

# Integrated model predictive control of water resource recovery facilities and sewer systems in a smart grid: example of full-scale implementation in Kolding

P. A. Stentoft, L. Vezzaro , P. S. Mikkelsen , M. Grum, T. Munk-Nielsen, P. Tychsen, H. Madsen and R. Halvgaard

## ABSTRACT

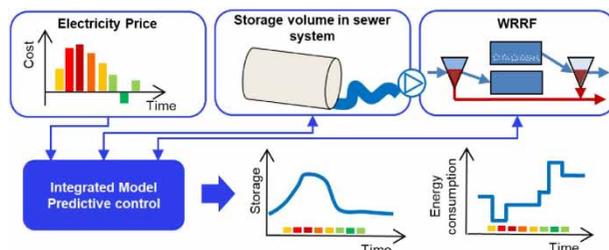
An integrated model predictive control (MPC) strategy to control the power consumption and the effluent quality of a water resource recovery facility (WRRF) by utilizing the storage capacity from the sewer system was implemented and put into operation for a 7-day trial period. This price-based MPC reacted to electricity prices and forecasted pollutant loads 24 hours ahead. The large storage capacity available in the sewer system directly upstream from the plant was used to control the incoming loads and, indirectly, the power consumption of the WRRF during dry weather operations. The MPC balances electricity costs and treatment quality based on linear dynamical models and predictions of storage capacity and effluent concentrations. This article first shows the modelling results involved in the design of this MPC. Secondly, results from full-scale MPC operation of the WRRF are shown. The monetary savings of the MPC strategy for the specific plant were quantified around approximately 200 DKK per day when fully exploiting the allowed storage capacity. The developed MPC strategy provides a new option for linking WRRFs to smart grid electricity systems.

**Key words** | control, electricity price, optimization, smart water

## HIGHLIGHTS

- A model predictive control strategy to control pumping power consumption and effluent quality was implemented.
- The strategy considers electricity prices to prioritize pumping 24 hours ahead.
- The strategy was tested full-scale as it was put into operation for a total of 7 days.
- The strategy demonstrated savings of approximately 200 DKK per day.

## GRAPHICAL ABSTRACT



This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY 4.0), which permits copying, adaptation and redistribution, provided the original work is properly cited (<http://creativecommons.org/licenses/by/4.0/>).

doi: 10.2166/wst.2020.266

P. A. Stentoft (corresponding author)

L. Vezzaro 

M. Grum<sup>†</sup>

T. Munk-Nielsen

P. Tychsen<sup>‡</sup>

R. Halvgaard<sup>§</sup>

Krøger A/S, Veolia Water Technologies,  
Søborg,  
Denmark

E-mail: [pas@kruger.dk](mailto:pas@kruger.dk)

P. A. Stentoft

H. Madsen

Department of Applied Mathematics and  
Computer Science,  
Technical University of Denmark,  
Kongens Lyngby,  
Denmark

L. Vezzaro

P. S. Mikkelsen 

Department of Environmental Engineering,  
Technical University of Denmark,  
Kongens Lyngby,  
Denmark

<sup>†</sup>Current address: DHI Denmark, 5 Agern Allé,  
Hørsholm, DK-2970, Denmark

<sup>‡</sup>Current address: WaterZerv, Founders House,  
Njalsgade 19D, 2300 Copenhagen

<sup>§</sup>Current address: Lobster, Folevadsvej 18,  
2400 København

## INTRODUCTION

The transition towards an increasing share of renewable energy sources is an essential step to reduce CO<sub>2</sub> emissions and mitigate severe climate change. This transition requires the implementation of *smart grids*; that is, making electrical grids able to cope with highly fluctuating sources (such as wind and solar power) while being able to match supply and demand (Jørgensen *et al.* 2018). This can be obtained by either storing the electricity for later use or by modifying the consumption accordingly. Since energy storage is currently very expensive, a cheaper alternative is to modify the power consumption of flexible consumers by using intelligent control and communication methods (Madsen *et al.* 2015). The fluctuations in the electricity prices provide economic incentives to implement flexible controls of electricity consumption. This concept is also referred to as Demand Response (Palensky & Dietrich 2011; O'Connell *et al.* 2014).

As discussed in Olsson (2015), there is a great potential for interactions between the energy and the water sector. Integrated operation of urban wastewater systems or minimization of energy consumptions have been investigated by, for example, Kroll *et al.* (2018), who found that synchronizing sewer storage volume with WRRF aeration control led to savings of 2.5% in total energy and improved TN effluent as well as CSO activity. When looking at applications of Demand-Response systems, examples are mostly found for water supply systems, with examples focusing on energy optimization of wellfield operation for groundwater extraction (Bauer-Gottwein *et al.* 2016), or for pumping and treatment (Zimmermann *et al.* 2018). Wastewater transport and treatment can also potentially be integrated into a smart grid due to their large and geographically distributed consumption (Thompson *et al.* 2008; Reinhofer-Gubisch & Pucker 2014; Kirchem *et al.* 2018).

The idea of including electricity prices into control and operation of water resource recovery facilities (WRRFs) was first mentioned in Tassou (1988) over three decades ago. Aymerich *et al.* (2013, 2015) simulated the minimization of aeration costs based on varying energy tariffs through an ammonium controller and a modified BSM1 model (Gernaey *et al.* 2014). Savings were in the range of 4–11% while maintaining effluent quality, and storing peak flows in expensive energy periods resulted in 13% savings. Stentoft *et al.* (2019a) showed up to 21% reduction in costs of effluent taxes and electricity by using variable electricity prices in a model predictive control (MPC) strategy as compared with a

rule-based control. Brok *et al.* (2019) showed a methodology to incorporate flexibility in aeration control for providing flexibility on short term electricity markets (i.e. providing regulating power capacity). These controls sometimes increased the total energy consumption, but lowered the total cost when moving the peak consumption to cheaper operating hours, and the savings depend on various performance criteria. Beltrán *et al.* (2013) furthermore minimized aeration costs based on a model that can be extended to include time-varying electricity costs, and Douglass *et al.* (2012) and Kebir *et al.* (2014) mainly considered the pumps at the WRRF as flexible on short-term electricity markets. ESWA (2014) also demonstrated Demand-Response savings in Denmark.

In practice, connecting a WRRF within Demand-Response systems requires the ability to buffer the incoming wastewater and delay wastewater treatment to periods with cheaper electricity prices while complying with environmental discharge regulations. This implies the ability to store wastewater during high-price periods. This storage is usually available in combined sewer systems, which are designed to cope with the high flows taking place during wet weather periods. In fact, combined sewer systems are in dry weather conditions during most of their operational time; that is, there is an excess storage capacity that can be used to delay power consumption for pumping and treatment. Also, an integrated MPC is needed in order to comply with environmental discharge limits, avoid an increase in flooding risk, and minimize the WRRF operational costs based on forecasts of incoming pollutant loads and future electricity prices. Although there are several applications of MPC in combination with Demand Response in, for example, chemical manufacturing plants (Mendoza-Serrano & Chmielewski 2013) or supermarket refrigeration (Hovgaard *et al.* 2012), no examples are yet found in literature for integrated urban wastewater systems.

