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Chapter 1

Introduction

The European Union (EU) has set a goal that 20 % of the gross final energy consumption in the EU should be produced by renewable energy sources in the year 2020 (Holm-Nielsen et al., 2009). Between the years 2004 and 2011 in the EU this share increased from 8.1 % to 13.0 % (Eurostat, 2013).

In Germany 7.0 % of the gross electrical energy production in 2012 was produced out of biomass (22.6 % of gross electrical energy production was from renewable sources), whereas biogas produced from biomass had the greatest share (FNR, 2013). Biogas mainly consists of methane and carbon dioxide and is produced in so-called biogas plants. In such plants, one of the key components is the digester. In the digesters there is an absence of oxygen, allowing the bacteria to convert the anaerobic degradable biomass in to biogas. Some examples for biomass are manure, grass, energy crops, organic fraction of municipal solid waste (OFMSW), biodegradable wastes from industrial production, wastewater and many more.

Once produced, there are various utilization pathways for biogas. Among them are production of heat (e.g. in third world countries) as well as of electrical and thermal energy while burning it in cogeneration units (also called combined heat and power plants (CHP)) and upgrading biogas to biomethane by removal of carbon dioxide. The latter allowing for the possibilities of either injecting the biomethane into the natural gas grid or utilizing it as vehicle fuel (Holm-Nielsen et al., 2009).

The Renewable Energy Sources Act (EEG) (BMU, 2012a) in Germany fosters the energy production out of renewable energy sources. For the year 2013 FNR (2013) predicts 7,772 biogas plants with an installed electrical power of 3,530 MW. With these numbers Germany has the leading role in the EU regarding biogas production (OBSERV'ER, 2012). In Germany 0.8 million hectares of maize are cultivated for subsequent biogas production (FNR, 2013). This is still "only" one third of the total maize cultivation (FNR, 2013), but it clearly shows that biogas production, as currently carried out in Germany also comes at an ecological cost. To be able to promote and foster biogas under these circumstances as a sustainable energy source, optimal use of valuable resources is absolutely necessary. This aspect is also considered in the recently announced new 2014 Renewable Energy Sources Act. The first draft suggests that the German government is focusing on the digestion of waste products in the near future, thus trying to reduce ecological costs introduced by the cultivation of maize for energy production.[1]

The Netherlands was ranked at the 5th position regarding primary biogas production in the EU in the year 2011 (OBSERV'ER, 2012). In 2013, there was a total of 105 co-digestion plants with an installed electrical power of 129 MW (Agentschap NL, 2013). The current funding scheme for renewable energy in the Netherlands is the Renewable Energy Production Incentive Scheme (SDE+, Dutch: stimuleringsregeling duurzame energieproductie) (Statistics Netherlands, 2012). In 2012 the renewable energy share of gross final energy consumption in the Netherlands was 4.4 % with the 2020 goal being 14 % (Centraal Bureau voor de Statistiek, 2013).

Operation of biogas plants is only economically feasible if they are operated near their optimal operating point. One key aspect for optimization is to choose the most suitable biomasses, called substrates, and their daily throughput. The substrates used strongly effect biogas production, population sizes of different bacteria species in the digesters and digestate quality. Thus, by optimizing the substrate feed, economical, ecological and stability criteria of plant operation can be optimized. At present, most biogas plants in Germany are operated at steady-state, ideally producing sufficient biogas to power an electrical generator at maximum capacity. This allowed biogas plant owners to ensure that they obtained the maximum possible funding (BMU, 2009), until the EEG was amended in 2012. The 2012 amendment introduced the possibility for biogas plants to sell the produced electrical energy directly to an interested customer (BMU, 2012a). Consequently, higher revenues compared to conventional remuneration schemes are possible. Selling energy under the EEG feed-in tariff on EPEX SPOT's Day-Ahead market became an interesting option. EPEX SPOT[2] is a European power spot market covering France, Germany, Austria and Switzerland. Therefore, there is a need for highly flexible biogas and power production, which in turn requires a closed-loop substrate feed control that is able to track a given setpoint and adjust the substrate mix in an optimal manner.

