Multi-objective nonlinear model predictive substrate feed control of a biogas plant

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Abstract

In this paper a closed-loop substrate feed control for agricultural biogas plants is proposed. In this case, multi-objective nonlinear model predictive control is used to control composition and amount of substrate feed to optimise the economic feasibility of a biogas plant whilst assuring process stability. The control algorithm relies on a detailed biogas plant simulation model using the Anaerobic Digestion Model No. 1. The optimal control problem is solved using the state-of-the-art multi-objective optimization method SMS-EGO. Control performance is evaluated by means of a set point tracking problem in a noisy environment.

Results show, that the proposed control scheme is able to keep the produced electrical energy close to a set point with an RMSE of 0.9 %, thus maintaining optimal biogas plant operation.

1 Introduction

Optimising the operation of biogas plants is and will be one of the main challenges in the field of anaerobic digestion (AD) in the near future. A closed-loop substrate feed control, maximizing profit while minimizing ecological impact and maintaining biogas plant stability, is crucial for efficient optimisation of biogas plant operation. To the authors' knowledge, such a control has not yet been developed and implemented at a full-scale biogas plant. Main reasons are a lack of reliable measurement sensors on most full-scale biogas plants (Wiese & König 2009) and the complexity of the anaerobic digestion process. Nevertheless, advances in the development of reliable and robust measurement sensors as well as detailed AD models give hope that these limitations will be lifted in the coming years (Madsen et al. 2011). In this paper a multi-objective nonlinear model predictive substrate feed control is proposed, which is designed to optimally control the substrate feed of pilot-scale as well as full-scale agricultural biogas plants. This substrate feed control uses a calibrated model of the controlled biogas plant, whereas the AD process is modelled by the Anaerobic Digestion Model No. 1 (ADM1) (Batstone et al. 2002). Using this model, the effect of different substrates and varying substrate mixtures on the AD process can be predicted. Furthermore, produced electrical and thermal energy as well as consumed electrical energy needed for plant operation can be calculated (Lübken et al. 2007).

2 Multi-objective non-linear model predictive feed control

Consider an agricultural biogas plant fed with $u \in \mathbb{N}$ substrates. Its $n \in \mathbb{N}$ dimensional system state is symbolized by $\mathbf{x}: \mathbb{R}^+ \to X$ and its substrate feed by $\mathbf{u}: \mathbb{R}^+ \to U$, $X \subseteq \mathbb{R}^n$ and $U \subseteq \mathbb{R}^u$ denote the state and input space, respectively. In nonlinear model predictive control a time $t \in \mathbb{R}^+$ dependent optimization problem over a finite time horizon, called prediction horizon $T_\mathrm{P} \in \mathbb{R}^+$, is solved at every discrete time instant $t_k := k \cdot \delta$, with sampling time $\delta \in \mathbb{R}^+$ and $k = 0,1,2,\ldots$ (Findeisen et al. 2003). The objective is to minimize a two-dimensional objective function $\mathbf{J}: X \times U \to \mathbb{R}^2$, which depends on the open loop state $\underline{\mathbf{x}}: \mathbb{R}^+ \to X$ and the open loop substrate feed $\underline{\mathbf{u}}: \mathbb{R}^+ \to U$ of the controlled biogas plant, approximately modelled by a set of nonlinear differential equations $\underline{\mathbf{x}}'(t) = \mathbf{f}\left(\underline{\mathbf{x}}(t), \underline{\mathbf{u}}(t)\right)$, called the biogas plant model $\mathbf{f}: X \times U \to \mathbb{R}^n$. The optimization problem is solved by choosing the optimal substrate feed over a control horizon $T_\mathrm{C} \in \mathbb{R}^+$, $\delta \le T_\mathrm{C} \le T_\mathrm{P}$. The problem can be stated like this:
For each k =0,1,2,…. set $t_\mathrm{k} = k \cdot \delta$ and solve:

