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Smart Power, Cost-Effective MPC of Stochastic Wastewater Treatment Process

Peter A. Stentoft *,** **Thomas Munk-Nielsen** *
Peter S. Mikkelsen *** **Henrik Madsen** ** **Luca Vezzaro** *,***
Jan K. Møller **

* *Krüger A/S, Veolia Water Technologies, Søborg, Denmark (e-mail: pas@kruger.dk)*
** *Department of Applied Mathematics and Computer Science, Technical University of Denmark (DTU), Lyngby, Denmark (e-mail: past@dtu.dk)*
*** *Department of Environmental Engineering, Technical University of Denmark (DTU), Lyngby, Denmark (e-mail:luve@env.dtu.dk)*

Abstract: Wastewater treatment aeration accounts for a large amount of societal electricity consumption. This abstract suggests MPC driven by stochastic differential equations and genetic optimization, under legal and equipment constraints to prioritize aeration in selected periods. Thereby we reduce costs and empower smart use of green electricity from e.g. wind turbines.

Keywords: Stochastic Systems, Genetic Algorithms, Process Control, Predictive Control, Water Pollution, Smart Power Applications

1. INTRODUCTION

Wastewater Treatment Plants (WWTP) reduce nutrients, such as nitrogen (N), by up to 95% before treated water is discharged to environment. This treatment is carried out by specialized bacteria that need aerobic (O_2 present) and anoxic (O_2 absent) conditions to reduce ammonium (NH_4) in wastewater to nitrate (NO_3, nitrification) and then NO_3 to nitrogen gas (denitrification). This is the alternating Activated Sludge Process (ASP) which in WWTPs is operated in large tanks with aeration equipment that is turned on and off in cycles to secure good treatment.

While the ASP is important for maintaining water quality in local streams and lakes, it is also costly. Municipal wastewater treatment accounts for 0.8% of total electricity consumption in the US (Pabi et al., 2013) and typically 50-60% of the electricity used by a WWTP is aeration (Ingildsen, 2002). Furthermore, in some countries the discharge of nitrogen is taxed; e.g. 5$/kg discharged Nitrogen in Denmark. Consequently the optimal aeration control is a balance between effluent taxes and electricity consumption/costs constrained by legislation and equipment.

2. METHODOLOGY

2.1 Prediction Model

The ASP is well described by the family of Activated Sludge Models (ASM) (e.g. (Henze et al., 2000)). The ASMs consist of at least 13 nonlinear-ODEs based on Monod-kinetics and Mass-balances. Based on the ASMs, a stochastic ASM (SASM) (Stentoft et al., 2018) is developed to predict nitrogen removal based on online measurements. The SASM contains 3 coupled Stochastic Differential Equations (SDEs) which describe ammonium, nitrate and available O_2 in the aeration tank as a function of the aeration control signal. The parameters of the SASM are estimated with historical online measurements of NH_4 and NO_3 and the historical aeration control signal. The estimation of parameters in the SDEs is done by maximizing the likelihood function. The noise on the online measurements and the model noise are split into two terms and managed by an Extended Kalman Filter (EKF). Predictions are performed following a numerical integration scheme. This methodology is specified in Juhl et al. (2016) and Kristensen et al. (2004) and the SASM implementation is more thoroughly described in Stentoft et al. (2018).

2.2 Optimal Control

The cost is optimized with respect to two categories of constraints; (i) Equipment constraints related to the creation of the aeration control signal, and (ii) Legislational constraints related to effluent concentrations.

Aeration signal is the setpoint sent to actuators, O_s. It describes how much O_2 should be transferred into the water. This setpoint is constrained by possible actuator setpoints as well as bounded nitrification (aeration on) and denitrification (aeration off) times.

Legal requirements dictate that NH_4 and total-N concentrations in the effluent must, on a 24-hour weighted average, be below 2 and 8 mgN/L, respectively. This is secured by evaluating the SASM with respect to NH_4 and NO_3 and the uncertainties given as 95% prediction interval provided by the uncertainty of the SDEs.

The total operational costs at time t, C_t is given by

$$C_t = Tax(N_t(Os), T) + E(Os_t, Ep_t) \qquad (1)$$

Where $Tax(N_t(Os), T)$ is the nitrogen tax as a function of nitrogen discharged, $N_t(Os)$ and the price of discharging Nitrogen, T. $E(Os_t, Ep_t)$ is the electricity consumed as a function of the aeration signal, Os_t and the electricity price, Ep_t. The optimal control is the Aeration signal, O_s that minimizes diurnal costs while considering constraints.

$$\underset{Os}{\textbf{minimize}} \sum_{i=0}^{24h} C_i \tag{2}$$

To solve the minimization problem in (2) we use a genetic optimization algorithm suggested by Mebane and Jasjeet (2011). This is to secure an optimization which manages in a robust way that the aeration signal is a step function, i.e. it is not even differentiable and contains mixed integers (on/off decisions) and real values (set points).

3. RESULTS

The strategy is simulated and compared with data from a small WWTP located in Nørre Snede, Denmark. The plant serves a catchment with 4000 inhabitants and a few small industries.

3.1 Example: Predicted control

The parameters of the SASM are estimated with 4 days of data. The optimal operation is then found for the 5th day as a function of the electricity prices from the day-ahead market (Figure 1).

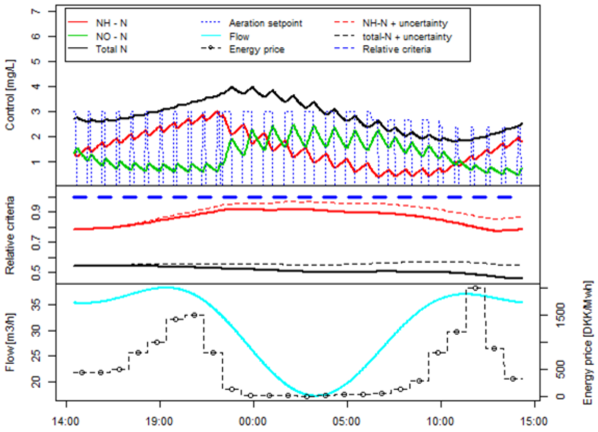

Fig. 1. Upper: Example of optimal aeration signal and the expected development in NH_4, NO_3 and total-N. Middle: Relative criteria compared to legislational requirements. Bottom: Predicted inflow and Electricity prices from day-ahead-market

3.2 Potential savings

The MPC performance is compared with the currently implemented rule-based control that controls aeration only as a function of current NH_4 and NO_3 measurements (Nielsen and Önnerth, 1995). This is done by fitting SASM to 4 days of data, predicting best control on the following day, and then compare total estimated costs with the rule-based control. This is carried out with data from 15 days without precipitation. The simulated savings in terms of electricity costs and effluent taxes is 296$, relative to the currently implemented rule-based control this is 26.2% less during these 15 days. This corresponds to potential annual savings of approximately 5400$. However to manage wet weather and other nutrients such as phosphorous more development is required.

4. CONCLUSION AND OUTLOOK

A stochastic MPC strategy for cost-optimization in municipal wastewater treatment aeration is developed and;

- The strategy performs well in prioritizing electricity consumption in timeslots with cheap electricity
- Comparison with rule-based control shows a 26.2% reduction in cost on Nørre Snede WWTP
- The strategy needs more development to manage wet weather control and other nutrients such as phosphorous and carbon

Consequently this is a method for balancing electricity costs and taxation related to wastewater treatment aeration. Finally this is considered a step towards using wastewater treatment as a "battery" for cheap energy.

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