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"Green MPC" – an approach towards predictive control for minimimal environmental impact of activated sludge processes

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Abstract: The environmental impact related to alternating activated sludge processes (ASP) includes both global warming potential (GWP) and eutrophication. Here we present a model predictive control approach which minimizes this impact, calculated as CO_2-emissions related to electricity production, nitrous oxide emissions from the ASP and eutrophication related to discharge of ammonium and nitrate. We compare solutions for two different set of assumptions regarding released nitrous oxide and eutrophication impact. This results in controls with different resulting emissions and hence we show that the strategy can be used to prioritize environmental impacts.

Keywords: Model predictive control; Optimization; Activated Sludge Process; Environmental impact

Introduction

The activated sludge process (ASP) is widely applied for biological removal of nitrogen from wastewater. Aerobic processes require oxygen as electron acceptor, which is transferred to wastewater through aeration processes. Thanks to the nitrification-denitrification processes, nitrogen is transferred from wastewater (where it is mostly in the ammonium form) to the atmosphere (mainly as N_2) or sequestered into the biomass. This is an important part of municipal wastewater treatment because the reduction of large nutrient-loads protects recipients against eutrophication.

However, a fraction of the nitrogen released to atmosphere is Nitrous Oxide (N_2O) (IPCC, 2006) which is a strong greenhouse gas (GHG) with approximately 300 times the global warming potential (GWP) greater than CO_2. Furthermore, the aeration process, adding air to the wastewater, requires large amounts of electricity. Depending on the electricity production mix (wind, coal, hydro, etc.), this process results in different GHG-emission ranges, as shown in Table 1.

As one of the overall goals for wastewater treatment is to protect the environment, an optimal control of the ASP should not only consider the water compartment, but it should aim at reducing emissions to different environmental compartments and various impact categories. In this contribution we suggest a predictive optimization method which takes both eutrophication and GWP into account for minimizing the environmental impact related to alternating control of ASP-based plants.

Table 1: Summary of GHG emissions from electricity production in Denmark from 2018-08-28 to 2019-02-18. The unit is g-CO2-eq/kWh as an average over 5 minutes. Source Energinet (2019)

	Min	*Mean*	*Median*	*Max*
CO2-emission [g-CO2-eq/kWh]	38	181	166	461

Methodology

“Green MPC” is here a short term that refers to a Model Predictive Control (MPC) strategy which considers environmental impact rather than costs. Hence to execute such a strategy in an alternating ASP, a prediction model that estimates the effect of aeration control and an objective function that defines desirability of control are needed. In the following these are described.

Ammonium and nitrate concentrations in an alternating ASP can be predicted by using Stochastic Differential Equations (SDE) with the structure suggested by Stentoft et al. (2018). Here changes in ammonium (NH_4), nitrate (NO_3) and available oxygen are modelled as three coupled differential equations. The signal controlling aeration ($\boldsymbol{O}$) goes into the oxygen state. The system of SDEs is showed in Equation (1) to (3)

$$dS_{NH_4} \approx -\theta_1\left(\frac{S_{NH_4}}{K_{NH_4,ANO}+S_{NH_4}}\right)S_{O,MO}dt + (r_c+\rho Q)\left(\mu_{NH_4,in} + \Sigma_{i=1}^{n=2}[s_i\sin(iwt) + c_i\cos(iwt)\right] - S_{NH_4})dt + \sigma_{11}d\omega_1 \quad (1)$$

$$dS_{NO_3} \approx \theta_1\left(\frac{S_{NH_4}}{K_{NH_4,ANO}+S_{NH_4}}\right)S_{O,MO}dt - \theta_2\left(\frac{S_{NO_3}}{K_{NO_3,OHO}+S_{NO_3}}\right)\left(1-S_{O,MO}\right)dt + (r_c + \rho Q)(\mu_{NO_3,in} - S_{NO_3})dt + \sigma_{22}d\omega_2 \quad (2)$$

$$dS_{O,MO} \approx -\left(\theta_3 + \theta_4\left(\frac{S_{NH_4}}{K_{CNH_4,ANO}+S_{NH_4}}\right)\right)S_{O,MO}dt + k_1 O\left(S_{O,MOmax} - S_{O,MO}\right)dt + \sigma_{33}d\omega_3 \quad (3)$$