In this paper, we propose an integrated MPC strategy connecting WRRFs and sewer systems and offering flexible energy consumption in a smart grid system. We apply a Demand-Response control to exploit the excess storage capacity in the sewer system in order to change the WRRF power consumption according to electricity prices. Because of this Demand-Response setup, the method will be directly applicable in the remaining part of the Nordic electricity market. Furthermore, it is believed that only a few modifications in the correspondence time and prediction horizon

will be needed to apply in other markets worldwide. Since the major energy-demanding process is wastewater aeration to remove nitrogen, we consider the total nitrogen in the effluent as a measure of treatment quality. We show how to implement an MPC strategy that changes the inlet flow to the WRRF and minimizes the electricity costs while keeping effluent quality within regulatory limits. After testing the strategy in a simulation study, we provide results and evaluate the performance from actual operation of the Kolding WRRF, Denmark.

## MATERIAL AND METHODS

### Case study

#### The Kolding integrated catchment

The integrated MPC was developed and tested for the integrated system (combined sewer and WRRF) in Kolding, Denmark. The hydraulic performance and the availability of storage volumes in the combined sewer system for control purposes was investigated in Bjerg *et al.* (2015). Wastewater from the Kolding urban area is conveyed to a pumping station, which pumps it to the 125,000 PE WRRF located 8 km away. There are 21 storage basins spread across the catchments, with a total storage volume of 30,000 m<sup>3</sup>. However, for this initial study, only a large storage pipe located upstream of the plant inlet (with a volume of approximately 6,000 m<sup>3</sup>) is considered. A water level sensor is located in the pipe and used to estimate the stored water volume.

The Kolding WRRF utilizes the BioDenitro process (Bundgaard *et al.* 1989) for N removal, with two alternating aeration tanks for each of the two plant lines. The maximum power capacity for the biological aeration process is 720 kW, and aeration is responsible for at least 60% of the power consumption of the WRRF, in line with similar values found in literature (Plappally & Lienhard 2012; Gu *et al.* 2017).

The plant electricity bill is currently paid via a retailer, EnergiDanmark, and a small part of the price changes every hour. This hourly price is known 12 to 36 hours ahead and originates from the power exchange NordPools day-ahead market. The estimated yearly consumption of the Kolding is 2.7 GWh.

#### Electricity price

In Denmark, larger consumers with an annual energy consumption above 100 MWh are billed an hourly

time-varying electricity price, the Elspot price. This price is settled every day at noon for the coming day from midnight to midnight in the different geographical areas of the electricity market. Consequently, after settlement at noon, the price is known 36 hours ahead. Before settlement at noon, the price is known and fixed at least 12 hours ahead. Our prediction horizon is  $N_p = 24$  hours, so consequently we need forecasts of the price from midnight to noon where the price is known less than 24 hours ahead. EnergiDanmark, the Balance Responsible Party of Kolding WRRF, provides online forecasts of the price. Modelling and forecasting this price is not part of this work, but details can be found in Jónsson *et al.* (2013). Due to the composition of the Danish electricity system, wind power plays a major role in price fluctuations (Jónsson *et al.* 2013); that is, a higher share of renewables sources results in lower electricity prices.

#### Effluent concentration limits and taxation

The maximum allowed discharge concentration for total nitrogen is  $S_{N,max}$  8 mgN/l. In addition, the Danish legislation imposes taxation on pollutant loads discharged by WRRFs, with the fee for total nitrogen set at  $p_{fee} = 30$  DKK/kgN for 2019–2020. The taxed annual loads are calculated based on 24-hr composite samples that are collected at fixed intervals (2–4 weeks according to the plant capacity). These discrete concentration values are combined and then multiplied by the total annual discharged volume.

#### Overall MPC strategy

In model predictive control of integrated sewer and wastewater systems, the optimal control is recursively recalculated over a specified, finite time horizon (here  $N_p = 24$  hours) based on current and updated information about the state of the system as well as information about future inputs to the system. For this purpose, an MPC model with associated forecasts of the inlet flow, effluent quality and power consumption is needed, and an MPC optimization model, needs to be specified. The MPC operates only in dry weather conditions. When rainfall is predicted by Numerical Weather Predictions (similarly to the example presented by Courdent *et al.* (2017)), the integrated system switches to a rule-based wet-weather control, aiming at minimizing the risk of combined sewer overflows.

## MPC model structure and input forecasts

### System conceptualization

The Kolding integrated wastewater system is schematized in Figure 1. The storage pipe upstream from the pumping station is described by the volume  $V$ , while its inflow is defined as  $\hat{q}_{in}(t)$ . The only actuator controlled by the MPC is the pumping station, and the control strategy defines setpoints for the outflow  $q(t)$  from the pumping station (i.e. the inflow to the WRRF). The MPC only controls the pumps that are normally active during dry weather and hence, for full-scale tests, the upper bound on  $q(t)$  is lower than the true. The WRRF is described as a noncontrollable unit that removes the nitrogen in the incoming wastewater load; that is, aeration is controlled by the existing WRRF control. The WRRF effluent concentration is defined as  $S_N$  (mg/l).

The total energy consumption  $u$  is the sum of the energy consumption for pumping ( $u_{pump}$ ) and aeration ( $u_{WRRF}$ ), both expressed as kW.

The water balance in the storage volume  $V$  [l] is defined as:

$$\frac{dV(t)}{dt} = q_{in}(t) - q(t) \quad (1)$$

The volume and the flow are physically limited and must lie within some operator-specified bounds to avoid an increased risk of overflows and flooding.

