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Total ammonia aeration control (TAAC) theory – An innovative ammonia-based aeration controller

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ABSTRACT

Water resource recovery facilities (WRRFs) need optimized and robust solutions to ensure efficient and reliable operation for this critical environmental service. Secondary treatment aeration control is a prime example as the activated sludge treatment process consumes the largest amount of energy for WRRFs, which require oxygen to biologically remove the ammonia content through nitrification. The selected control strategy will directly impact system efficiency and ability to maintain discharge permit compliance levels. The use of an ammonia-based aeration controller has two major benefits for these systems: (1) cost savings, through minimization of energy usage, and (2) enhanced performance from a steady effluent ammonia concentration. These benefits come from an increase in the system biological kinetics. The process control improvements result in a higher rate of total nitrogen removal, via simultaneous nitrification/denitrification, through delivery of the minimum instantaneous oxygen necessary over time. The thesis contained herein is a novel controller algorithm, which leverages the relationship between primary input and output variables of this complex treatment process. The approach provides continuous output stability and a substantial reduction of the overall system costs, through decreased wear of large-budget equipment and by requiring fewer algorithm input data sources than any other possible solution.

Key words: 4-element controller, ABAC, aeration control, energy savings

HIGHLIGHTS

- Novel design of an aeration controller does not use dissolved oxygen as a primary control variable.
- A three-element proportional–integral–derivative controller coupled with feedback linearization is used to create a four-element controller.
- The controller detailed is the optimal solution requiring the minimum amount of process data and field devices.

1. INTRODUCTION

There has been much progress in the improvement of controls for aeration in secondary treatment processes at water resource recovery facilities (WRRFs) over recent years. Historically, many WRRFs have adjusted the air supplied to secondary biological nutrient removal (BNR) systems to maintain a dissolved oxygen (DO) content of the process aerated zones, generally around 1.0–2.5 mg/L (Åmand 2014). Energy use from aeration has been vastly researched because it quantifies commonly as half of the consumption of a WRRF (WEF 2009), and some reports show this to be as high as 75% (Reardon 1995). Many case studies of full-scale implementations have shown that ammonia-based aeration control (ABAC) results in increased treatment effectiveness and a substantial reduction of energy consumption from aeration, often 15–25% (Rieger *et al.* 2012a).

It has been proven that migration to a supervisory controller that is ammonia based will provide cost savings by reducing the DO setpoints to lower levels, versus overaerating the media to ensure full nitrification of the ammonia content. Another benefit is an increase in the overall nitrogen removal through simultaneous nitrification/denitrification (SND) (Jimenez *et al.* 2013). In this article, I will detail the development of a novel controller for these systems that use the total influent ammonia rate to provide optimal control stability of the primary output variable, ammonia concentration, achieved from the minimal information necessary for the process. This method enables WRRF entities to utilize a real-time data-driven model and precise aeration setpoints, without being encumbered with the additional effort for installation and maintenance of devices required for traditional control approaches.

1.1. Removing nitrogen: nitritation, nitrification, and denitrification

A brief overview of the purpose of aeration for the conventional secondary treatment process: the activated sludge process uses oxygen as the catalyst for a two-step biological reaction, followed by a second biological reaction that produces nitrogen gas. The two-step reaction includes: (1) nitritation, where ammonia-oxidizing bacteria population converts ammonia to nitrite; and (2) nitrification, where a population of nitrite-oxidizing bacteria converts nitrite to nitrate (Rieger *et al.* 2013). The nitrification of ammonia to nitrate is the precursor to the denitrification reaction, sometimes required depending on effluent limits, where a population of heterotrophic bacteria will convert the nitrate to nitrogen gas. This gas will dissipate into the atmosphere with the final results of all of the reactions from this process driving a total nitrogen removal rate.

These systems develop an inherit nitrogen removal rate that is primarily determined by the existing nitrifier biomass, set by the average ammonia load and the solids retention time (SRT) (Rieger *et al.* 2013). This rate is the most direct quantification of efficiency of the treatment process and can be increased significantly via SND. It has been shown that SND is possible via two paths: (1) conventional, reactions mentioned earlier in this section occur concurrently, and (2) nitritation–denitrification (nitrite-shunt), where the nitrification step is inhibited, and denitrification converts nitrite directly to nitrogen gas. It has been shown that this is of particular interest for potential savings, but controlling the DO to the proper setpoint is challenging (Jimenez *et al.* 2013).