The equations represent a simplified version of ASM1 (Henze et al 1987) and hence they can be interpreted as a combination of nitrogen mass-balances and Monod kinetics governing the N-removal. Incoming Nitrogen is modelled by as flow to the tank arriving with rate $r_c + \rho Q$. Uncertainty is managed by the derivative of Brownian motion ($d\omega_i$) which is also referred to as a Wiener process. Several frameworks for estimating parameters in such a model. Here we use a framework which allows for fast updates and hence utilizes the online setting (with real time data). The framework is described by Kristensen et al. (2004) It uses an objective function that is based on maximum likelihood where the conditional probability of observing the parameters (given observations) is calculated from both model noise and measurement noise. The updating of the model with new observations is managed by an extended Kalman filter. The implementation is managed using the R-package; CTSM (2018) and it is described in Stentoft et al. (2018) where the implementation related to this specific model (in (1) to (3)) is presented.

The above stochastic ASM is previously used for predictive control in Stentoft et al., (2019) and a similar version is used in Brok et al. (2019). In these studies costs in terms of aeration electricity consumption and effluent nitrogen taxation are minimized with respect to a parameterized aeration signal. Here the aeration signal is parameterized similar to Brok et al. (2019) where sigmoid functions describe aeration starting and stopping times (to accommodate alternating operation of the ASP aeration needs to be switched “on” and “off”). The parameterized aeration can be described as presented in (4)

$$\mathrm{O}(\mathrm{t}|\tau_{\mathrm{i,j}}) = \sum_{i=1}^{N} \frac{1}{(1+e^{-k(t-\tau_{i,1})})(1+e^{k(t-\tau_{i,2})})} \tag{4}$$

This parameterization is the sum of the product of two sigmoid functions. When setting the parameter k sufficiently large, this implies that $\mathrm{O}(\mathrm{t}|\tau_{\mathrm{i,j}})$is 1 when $t > \tau_{i,1}$ and $t < \tau_{i,2}$ and 0 elsewhere. The summing over N cycles allows for more switching on and off and hence longer optimization horizons. To secure feasible control signals where aeration is turned on and off within reasonable time limits, we constrain the length of aeration periods and periods without aeration as presented in (5) to (6)

$$\mathrm{A}_{\mathrm{on,min}} \le \tau_{\mathrm{i,2}} - \tau_{\mathrm{i,1}} \le \mathrm{A}_{\mathrm{on,max}} \tag{5}$$

$$\mathrm{A}_{\mathrm{off,min}} \le \tau_{\mathrm{i+1,1}} - \tau_{\mathrm{i,2}} \le \mathrm{A}_{\mathrm{off,max}} \tag{6}$$

Now the effect of control on the ASP in terms of changing $\tau_{\mathrm{i,j}}$ can be estimated by inserting $\mathrm{O}(\mathrm{t}|\tau_{\mathrm{i,j}})$ into (3) and thus an arbitrary MPC objective function can be evaluated.

