestion process and tested on BSM2 benckmark. The results of our research indicate an improvement of the closed loop performance in terms of variability and justify future steps to investigate the optimization of this complex process.

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