Controlling the COD removal of an A-stage pilot study with instrumentation and automatic process control

Mark W. Miller, Matt Elliott, Jon DeArmond, Maureen Kinyua, Bernhard Wett, Sudhir Murthy and Charles B. Bott

ABSTRACT

The pursuit of fully autotrophic nitrogen removal via the anaerobic ammonium oxidation (anammox) pathway has led to an increased interest in carbon removal technologies, particularly the A-stage of the adsorption/bio-oxidation (A/B) process. The high-rate operation of the A-stage and lack of automatic process control often results in wide variations of chemical oxygen demand (COD) removal that can ultimately impact nitrogen removal in the downstream B-stage process. This study evaluated the use dissolved oxygen (DO) and mixed liquor suspended solids (MLSS) based automatic control strategies through the use of *in situ* on-line sensors in the A-stage of an A/B pilot study. The objective of using these control strategies was to reduce the variability of COD removal by the A-stage and thus the variability of the effluent C/N. The use of cascade DO control in the A-stage did not impact COD removal at the conditions tested in this study, likely because the bulk DO concentration (>0.5 mg/L) was maintained above the half saturation coefficient of heterotrophic organisms for DO. MLSS-based solids retention time (SRT) control, where MLSS was used as a surrogate for SRT, did not significantly reduce the effluent C/N variability but it was able to reduce COD removal variation in the A-stage by 90%.

Key words | A/B process, A-stage, high-rate activated sludge, on-line sensors, process control

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INTRODUCTION

The A-stage of the adsorption/bio-oxidation (A/B) process was developed in the late 1970s as a cost-effective method of decreasing the volumetric requirements of nitrifying activated sludge processes (i.e., B-stage) by reducing the influent chemical oxygen demand (COD) load (Böhnke 1977). The A-stage is a separate stage high-rate activated sludge (HRAS) process typically designed with a hydraulic residence time (HRT) of 30 min and operated at a solids retention time (SRT) between 0.2 to 1 days, depending on the influent COD load, temperature, and desired COD removal efficiency. A-stage processes are not preceded by primary clarifiers and are generally designed to remove 50–70% of the influent COD as opposed to more conventional HRAS processes (i.e., SRT = 1–4 days; HRT = 1–3 h) that are operated to meet secondary discharge standards (i.e., 30 mg/L total suspended solids (TSS) and biochemical oxygen demand (BOD_5)) (Feyen 1992; Böhnke *et al.* 1998; Wandl *et al.* 2006; Orhon 2014). The main disadvantage of the A/B

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process, when conventional nitrification and denitrification is used for nitrogen removal, is that the COD removed by the A-stage is no longer available as an internal organic carbon source for denitrification in the B-stage (de Graaff & Roest 2012). Typical A-stage effluent COD/total Kjeldahl nitrogen (COD/TKN) ratios range from 4 to 6 (Wan *et al.* 2016) while optimal COD/TKN ratios for good nitrogen removal in conventional biological nitrogen removal (BNR) processes range from 7 to 9 (Grady *et al.* 2011). To cope with this limitation, nitrogen removal in the B-stage has been optimized using *in situ* nutrient sensors and automatic process control (Sorensen *et al.* 1994). One example is ammonia-based aeration control, which is a form of dissolved oxygen (DO) control that ensures the entire aerobic treatment capacity of the B-stage is utilized for nitrification (Åmand *et al.* 2013). However, even with these control strategies, it is difficult to obtain effluent total nitrogen concentrations below 5 mg-N/L in A/B processes because denitrification requires approximately 4.5 g-COD/g-N removed (Tchobanoglous *et al.* 2003).

Considerable research has been undertaken in an effort to decrease the amount of COD required for nitrogen removal through the development of shortcut BNR technologies like nitrite shunt (nitritation/denitritation) and deammonification (partial nitritation/anaerobic ammonia oxidation), which only require influent COD/TKN ratios of 5 to 8 and <2, respectively (Winkler *et al.* 2012; De Clippeleir *et al.* 2013; Wett *et al.* 2013; Lotti *et al.* 2014; Regmi *et al.* 2015). One common requirement of deammonification processes in particular, other than the out-selection of nitrite oxidizing bacteria (NOB), is that COD removal is required upstream of the shortcut BNR process. This is due in part to heterotrophic bacterial competition with anaerobic ammonia oxidizing (anammox) bacteria for nitrite and with ammonia oxidizing bacteria (AOB) for dissolved oxygen (DO) (Xu *et al.* 2015). One strategy to out-select NOB in both types of shortcut BNR processes is to operate at SRTs near the critical or washout SRT of NOB. This SRT pressure is likewise also applied to AOB and therefore high total ammonia nitrogen (TAN) loading rates (>0.2 kg-TAN/m^3·day) are often used to ensure AOB are not substrate limited and growing at their maximum rate. However, this type of operation subjects the shortcut BNR processes to an increased risk of failure in the event of process upsets or significant load variations (Regmi *et al.* 2014; Smitshuijzen 2014). While the development and use of more advanced automatic process controllers in the B-stage, like ammonia versus NOx-N (AvN) aerobic volume control (Regmi *et al.* 2014), has improved process stability, nitrogen removal efficiency in the B-stage has still been hampered by the variability of influent COD/TKN from the A-stage or other upstream COD removal processes (Regmi *et al.* 2015; Xu *et al.* 2015). Therefore, the application of automatic process control using *in situ* on-line sensors in the A-stage with the goal of controlling COD removal and the influent COD/TKN ratio for the B-stage is critical. Additionally, automatic process control can be used to balance COD removal with COD capture as waste sludge in the A-stage to recover energy in the form of biogas (Jetten *et al.* 1997).

Other than DO setpoint control, most full-scale A/B facilities put little effort into dynamically controlling the A-stage to generate a consistent influent COD/TKN for the B-stage (de Graaff & Roest 2012). Although the use of DO and SRT controllers in activated sludge processes operated at SRTs >1 day has been well documented (Olsson 2012), their use in an A-stage process operated with the goal of controlling the C/N input to a shortcut BNR process has not been documented. Therefore, the objective of this study was to evaluate well-established forms of automatic process control using readily available *in situ* on-line sensors so that full-scale adoption would be straightforward and familiar to facility operators. Prior to the evaluation of control strategies, ten different *in situ* on-line sensors that measured DO, TSS, turbidity, ammonium, oxidation reduction potential, and COD were evaluated for their accuracy, precision, and long-term reliability (Miller *et al.* 2014). After sensor evaluation, cascade DO control and mixed liquor suspended solids (MLSS)-based SRT control were evaluated in terms of COD removal performance and process variability in the A-stage of an A/B pilot study treating municipal wastewater.