1.2. Ammonia-based aeration control

The selection of these advanced aeration controllers has been proven to be a crucial operational element, which will benefit treatment and reduce costs. The reactions covered in the previous section imply that a solution that provides the minimum oxygen necessary over time would be optimal. Any supervisory controller for aeration which is derived from the ammonia content of the substrate can be classified as ABAC. There are two distinct approaches for ABAC: feedforward and feedback. A simple version of ABAC uses feedback of an effluent ammonia concentration measurement to drive cascaded proportional–integral–derivative (PID)-based controllers (Figure 1). The first controller for ammonia that determines the relevant zone DO setpoints, a subsequent controller for DO that sets the airflow rate per zone, and the final element controller that maintains the airflow setpoint for each zone (Anderson *et al.* 2018).

Feedback control has been widely regarded as the preferred method since the first controller loop can be switched off or even fail with the DO controller used as a backup (Rieger *et al.* 2013). However, the nitrification rate is logarithmically related

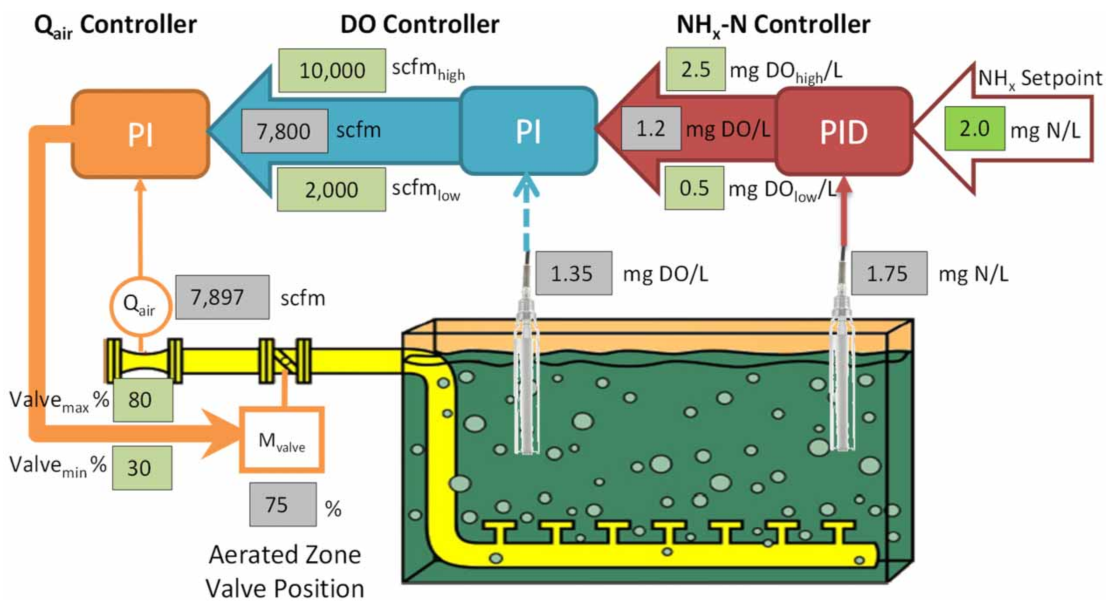

Figure 1 | Feedback ABAC, using ammonia concentration driven cascaded PID controllers (Anderson *et al.* 2018).

to the DO concentration of the substrate, which means that there is diminished return on the efficiency benefits as the rate of oxygen added to the system is increased in proportion to the loading (Figure 2). This is a key factor in the ability of the PID controller to provide stable control of DO, as the algorithm is designed for use with linearly related variables. This item leads to control issues, even in the case of basic valve position control, due to nonlinearity across the range of operation. These issues lessen the advantage of feedback ABAC solutions by permitting improper control at various levels of DO (e.g., oscillation around the setpoint) or complicate the implementation by requiring adaptive PID tuning parameters.