Here the purpose is to minimize environmental impact of the ASP by using predictive control. Hence we define environmental impact of the ASP as eutrophication potential and GWP. We note, that this is a limitation which ignores some impacts, including acidification. Furthermore, we only consider nitrogen in the following forms: ammonium (NH_4), Nitrate (NO_3) and Nitrous Oxide (N_2O). Hence the control with minimal environmental impact is found as the solution to (7) with respect to the soft constraints in (8) and the hard constraints in (5) and (6).

$$\min_{\tau_{ij}} \int_{\mathrm{t_0}}^{\mathrm{t_0+x}} [\mathrm{GWP_{CO2}}(\mathrm{O}(\mathrm{t}|\tau_{\mathrm{i,j}}), \mathrm{E_{CO_2}})/\mathrm{C_1} + \mathrm{GWP_{N2O}}(\mathrm{NH_4}(\mathrm{O}(\mathrm{t}|\tau_{\mathrm{i,j}})), \mathrm{P_{N_2O}}, \mathrm{C_{N_2O}})/ \\ \mathrm{C_1} + \mathrm{Eut}(\mathrm{NH_4}(\mathrm{O}(\mathrm{t}|\tau_{\mathrm{i,j}})), \mathrm{NO_3}(\mathrm{O}(\mathrm{t}|\tau_{\mathrm{i,j}})), \mathrm{C_{NH_4}})/\mathrm{C_2}]\mathrm{dt} \tag{7}$$

Subject to

$$E[NH_4]_{24h} \le L_1, \quad \mathrm{E}[\mathrm{NH_4} + \mathrm{NO_3}]_{24\mathrm{h}} \le \mathrm{L_2} \tag{8}$$

Where the components are further described and presented in Table 2. This formulation implies that the optimal aeration signal can be found by predicting ammonium and nitrate as a function of $\tau_{\mathrm{i,j}}$ concentrations with an adequate solver.

Table 2: Components used in the optimization of environmental impact

Name	*Short description*	*Value range*
C_1	Conversion factor from CO_2-eq to comparable environmental impact as given by Miljøministeriet (2005)	[9.135;9.744]tonnes-CO_2-eq/pers/year
C_2	Conversion factor from NO_3-eq to comparable environmental impact as given by Miljøministeriet (2005)	[120.65;399.32] kg-NO_3-eq/pers/year
C_{N2O}	Conversion factor from released N_2O to CO_2-eq	310 CO_2-eq/N_2O
C_{NH4}	Conversion factor from released NH_4 to NO_3-eq	3.64 NO3-eq/NH_4
E_{CO2}	The GWP related to electricity production as given by Energinet (2019)	[38;461]CO2-eq/kWh
Eut	Calculation of eutrophication potential of released NH_4 and NO_3	
$E[NH_4]_{24h}$	The mean value of effluent ammonium over 24 hours	

$E[NH_4 + NO_3]_{24h}$	The mean value of effluent ammonium plus nitrate over 24 hours	
GWP_{CO2}	Linear conversion of a given control sequence to the related GWP	
GWP_{N2O}	Linear conversion of removed NH_4 to released N_2O and conversion to corresponding CO_2-eq	
L_1	The legislational requirement for effluent ammonium	[1; 4]mgN/L
L_2	The legislational requirement for total – N	[6; 10]mgN/L
NH_4,NO_3	Predictions of ammonium and nitrate as a function of O.	[0;10] mgN/L
O	The decision on when to turn aeration on and off during the optimization period.	0: aeration off 1: aeration on
P_{N2O}	Percentage of removed NH_4 that is converted to N_2O as given by IPCC (2006) and Delre (2018)	[0.035; 5.2] %
x	Length of period to optimize control	24 hours

To illustrate how different constants and electricity production GWP effect how optimal control looks, We use data from a medium sized (30.000 PE) recirculation plant with alternating operation. Online measurements (ammonium and nitrate concentrations, aeration signal) provide the data background for fitting a model of the plant as described in Stentoft et al (2018).

we look at two different scenarios, S1 and S2:

- **S1** puts a higher weight on CO_2-eq from N_2O, assuming that 1% of N is transformed into N_2O (P_{N2O} = 1%). Eutrophication potential is calculated using C_2 = 399.32 kg-NO_3-eq/pers/year meaning that it is weighted less
- **S2** puts a lower weight on CO_2-eq from N_2O, assuming that 0.035% of N is transformed into N_2O (P_{N2O} = 0.035%). Eutrophication potential is calculated using C_2 = 120.65 kg-NO_3-eq/pers/year meaning that it is weighted more

In both scenarios a GWP conversion, C_1 = 9.44 tonnes-CO_2-eq/pers/year, is used.

