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Stochastic Greybox Modeling of an Alternating Activated Sludge Process

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Summary of key findings

We found a greybox model for state estimation and control of the BioDenitro process based on a reduced ASM1. We then applied Maximum Likelihood Estimation on measurements from a real full-scale waste water treatment plant to estimate the model parameters. The estimation method also incorporates the Extended Kalman Filter that provides estimates of any unmeasured states, e.g. the NH4 and NO3 concentrations in both aeration tanks, and more importantly, the NH4 inlet concentration. This will improve control performance without the need for extra sensors and improve forecasts of the load.

Background and relevance

The nitrogen removal processes in WWTPs can be modeled by the state-of-the-art Activated Sludge Model no. 1 [3]. Most WWTP control related literature use this model or reductions of it. Unfortunately, most also assume a perfect model and all predictions of load and flow are available, especially since the introduction of the BSM1 control benchmark plant and scenarios. Very little effort is put into key areas such as model parameter estimation, model uncertainty, observing inlet concentrations, and load forecasting. As the typical dry weather operation cycle is diurnal, we consider a control horizon of 24 hours that is sufficient for NH4 and NO3 control. We then calibrate a dynamical model to the operating conditions repeatedly, i.e. we estimate the parameters in a greybox model and update the state estimates using the Kalman Filter. The aim of the model is to use it for predictions of the process including uncertainty, for dynamic control and for estimating unmeasured states, i.e. a soft sensor. We use data from a WWTP in Denmark that runs a BioDenitro process. This is an alternating process setup primarily used in Denmark [1].

Compared to traditional recirculating plants the alternating BioDenitro process: shows good treatment efficiency and effluent quality, lower hydraulic retention times (faster throughput), smaller reactor tank volumes, a flexible plant configuration that can adapt to different waste water compositions, and finally, a continuous alternating excitation of the dynamics that makes it easier to estimate the model parameters and process rates through system identification. The latter is exploited in this work and we use Maximum Likelihood Estimation and greybox models for system identification.
STAR is a commercially available control system for the BioDenitro process developed by Krüger A/S. STAR drives the treatment process through a number of phases, i.e. different aeration patterns, and adaptively controls the phase lengths from the measured NH4, NO3, and O2 concentrations based on a Rule-Based Controller (RBC) with tuneable set points.

As the computational speed has increased significantly over the past decades these RBC strategies are now replaceable by optimized, adaptable and model based control strategies like Model Predictive Control (MPC) that has been applied extensively to the chemical process industry. By modeling and predicting the process outcomes more accurately the process can be optimized even further in terms of effluent quality and energy consumption. However, an increased performance with model-based control and predictions require sufficient models and uncertainty estimates.

Simple linear models of the process were developed [7] including several heuristic model based strategies [6]. [3] developed stochastic greybox models and applied parameter estimation of reduced ASM1 models on real alternating plants with the aim of process prediction and control. Several simple RBC strategies were deducted from model simulations to evaluate the operating costs for nutrient discharge and energy consumption. [3] concluded that greybox models of the wastewater processes performed significantly better than the traditional blackbox models like ARMAX models. [4,9] provide great summaries of other literature that deals with control and modeling of alternating plants. [9] specifically focuses on the BioDenitro process.

Many control-oriented models of the alternating activated sludge process are based on reductions of the ASM1. These reduced models are often nonlinear with Monod-expressions and time-varying parameters. Given a mathematical model structure and a set of plant measurements, we can estimate the model parameters. Using greybox models it is possible to evaluate the parameter uncertainty as well. We use the statistical likelihood function to evaluate the model fit and select the best set of model parameters. Evaluating the likelihood function requires output residuals, i.e. the difference between the model and actual measurements, and a known initial probability density. A Kalman filter provides exactly this for Gaussian noise densities, i.e. a state estimate and a covariance, even for nonlinear models when applying the extended linearizing version: the Extended Kalman Filter (EKF). The EKF estimates the mean and variance input to the likelihood function. We then solve the nonlinear optimization problem that maximizes the likelihood function and returns the parameters. The R package CTSM-R (www.ctsm.info) [8] solves exactly this optimization problem and provides estimates of the parameters and their uncertainties. CTSM-R handles irregular sampling since the model is continuous enabling variable step size lengths in the solver. Occasional outliers are removed automatically using Huber weights. Multiple independent data sets can be combined into the same estimation procedure. The built-in EKF provides state estimates even when observations are missing, i.e. when there are holes in the data set caused by calibrating sensors or communication faults.

Results

Our case study data is 26 hours of dry weather data from a Danish WWTP with a 120.000 PE capacity. The plant has four aeration tanks, i.e. two BioDenitro tank sets, equipped with O2 sensors. We built a two state model of the NH4 concentrations in one aeration tank set, and refer to them as tank A and B. Only tank A has a NH4 and a NO4 sensor.