MATERIALS AND METHODS

A-stage pilot configuration and operation

The A-stage pilot consisted of three bioreactors (tanks 1–3) in series to achieve a plug-flow regime. The bioreactors were followed by a clarifier and effluent equalization (EQ) tank (Figure 1). The total working volume of the three bioreactors was 0.51 m^3 and with a side water depth of 3.4 m. The clarifier had a working volume of 1.7 m^3 with a surface overflow rate of 17 m^3/m^2·day at the design influent flow of 17 L/min. The HRT of the bioreactors and clarifier was 30 min and 1.7 h, respectively. The pilot was fed screened (2–3 mm openings) and degritted municipal wastewater (Table S1, available with the online version of this paper) after the wastewater temperature was adjusted to a user

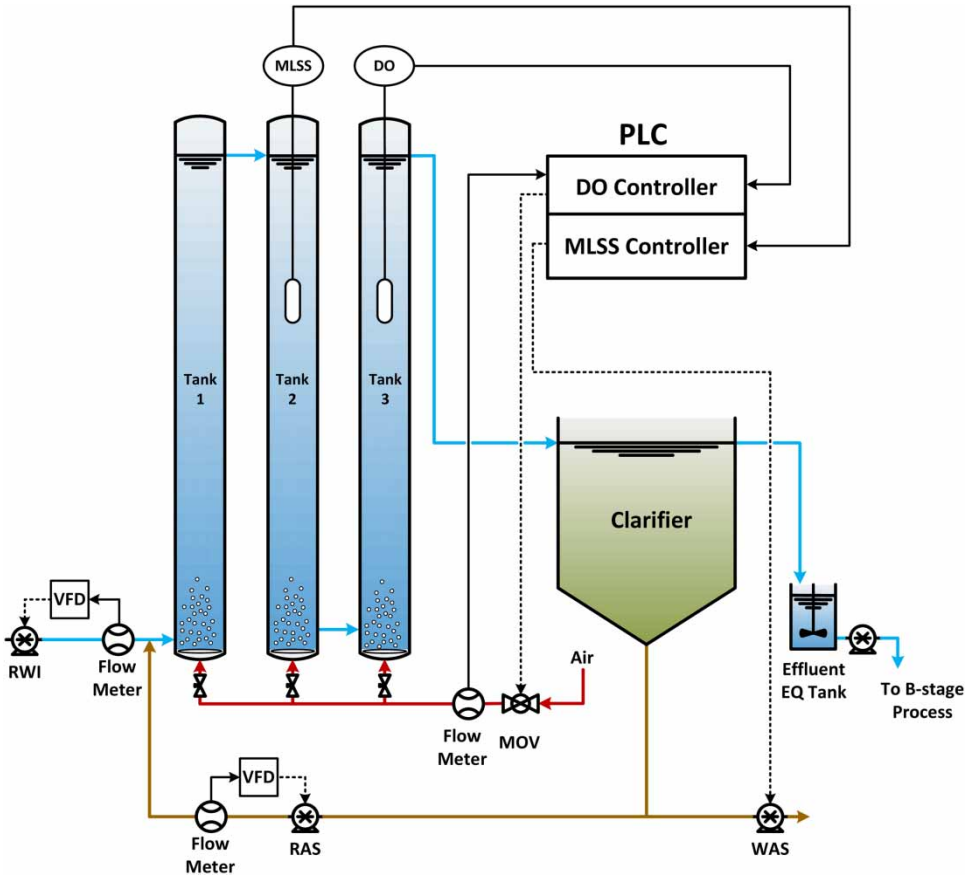

Figure 1 | A-stage pilot schematic. (—) process water; (—) solids; (—) process air; (–) sensor signal; (—) controller output. RWI: raw influent wastewater; RAS: return activated sludge; WAS; waste activated sludge.

setpoint between 15–25°C using submersible heaters (OEM OTS, Minneapolis, MN) or a water chiller (Aqualogic MT-9, San Diego, CA). The influent and return activated sludge (RAS) flows were flow-paced using progressive cavity pumps (Seepex BW5, Bottrop, Germany) with variable frequency drives and magnetic flow meters (Rosemount 8705, Houston, TX). The RAS flow rate was maintained at 100% of the influent flow in order to maintain a low sludge blanket in the clarifier. Waste activated sludge (WAS) was removed from the underflow of the clarifier using a digital, speed-controlled peristaltic pump (Masterflex L/S, Vernon Hills, IL). The total SRT, considering only the mass of solids in the bioreactors and accounting for effluent suspended solids, was maintained between 0.1–0.3 days. Aeration was provided using compressed air through a single mechanically operated valve (MOV; v-notch ball valve) to fine-pore membrane disc diffusers (17.8 cm diameter) mounted on the bottom of each bioreactor as shown in Figure 1. Airflow to each of the three bioreactors was balanced using separate needle valves in order to mimic a single diffuser zone. A DO sensor (InsiteIG Model 10, Slidell, LA) was installed in tank 3 and an MLSS sensor (InsiteIG Model 15, Slidell, LA) in tank 2. The DO sensor was mounted in the last bioreactor (i.e., tank 3) to match full-scale facilities that install DO sensors at the end of aeration tanks or controlled diffuser fields. The MLSS sensor was installed in the middle bioreactor (i.e., tank 2) as that reactor should represent the average MLSS of the three bioreactors.

Instrumentation and maintenance frequency

To evaluate the accuracy of the *in situ* DO and MLSS sensors used in this study the sensor values were compared to either reference DO values measured using a handheld DO sensor or by taking grab mixed liquor samples and measuring TSS. The technical specifications of the *in situ* on-line sensors and the handheld DO sensor used for the reference measurements are listed in Table 1. The *in situ* sensors were mounted vertically in the bioreactors at one-third the side water depth from the water surface and equipped with an airblast cleaning mechanism according to the manufacturers' specifications. Due to persistent

Table 1 | Technical specifications of the *in situ* and reference sensors used in this study

Sensor manufacturer	Sensor model	Measurement principle	Range	Sensor accuracy	Response time ($T_{90\%}$)	Averaging time	Auto cleaning mechanism
Hach	IntelliCAL™ LDO101	Luminescent dissolved oxygen (LDO)[a]	0.1–20.0 mg O_2/L	±0.1 mg/L (DO < 8 mg/L) ±0.2 mg/L (DO >8 mg/L)	10 secs	0 secs	N/A
InsiteIG	Model 10	Fluorescent dissolved oxygen (FDO)	0–25.0 mg O_2/L	±1% of sensor reading or ±0.02 mg/L, whichever is greater	60 secs	12 secs	Airblast
InsiteIG	Model 15	Infrared TSS	0.25–30 g SS/L	±5% of sensor reading or ±100 mg/L, whichever is greater	60 secs	300 secs	Airblast

[a]Handheld LDO sensor was used for reference measurements against the *in situ* DO sensor.
N/A, Not available.

biofouling in the bioreactors, the required airblast frequency was every 10 min. The sensors were also manually cleaned weekly and on an as needed basis after comparison to daily reference DO and laboratory MLSS values. Initial sensor calibrations were performed according to the manufacturers' instructions and on an as needed basis. Both *in situ* and reference DO sensors were calibrated using the zero-point (i.e., offset adjustment at 0% DO saturation) and reference-point (i.e., slope adjustment at 100% DO saturation) methods. The MLSS sensor was calibrated using the reference-point method (i.e., offset adjustment at a known MLSS concentration). Since the effluent from the A-stage pilot continuously fed the B-stage pilot, routine calibration of the sensors was required. Therefore, long-term sensor drift was not evaluated as part of this study.