### Dry weather inlet flow forecast

The diurnal inlet flow during dry weather to the storage pipe  $\hat{q}_{in}(t)$  is often modelled as a second order Fourier series (Langergraber et al. 2008). Using a period of  $T=24$  h, the model is locally linear with frequency  $\omega = 2\pi/T$ . The parameters  $a$  and the flow  $q_{in}$  can be estimated for each time step as a least squares optimization problem:

$$\text{minimize} \int_{t-T}^t W(t)(\hat{q}_{in}(t) - q_{in}(t))^2 dt \quad (2a)$$

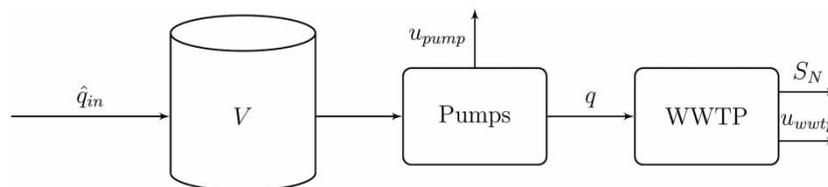


Figure 1 | Simplified control architecture of the integrated system.

$$\text{with } \hat{q}_{in}(t) = a_0 + a_1 \sin(\omega t) + a_2 \cos(\omega t) + a_3 \sin(2\omega t) + a_4 \cos(2\omega t) \quad (2b)$$

$$q_{in}^{min} \leq \hat{q}_{in}(t) \leq q_{in}^{max} \quad (2c)$$

The flow constraints ( $q_{in}^{min}$ ,  $q_{in}^{max}$ ) ensure positive flows. Exponential weights  $W$  are used to prioritize the newest measurements in the parameter estimation dataset (e.g. Madsen 2008). Wet weather periods are removed from the estimation data set by eliminating inlet flows above a certain threshold. This approach is useful for describing slowly varying parameters, and the model adapts to changing conditions and long term variation in the parameters. The estimate is run with same frequency as the MPC (hourly time steps).

### Effluent quality model

The main control inputs of the BioDenitro process are phase time and aeration intensity (Isaacs et al. 1995). The effect of these on nutrient removal can be modelled effectively using real-time nutrient measurements in the data-driven modelling framework suggested in Stentoft et al. (2018). However, as the investigated MPC controls the effluent quality and the power consumption by manipulating the plant inflow  $q(t)$  and hence not the before-mentioned signals. Therefore, the MPC requires an even simpler model that does not use online nutrient measurements but yet describes the short term nitrogen removal processes over the time horizon used for optimization (here, 24 hours). Based on hourly time steps, the following linear model was found by visual inspection to fit the effluent concentrations in a satisfactory manner:

$$\frac{dS_N(t)}{dt} = \theta_0 + \theta_1 S_N(t) + \theta_2 q(t) \quad (3)$$

where  $\theta_i$  are coefficients to be estimated. The total effluent nitrogen concentration  $S_N$  is approximated by using the 2-min concentration measurements of  $NH_4$  and  $NO_3$  from the aeration tank. These measurements are resampled to

hourly values and then used as a model estimation data set. The coefficients  $\theta_i$  and the current total N ( $S_N$ ) concentration are continuously estimated by using Maximum Likelihood Estimation and a Kalman Filter (Kristensen et al. 2004). These methods are implemented in the R-package ctsmr (Juhl et al. 2016; R Core Team 2019). The Kalman Filter also estimates the missing observations in the dataset.

During normal pump operations, flow and effluent concentrations appear to be correlated and to show a daily pattern. However, this correlation decreases once the MPC is implemented. Storing wastewater in the storage volume  $V$  may furthermore build up the  $\text{NH}_4$  concentration in a non-linear way that is not taken into account in Equation (3). However, since no water quality measurements are available in the combined sewer system to model such behaviour, this was neglected in this first version of the MPC.

### Power consumption model

Figure 2 shows measurements of the pumping flow rate  $q(t)$  along with the corresponding pump power consumption  $u_{\text{pump}}$ . While the pumping power consumption for a single pump usually grows quadratically with flow, the pumping station in Kolding includes a set of pumps that operate in different flow setpoint intervals. This leads to a more complex relationship between flow and power consumption, which is still, considering the local and short-term dynamics, approximately linear:

$$u_{\text{pump}} = \theta_u^0 + \theta_u^1 q \quad (4)$$

where  $\theta_u$  are coefficients to be estimated.

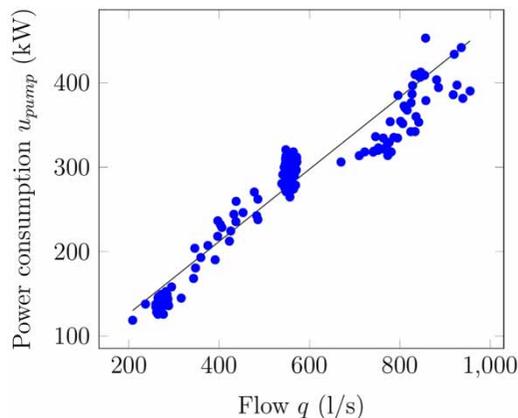


Figure 2 | Power consumption and flow rate in the sewer pumping system. 24 hours of data from November 2015 resampled to 10 min values.

Similar to Bjerg et al. (2015), a linear relationship is assumed between flow and power consumption at the WRRF:

$$u_{\text{WWTP}} = \theta_u q \quad (5)$$

with  $\theta_u = 0.174 \text{ k Wh/m}^3$ .

### MPC optimization model

A linear objective function is used to formulate an Economic MPC (Jørgensen et al. 2011; Halvgaard et al. 2012) in order to control the system. Compared to traditional control methods, MPC takes any variable constraints and predictions into account, and it is able to react ahead of time. In this case the MPC moves power consumption to periods with cheaper electricity and larger shares of wind power, while meeting the treatment objectives.

### Minimizing electricity cost

The controlled pump flow rate  $q(t)$  is formulated as a vector  $q \in \mathbb{R}^{N_p}$  over the prediction horizon of  $N_p$  samples (with sampling period of 1 hour and  $N_p = 24$ ). So  $q$  contains one flow setpoint for each hour the next 24 hours. After finding the optimal flow set points, only the first value for the current time step is sent to the pumping station and actuated. This process is repeated in the following time step when new measurements and predictions are available, providing closed-loop feedback and adjusting for model and prediction errors.

The following optimization problem defines the MPC that calculates the optimal pumping flow rate setpoints given a forecast of electricity prices and inlet flow:

$$\text{minimize } \rho^T s + P_{\text{elspot}}^{*T} u \quad (6a)$$

$$\text{subject to } \frac{dV(t)}{dt} = q_{\text{in}}^* - q \quad (6b)$$

$$V_{\text{min}} - s \leq V(t) \leq V_{\text{max}} + s \quad (6c)$$

$$s \geq 0 \quad (6d)$$

$$u = u_{\text{pump}}(q) + u_{\text{WWTP}}(q) \quad (6e)$$

$$q_{\text{min}} \leq q \leq q_{\text{max}} \quad (6f)$$

$$\Delta q_{\text{min}} \leq \Delta q \leq \Delta q_{\text{max}} \quad (6g)$$

$$\Delta q = q_k - q_{k-1} \quad (6h)$$

where  $P_{\text{elspot}}^*$  is the Elspot price forecast;  $u$  is the total power consumption that should be minimized over the price;  $q_{\text{min}}$  and  $q_{\text{max}}$  are the flow setpoint constraints ([0, 900] l/s);  $V_{\text{min}}$  and  $V_{\text{max}}$  are the storage volume constraints, which were set to [1,500, 5,500] m<sup>3</sup> in the demonstration period;  $\Delta q_{\text{min}}$  and  $\Delta q_{\text{max}}$  limit the hourly changes in flow set points. These act as a tuneable smoothing effect of the controlled flow that prevents hydraulic waves to the WRRF, and they were set to  $\Delta q_{\text{max}} = q_{\text{max}}/5$  and  $\Delta q_{\text{min}} = -q_{\text{max}}/5$ .