The current state of control and automation on most full-scale biogas plants is very basic (Wiese and König, 2009). On agricultural biogas plants (ABP) the substrate feed is usually changed on a daily basis based on simple calculations or a rule of thumb (Dewil et al., 2011). Due to a lack of online process instrumentation, it is often not possible to make reliable predictions of expected biogas production and the state of the process. Advances in the development of reliable and robust measurement sensors, as

[1] `https://www.clearingstelle-eeg.de/`

[2] `http://www.epexspot.com/en/`

well as detailed anaerobic digestion (AD) models give hope that these limitations will be lifted in the coming years (Madsen et al., 2011). Nevertheless, it is questionable as to whether biogas plants will ever have adequate instrumentation fitted as standard. Therefore, presently and in the future, control and optimization methods fitted to biogas plants should cope with these limitations. Following this idea in this thesis, the developed real-time feed optimization method requires only very basic instrumentation, so that it will be possible to use it on ordinary full-scale biogas plants.

However, simulation and control of waste digestion is much more challenging than for ABPs. The reason is that feed based on municipal waste will change its composition continuously, requiring continuous adjustment and control of the plant. Nevertheless, the dissemination of the technologies developed in this work will be absorbed by a market that specifically requires these solutions.

1.1 Aim and Objectives

In this thesis a dynamic real-time optimization (RTO) scheme is developed to achieve optimal substrate feed control for biogas plants. RTO continually alters the substrate feed to maximize the economic productivity of the biogas plant while at the same time predefined stability criteria are maintained. In Figure 1.1 the developed dynamic RTO control loop is visualized. An important part of the dynamic RTO scheme is the

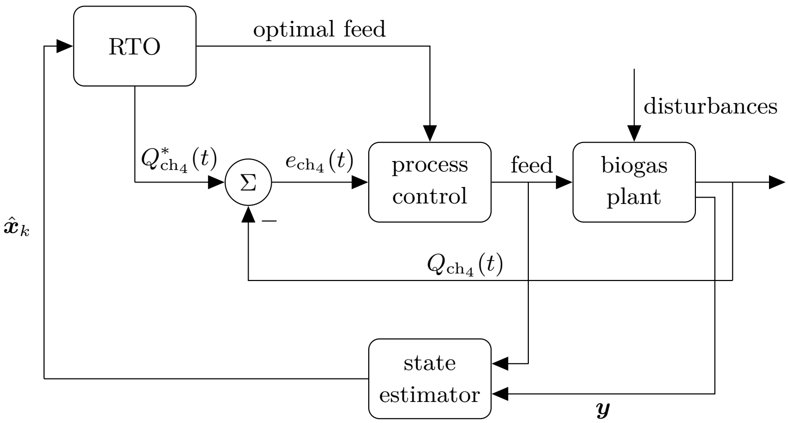

Figure 1.1: Dynamic Real-Time Substrate Feed Optimization. The RTO determines the optimal substrate feed and returns the optimal volumetric methane flow rate $Q^*_{\mathrm{ch}_4}(t)$. The process control adapts the optimal feed to stabilize the produced methane flow rate $Q_{\mathrm{ch}_4}(t)$ of the biogas plant around the given setpoint $Q^*_{\mathrm{ch}_4}(t)$. As a dynamic model is used for prediction, a state estimator is needed that estimates at each time step k the current state estimate $\hat{\boldsymbol{x}}_k$ given the current feed and plant measurements $\boldsymbol{y}$.

dynamic simulation model of the biogas plant which is used for prediction purposes.

The developed method for the dynamic real-time substrate feed optimization is dedicated to assisting the biogas plant operators in the selection of the optimal substrate feed on a daily basis, ultimately with the goal of autonomously controlling the feed of the plant. The following features are expected from the RTO scheme:

- Determination of optimal substrate mixture for anaerobic co-digestion plants.
- Keeping the plant stable by all means due to prediction.
- Consideration of changing substrate availabilities in the chosen substrate feed.
- Robust stable setpoint tracking.
- Flexibility and extensibility with respect to the optimization goal.

In order to realize a sophisticated real-time feed optimization that is practical to implement, there are multiple objectives that must be achieved.

The first objective is to create a detailed dynamic simulation model for biogas plants. This model is used in the dynamic RTO to continually predict the optimal substrate feed for the controlled plant. Performance and practical usability of RTO is highly dependent upon the underlying model, consequently, a significant amount of effort is necessary to ensure realistic modeling of full-scale biogas plants.