Process automation and control

A block diagram of the process automation used in this study for DO cascade control and MLSS setpoint control is provided in Figure 2. Process automation and control was achieved in the pilot using a programmable logic controller with integrated proportional-integral-derivative (PID) controls (Allen-Bradley SLC 500, Milwaukee, WI). Controller tuning was performed initially using the Ziegler-Nichols method and then manually adjusted to reduce output

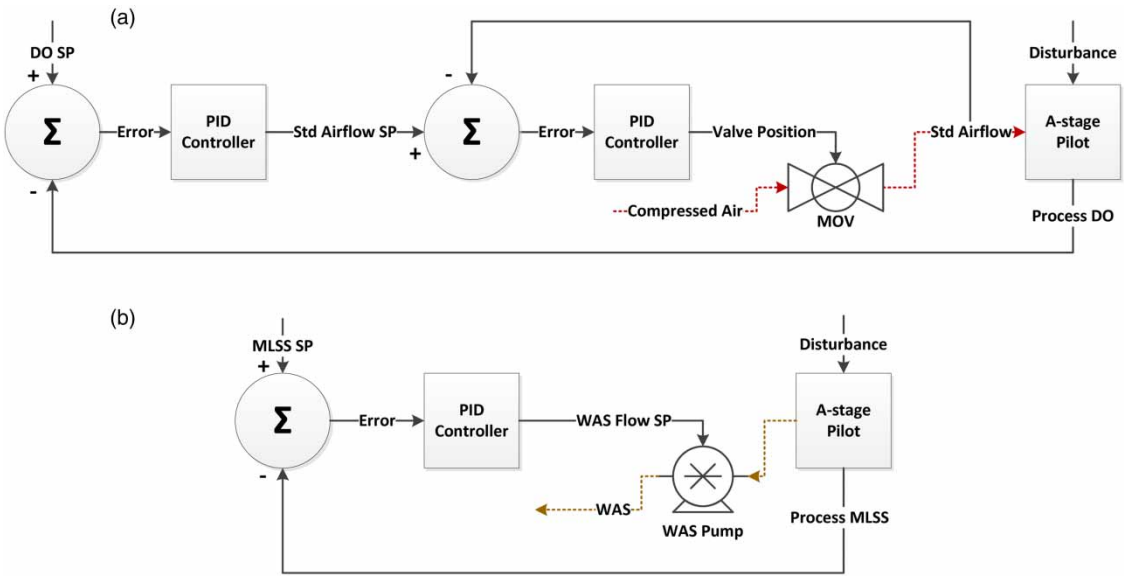

Figure 2 | Process control block diagram for (a) cascade DO setpoint (SP) control and (b) WAS flow-based MLSS setpoint control. Standard: Std; Setpoint: SP.

oscillation and increase controller stability. The DO sensor installed in tank 3 and a gas mass flow meter (Alicat M-Series, Tucson, AZ; standard temperature pressure = 25°C, 1 atm) on the compressed air line provided the feedback signals for the cascade DO controller (Figure 2(a)). The primary or master PID loop would compare the DO feedback signal to the user DO setpoint and output an airflow setpoint to the secondary or slave PID loop accordingly. The secondary PID loop would then act upon the MOV in order to match the process airflow to the airflow setpoint. The airflow controller was bounded (20–90 standard L per minute; SLPM) to ensure that the process was always well mixed and to limit the oxygen transfer rates (OTR) to 150 mg-O_2/L h, which is a typical limit of full-scale aeration systems.

The MLSS sensor located in tank 2 provided the feedback signal for the WAS flow-based MLSS controller (Figure 2(b)). The MLSS PID loop compared the MLSS feedback signal to the user MLSS setpoint and output a WAS pump speed. To increase the MLSS concentration in the A-stage process, the pump speed was decreased and vice versa to decrease the MLSS concentration of the A-stage.

Analytical methods and data analysis

The performance of the A-stage pilot was assessed by collecting 24-h flow-weighted composite samples of raw wastewater influent (RWI) and A-stage effluent, where the RWI samples were collected from the grit and scum removal tank (not shown) and the effluent samples from the EQ tank (Figure 1). RWI and effluent samples were analyzed for COD, soluble COD (1.5 μm glass microfiber filtered), TSS, volatile suspended solids, total phosphorus, alkalinity, pH, TKN, and TAN, according to *Standard Methods* (APHA/AWWA/WEF 2012). Filamentous bacteria were identified in grab mixed liquor samples by staining and microscopic observation according to Jenkins *et al.* (2004). Diurnal profiles of A-stage influent, effluent, and mixed liquor were obtained by either collecting 24 or 12 discrete samples over a 24-h period using an autosampler with sample refrigeration (~4°C).

Reference DO concentrations were determined using a handheld DO sensor (Table 1). Outlier determination and calculation of the width of the 95% prediction interval (PI) at the mean laboratory value was performed according to Rieger *et al.* (2005). Sensor values are considered outliers when they have the highest absolute residual value between the linear regression function and the measured sensor value, and their removal from the dataset statistically improves the standard deviation of the residuals. Outliers are presented but were not included in the statistical analyses of sensor data. All other statistical analyses, including the Pearson product moment correlation, Shapiro-Wilk normality test, t-test, linear regression, 95% confidence and prediction intervals (PI), mean, and standard deviation, were performed using SigmaPlot (Systat Software Inc., Bangalore, India).

RESULTS AND DISCUSSION

Initial A-stage performance

Initial diurnal COD profiles of the raw influent and A-stage effluent were conducted before the implementation of any process control to evaluate the variability of the A-stage pilot performance (Figure 3). Four separate profiles (1–4) of the raw influent and A-stage effluent were collected during a 2-week span with two profiles collected on weekdays (profiles 2 and 4) and two on weekends (1 and 3). For each sample point and profile, flow-weighted samples were collected every two hours over a 24-h period for a total of 12 samples. As seen in Figure 3(a), the influent COD was highly variable ranging from 386–542 mg/L (mean (μ) = 460; standard deviation (σ_x) = 43). Although profile 1 exhibited a typical diurnal pattern (Tchobanoglous *et al.* 2003), the other profiles did not follow a consistent trend. A possible explanation for this is the fact that the influent wastewater samples included recycles from the full-scale facility's solids dewatering process and therefore were impacted by facility activities. The effluent COD ranged from 251–387 mg/L ($\mu = 332$; $\sigma_x = 41$). The effluent COD variations were attenuated due to COD removal in the A-stage and EQ in the clarifier (Figure 3(b)).

The influent COD/TKN ratio varied from 8.3–11.4 mg-COD/mg-TKN ($\mu = 9.8$; $\sigma_x = 0.8$). The variability of the influent COD concentrations (386–542 mg/L) and COD removal efficiencies (5–44%) resulted in no improvement of the effluent COD/TKN ratios (Figure 3(c)), which varied from 6.0–9.1 mg-COD/mg-TKN ($\mu = 7.6$; $\sigma_x = 0.8$). This variability in effluent COD/TKN directly affected the stability and nitrogen removal performance of the proceeding bio-oxidation (B-stage) process when the B-stage was operated aggressively in terms of ammonia loading and SRT (Regmi *et al.* 2014; Regmi *et al.* 2015).