If the volume exceeds the capacity, a slack variable  $\rho \in \mathbb{R}^{N_p}$  accounts for the overflow volume in dry weather (i.e. to avoid unwanted spills of the stored wastewater). This is heavily penalized in the objective function by using a high cost ( $\rho = 1,061$ ). The slack variable is not only a measure of the overflow, it also makes sure that the optimization problem is feasible even though a small overflow might exceed the constraints, for example due to uncertainty in the dry weather flow or noisy volume measurements near the constraints. The volume measurement error is assumed to be negligible compared to the volume size, and thereby no data assimilation is included to update the modelled storage volume. MPC aiming at reducing CSO in wet weather typically adopt additional terms to increase robustness (e.g. penalization of stored volumes). These would however be in direct contrast with the objective of the proposed approach, which only operates in dry weather.

### Minimizing electricity cost and respecting regulatory effluent quality limits

In the MPC problem, the effluent concentration  $S_N$  is assumed to be a continuous variable that must be minimized. The average effluent concentration is:

$$\tilde{S}_N = \frac{\int_0^T q(t)S_N(t)dt}{\int_0^T q(t)dt} \quad (7)$$

where the plant effluent is assumed to equal the influent to the plant,  $q(t)$ . The nitrogen load  $\tilde{m}_N$  used for taxation can then be expressed as:

$$\tilde{m}_N = \int_0^T q(t)S_N(t)dt \quad (8)$$

Combining the flow weighted effluent quality model (Equation (3)) with the MPC optimization model (Equation

(6)) results in the following problem:

$$\text{minimize } \rho^T s + P_{\text{elspot}}^{*T} u + P_{\text{fee}} \tilde{m}_N(q) \quad (9a)$$

$$\text{subject to: } S_N \leq S_N^{\text{max}} \quad (9b)$$

$$(3), (6b), (6c), (6d), (6e), (6f), (6g) \quad (9c)$$

The objective function has a non-linear term  $\tilde{m}_N(q)$  defined in Equation (8) as the product between two of the optimization variables. This nonlinear term is replaced by an impulse response model of Equation (3) with impulse response matrix  $H_u$ . The objective term then changes to

$$P_{\text{fee}} \tilde{m}_N(q) = P_{\text{fee}} q^T H_u(\theta) q + p_0^T q \quad (10)$$

with the constant vector  $p_0 = (H_0 x_0 + H_d d) p_{\text{fee}}$ . This transforms the problem from Equation (9) into a Quadratic Programming (QP) problem. The MPC now reflects the most important economic operation costs.

### Solving the MPC optimization problem

A MPC problem can be formulated on a more general form as:

$$\text{minimize } x^T H x + g^T x \quad (11a)$$

$$\text{Subject to } A x \geq b \quad (11b)$$

The MPC problem described previously in (6) has only a linear objective term (i.e.  $H=0$  in Equation (11a)), and it can be solved by using a Linear Programming (LP) solver in R (Berkelaar et al. 2015). Consequently, the differential Equation (6b) can be rewritten as a sum of matrix vector multiplications; that is, the impulse response model (Prasath & Jørgensen 2008). This impulse response model fits into the solver as the linear matrix inequality (11b). This implies that the MPC optimization problem (Equation (9)) can be managed by converting it to a standard Quadratic Programming (QP) form (11) where the optimization variables are augmented in  $x = [q^T; u^T; s^T]^T$ . This problem can be solved by using a QP solver, which finds the optimal  $x$  that minimizes the objective function. The QP solver from the R-library quadprog (Goldfarb & Idnani 1983; R Core Team 2019) was used in this study. Running this solver on the WRRF control system hardware solves this relatively small convex MPC problem in milliseconds.

## MPC performance evaluation

### Electricity savings

The MPC described in Equation (6) (focusing only on electricity cost minimization) was simulated by using the measured inlet flows from a 160 day period starting on 1 September 2015. Electricity prices and future inlet flows were assumed to be known; that is, these simulations indicate the upper bound for the performance of the MPC.

### Effluent quality and electricity savings trade-off

The trade-off between electricity costs and effluent quality was investigated by using the MPC from Equation (9) with a different objective function:

$$\alpha p_{fee} \tilde{m}_N + (1 - \alpha) p_{elspot}^T u \quad (12)$$

In this formulation, a tuneable parameter  $\alpha \in [0; 1]$ , weighting the trade-off between the effluent quality and electricity cost savings for one particular day, is introduced. When  $\alpha = 1$ , only the effluent quality is maximized. When  $\alpha = 0$ , the power consumption is moved to the cheapest period possible without taking effluent quality into account.

### Full-scale demonstration

The MPC was tested in full-scale operations for 2 and 5 days in November and September 2015, respectively.

## RESULTS AND DISCUSSION

### Dry weather inlet flow forecast

An example of the fitted inlet flow forecast model is shown in Figure 3, which shows the hourly measurements of the inlet flow  $q_{in}(t)$  over one day, along with fitted the Fourier series model and the expected future (i.e. forecasted) inlet flow for the next 24 hours.

### Modelled MPC performance

#### Electricity savings

Figure 4 shows the daily savings obtained for the 160 days simulation period with average daily savings of 170 DKK/day

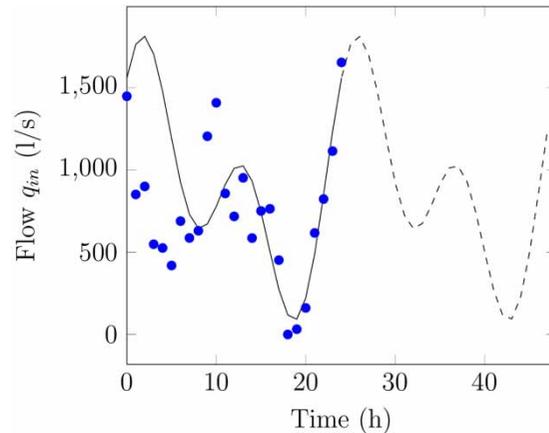


Figure 3 | Example of inlet flow measurements (dots), model fit (solid line), and prediction (dashed line).

