Optimal Control of Biogas Plants using Nonlinear Model Predictive Control

Daniel Gaida[*†], André Luis Sousa Brito[*], Christian Wolf[*+], Thomas Bäck[†], Michael Bongards[*], Seán McLoone[+]

**Institute of Automation & Industrial IT*
Cologne University of Applied Sciences, Germany
email: daniel.gaida@fh-koeln.de

†Leiden Insitute of Advanced Computer Science
Leiden University, the Netherlands
email: baeck@liacs.nl

+Department of Electronic Eng.
National University of Ireland Maynooth,
Maynooth, Co. Kildare, Ireland
email: sean.mcloone@eeng.nuim.ie

Abstract— **Optimal control of biogas plants is a complex and challenging task due to the nonlinearity of the anaerobic digestion process involved in the conversion of biodegradable input material to biogas (a mixture of the energy carrier methane and carbon dioxide). In this paper a nonlinear model predictive control (NMPC) algorithm is developed to optimally control the substrate feed of the anaerobic digestion process on biogas plants. The implemented algorithm is investigated in a simulation study using a validated simulation model of a full-scale biogas plant with an electrical power of 750 kW, where the control objective is to achieve high biogas production and quality while maintaining stable plant operation. Results are presented demonstrating the feasibility of the proposed approach. The optimal operating state identified by the controller provides an additional return of investment of 650 €/day compared to a nominal operating state. Using the proposed algorithm it will be possible in the near future to optimize full-scale biogas plants using nonlinear model predictive control and therefore to advance the use of anaerobic digestion for eco-friendly energy production.**

Keywords **– anaerobic digestion, control, Nonlinear Model Predictive Control, optimization**

I INTRODUCTION

The digestion of energy crops as well as organic degradable waste in so-called biogas plants to produce biogas, which contains the energy carrier methane, has proven to be a very promising technology for renewable energy production [1, 2]. Through the burning of biogas in cogeneration units electrical and thermal energy is produced, which can be either supplied to the local grid or to a district heating grid.

To get the greatest possible benefit out of the substrate fed to the digesters of a biogas plant, plant operation and control have to be optimized. Next to the potential for technological optimisation with regard to plant location, stirrer operation, utilization of produced heat and digestate, etc. [3], the substrate mixture offers the greatest potential for optimisation. Given access to different substrates such as maize, grass, rye, manure and manure solids the question arises as to the total amount and relative proportions of each substrate that should be fed to the digesters on a biogas plant in order to optimise performance in terms of the balance between substrate/energy costs and the revenue from the electrical/thermal energy produced. In fact, currently plant operation is often far from optimal, so that cost-benefit ratios can turn out to be negative. One reason for non-optimal plant operation is the fear of a very expensive plant failure, which is more likely to occur at plants that operate at very high capacity utilization close to the stability limit. This kind of plant operation requires continuous online-monitoring of the digestion process to avoid catastrophic failure.

Since the optimal substrate feed of a given digester depends heavily on its current operating state, substrate feed control systems need to be developed that explicitly take into account the current state of a digester. Since anaerobic digestion is a very complex process, determination of the current state of the anaerobic digestion process is not a trivial task.

Unfortunately, measurement equipment for critical biogas process parameters, which make state identification possible, is non-standard, very expensive and requires extensive maintenance and expert knowledge from plant operators. This is why mostly only basic measurement systems are available on agricultural biogas plants in particular. Usually, only biogas production, biogas composition, pH value, redox potential, total solids content and temperature are measured [4]. The use of these basic online-measurement systems alone makes state identification and hence comprehensive monitoring of anaerobic digestion processes, almost impossible.

Instead, a feasible approach is to use simulation models of biogas plants in combination with existing online-measurement systems to properly define and monitor the state of biogas plants. A very popular simulation model for anaerobic digestion is the Anaerobic Digestion Model No. 1 (ADM1) [5]. Recent work has shown that using this model full-scale agricultural biogas plants can be reliably modelled [6–8]. This model, not only defines the state of an anaerobic digester, but also gives the mathematical connection between the operating state and measured process parameters.

The third author of this paper has used the ADM1 for several years to find optimal and constant substrate mixtures for long-term optimal steady-state operation of full-scale biogas plants [9]. Although this approach yields very good results, it is essentially only an open loop control strategy. Thus, in this paper, a closed loop optimal control system is developed that takes into account modelling mismatch between the biogas plant model and the real plant. Modelling mismatch is considered by estimating the current plant operating state in each control iteration step, so that the optimal substrate feed is adapted according to the current state of the plant.