Sensor evaluation

The first step in developing process controllers aimed at controlling COD removal in the A-stage pilot process was to

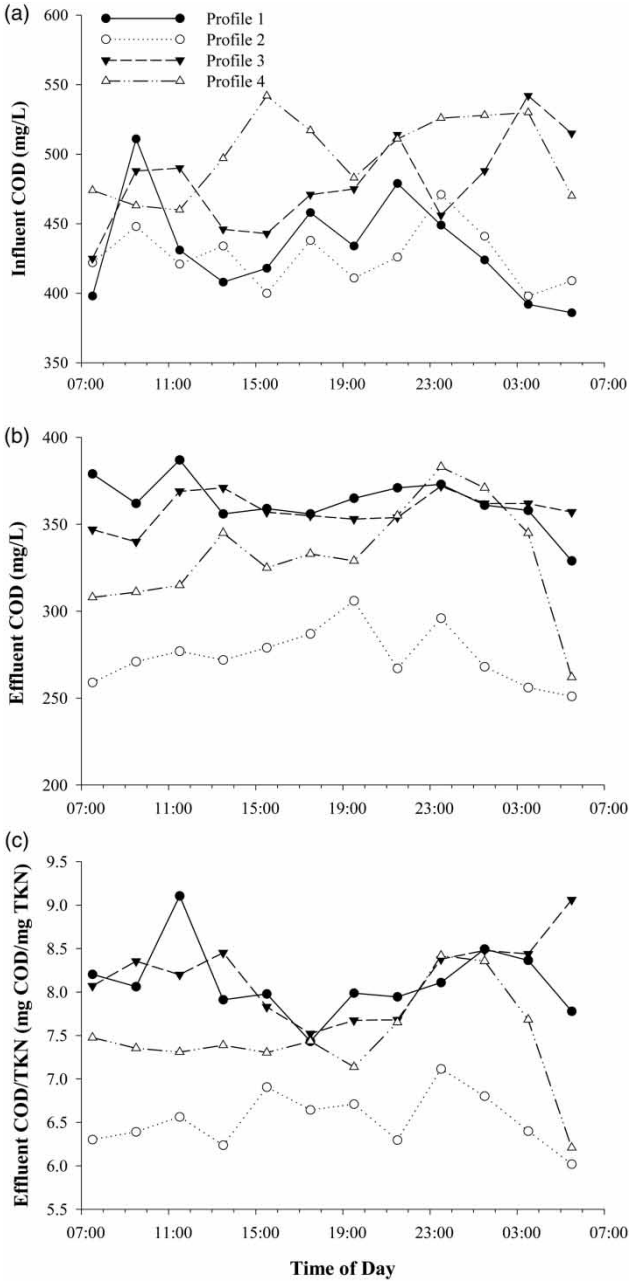

Figure 3 | Diurnal sampling results of the A-stage pilot: (a) influent COD; (b) effluent COD; (c) effluent COD/TKN.

evaluate and select appropriate sensors that were capable of measuring a controllable variable. As DO and SRT were predetermined to likely have the most significant impact on COD removal efficiency, a total of three optical DO sensors (InsiteIG Model 10; Hach LDO sc; WTW FDO® 700 IQ) and three suspended solids/turbidity sensors (InsiteIG Model 15; WTW VisoTurb® 700 IQ; WTW ViSolid® 700 IQ) were evaluated as discussed in Miller *et al.* (2014). The results of this study found that the Hach and WTW sensors were not able to accurately monitor DO and suspended solids primary due to biofouling issues and the variability of mixed liquor characteristics. Additional sensors were not evaluated because the scope of this project was just to develop A-stage process controllers and not to evaluate all available sensors. From the sensors that were evaluated, the InsiteIG Model 10 FDO and InsiteIG Model 15 suspended solids sensors were selected for further evaluation (Table 1).

The InsiteIG FDO sensor was selected because of its ability to withstand damage from frequent airblast cleaning that occurred every 10 min to avoid biofouling. The FDO sensor's durability was attributed to the fact that the airblast was integrated into the sensor body and the sensing material was embedded in hard epoxy resin. Compared to the FDO sensor, the sensing material of an LDO sensor was delicate and prone to damage from the required frequent airblast cleaning. Once damaged, the LDO sensor's response time increased to a point after which the sensor would no longer calibrate.

The InsiteIG suspended solids sensor was selected because of its ability to produce stable MLSS measurements. Although the WTW ViSolid® performed well in the B-stage pilot process (Miller *et al.* 2014), the sensor could not produce stable measurements when installed in the A-stage pilot. The extreme variability of the sensor was attributed to the highly variable A-stage mixed liquor characteristics such as color, turbidity, and particle size distribution. However, this was never confirmed as it was outside of the scope of this project. The WTW VisoTurb® was also not selected to measure A-stage effluent suspended solids for the same aforementioned reasons.

The InsiteIG FDO sensor was evaluated by performing daily (during normal workdays) measurement checks against a handheld LDO sensor (Table 1) over a period of 300 days. The results from this period are presented in Figure 4(a) along with the ideal correlation (i.e., slope = 1) and the linear regression function with 95% confidence (CI) and PI. The 95% PI at the mean reference value of 0.70 mg/L was ±0.75 mg/L. This means that a future single reference value has a 95% probability of falling within 0.05 and 1.40 mg/L. This variability was mainly associated with sensor biofouling as the sensor has an accuracy of 1% of the sensor reading or ±0.02 mg/L, whichever is greater, in clean water (Table 1). While the integrated airblast was effective at controlling biofouling, especially when compared to other optical DO sensors, biofouling was often severe and required manual cleaning of the sensor to

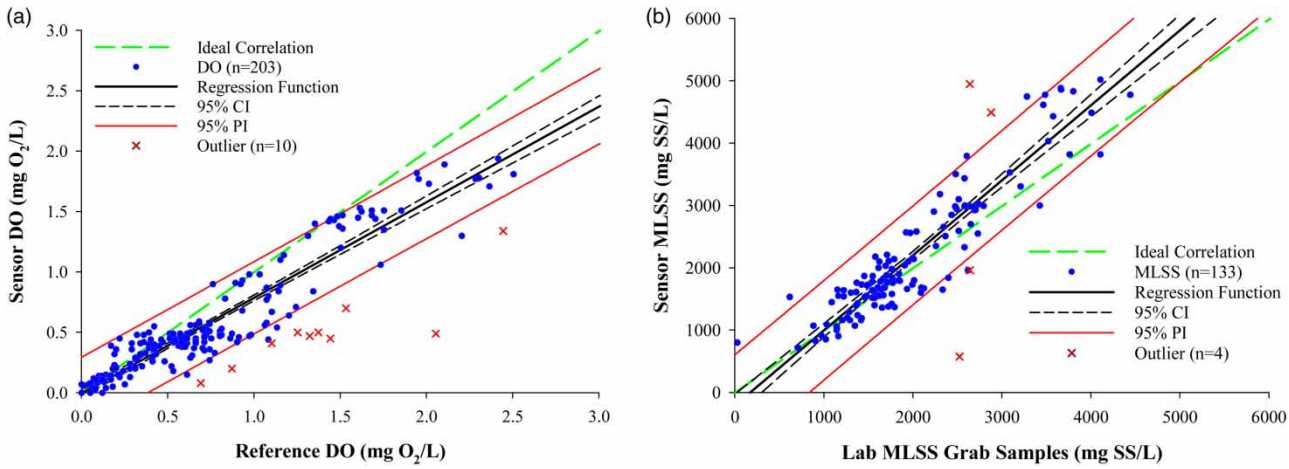

Figure 4 | Comparison of (a) *in situ* FDO sensor values to reference handheld LDO sensor values and (b) *in situ* MLSS sensor values to laboratory MLSS grab samples. Ideal correlation represents what should be expected (i.e., sensor = reference) when the sensor is correctly calibrated. PI: prediction interval; CI: confidence interval.

maintain sensor accuracy. Since sensor biofouling caused the *in situ* sensor reading to be lower than the reference DO sensor (i.e., slope <1) it was likely that the true calibration function was closer to the ideal correlation line than what was predicted by the linear regression function (slope = 0.79; offset = −0.004; $R^2 = 0.90$). Therefore, errors in DO readings were likely associated with biofouling rather than sensor accuracy or calibration errors.