Results and Discussion

Figure 1 shows the results of the control scenarios resulting in minimal environmental impacts under scenario S1 and S2, subdivided into the components of the objective function (eq. 1). It is seen that the magnitude of the different components of the varies heavily depending on the assumptions regarding normalization and production of nitrous oxide. The totals are found to 0.0513 for S1 and 0.0794 for S2. In Table 3 we calculate the relative difference between the resulting control of the two minimizations by assuming the same constants govern the eutrophication and nitrous oxide production.

In Table 3 we see the relative difference between S1 and S2. S1 prioritizes GWP more and hence CO2 emissions related to electricity consumption and nitrous oxide emissions are lower in S1. On the other hand, eutrophication potential is lower in S2 as expected because of the difference in C_2. This indicates that the optimization is driven towards minimizing the effluent concentration and hence minimizing the environmental impact caused by eutrophication.

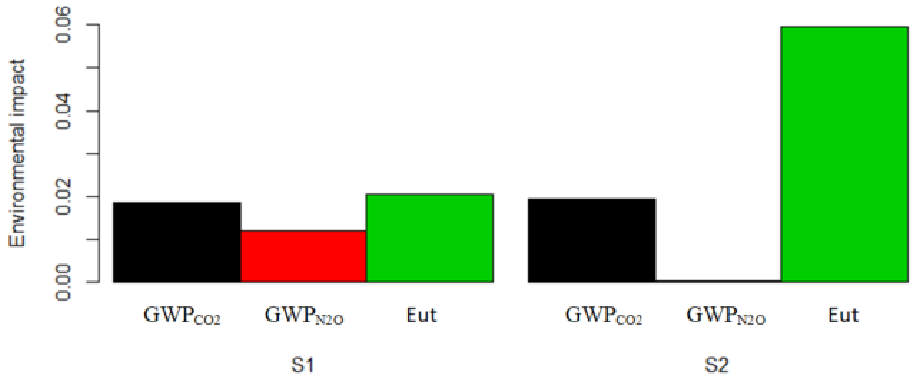

Figure 1 The optimal control with respect to S1 and S2 divided into the components of the objective function (1). Note that there are large differences in the contributions of Eutrophication and GWP (related to nitrous oxide) in the two scenarios.

Table 3 Summary of differences between S1 and S2. Percentages are S1 relative to S2.

Difference in CO_2-eq emissions related to GWP_{CO2}	-5%
Difference in N_2O emissions as calculated in GWP_{N2O}	-1.2%
Difference in Eutrophication in NO_3-eq	+13%

However, this is strongly impacted by the assumptions of the value of C2, which should be carefully considered, when making these types of optimization and evaluations. Hence it indicates that different environmental impacts can be prioritized in the control of an ASP by choosing weights and constants adequately to the case.

We remark that some components are not included or simplified in this optimization and thereby leaving space for further development. This includes acidification related to effluent ammonia and GWP related to methane and CO_2 emissions from the ASP. Furthermore nitrous oxide emissions are estimated using a fixed rate, and hence the dynamics of nitrous oxide production are not caught. This implies that for improved model predictive control, states governing released N_2O should be included in the SASM. Lastly, comparisons with an economic MPC would benefit a discussion of “optimal control” as it would highlight the related costs.

Conclusions

A predictive control strategy that optimizes environmental impact from activated sludge processes (ASP) is developed. The strategy is tested with two different assumptions regarding nitrous oxide emissions and eutrophication. Comparison shows a difference in global warming potential and eutrophication potential, and hence this is considered a step towards prioritizing different environmental impacts in the ASP.

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