A commonly used optimal control scheme for nonlinear systems is Nonlinear Model Predictive Control (NMPC) [10]. In NMPC a nonlinear model of the given plant is used to optimize a fitness criterion over a prediction horizon by determining the optimal sequence of input values for the plant. After applying the first input value of the sequence to the real plant the optimization problem is started again. In contrast to MPC the optimization problem, which has to be solved, is not convex anymore, so that optimization methods that are particularly suited for very complex optimization problems are needed. As solving a non-convex optimization problem needs more resources and is more time consuming than solving a convex one, NMPC is usually not as fast as MPC [10]. However, since biogas plants are very slow systems, with response time constants of the order of several hours and days, this restriction is not a barrier to their application in biogas plant control.

In this paper a Nonlinear Model Predictive Control algorithm is developed for substrate feed control that optimises plant performance while taking into account safe operating/process constraints. A calibrated simulation of a 750 kW commercial agricultural biogas plant is used as a case study to evaluate the performance of the proposed algorithm. The simulation uses the IWA taskforce Anaerobic Digestion Model 1 (ADM1) to model the substrate digestions processes [5]. Although there are many contributions in the literature on control of anaerobic digestion processes (e.g. [11, 12]), to the authors knowledge, NMPC has not previously been used with ADM1 employed as a model.

The remainder of the paper is organized as follows. In the next section the proposed NMPC method is described. Then in section III the results of the case study are reported and analysed. Finally, conclusions are presented in section IV.

II METHODS

In this section the proposed Nonlinear Model Predictive Control method is described. As a precursor, the environment in which the algorithm is implemented is briefly introduced.

a) BioOptim Toolbox

BioOptim is a MATLAB® toolbox developed by Gaida *et al.* [13] to simulate, optimise and control full-scale biogas plants. In the toolbox digestion processes are simulated using ADM1 [5], a structured 37 state nonlinear state space model incorporating disintegration and hydrolysis, acidogenesis, acetogenesis and methanogenenesis steps. Within the scope of this toolbox the NMPC algorithm is implemented and validated.

b) NMPC

In Figure 1 the pseudo-code of the NMPC method to optimally control biogas plants is sketched. The following subsections are devoted to the steps that are implemented in the algorithm.

Control & Prediction Horizon. For practical reasons the substrate feed has to be set as piecewise constant. As mentioned previously, biogas plants have very long time constants, hence sampling time for measurement and control can usually be selected to be of the order of a couple of hours. In the case of agricultural biogas plants in particular, the degree of automation is very low [14], with substrate feed usually changed at most once a day. This is why in the current implementation of the NMPC algorithm the substrate feed is set to be constant over the control horizon. Thus, the control sampling time and the control horizon are actually equal, and usually set to be one or a few days. This leaves more than enough time to solve the optimization problem inside the NMPC control loop and thus enables optimal online control of biogas plants to be implemented. The prediction horizon is set so that the biogas plant has enough time to reach a new steady state, which usually is obtained after a couple of weeks or months. The influence of the control and prediction horizon on the control performance is evaluated in the result section.

State Estimation. It is essential for the MPC to know the current state of the plant, so that the simulation using the plant model can be started at the current operating state. Since the ADM1 is used as the core of the biogas plant model its state vector has to be estimated. Normally state estimation filters [15] are used to estimate the current state of a plant using a model and current online-measurements. However, such filters suffer from the fact that they need to be initialised with an estimate of the plant's initial operating state. As this initial operating state of a biogas plant is very difficult to determine, standard state estimation filters are not easily applied in this particular case. In [16] an alternative model based approach to estimate the ADM1 state vector is proposed, in which pattern recognition methods are used to model the relation between current and past plant measurements and the current state of the plant.

Here the controlled plant is a simulation, hence the state information is directly available without the need for estimation. Furthermore, since the model used for the MPC is an exact replica of the simulated plant this is essentially the best case scenario of perfect knowledge. Hence, the case study provides an upper bound on the performance gains achievable by the proposed NMPC. In future work, the authors plan to combine the state estimator developed in [16] with the NMPC proposed in this paper to achieve a practical setup for deployment on real full-scale biogas plants.