A comparison of MLSS sensor values to grab MLSS samples for the A-stage pilot process is presented in Figure 4(b). The 95% PI at the mean laboratory value of 2,000 mg/L was ±1,320 mg/L. It is unclear if the variability was associated with sensor biofouling, grab sample collection and analysis error, or the true error of the sensor. The linear regression function (slope = 1.20; offset = −200; $R^2 = 0.86$) was off from the ideal correlation suggesting that the sensor calibration function could have been improved. However, this does not explain the variability of the sensor. Regardless, the sensor was deemed accurate enough for testing with automatic process control.

Assessment of DO and MLSS variability

To evaluate the impact of diurnal influent COD patterns on DO and MLSS in the A-stage process a 24-h profile of DO and MLSS in tank 3 was performed using the FDO sensor and collecting discrete mixed liquor samples once per hour and analyzing for TSS (Figure 5). The aeration, RAS, and WAS flow rates were maintained constant during this period. Over the 24-h period, the DO concentration varied between 0.5 and 1.3 mg/L ($\mu = 0.9$; $\sigma_x = 0.2$) and MLSS varied between 810 and 1,270 mg/L ($\mu = 1{,}040$; $\sigma_x = 142$).

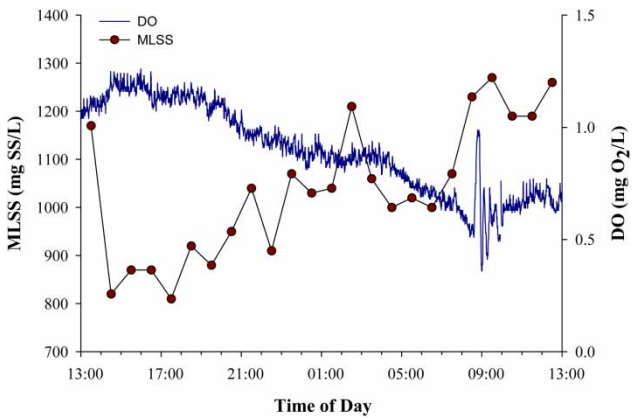

Figure 5 | Time series of DO and MLSS concentrations in the A-stage pilot. DO was logged from the *in situ* DO sensor and MLSS concentrations were from discrete samples ($n = 24$) over 24 h.

A fluctuation in DO around 09:00 was due to daily maintenance procedures that required temporarily stopping the influent feed. The sudden drop in MLSS after the first sample was not associated with any process changes. It was unclear what caused the sudden decrease in MLSS since it occurred during a time of day that experiences high influent loads. Assuming that the first data point was a sampling error, the MLSS trend did not follow a diurnal trend. The DO trend also suggests the same since the DO concentration did not return to its original value of 24-h previous. Regardless, the trends demonstrated that the A-stage was not a stable process and was susceptible to dynamic influent loads.

Although the bulk DO concentration varied throughout the day, it likely only had a slight impact on COD removal efficiency since heterotrophic organisms have a high affinity for

DO and the DO was maintained above the heterotrophic half saturation coefficient ($K_{DO} \approx 0.2$ mg/L) (Henze *et al.* 2000; Grady *et al.* 2011). However, variable MLSS likely affected A-stage performance because the specific loading rate (SLR; kg-COD/kg-MLSS·day) inversely correlates with COD removal efficiency in A-stage processes (Böhnke 1977). Since the SRT of the A-stage pilot process was not automatically controlled and the WAS flow rate was maintained constant, the MLSS concentration and, thus, the SRT would vary throughout the day. The result of constant wasting regardless of the influent load was that the MLSS concentration would decrease to its lowest concentration in the early morning hours when the influent load was lowest. Then, the influent load would increase according to diurnal variations faster than the time it would take for the MLSS concentration to recover resulting in an increase in the SLR and therefore lower COD removal efficiencies were observed.

Development of automatic process controllers

Based on the variability of the effluent COD/TKN ratio of the A-stage pilot process (Figure 3(c)), several automatic process controllers aimed at reducing fluctuations in COD removal efficiency were considered (unpublished data). These included single-loop and cascade DO setpoint controllers using DO sensors, an SRT setpoint controller using effluent and WAS TSS sensors, an oxygen uptake rate (OUR)-based SRT controller, and an MLSS-based SRT controller. Of these, cascade DO control and MLSS-based SRT control were selected for evaluation as discussed herein.

Cascade DO control

Cascade DO control was evaluated in the A-stage to determine the impact of DO on COD removal efficiency and to improve the effluent COD/TKN variability. A 24-h profile of DO and the standard airflow rate of the A-stage pilot process while under cascade DO control at a DO setpoint was 0.5 mg/L is shown in Figure S1 (available with the online version of this paper). The DO controller was able to maintain the DO setpoint of 0.5 mg/L by automatically adjusting the airflow rate. Using cascade DO control, the impact of the bulk DO concentration on COD removal efficiency was evaluated in the A-stage by operating at different DO setpoints ranging from 0.2 to 1.5 mg/L. However, no significant linear correlation ($R = 0.16$; $p = 0.042$; $n = 162$; Figure S2, available with the online version of this paper) of DO concentration to COD removal efficiency was detected. As mentioned previously, the lack of correlation between the DO concentration and COD removal efficiency was likely due to the fact that the DO was greater than the K_{DO} for heterotrophic organisms. Through the use of model simulation, Nogaj *et al.* (2015) reported that DO only significantly impacts substrate removal when the bulk DO is below 0.5 mg/L in an HRAS process operated at a 1 day SRT.

Attempts were made to operate the A-stage pilot at DO concentrations below 0.5 mg/L; however, due to sensor biofouling issues, it proved very difficult to precisely control DO in the range that would likely affect COD removal. Operating the pilot at a DO <0.2 mg/L also resulted in bulking conditions with sludge volume indexes exceeding 150 mL/g. Bulking episodes would occur when the process OUR exceeded the aeration system's oxygen transfer capabilities for an extended period (e.g., >2 times the SRT). The filamentous bacteria responsible for sludge bulking were identified as Type 1,863, which are known to proliferate when the SLR is >0.6 kg-COD/kg-MLSS·day and the DO is <0.1 mg/L. Bulking was resolved by decreasing the MLSS concentration by lowering the SRT.

MLSS-based SRT control

Since DO control did not offer the ability to control COD removal and COD removal correlated better with the A-stage MLSS concentration ($R = 0.59$; $p < 0.01$; $n = 308$; Figure S3, available with the online version of this paper), MLSS-based SRT setpoint control was investigated. Previous attempts to implement SRT control were unsuccessful because of the lack of reliable *in situ* MLSS and TSS sensors (unpublished data). The premise of the automatic SRT controller was to monitor MLSS and effluent TSS concentrations and vary the WAS flow to meet the desired SRT setpoint. However, using two sensors with automatic process control could result in a very unstable controller since the error of each sensor would add to the total error of the controller. In addition, small changes in MLSS would only have had a minor effect on the SRT while the effluent TSS (Table S1) accounted for almost half of the solids leaving the A-stage. Even a small error in the measurement of effluent TSS could have detrimental effects on the SRT controller. When compared to more conventional HRAS processes that typically maintain effluent TSS values <20 mg-SS/L, the impact of effluent TSS is not as significant.