$$\begin{aligned}
&\underset{\underline{u}}{\text{minimize}} \quad && \mathrm{J}\left(\underline{\mathrm{x}}(\tau), \underline{\mathrm{u}}\right) \\
&\text{subject to} \quad && \underline{\mathrm{x}}'(\tau) = \mathrm{f}\left(\underline{\mathrm{x}}(\tau), \underline{\mathrm{u}}(\tau)\right), \qquad (1)
\end{aligned}$$

$$\underline{\mathrm{x}}(t_\mathrm{k}) = \mathrm{x}(t_\mathrm{k}), \quad \underline{\mathrm{x}}(\tau) \in X, \quad \forall \tau \in [t_\mathrm{k}, t_\mathrm{k} + T_\mathrm{P}],$$

$$\underline{\mathrm{u}}: [t_\mathrm{k}, t_\mathrm{k} + T_\mathrm{C}] \to U, \quad \underline{\mathrm{u}}(\tau) = \mathrm{u}(t_\mathrm{k} + T_\mathrm{C}), \ \forall \tau \in (t_k + T_c, t_k + T].$$

In case the state of the system $\mathbf{x}(t_k)$ cannot be measured at each time t_k, as it is the case for most biogas plants, $\mathbf{x}(t_k)$ has to be estimated. Notice, that the dimension of the state vector is defined by the ADM1, which is $n = 37$ in the used implementation. In Gaida et al. 2012a a state estimator is proposed, which can be used as a state estimator for a nonlinear substrate feed control as is demonstrated in Gaida et al. 2012b.

As the objective function $\mathbf{J} := (J_1, J_2)^T$ is a vector function, not only one optimal solution but many optimal solutions exist to problem (1). Those are trade-off solutions, which are all optimal with respect to (1) and collected in the so-called Pareto optimal set P_k^* (Coello Coello 2011). The trade-off solution applied to the plant, $\underline{\mathbf{u}}_k^*$ is given by a weighted sum, $\omega_1, \omega_2 \in \mathbb{R}$:

$$\underline{\mathbf{u}}_k^* := \arg \min_{\forall \underline{\mathbf{u}} \in P_k^*} \left[\omega_1 \cdot J_1\left(\underline{\mathbf{x}}, \underline{\mathbf{u}}\right) + \omega_2 \cdot J_2\left(\underline{\mathbf{x}}, \underline{\mathbf{u}}\right)\right] \quad (2)$$

and then applied for the duration of the sampling time δ:

$$\mathbf{u}(t) = \underline{\mathbf{u}}_k^*(t), \qquad t \in [t_k, t_k + \delta) \tag{3}$$

Notice, that the weights ω_1, ω_2 could also be state dependent as in (Valera García et al. 2012).
The objective functions J_1 and J_2 are defined as follows:

$$J_1 := \int_{t_k}^{t_k+T_P} \text{cost}\left(\underline{\mathbf{x}}(\tau), \underline{\mathbf{u}}(\tau)\right) - \text{benefit}\left(\underline{\mathbf{x}}(\tau), \underline{\mathbf{u}}(\tau)\right) d\tau$$

$$J_2 := \int_{t_k}^{t_k+T_P} \left[\sum_{i=1}^{C} \nu_i \cdot \text{constraint}_i\left(\underline{\mathbf{x}}(\tau), \underline{\mathbf{u}}(\tau)\right)\right] + \left\|\underline{\mathbf{u}}'(\tau)\right\|_2^2 d\tau \tag{4}$$

$$\text{constraint}_i := \begin{cases} 0 & \text{if inactive} \\ 0 < \ldots \leq 1 & \text{if active} \end{cases}$$