Optimization Problem. The minimization task to be solved inside the NMPC control loop is, due to the nonlinear model, a multi-dimensional, non-convex optimization problem. Therefore, there is a need for optimization methods, which can handle such difficult problems. Global stochastic optimization algorithms were employed as these have proven to be well suited for such problems [17]. Currently, a number of optimization methods are implemented in *BioOptim* that can be used to solve the NMPC minimization problem, namely:

- ✓ Particle Swarm Optimization (PSO) [18]
- ✓ Covariance Matrix Adaptation Evolution Strategy (CMAES) [19]
- ✓ Differential Evolution (DE) [20]

Results comparing the performance of each of these methods are presented in Section III. In the pseudo-code for the NMPC algorithm presented in Figure 1 the third step defines the optimization problem being solved. Here, the model of the biogas plant is represented by the nonlinear state vector function $\mathbf{f}_{\text{ADM1}} : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}^n$.

Fitness Function. Through the definition of the fitness function various optimization criteria of interest can be taken into account. In *BioOptim* the selection of different optimization criteria is facilitated by an interactive GUI. Typical criteria include cost vs. benefit (with respect to the new Renewable Energy Sources Act (EEG 2009) in Germany [21]), stability of substrate degradation processes and operating constraints such as upper and lower pH limits, maximum FOS/TAC [22] value, maximum total solids content of the substrate feed, minimum methane concentration of the biogas and manure bonus. Thus, the developed NMPC algorithm can be used to control the substrate feed to reach every desired operating state by defining the characteristics of this state in the fitness function.

Let $m \in \mathbb{N}^+$ be the number of available substrates and $n \in \mathbb{N}^+$ the dimension of the modelled state vector.
Set control horizon $T_C \in \mathbb{R}^+$ and prediction horizon $T_P \in \mathbb{R}^+$ with $T_C \le T_P$.
Set substrate feed lower $\mathbf{LB} \in \mathbb{R}^m$ and upper boundaries $\mathbf{UB} \in \mathbb{R}^m$ with $\mathbf{UB} \ge \mathbf{LB}$.

Set optimal substrate feed, at $k = 0$, $\mathbf{u}_{\text{opt},0} \in \mathbb{R}^m$ to the current substrate feed of the plant.

For $k = 1, 2, 3, \ldots$

1. Estimate the current operating state of the plant $\hat{\mathbf{x}}_{k-1} \in \mathbb{R}^n$.

2. Define substrate feed boundaries $\mathbf{lb} \in \mathbb{R}^m$ and $\mathbf{ub} \in \mathbb{R}^m$ such that:
   $\mathbf{lb} := \max\left((1-c)\cdot \mathbf{u}_{\text{opt},k-1}, \mathbf{LB}\right)$,
   $\mathbf{ub} := \min\left((1+c)\cdot \mathbf{u}_{\text{opt},k-1}, \mathbf{UB}\right)$,
   $c \in (0,1)$, satisfying $\mathbf{lb} \le \mathbf{ub}$

3. Find optimal substrate feed $\mathbf{u}_{\text{opt},k}$ minimizing the fitness function $F : \mathbb{R}^n \times \mathbb{R}^m \to \mathbb{R}$:

   $$\mathbf{u}_{\text{opt},k} := \arg\min_{\mathbf{u} \in \mathbb{R}^m} F\left(\mathbf{x}\left(T_P\right), \mathbf{u}\right)$$

   w.r.t. $\mathbf{lb} \le \mathbf{u} \le \mathbf{ub}$
   $\mathbf{x}'(\tau) = \mathbf{f}_{\text{ADM1}}\left(\mathbf{x}(\tau), \mathbf{u}(\tau)\right)$
   $\mathbf{x}(0) := \hat{\mathbf{x}}_{k-1}$
   $\mathbf{u}(\tau) = \mathbf{u} = \text{const.} \forall \tau \in \left[0, T_P\right]$

4. Apply optimal constant substrate feed $\mathbf{u}_{\text{opt},k}$ to the real biogas plant for time duration T_C.

End For

Figure 1: Pseudo-Code of NMPC for biogas plants

As can be seen in Figure 1 the fitness function is only evaluated at the end of the prediction horizon. This is done because the aim of the NMPC is to find an optimal steady-state operating state for the biogas plant. Thus, the fitness is only calculated at the last simulated state, which is as close as possible to a steady-state. The question of how it can be assured that the biogas plant never gets unstable over the complete prediction horizon is dealt with in the next paragraph.

Stability Issues. The operating states of anaerobic digestion processes can be divided into three different classes. The first class contains all possible stable operating states. The other two classes are the washout states and all inhibited states which are either unstable or problematic.

If a biogas plant is fed with too much substrate, such that the overall throughput is too high, the biomass inside the plant is washed out due to a rapidly decreasing retention time, resulting eventually in washout states where biogas is no longer produced. Since the substrate feed is not varied over the prediction horizon, washout states are automatically reflected in the fitness function which is computed at the end of the prediction horizon.