Many activated sludge facilities try to maintain a constant MLSS concentration by adjusting HRT and SRT in order to maintain a consistent solids loading of the secondary clarifiers. However, this is now discouraged in practice because the main variable of concern in terms of treatment performance (e.g., nitrification) is SRT and not the MLSS

concentration. In the case of the A-stage pilot, however, MLSS-based SRT control was adopted since MLSS linearly correlated with SRT ($R = 0.82$; $p < 0.001$; $n = 359$) as seen in Figure 6. This was possible in the A-stage because the range of SRT operation was narrow enough that the MLSS increased linearly with SRT, which is not the case over a longer range of SRTs. This means that although the controller was based on an MLSS setpoint, MLSS was just used as a surrogate for SRT.

A 24-hr snapshot of the MLSS-based SRT controller in action is provided in Figure 7. The MLSS setpoint was set at 4,000 mg/L during this period resulting in an average SRT of approximately 0.35 days. Although the pilot process was typically operated at MLSS concentrations between 1,000–3,000 mg/L, a high MLSS setpoint was selected to demonstrate the controller was effective at both high and low MLSS concentrations. The controller was able to maintain the MLSS setpoint; however, the controller tuning could have been improved to reduce WAS pumping variability. A full-scale facility would experience operational issues, such as variable solids and hydraulic loading on the downstream thickening processes if the WAS flow was not dampened or equalized. While the controller successfully stabilized the process MLSS concentration, no significant improvement in the variability of the effluent COD fractions and their removal efficiency was seen (Figure S4, available with the online version of this paper).

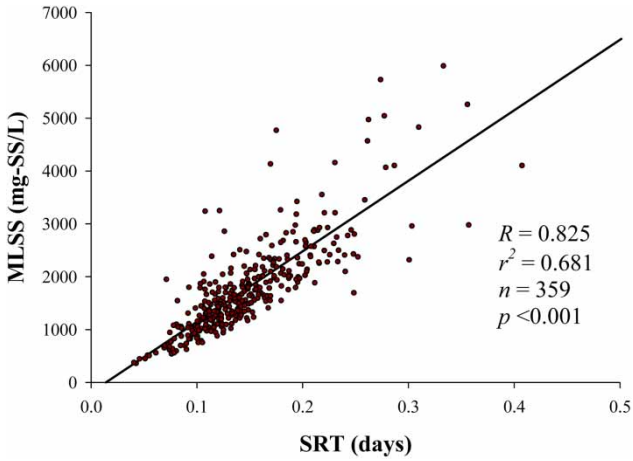

Figure 6 | Influence of SRT on the A-stage MLSS concentration.

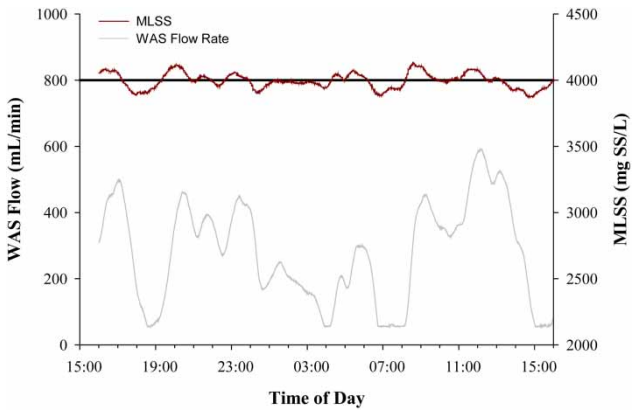

Figure 7 | Time series of MLSS and WAS flow when MLSS setpoint control is in use. The horizontal line represents MLSS setpoint of 4,000 mg/L.

A-stage performance with process control

Due to the frequent changes in operating conditions (i.e., DO, HRT, SRT) and unavoidable mechanical issues, like pump failures, long-term COD removal and process variability were not comparable during the periods before and after the implementation of cascade DO and MLSS setpoint control. Instead, the influent and A-stage effluent COD/TKN ratios and COD removal efficiency were compared (Figure 8) between two periods when the A-stage pilot was stable and operated under similar conditions (20°C; HRT = 30 min; average SRT = 0.15 days; DO = 0.5 mg/L). The influent COD and COD/TKN ratio for the period before MLSS control averaged 585 ± 88 mg/L and 12.6 ± 1.5, respectively, while the influent COD and COD/TKN ratio for the period after implementation of the controller averaged 598 ± 54 mg/L and 13.0 ± 0.9, respectively. The MLSS averaged 2,206 ± 655 mg/L before MLSS control and 1,735 ± 178 mg/L after implementation. As shown in Figure 8(a), the effluent COD/TKN before and after MLSS control did not vary significantly. Before control the COD/TKN averaged 7.1 ± 0.7 and after control averaged 7.4 ± 0.7. During both periods, the variance of COD/TKN was less than 1%. This demonstrated that the MLSS controller did not reduce the day-to-day variability of the COD/TKN ratio.

The MLSS controller was able to reduce the daily variability of COD removal as shown in (Figure 8b). Although the means of COD removal (49.2% before; 48.4% after) of each dataset were not statistically different ($p = 0.616$), the variances (110.1% before; 20.4% after) between the two periods were statistically different ($p = 0.002$). This means that while both periods averaged the same COD removal efficiency, the use of MLSS-based SRT control reduced the variability of COD removal by 90%. These observations indicate that an additional layer of control is needed to actually control the effluent COD/TKN of the A-stage process.

Further improvement of the MLSS controller could entail the use of either *in situ* on-line sensors or *ex situ* on-line analyzers that measure organics such as COD, BOD, ultraviolet

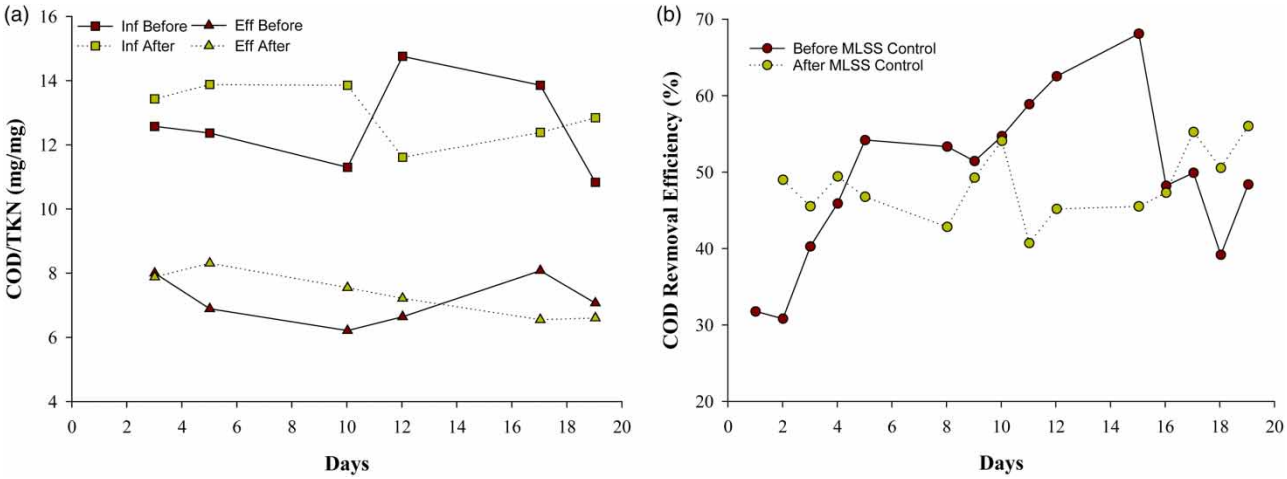

Figure 8 | Comparison of (a) raw influent and A-stage effluent COD/TKN and (b) A-stage COD removal efficiency before and after implementation of MLSS setpoint control.