$$\sum_{i=1}^{C} \nu_i = 1 \qquad \nu_i \in \mathbb{R}^+$$

In equation (4) the function is defined by the sum of the substrate and energy costs and the benefit function is defined by the profit obtained selling the produced electrical and thermal energy, which, in Germany, is determined by the Renewable Energy Sources Act – EEG (BMU 2012). Examples for the $C \in \mathbb{N}$ constraint functions constraint$_i$ i = 1 ,...$\boldsymbol{C}$, are upper and lower boundaries for VFA/TA, COD degradation rate, pH value, OLR, HRT, NH_4-N and VFA. A further constraint could be a set point for any process value as it is the case for the experiment below.
Problem (1) can be solved using a multi-objective optimization algorithm. In this paper the multi-objective metamodel-assisted efficient global optimization algorithm SMS-EGO is used. Details can be found in (Ponweiser et al. 2008; Wagner et al. 2011). Due to the simulation of the biogas plant model an objective function evaluation is quite time consuming, SMS-EGO performs the optimization on a metamodel (Jones et al. 1998) to keep the number of simulations to a minimum (120 simulations are performed for each k). To reformulate the optimal control problem into a finite dimensional nonlinear programming problem, the substrate feed trajectories are parameterized by $(T_c / \delta) \in \mathbb{N}$ dimensional vectors, resulting in a piece-wise-constant substrate feed.

3 Results

In this section the proposed substrate feed control is applied to a model of a full-scale agricultural biogas plant with an electrical power output of 776 kW. The first of two digesters is fed with the u = 2 substrates $\boldsymbol{u} := (u_1, u_2)^T$, being maize silage $u_1 / [t/d]$ and liquid cow manure $u_2 / [m^3/d]$.
The substrate feed of the biogas plant is controlled, such that the produced electrical energy follows a constant electrical power set point of 776 kW. The set point is defined as a soft constraint in $\boldsymbol{J}_2$. As disturbances, the nominal values of some parameters of the substrates are randomly varied up to 20 %. For maize silage total solids (TS) as well as pH value are changed and for liquid manure NH_4-N is varied as well. The disturbances occur over a period of 40 days (see Fig. 1c). Over this period the control solves problem (1), so that a constant electrical power is produced and optimal plant operation is maintained at all times. The feed control was started four days before the disturbances were applied and ran until four days after the substrate parameters were set back to their nominal values again (see Fig. 1).
The substrate feed control is parameterized as follows. The sampling time is set to $\delta = 4$ days and the control horizon T_C is set to eight days. Thus, each substrate is parameterized by a two-dimensional vector, resulting in a total of four optimization variables for both substrates together. The prediction horizon T_P is set to 25 days and 50 days, respectively, and U is set to:

$$U := \left\{ \bar{\mathbf{u}} := (\bar{u}_1, \bar{u}_2)^T \in \mathbb{R}^2 \,\middle|\, (37.5, 20)^T \leq \bar{\mathbf{u}} \leq (51.5, 30)^T \right\}$$

$$, \bar{u}_1 / [t/d], \bar{u}_2 / [m^3/d]$$

In Figure 1a) the resulting electrical power trajectories are visualized for two different feeding stratgies. The first strategy 'closed-loop' (for T_P=50 *days* and T_P=25 days) depicts the results obtained with the proposed control and the second strategy 'open-loop' visualizes the results, when the feed is kept constant for maize at 46.9 t/d and for manure at 25.7 m³/d. As can be seen the closed-loop controls closely track the set point with an RMSE of 11.4 kW and 6.7 kW (T_P=25 *days*), respectively. As the set point is set to the maximal possible electrical power output of the plant, overshooting the set point directly leads to excess biogas production. The control significantly reduces in excess produced biogas from 8.411 m³ for the open-loop case down to 720 m³ (216 m³, T_P=25 *days*) for the duration of the given scenario. Nevertheless, there are differences between the set point and the trajectories, because the control does not only track the set point but at the same time optimizes all other criteria defined in the objective function $\boldsymbol{J}$. In this experiment the control with the shorter prediction horizon has a better performance, but for a more thorough analysis a parameter study for the control parameters T_C, T_P and δ will be performed in subsequent work.