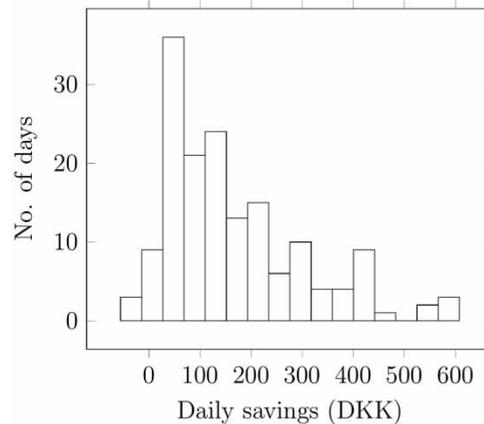
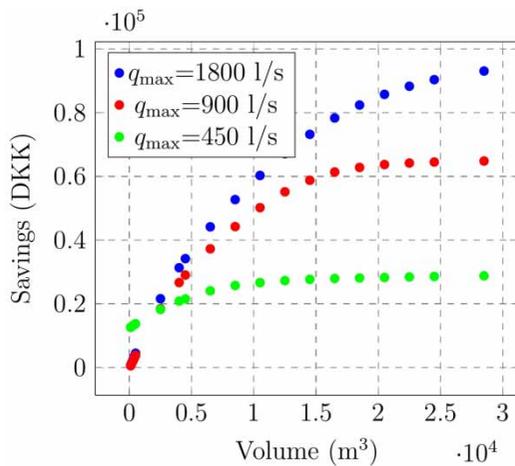


Figure 4 | Histogram of simulated daily savings over 160 days (7.5 DKK = 1 EUR).

relative to the normal operation where the dry weather flow is sent directly to the WRRF. Figure 5 shows the value of potentially using additional storage basins across the catchments and thereby increasing the storage volume and increasing the maximum pump flow  $q_{max}$  from Equation (6f). After a certain volume, the increase in the savings slowly decline. The savings can also be boosted by increasing the allowed maximum flow. Indeed, to fully exploit the storage capacity available in the system (above 30,000 m<sup>3</sup>), a high  $q_{max}$  should be used. This is particularly interesting, as most implementations of the algorithm will require considerations of the upper bound on the volume,  $V_{max}$ . In this context,  $V_{max}$  close to the actual physical limit for CSOs means that the system is not very robust against unpredicted events, without providing significant improvements in terms of savings. Hence, changing  $V_{max}$  represents a trade-off between savings and robustness.

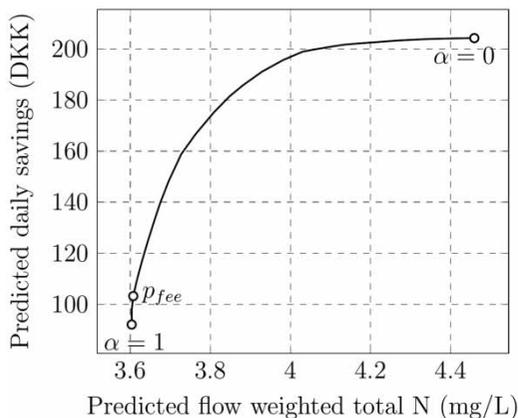


**Figure 5** | Savings from electricity costs over 160 days as a function of the flexible volume size and the maximum pump flow. Changing the flexible volume size corresponds to changing the volume constraints in the MPC.

Note that the effluent concentrations are not included in this approach, and hence the regulatory fee is not included in the savings. This is however discussed using (12) in the next section.

### Effluent quality and electricity savings trade-off

Figure 6 shows the trade-off between effluent quality and electricity costs when  $\alpha$  is varied between 0 and 1. The savings and effluent quality were calculated for a single open-loop trajectory that provided the optimal flow setpoints over one day. However, the MPC optimization model in Equation (9) has real prices as weights in the objective



**Figure 6** | Tradeoff between effluent quality ( $S_N$ ) and savings in electricity costs for the MPC optimization (9) with the tunable objective function (12). The calculations were based on predicted open-loop trajectories at 3 November 2015 09:00. The point  $p_{fee}$  indicates the point where the actual economic values of the electricity prices and the regulatory fee together determine the objective function weights.

function and it is not tuneable. However, it is possible to find the point when the weights are equal to the actual prices; that is, the current regulatory fee  $p_{fee} = 30$  DKK/kg and the Elspot prices for that chosen day. As expected, the higher regulatory fee reduces the potential electricity cost savings on the particular day, as shown in Figure 6, but it reduces the emission of nitrogen to the environment. This is because a higher regulatory fee implies a lower weight on the electricity prices in the optimization of the economical objective function (12), and hence the daily savings in electricity costs are lowered. However, it is noted that the total savings (including electricity and fee) might not be equally lowered.

### Full-scale demonstration

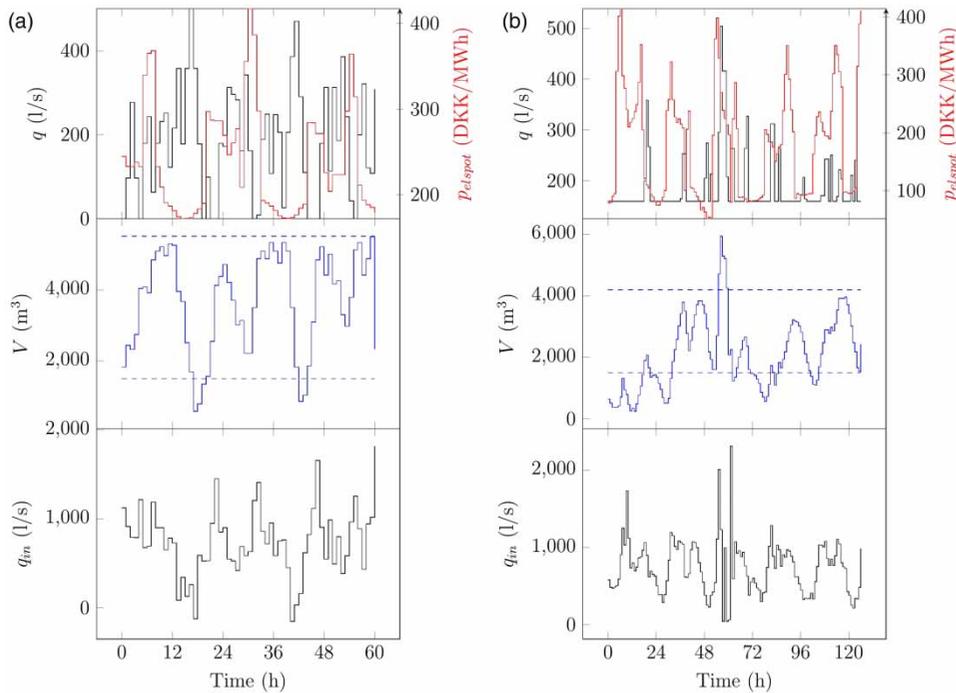
Figure 7 shows how the MPC optimization aimed at minimizing electricity costs (Equation (6)) controlled the flow in full-scale operation for 2 and 5 days in November and September 2015. The MPC adjusted the flow setpoint  $q$  based on the predictions of both the electricity price and the incoming flow. It did not take the effluent quality into account, but it did include the power consumption.