The NH4 inlet concentration is not measured. We know that this concentration is correlated with the inlet flow and is an important of the load to the plant. We can estimate it using the Kalman filter and our greybox model. We add the inlet NH4 concentration, NH4in, to the model as a third state driven by noise such that d NHin = 0 dt + sigma dw. This is a stochastic differential equation and fits within the CTSM-R model framework method described above. Note that any model discrepancies will be transferred to this state and this might corrupt the physical interpretation of the state. Since the NH4 concentration in tank B, is also not measured, we also get an estimate of this. The results are shown in the Figure 1.1 as a function of time in minutes over 26 hours. The upper most plot shows the measured NH4 concentration in aeration tank A (circles). The dotted black line is the oxygen level in tank A. When aeration is turned on the oxygen increases and NH4 is removed. This is repeated in an alternating pattern. The red line is the estimated one-step prediction while the residual is at the bottom plot in the figure. The second plot below shows the unmeasured and estimated NH4 concentration in tank B. The third plot shows the estimated inlet NH4 concentration that is diurnally varying.

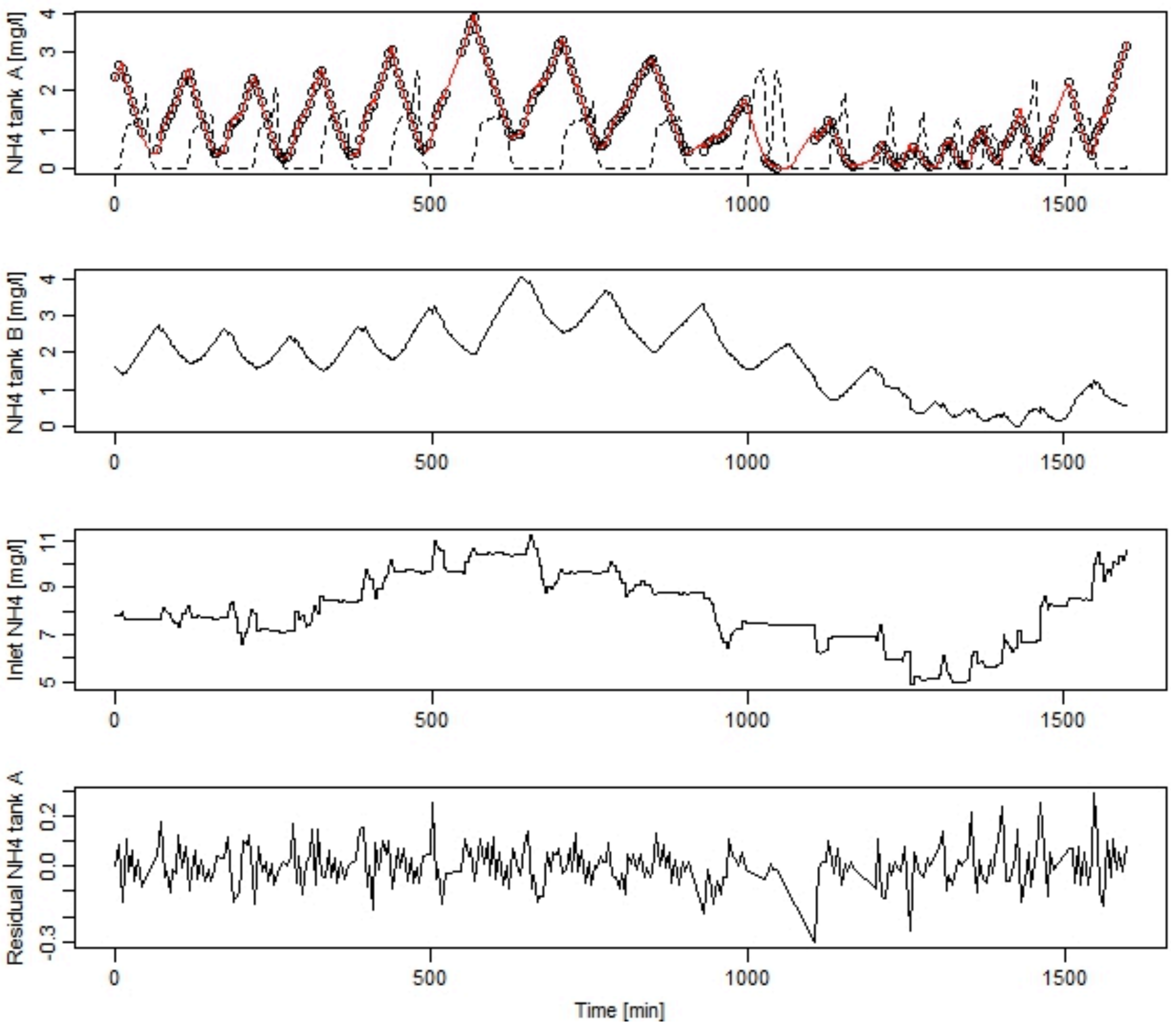

Figure 1.1

Conclusion

We modeled the BioDenitro process and estimated unmeasured NH4 concentrations including the load to a real WWTP. We also estimated the parameters and their statistical uncertainty. The method provides a greybox model of the process and a Kalman filter that is necessary for Model Predictive Control purposes and an optimized plant operation in terms of energy consumption and better effluent quality.

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