At the moment it is not known if a badly inhibited state can recover itself under fixed substrate mix conditions. Thus, further analysis is needed to determine if checking for inhibited states at the end of the prediction horizon is sufficient to detect all inhibited states. As second open question which needs to be addressed is how to determine the distance of the current state from the boundaries of the regions of attraction of the problematic/unstable process states.

Plant Control. At the end of each control loop iteration the current solution, i.e. the optimal substrate feed, is applied to the real plant.

III RESULTS

In this section the proposed NMPC method is evaluated on a validated simulation model of a full-scale agricultural biogas plant and the influence of important algorithm parameters is studied.

a) The Biogas Plant

The biogas plant under consideration is a full-scale agricultural biogas plant with an electrical power of 750 kW located in Germany. The plant contains two digesters with a volume of about 3000 m³ each. The first digester is fed with substrates such as maize silage, grass, manure and manure solids and the digestion sludge is recirculated between both digesters. For this plant a detailed simulation model using the ADM1 was developed and calibrated using locally available measurements and laboratory analysis of the substrates and digester probes.

b) Basic Settings

The tests presented in subsections c) and d) all have the following basic settings. The fitness function is defined to be a weighted sum of the net income (income from selling electrical and thermal energy less the operating energy and substrate costs) and a number of operating stability constraints. The constraints considered include a limit on the pH value inside the digesters, a maximum dry matter content of the substrate mixture, a maximum FOS/TAC value and a minimum methane fraction of 50 % inside the produced biogas.

All tests are started from the same initial equilibrium state. The corresponding substrate feed is 30 m³/day maize silage, 15 m³/day manure and 3 m³/day manure solids.

The control period is set to 100 days. Thus, using e.g. a sampling time of 2 days leads to a ‘for loop’ with 50 iterations. The total time needed by the algorithm to perform the amount of iterations is referred to as the ‘controller execution time’. All tests are performed on a Windows XP PC with an Intel® Core™ 2 Quad CPU (2.4 GHz) and 3.25 GB RAM.

c) Control

Figure 2 shows the evolution of the fitness for an algorithm test over a simulated period of 100 days. For this test optimisation is performed using the CMAES method with 4 generations and a population size of 8. The parameter c in Figure 1 is set to $c = 0.05$. The individual points (squares) plotted in Figure 2 represent the simulations performed in the constrained optimization problem over the prediction horizon. It can be seen that the plant’s operating state was poor in the beginning (warm colours) but improved as the controller drove the plants towards an optimal solution (cold colours). In practical terms the -0.1 improvement in fitness value (from -0.38 to -0.48) achieved by the NMPC represents an additional gain of about 650 €/day for the biogas plant operator.

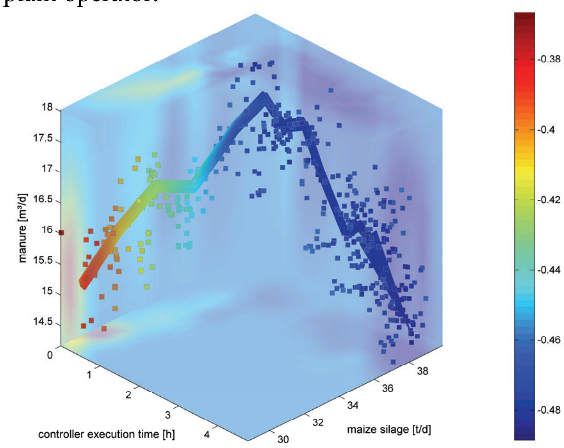

Figure 2: Overall fitness of the evaluated substrate mixes during the optimal control estimation process using NMPC (the smaller the value (the colder the colour), the better the substrate mix)

d) Parameter Investigations

Control & Prediction Horizon. In Figure 3 the influence of the prediction and control horizon on the fitness of the resulting final operating state of the biogas plant is shown. All tests were performed using CMAES with 4 generations and a population size of 8 and $c = 0.01$. The influence of the number of generations and population size is investigated in the next paragraph. Since the control horizon was set equal to the sampling time the fitness improves significantly with decreasing sampling time. However, the controller execution time increases substantially for sampling times of less than 3 days while wielding only a small improvement in performance. The influence of the prediction horizon on the fitness is not that strong. An increase of the prediction horizon improves the fitness but also increases the controller execution time as the colour in Figure 3 visualizes. Hence it does not seem to be useful to set the prediction horizon higher than the hydraulic retention time of the plant, which in this case is about 100 days.