light absorbance at 254 nm (UV254), or total organic carbon, to provide an effluent organics feedback signal. The effluent organics measurement could then be coupled with a measurement of effluent nitrogen (e.g., TAN analyzer) to provide effluent C/N values that can be used as a feedback signal to control the MLSS controller and ultimately COD removal in the A-stage. Although the technology is available to monitor the parameters of interest such as COD, MLSS, and DO, further research needs to be done to fully understand COD removal mechanisms and how they can be effectively controlled in short SRT processes like the A-stage.

CONCLUSIONS

This research documented the implementation of automatic process control, using commercially available sensors, in an A-stage process operated at SRTs < 0.5 days in order to obtain a consistent effluent COD/TKN ratio of approximately 6–8 for the downstream short nitrogen removal process performing nitrite shunt. Although the combination of DO and MLSS-based SRT controllers were able to reduce COD removal variation by 90%, the effluent COD/TKN variability was not significantly improved. However, the potential exists to couple the MLSS-based controller with an effluent C/N feedback loop to further improve the stability of the A-stage process.

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REFERENCES

Åmand, L., Olsson, G. & Carlsson, B. 2013 Aeration control – a review. *Water Science and Technology* **67** (11), 2374–2398.

APHA/AWWA/WEF 2012 *Standard Methods for the Examination of Water and Wastewater*, 22nd edn. American Public Health Association/American Water Works Association/Water Environment Federation, Washington, DC, USA

Böhnke, B. 1977 Das adsorptions-belebungsverfahren. *Korrespondenz Abwasser* **24** (2), 33–40.

Böhnke, B., Schulze-Rettmer, R. & Zuckut, S. W. 1998 Cost-effective reduction of high-strength wastewater by adsorption-based activated sludge technology. *Water Engineering Management* **145** (12), 31–34.

De Clippeleir, H., Vlaeminck, S. E., De Wilde, F., Daeninck, K., Mosquera, M., Boeckx, P., Verstraete, W. & Boon, N. 2013 One-stage partial nitritation/anammox at 15 °C on pretreated sewage: feasibility demonstration at lab-scale. *Applied Microbiology and Biotechnology* **97** (23), 10199–10210.

de Graaff, M. & Roest, K. 2012 *Inventarisatie van AB-systemen – optimale Procescondities in de A-trap*. Report No. 2012.094, Watercycle Research Institute (KWR), Nieuwegein, The Netherlands.

Feyen, H. A. 1992 Upgrading of the Stolberg sewage treatment plant for biological nitrogen and phosphorus removal. *Water Science and Technology* **25** (4–5), 355–362.

Grady Jr, C. P. L., Daigger, G. T., Love, N. G. & Filipe, C. D. M. 2011 *Biological Wastewater Treatment*, 3rd edn. CRC Press, Boca Raton, FL, USA.

Henze, M., Gujer, W., Mino, T. & van Loosdrecht, M. C. M. 2000 *Activated Sludge Models ASM1, ASM2, ASM2d and ASM3.* IWA Task Group on Mathematical Modelling for Design and Operation of Biological Wastewater Treatment, London, UK.

Jenkins, D., Richard, M. G. & Daigger, G. T. 2004 *Manual on the Causes and Control of Activated Sludge Bulking, Foaming, and Other Solids Separation Problems*, 3rd edn. CRC Press, Boca Raton, FL, USA.

Jetten, M. S. M., Horn, S. J. & van Loosdrecht, M. C. M. 1997 Towards a more sustainable municipal wastewater treatment system. *Water Science and Technology* **35** (9), 171–180.

Lotti, T., Kleerebezem, R., Kip, C. v. E. T., Hendrickx, T. L. G., Kruit, J., Hoekstra, M. & van Loosdrecht, M. C. M. 2014 Anammox growth on pretreated municipal wastewater. *Environmental Science and Technology* **48** (14), 7874–7880.

Miller, M. W., Regmi, P., Wett, B., Murthy, S. & Bott, C. B. 2014 On-line sensors for the control and optimization of an adsorption-style HRAS pilot study. In: *Proceedings of the IWA World Water Congress & Exhibition*, *Lisbon, Portugal*, September 21–26.

Nogaj, T. M., Randall, A. A., Jimenez, J. A., Takács, I., Bott, C. B., Miller, M. W., Murthy, S. & Wett, B. 2015 Modeling of organic substrate transformation in the high-rate activated sludge process. *Water Science and Technology* **71** (7), 971–979.

Olsson, G. 2012 ICA and me – A subjective review. *Water Research* **46** (6), 1585–1624.

Orhon, D. 2014 Evolution of the activated sludge process: the first 50 years. *Journal of Chemical Technology Biotechnology* **90** (4), 608–640.

Regmi, P., Miller, M. W., Holgate, B., Bunce, R., Park, H., Chandran, K., Wett, B., Murthy, S. & Bott, C. B. 2014 Control of aeration, aerobic SRT and COD input for mainstream nitritation/denitritation. *Water Research* **57**, 162–171.

Regmi, P., Holgate, B., Fredericks, D., Miller, M. W., Wett, B., Murthy, S. & Bott, C. B. 2015 Optimization of a mainstream nitritation-denitritation process and anammox polishing. *Water Science and Technology* **72** (4), 632–642.

Rieger, L., Thomann, M., Gujer, W. & Siegrist, H. 2005 Quantifying the uncertainty of on-line sensors at WWTPs during field operation. *Water Research* **39** (20), 5162–5174.

Smitshuijzen, J. 2014 *Modelling the AB-process to Implement Cold CANON*. MS thesis, Delft University of Technology, The Netherlands.

Sorensen, J., Thornberg, D. E. & Nielsen, M. K. 1994 Optimization of a nitrogen-removing biological wastewater treatment plant using on-line measurements. *Water Environment Research* **66** (3), 236–242.

Tchobanoglous, G., Burton, F. L. & Stensel, H. D. 2003 *Wastewater Engineering: Treatment and Reuse*, 4th edn. McGraw-Hill, Boston, USA.

Wan, J., Gu, J., Zhao, Q. & Liu, Y. 2016 COD capture: a feasible option towards energy self-sufficient domestic wastewater treatment. *Sci. Rep.* **6**, 25054.

Wandl, G., Kroiss, H. & Svardal, K. 2006 The main wastewater treatment plant of Vienna: an example of cost effective wastewater treatment for large cities. *Water Science and Technology* **54** (10), 79–86.

Wett, B., Omari, A., Podmirseg, S. M., Han, M., Akintayo, O., Brandón, M. G., Murthy, S., Bott, C., Hell, M., Takács, I., Nyhuis, G. & O'Shaughnessy, M. 2013 Going for mainstream deammonification from bench to full scale for maximized resource efficiency. *Water Science and Technology* **68** (2), 283–289.