Feedforward controllers have traditionally used established models to predictively generate DO or airflow setpoints (Åmand & Carlsson 2013). The use of the latter will result in less significant airflow changes during operation, which is beneficial by reducing wear on the primary aeration equipment (blowers and valves). In particular, WRRFs that have large spikes of influent ammonia would benefit from utilizing feedforward. For these cases, the plug flow return will have a higher concentration of ammonia and compound these events when using only feedback control strategies. This is because the error deviation from setpoint must occur at the effluent measurement point prior to any corrective action being taken (Rieger *et al.* 2013). This leads to the question, Could both feedforward and feedback methods be combined into a single controller to derive the benefits of both and negate the pitfalls?

The result of this question is the thesis of this article. Total ammonia aeration control (TAAC) is a four-element controller that uses PID feedback control in conjunction with recent historical data to directly determine airflow setpoints. It leverages statistical analysis to find the current linear relationship between: (1) influent loading, the rate of total ammonia (flow rate × ammonia concentration) entering the treatment area, and (2) the oxygen rate required given the existing system conditions to achieve the desired effluent setpoint. This analytic is often referred to as the *specific air* of the process, but in general terms, it is the quantification of the process efficiency. The algorithm uses this analytic to initially calculate a feedforward component. The TAAC algorithm then makes an adjustment, via the feedback component, which modifies this calculated real-time air demand to account for disturbances and/or changes that occur over time within the system (e.g., temperature, pH, SRT (Åmand *et al.* 2013)).

2. METHODS

2.1. Control theory

Increased capacity and enhanced performance via optimization of a system through control improvements come at low costs for implementation, especially when compared to alternatives that require physical modifications. As operational excellence efforts are conducted across multiple industries, there have been major strides made in controller design for complex systems, such as aeronautical flight control and wastewater aeration. This section provides an informational brief on how the progression of PID controller design has contributed to major parts of the advancement in the process control domain.

2.2. The PID algorithm

The PID algorithm is the most widely used method for providing closed-loop (feedback) control of a system, with most analog signal controllers in operation using the core principles. The algorithm generates a response to the error between the output

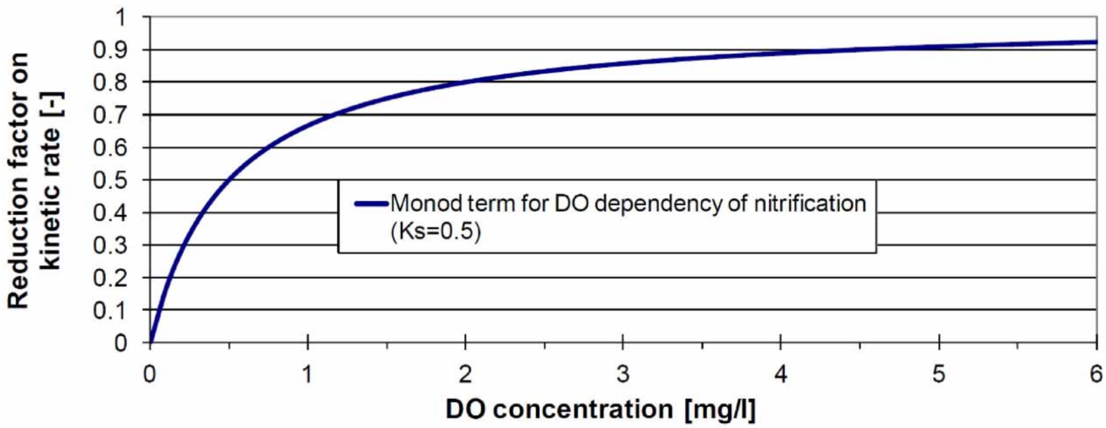

Figure 2 | Monod term for DO dependency of nitrification of a half-saturation constant of 0.5 mg/L (Rieger *et al.* 2012a).

variable and a process setpoint. The gain parameters embedded in the equation allow for weight assignments of each component that enables this algorithm to account for differences in system attributes (e.g., lag, capacitance, and resistance). There are several variations of the PID that can be used in different applications, with the *independent or parallel* version shown in Equation (1) (Erickson 2005). An operator command (e.g., valve position or pump speed) can be supplied from the output of a tuned PID, which drives the controlled variable to meet the desired setpoint. A PID-based controller depends heavily on the near-linearity of the controlled variable (e.g., flow, pressure) response to changes in operator command via the function output.