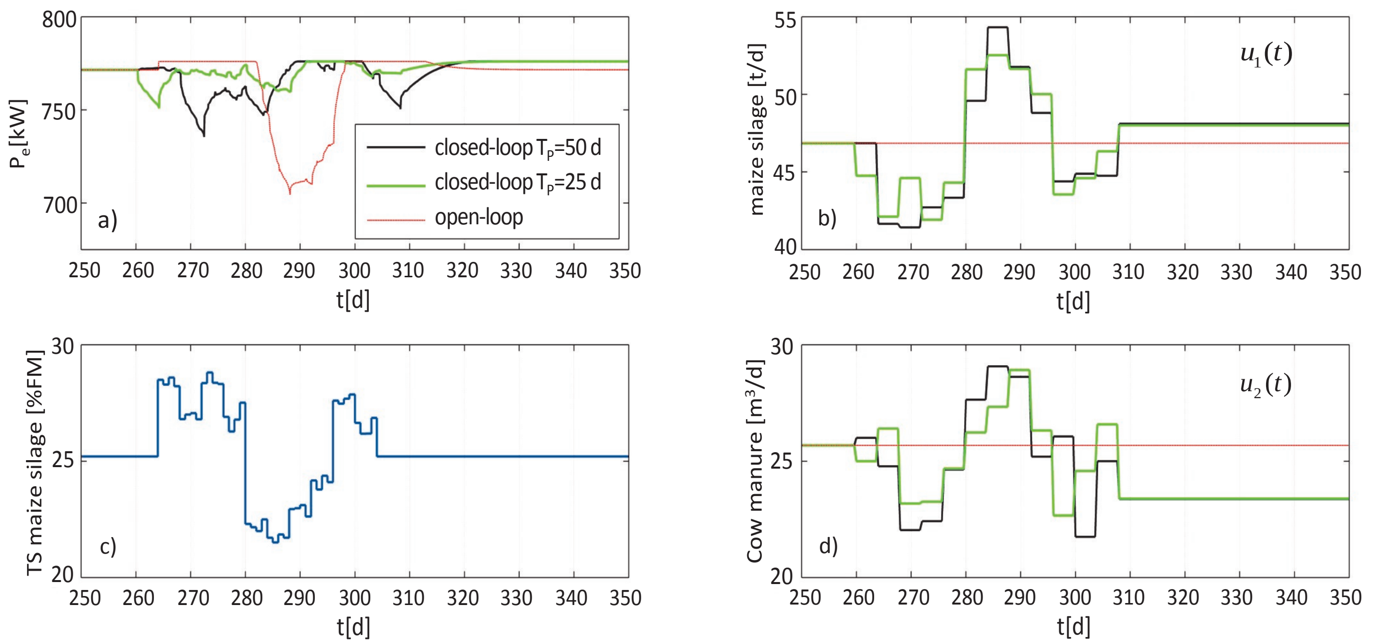

Figure 1: a) Electrical power output of the biogas plant. b) & d) Substrate feed of maize silage and cow manure, respectively. c) Random change of substrate parameters, as an example the TS of maize silage is visualized. To guarantee that we start from a steady state, the control is started at day 260 and the substrate parameters are changed between days 264 and 304. At day 308 the control is stopped and the last optimal substrate feed of the control is applied until the end of the simulation at day 350.

4 Conclusion

In this paper a model predictive substrate feed control was proposed. Its performance is demonstrated through a set point tracking problem. The control is able to track an electrical power set point with an RMSE of 1.5 % (0.9 %, T_P=25 *d*) and it reduces the in excess produced biogas significantly by 91 % (97 %) for the given scenario. As a result, the lost benefit is decreased from 3.174 € down to 409 € (90 €).

Parameterizing the objective function accordingly it would be possible to track the set point more closely and to avoid biogas excess, but this would discriminate some other criteria of the objective function.

A trial of the proposed NMPC is scheduled for summer 2013 in order to optimally control a pilot-scale biogas plant.

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