Winkler, M. K. H., Kleerebezem, R. & van Loosdrecht, M. C. M. 2012 Integration of anammox into the aerobic granular sludge process for mainstream wastewater treatment at ambient temperatures. *Water Research* **46** (1), 136–144.

Xu, G., Zhou, Y., Yang, Q., Lee, Z.-P., Gu, J., Lay, W., Cao, Y. & Liu, Y. 2015 The challenges of mainstream deammonification process for municipal used water treatment. *Applied Microbiology Biotechnology* **99** (6), 2485–2490.

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SUPPLEMENTARY MATERIAL

Table S1. Average RWI and A-stage pilot effluent concentrations (n >77) and removal efficiencies (± standard deviation).

Parameter	RWI	Effluent	Removal (%)
COD (mg/L)	562 (± 88)	287 (± 69)	48 (± 13)
sCOD (mg/L)	213 (± 29)	137 (± 32)	36 (± 12)
pCOD (mg/L)	350 (± 86)	151 (± 50)	55 (± 16)
TSS (mg-SS/L)	207 (± 71)	94 (± 29)	55 (± 14)
VSS (mg-SS/L)	183 (± 63)	81 (± 25)	54 (± 15)
TKN (mg-N/L)	43 (± 4)	38 (± 4)	14 (± 7)
TAN (mg-N/L)	35 (± 4)	32 (± 4)	11 (± 5)
TP (mg-P/L)	5.8 (± 0.7)	4.4 (± 1.1)	24 (± 11)
Alkalinity (mg-$CaCO_3$/L)	178 (± 18)	167 (± 17)	8 (± 5)
pH	6.6 (± 0.1)	7.0 (± 0.1)	–

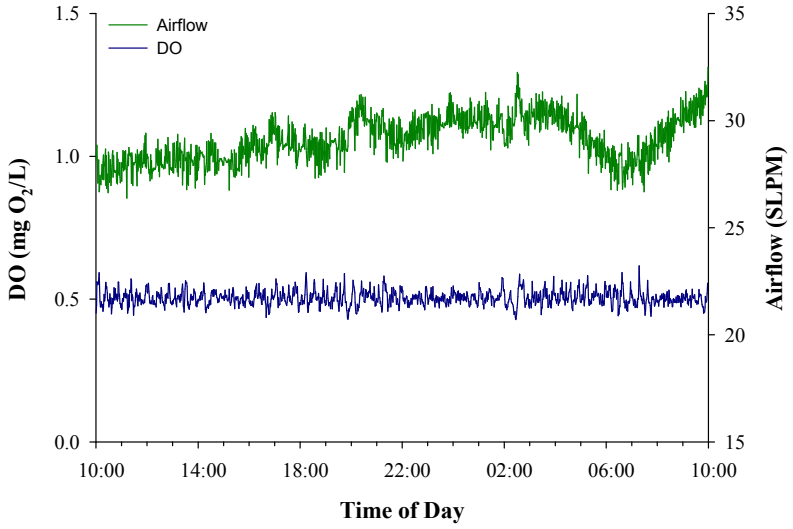

Figure S1. Time series of sensor DO concentration and measured airflow when cascade DO control is operational. User DO setpoint was 0.5 mg/L during operation.

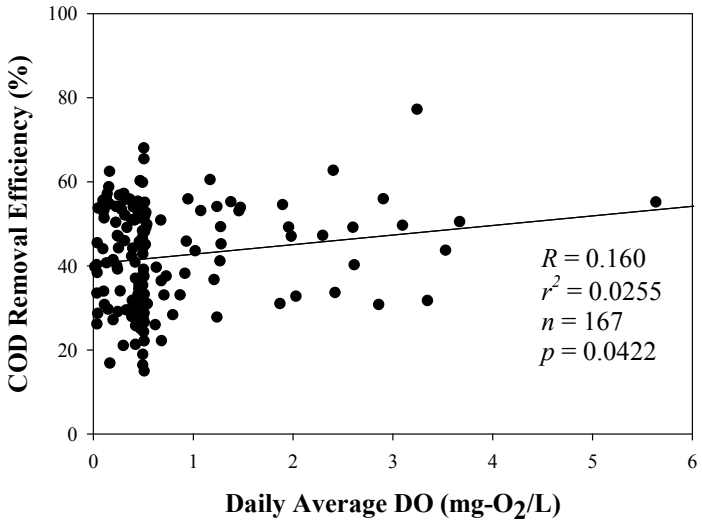

Figure S2. Comparison of daily average DO concentration to COD removal efficiency of the A-stage pilot process.

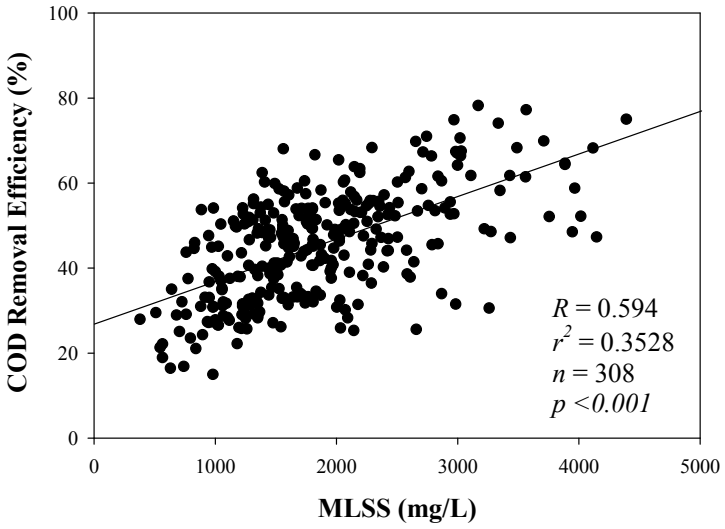

Figure S3. Comparison of MLSS concentration to COD removal efficiency of the A-stage pilot process.

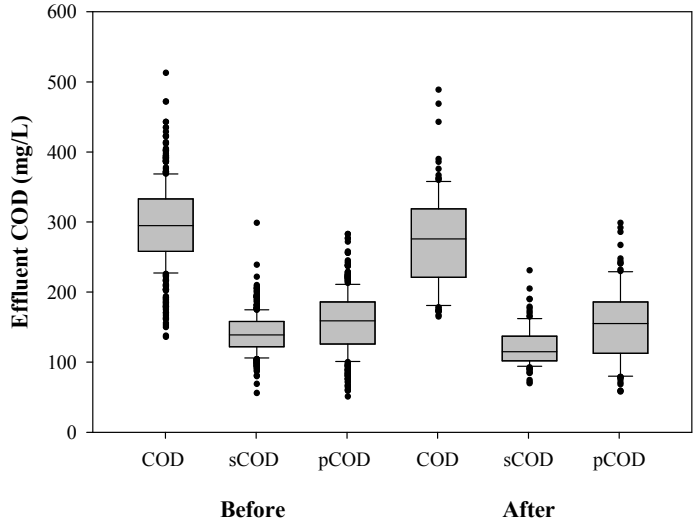

Figure S4. Comparison of A-stage effluent COD fractions before and after implementation of MLSS-based SRT control. Coefficient of variation of effluent COD, sCOD, and pCOD before: (0.20; 0.20; 0.28) and after: (0.25; 0.23; 0.35).