The optimization and prediction method implemented as a part of the RTO scheme, is nonlinear model predictive control (NMPC). Thus, the second objective is to develop and implement NMPC for the substrate feed of biogas plants. NMPC selects a substrate feed trajectory that optimizes an objective function over a prediction horizon. For biogas plants, such an objective function may contain economical, ecological and stability criteria and thus is of a multi-objective nature. Furthermore, it can be highly nonlinear. To solve the nonlinear multi-objective optimization problem, global multi-objective optimization methods such as evolutionary algorithms and efficient global optimization (EGO) are used.

In order to make NMPC predictions with the simulation model, the NMPC must know the current system state of the biogas plant. Therefore, the third objective is to develop a state estimation algorithm that is capable to continually estimate the state of the biogas plant. The challenge to develop a reliable state estimator increases with process model complexity. To achieve this task, supervised machine learning methods are used to estimate the current state given current and past measurement data.

1.2 Main Contributions of this Thesis

To the author's knowledge, dynamic real-time substrate feed optimization has not been applied to anaerobic co-digestion plants before. To achieve this goal, different components from various scientific fields had to be developed, implemented and combined. This is the first main contribution of this thesis.

The heart of the developed RTO scheme is the Anaerobic Digestion Model No. 1 (ADM1) which is the most complex model of the anaerobic digestion process available at present. There are multiple challenges when attempting to implement this model inside the NMPC. Three of these challenges are that predictions are time consuming, the underlying optimization problem is highly nonlinear and the state estimator must estimate a large state vector of a non observable process. To address the first two challenges, evolution strategies are used that in part use surrogate models to improve speed.

Solving the latter challenge results in the second main contribution of this thesis. This is the development of the state estimation algorithm. Using machine learning methods, a static function is created that maps measured process values to the state vector of the plant and therefore can be used for state estimation. Classical state estimation approaches such as the famous Kalman filter will not be stable because the observability criterion (Simon, 2006) in practice is not satisfied for the ADM1. Therefore, this new state estimation approach is needed.

The last contribution of this thesis to the scientific community is the MATLAB® toolbox for "Simulation, Control & Optimization of Biogas Plants" (Appendix B), which was developed for the purposes of this thesis.

1.3 Outline of this Thesis

This document is structured in five parts.

Part I presents the theoretical foundation to this work. As the proposed real-time optimization scheme uses multi-objective model predictive control, Chapter 2 presents the basics of model predictive control and multi-objective model predictive control. To solve the multi-objective optimization problem formulated in Chapter 2, Chapter 3 reviews multi-objective optimization algorithms which will be used to solve the control problem. They are SMS-EMOA and SMS-EGO which are based on the $\mathcal{S}$-Metric. For model predictive control a state estimation algorithm is necessary. Therefore, three different state estimation algorithms are described in Chapter 4 which concludes Part I. The state estimation algorithms are the well-known hybrid extended Kalman filter, moving horizon estimation and the newly developed state estimator based on machine learning methods. Using a simple model of an anaerobic digestion process, all three approaches are validated and compared.

Part II applies the concepts introduced in Part I to the application of controlling the substrate feed of biogas plants. It starts with an introduction of the anaerobic digestion process in Chapter 5, which is written for those not familiar with the process. Chapter 6 contains an extensive review of the state of the art of biogas plant feed control revealing the need for feed control particularly for agricultural biogas plants. In Chapter 7, a detailed model for biogas plants is proposed. This model is used within the predictive control algorithm and it is used for validation of the control in the simulation and optimization studies of Part III.

The 3rd part, Part III, starts with Chapter 8 that presents the results obtained with the self-developed state estimator for the biogas plant model of Chapter 7. Chapter 9 outlines the main result of this thesis, the dynamic real-time substrate feed optimization for co-digestion plants. The proposed RTO scheme is validated by means of extensive simulation and optimization studies revealing its performance.

The thesis is concluded by Chapter 10, in which the main results of this thesis and possible future work are summarized.

In the appendices, detailed technical descriptions of the used models are provided. In Part A of the appendix the AD model used in the experiments of Chapter 4 is presented. Part B presents the MATLAB® toolbox developed for this thesis in which all simulations and optimization runs are performed. The implementation of the Anaerobic Digestion Model No. 1 used in the biogas plant simulation model developed in Chapter 7 is given in Part C. Finally, all symbols and abbreviations can be reviewed in Part D.