The uppermost plot in Figure 7(a) shows how the flow setpoint is high during periods with low electricity prices and low during periods with high electricity prices. The middle plot shows the volume and the volume constraints. The lower bound is violated a few hours during two of the days. The main reason is the uncertainty in volume measurements at low storage volume.

The uncertainty in volume measurements also influences the estimation of low inlet flows: in fact, this was negative during these periods (bottom plot). The controller truncated all inlet flows below zero and did not account for this error.

Other factors impacting the constraint violations were inlet flow forecast errors and rate of flow setpoint change limitations. Faster sampling time and robust handling of uncertainty could eliminate some constraint violations. One computationally efficient way of dealing with this uncertainty is simply to tighten the volume constraints a bit. The error in flow forecasts might also lead to suboptimal control actions. This is for instance likely to be the case in Figure 7(a) at hour 37. Here pumping is reduced only to increase pumping in the following hour where electricity is more expensive. However, looking at the actual inflow in this period, it seems to follow a diurnal variation poorly.

The other test period depicted in Figure 7(b) also shows some problems with constraint violations. However, from



**Figure 7** | Results from full-scale operation of the MPC optimization aimed at minimizing electricity costs (Equation (6)). (a) 61 hours from 2 November 2015 at 06:00.  $q_{min} = 0$  l/s. (b) 127 hours from 30 September 2015 at 00:00.  $q_{min} = 160$  l/s,  $q_{max} = 520$  l/s. The lower plot shows the inlet flow to the controlled pipe volume. The middle plot shows the measured volume and its constraints. The upper plot shows the pumping flow rate determined by the MPC and the actual electricity prices.

the bottom plot it is obvious that the volume constraint violation was caused by sharp spikes in the dry weather flow (e.g. wastewater discharges deviating from typical daily profiles) that are not accounted by the dry weather forecast model. This stresses the fact, that for the general application of this methodology,  $V_{max}$  must be chosen wisely by including a safety margin to account for uncertainty in the inlet forecast model. In this test period, the minimum allowed flow setpoint for  $q$  was 160 l/s. Consequently, the controller was forced to pump out water even though the volume was below its minimum constraint. The upper volume constraint is also violated between hours 48 and 72. This is due to bad estimation of the volume caused by uncertain/noisy measurements. It is noted that this did not cause any CSO. Furthermore it is noted that the effluent requirements for the WRRF were satisfied during both entire test periods.

The MPC was also compared against a controller where the diurnally varying dry weather load is sent directly to the WRRF; that is,  $q(t) = q_{in}(t)$ . In practice, the volume is today controlled through rules reacting to volume levels. Unfortunately, the linear model used for including the effluent quality was not sufficient for control in all operating conditions. In future work, this model should be studied in detail using data that cover more operational periods

and/or extended with details describing the control of the WRRF (e.g. by using the model in Stentoft et al. (2018)).

As discussed earlier, the implementation of a new control strategy must not cause CSO events in dry weather. However, erroneous estimations of the stored volume and uncertainty in the inlet forecast might lead to unwanted discharges. Therefore the definition of  $V_{max}$  should include a safety factor with a buffer volume. Additionally, the dry weather forecast model might be improved by, for example, including a stochastic approach. Although negligible, the risk of CSO discharges in dry weather cannot be completely avoided, and it should therefore be included in the multi-criteria analysis performed before choosing to implement the proposed MPC.

Furthermore, there is an additional risk of increasing CSO in wet weather due to errors and false negatives in the NWP used to switch to wet-weather operation (which can e.g. lead to a late emptying of the storage volume). NWP application was discussed by Courdent et al. (2017), while Bjerg et al. (2015) showed a negative limited impact on the performance of the Kolding catchment for a simple energy-based control strategy.

In the 5-day test period the average savings were approximately 200 DKK/day as compared to a similar

historic period. Although such monetary value might appear negligible compared to the overall WRRF costs, this should not shadow the novelty represented by this first application of Demand-Response MPC to a full-scale integrated wastewater system. The entire control of the Kolding integrated system has recently been migrated to a cloud system, allowing integration with other energy based controls (e.g. Stentoft *et al.* 2019a) with possible increase in savings. Investigations of the proposed MPC for catchments with similar energy markets and more favourable characteristics (e.g. gravity driven flow to the WRRF) are suggested.

This simple model structure is in fact well suited for control and it provides an important building block for expanding the control to bigger sewer systems. Electricity prices are usually low in periods with high shares of renewables, so price based control creates an incentive to integrate more wind power in the system. In some hours of the year in Denmark, negative electricity prices are observed due to the high share of wind power in the power system. Prices can also be generated to provide ancillary services like voltage control or congestion management. The importance of these markets (and thereby the economic return) is growing due to the decreasing importance of traditional power plants (currently used for e.g. frequency stabilization) across electricity networks. Since WRRFs electricity demand corresponds to an average of 1% of a country's electricity consumption (Shi 2011), these could provide a substantial capacity reserve in the power markets. In fact, as the need for flexible energy increases (Morales *et al.* 2013), this reserve might become necessary to exploit. Furthermore, investments made by WRRFs to implement the proposed controls would spare society from the need to upgrade the existing infrastructure. These economic savings at the societal level could therefore be acknowledged and re-distributed to WRRF operators through economic incentives (e.g. changes in taxation), decreasing the return of investment of the MPC.

Focusing the MPC on a single performance indicator might lead to a worsening of other aspects, as in the example presented by Flores-Alsina *et al.* (2014). Current research is focusing on testing the proposed MPC on a dynamic WRRF model to allow for a long-term performance analysis for a range of different performance indicators. Following this philosophy, possible extensions of proposed control can include combination with other MPC strategies mainly focusing on control of the removal processes (e.g. Stentoft *et al.* 2019a), boosting their overall performance not only in monetary terms, but also in other performance criteria (e.g. CO<sub>2</sub> emissions, eutrophication impacts, acidification of receiving water bodies etc.) (Stentoft *et al.* 2019b).