$$u(t) = P = K_P e(t) + K_I \int_0^t e(\tau)d\tau - K_D \frac{d}{dt} y(t) + \text{Bias} \tag{1}$$

- $u(t)$: PID result (P)
- $y(t)$: Process variables (system output or controlled variable)
- $e(t)$: Error function, $(\text{SP}(t) - y(t))$ *or* $(y(t) - \text{SP}(t))$
    - $\text{SP}(t)$: System setpoint
- K_P: Proportional gain
- K_1: Integral gain
- K_D: Derivative gain
- t: Current time
- τ: Integration variable (taking on values of time over the integral range)
- Bias: A function offset that can be adjusted to the specific system

This implies that the use of a DO variable within any PID controller is not the optimal solution to maintain a stable ammonia concentration and will lead to some instability in ABAC implementations. It often results in the need for regular tuning of the PID parameters to adjust for system characteristics to create quality control.

2.3. Cascaded PIDs

A more advanced implementation is known as a cascade loop, where two or more PID algorithms in series create outer and inner PID functions, which results in a single controller output to a final element. This is the same type of approach commonly used for feedback ABAC solutions. The concept is presented here in the following example of a simpler system, control of the temperature in a large capacitance tank. The inner loop PID provides control of the smaller capacitance heat supply, which will require faster responses, while the outer loop controller provides the inner loop a varied setpoint based on operational conditions. This outer loop PID is the reaction to the error of the large tank temperature from the overall system desired setpoint. The two separate PID functions are able to be tuned with the proper parameters that meet the requirements of the different system properties. A visual depiction of this example is shown in Figure 3.

2.4. Three-element controller

A three-element controller is useful and sometimes necessary for systems that require precise manipulation. This method utilizes a feedforward aspect to set an input (manipulated) variable expectation and then applies a compensation based on the output from the controlled variable feedback PID controller. Generation of the feedforward component alters the setup of the feedback adjustment loop and enables the use of specifically tuned parameters for the given system, while the final closed-loop PID maintains the stability of the calculated input variable setpoint. This allows for feedforward and feedback factors that can be varied to account for differences in the mechanistic properties of a system. Boiler drum level controllers often use this design.

Description of the three-element controller components for boiler drum level control depicted in Figure 4:

- Feedforward: Estimates the amount of water consumed using the steam flow generated and the multiplier (K), which is the conversion factor from steam to water.
- Feedback loop: Drum level PID controller, real-time adjustment of the calculated feedforward estimate to provide a more accurate value for make-up water requirements of the boiler.
- Closed loop: Inlet flow PID controller, output sets the valve position to vary input flowrate.