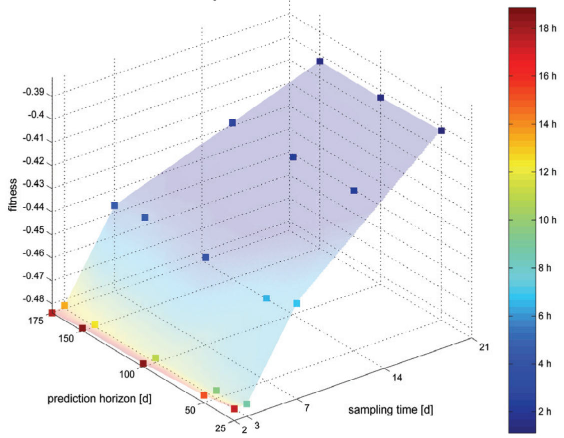

Figure 3: Overall fitness of the final operating state as a function of prediction and control horizon. The colour visualizes the controller execution time in hours [h].

Optimization method. Figure 4 presents the performance of the NMPC algorithm as a function of number of generations and population size of the optimization method employed inside the control loop for each of the three methods considered (CMAES, DE and PSO). For all tests the prediction horizon is set to 100 days, the control horizon to 7 days and $c = 0.01$. All methods yielded very satisfying results, with PSO giving the best results. However, PSO is also the slowest method since it evaluates about 25% more simulations than the other two methods, although the same population size and number of generations were selected for all three methods. This is due to the fact that the PSO implementation used runs one additional generation for initialization. Thus, in fact all three methods are about equally suitable for this task, with performance increasing with the number of generations and population size. It is interesting to note that even with very small parameter settings (number of generations= 2 and population size= 4) quite good results are obtained.

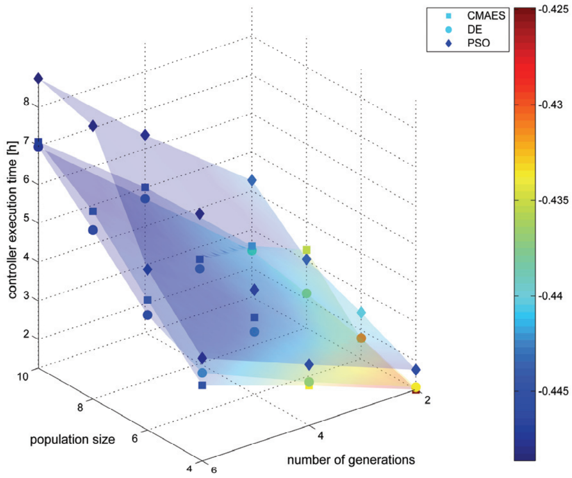

Figure 4: Controller execution time and overall fitness of the final operating state as a function of optimization method, population size and number of generations.

The box plots in Figure 5 reveal, that PSO seems to be the most insensitive method to changes in the number of generations and population size, whereas the performance of CMAES varies significantly with these two parameters. Since the controller execution time with PSO can be significantly reduced using a small number of evaluations, it can be suggested that for PSO the two parameters should be set to relatively small values to get a good result in a reasonable amount of time. For CMAES and DE both parameters should be chosen a little bit larger to get good results in the same amount of time.

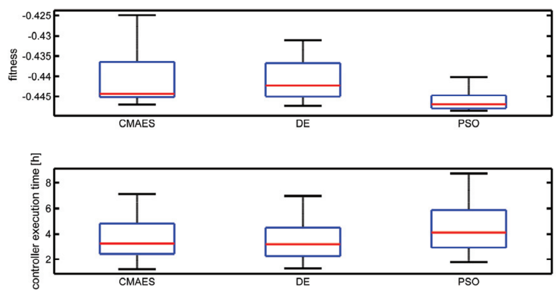

Figure 5: Box plots of the fitness of the final operating state and the controller execution time as a function of optimization method (for varying population size and number of generations).

IV CONCLUSION

In this paper a nonlinear model predictive control algorithm is proposed to optimally control substrate feed for full-scale agricultural biogas plants. The results show the applicability of the proposed approach and the optimization potential, which can be exploited by using this optimal control scheme. Combining the state estimator developed in [16] and the NMPC algorithm developed in this paper it is possible to optimally control real full-scale biogas plants. A trial of the proposed NMPC is scheduled for autumn 2011 in order to optimally control a full-scale biogas plant.

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