## CONCLUSION

This paper illustrates the first application of model predictive control (MPC) in a price-based, Demand-Response set-up to control an integrated sewer-wastewater system during dry weather. The control aims at storing wastewater in the sewer network during periods of high electricity prices, while enabling wastewater treatment in periods when electricity prices are lower. The main findings are as follows:

- The MPC optimized the operation of the WRRF over short-term (24-hour) predictions of the hourly electricity price from NordPool.
- The MPC used several dynamic mathematical models as part of the optimization, including models of the upstream storage volume, the power consumption of the pumps and the WRRF, and the inlet flow to and the effluent quality from the WRRF. Updating these models continuously to measurements allowed using simple and fast model structures sufficiently accurately for this short-term optimization problem.
- The proposed MPC showed its potential both in model simulations and full-scale applications at a medium-sized WRRF in Denmark.
- The monetary savings from the Kolding case study were limited (approximately 200 DKK per day). Additional simulations of the MPC over a longer period of time resulted in similar performance.
- A control method that takes the effluent quality at the WRRF into account by considering the sewer system and the WRRF jointly was also presented.

Although the application to the specific Kolding system did not provide great savings in monetary terms, the structure of the proposed MPC enables an easy application in any other catchment. Hence this can provide an important contribution towards the integration of WRRF and sewer system operation in electric smart grids.

## ACKNOWLEDGEMENTS

This research was funded by Innovation Fund Denmark through the Industrial PostDoc project 'W2E Smart Grid upgrade' and the first author's industrial PhD project 'Stochastic Predictive Control of Wastewater Treatment Processes', and partly by the Danish Council for Strategic Research through the CITIES project no. 1305-00027. Thanks to BlueKolding for providing all plant data.

## REFERENCES

- Aymerich, I., Pellicer, N., Poch, M. & Corominas, L. 2013 Model-based evaluation of cost saving strategies using real market variable energy tariffs. In: *11th IWA Conference on Instrumentation Control and Automation*, 18–20 September 2013, Narbonne, France.
- Aymerich, I., Rieger, L., Sobhani, R., Rosso, D. & Corominas, L. 2015 The difference between energy consumption and energy cost: modelling energy tariff structures for water resource recovery facilities. *Water Research* **81**, 113–123.
- Bauer-Gottwein, P., Schneider, R. & Davidsen, C. 2016 Optimizing wellfield operation in a variable power price regime. *Groundwater* **54**, 92–103.
- Beltrán, S., Irizar, I., Sota, A. D., Villanueva, J. M. & Ayesa, E. 2013 Model-based optimization of aeration systems in WWTPs. In: *11th IWA Conference on Instrumentation Control and Automation*, 18–20 September 2013, Narbonne, France.
- Berkelaar, M. 2015 lpSolve: Interface to 'Lp solve' v. 5.5 to Solve Linear/Integer Programs. Available from: <http://cran.r-project.org/package=lpSolve>
- Bjerg, J. E., Grum, M., Courdent, V., Halvgaard, R., Vezzaro, L. & Mikkelsen, P. S. 2015 Coupling of Weather Forecasts and Smart Grid-Control of Wastewater inlet to Kolding WWTP (Denmark). In: *Proceedings of 10th International Urban Drainage Modelling (UDM) Conference*, 20–23 September 2015, Mont-Saint-Anne, Quebec, Canada.
- Brok, N. B., Stentoft, P. A., Munk-Nielsen, T. & Madsen, H. 2019 Flexible Control of Wastewater Aeration for Cost-Efficient, Sustainable Treatment. In: *Proceedings of CSGRES 2019, Control of Smart Grid and Renewable Energy Systems*, 10–12 June 2019, Jeju, South Korea.
- Bundgaard, E., Andersen, K. L. & Pedersen, G. 1989 BioDenitro and BioDenitro systems – experiences and advanced model development: the Danish systems for biological N and P removal. *Water Science and Technology* **21**, 1727–1730.
- Courdent, V., Grum, M., Munk-Nielsen, T. & Mikkelsen, P. S. 2017 A gain-loss framework based on ensemble flow forecasts to switch the urban drainage-wastewater system management towards energy optimization during dry periods. *Hydrology and Earth System Sciences* **21** (5), 2531–2544.
- Dougllass, P. J., Garcia-valle, R., Nyeng, P., Østergaard, J. & Togeby, M. 2012 Smart demand for frequency regulation: experimental results. *IEEE Transactions on Smart Grid* **4** (3), 1713–1720.
- ESWA 2014 Energy Smart Water Utilities (ForskEL 10738) Tilpasning til SMART-Grid. Implementering og test af valgte løsninger (English: Energy Smart Utilities (ForskEL 10738) Adapting to smart grid. Implementation and test of chosen solutions). Tech. Rep., 2014.
- Flores Alsina, X., Arnell, M., Amerlinck, Y., Corominas, L., Gernaey, K., Guo, L. & Jeppsson, U. 2014 Balancing effluent quality, economic cost and greenhouse gas emissions during the evaluation of (plant-wide) control/operational strategies in WWTPs. *Science of the Total Environment* **466–467**, 616–624.
- Gernaey, K. V., Jeppsson, U., Vanrolleghem, P. A. & Copp, J. B. 2014 *Benchmarking of Control Strategies for Wastewater Treatment Plants*. IWA Publishing, London, UK.
- Goldfarb, D. & Idnani, A. 1983 A numerically stable dual method for solving strictly convex quadratic programs. *Mathematical Programming* **27** (1), 1–33.
- Gu, Y., Li, Y., Li, X., Luo, P., Wang, H., Robinson, Z. P., Wang, X., Wu, J. & Li, F. 2017 The feasibility and challenges of energy self-sufficient wastewater treatment plants. *Applied Energy* **204**, 1463–1475.
- Halvgaard, R., Poulsen, N. K., Madsen, H. & Jørgensen, J. B. 2012 Economic Model Predictive Control for Building Climate Control in a Smart Grid. In: *Proceedings of 2012 IEEE PES Innovative Smart Grid Technologies (ISGT)*. doi:10.1109/ISGT.2012.6175631.
- Hovgaard, T. G., Larsen, L. F. S., Edlund, K. & Jørgensen, J. B. 2012 Model predictive control technologies for efficient and flexible power consumption in refrigeration systems. *Energy* **44** (1), 105–116.
- Isaacs, S. H., Zhao, H., Soeberg, H. & Kummel, M. 1995 Modeling the nitrogen dynamics in an alternating activated sludge process. *Mathematics and Computers in Simulation* **39**, 617–626.
- Jónsson, T., Pinson, P., Nielsen, H. A., Madsen, H. & Skov Nielsen, T. 2013 Forecasting electricity spot prices accounting for wind power predictions. *IEEE Transactions on Sustainable Energy* **4** (1), 210–218.
- Jørgensen, J. B., Huusom, J. K. & Rawlings, J. B. 2011 Finite Horizon MPC for Systems in Innovation Form. In: *Proceedings 50th IEEE Conference on Decision and Control and European Control Conference (CDC-ECC)*, 12–15 December, 2011, Orlando, FL, USA, pp. 1896–1903.
- Jørgensen, B. H., Andersen, K. K. & Wilson, E. J. 2018 *International Energy Report Series: Accelerating the Clean Energy Revolution – Perspectives on Innovation Challenges*. DTU International Energy Report.
- Juhl, R., Møller, J. K., Jørgensen, J. B. & Madsen, H. 2016 Modeling and Prediction Using Stochastic Differential Equations. In: *Prediction Methods for Blood Glucose Concentration. Lecture Notes in Bioengineering* (H. Kirchsteiger, J. Jørgensen, E. Renard & L. del Re, eds). Springer, Cham, Switzerland.
- Kebir, F. O., Demirci, M., Karaaslan, M., Ünal, E., Dincer, F. & Arat, H. T. 2014 Smart grid on energy efficiency application for wastewater treatment. *Environmental Progress & Sustainable Energy* **33** (2), 556–563.
- Kirchem, D., Lynch, M., Bertsch, V. & Casey, E. 2018 Market effects of industrial demand response and flexibility potential from wastewater treatment facilities. In: *15th IEEE International Conference on the European Energy Market (EEM 2018)*, 27–29 June 2018, Łódź, Poland.
- Kristensen, N. R., Madsen, H. & Jørgensen, S. B. 2004 Parameter estimation in stochastic grey-box models. *Automatica* **40** (2), 225–237.
- Kroll, S., Fenu, A., Wambecq, T., Weemaes, M., Van Impe, J. & Willems, P. 2018 Energy optimization of the urban drainage

- system by integrated real-time control during wet and dry weather conditions. *Urban Water Journal* **15** (4), 362–370.
- Langergraber, G., Weissenbacher, N., Alex, J., Woerner, D., Ahnert, M., Frehmann, T., Halft, N., Hobus, I., Plattes, M., Sperring, V. & Winkler, S. 2008 Generation of diurnal variation for influent data for dynamic simulation. *Water Science & Technology* **57** (9), 1483–1486.
- Madsen, H. 2008 *Time Series Analysis*. Chapman & Hall, Boca Raton, FL.
- Madsen, H., Parvizi, J., Halvgaard, R., Sokoler, L. E., Jørgensen, J. B., Hansen, L. H. & Hilger, K. B. 2015 Intelligent Energy Systems. In: *Handbook of Clean Energy Systems*. Wiley & Sons Ltd, Hoboken, NJ, Vol. 4 - I, ch. Control of Electricity Loads in Future Electric Energy Systems, pp. 2213–2238.
- Mendoza-Serrano, D. I. & Chmielewski, D. J. 2013 Demand Response for Chemical Manufacturing using Economic MPC. In: *Proceedings of 2013 American Control Conference (ACC)*, 17–19 June 2013, Washington, DC, USA, pp. 6655–6660.
- Morales, J. M., Conejo, A. J., Madsen, H., Pinson, P. & Zugno, M. 2013 *Integrating Renewables in Electricity Markets: Operational Problems*, Vol. 205. Springer Science and Business Media, New York, NY.
- O'Connell, N., Pinson, P., Madsen, H. & O'Malley, M. 2014 Benefits and challenges of electric demand response: a critical review. *Renewable and Sustainable Energy Reviews* **39**, 686–699.
- Olsson, G. 2015 *Water and Energy: Threats and Opportunities*. IWA Publishing, London, UK.
- Palensky, P. & Dietrich, D. 2011 Demand side management: demand response, intelligent energy systems, and smart loads. *IEEE Transactions on Industrial Informatics* **7** (3), 381–388.
- Plappally, A. K. & Lienhard, J. H. 2012 Energy requirements for water production, treatment, end use, reclamation, and disposal. *Renewable and Sustainable Energy Reviews* **16** (7), 4818–4848.
- Prasath, G. & Jørgensen, J. B. 2008 Model Predictive Control based on Finite Impulse Response Models. In: *Proceedings of 2008 American Control Conference (ACC)*, 11–13 June 2008, Seattle, WA, USA, pp. 441–446.
- R Core Team 2019 *R: A Language and Environment for Statistical Computing*. R Foundation for Statistical Computing, Vienna, Austria. Available from: <http://www.r-project.org/>.
- Reinhofer-Gubisch, M. & Pucker, J. 2014 Loadshift – Lastverschiebung in kommunalen Kläranlagen: Ein relevantes Potenzial für Smart Grids? (English: loadShift – load shifting in municipal wastewater treatment plants: a relevant potential for smart grids?) *Osterreichische Wasserund Abfallwirtschaft* **66** (11–12), 424–432.
- Shi, C. Y. 2011 *Mass Flow and Energy Efficiency of Municipal Wastewater Treatment Plants*. IWA Publishing, London, UK.
- Stentoft, P. A., Munk-Nielsen, T., Vezzaro, L., Madsen, H., Mikkelsen, P. S. & Møller, J. K. 2018 Towards model predictive control: online predictions of ammonium and nitrate removal by using a stochastic ASM. *Water Science and Technology* **79** (1), 51–62.
- Stentoft, P. A., Guericke, D., Munk-Nielsen, T., Mikkelsen, P. S., Madsen, H., Vezzaro, L. & Møller, J. K. 2019a Model Predictive Control of Stochastic Wastewater Treatment Process for Smart Power, Cost-Effective Aeration. In: *proceedings of Dycops 2019, Dynamics and Control of Process Systems Including Biosystems*, 23–26 April, Florianopolis, Brazil.
- Stentoft, P. A., Munk-Nielsen, T., Møller, J. K., Madsen, H., Vezzaro, L., Mikkelsen, P. S. & Vangsgaard, A. K. 2019b 'Green MPC' – an approach towards predictive control for minimal environmental impact of activated sludge processes. In: *Proceedings of Watermatex 2019*, 1–4 September, Copenhagen, Denmark.
- Tassou, S. A. 1988 Energy conservation and resource utilisation in waste-water treatment plants. *Applied Energy* **30**, 113–129.
- Thompson, L., Song, K., Lekov, A. & McKane, A. 2008 Automated Demand Response Opportunities in Wastewater Treatment Facilities. In: *Proceeding of Distributech*, San Diego, CA, USA.
- Zimmermann, B., Gardian, H. & Rohrig, K. 2018 Cost-optimal flexibilization of drinking water pumping and treatment plants. *Water* **10** (7), 857.

First received 30 September 2019; accepted in revised form 15 May 2020. Available online 5 June 2020