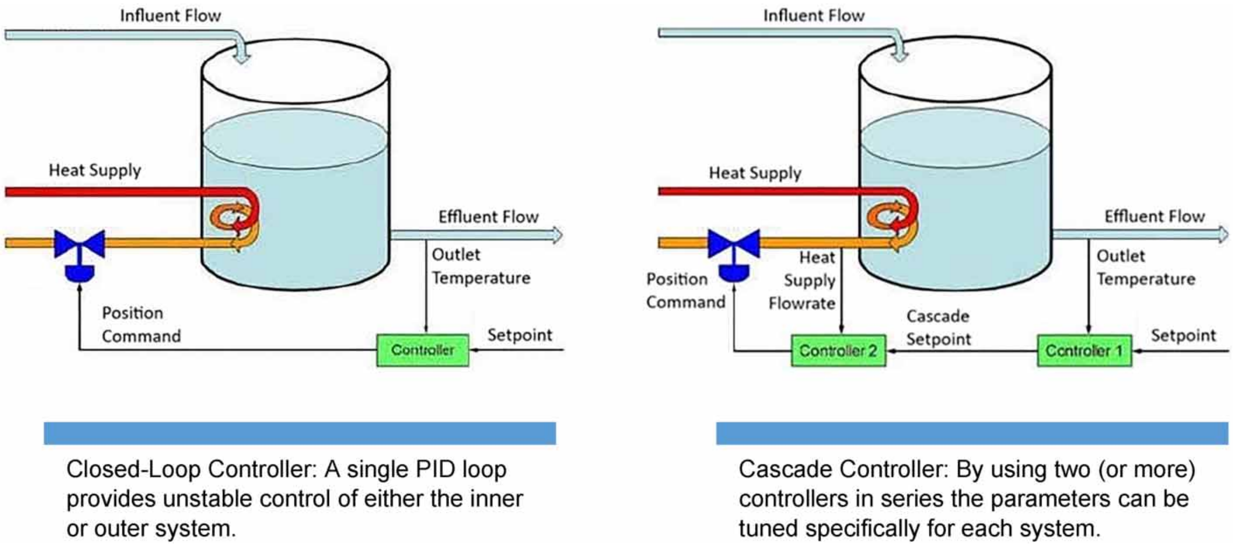

Figure 3 | PID versus cascade PID controller representation for large capacitance tank temperature control.

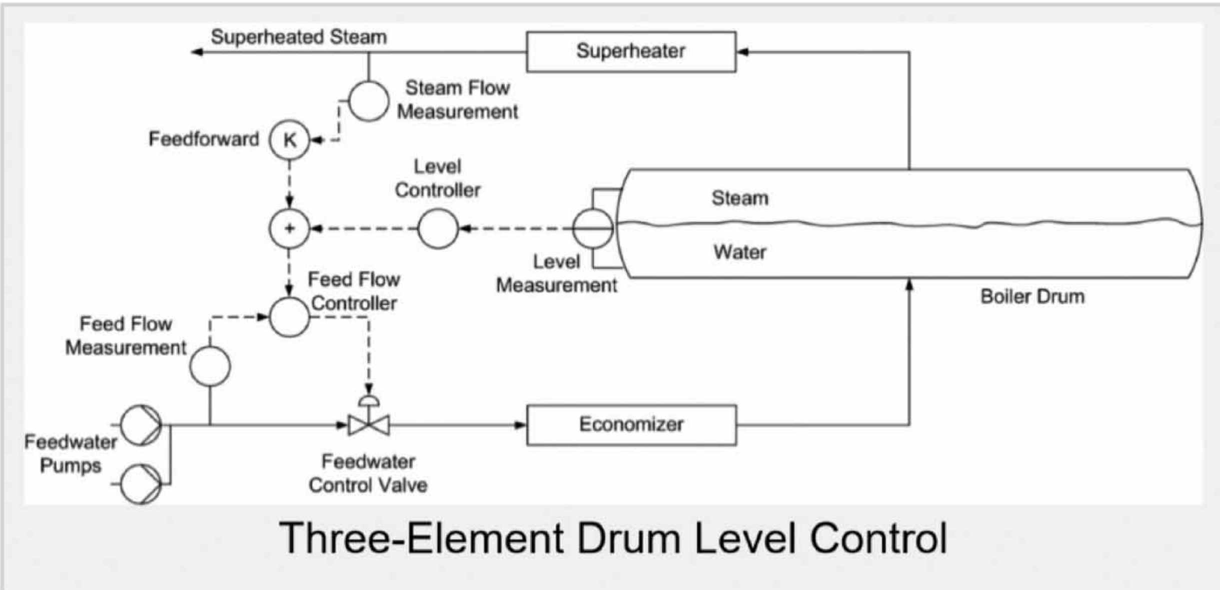

Figure 4 | Boiler drum level controller, visualization (Smut 2011).

2.5. Using the three-element controller

Previous aeration controllers that included a feedforward aspect have relied on biological modeling to predict the required air using loading inputs and system assumptions. These solutions would still often output a DO setpoint for the control zones and would not be able to account for inherited field device issues or variations over time of the model parameters (e.g., analyzer drift, changes in oxygen uptake rate).

There exists a short-term near-linear relationship between:

- Rate of total ammonia (flow × concentration) entering the system ($\dot{m}_{NH_3}$)
- The system airflow rate required to achieve an effluent ammonia concentration ($Q_{air,\, train_i}$)

This relationship, the specific air, allowed the development of a three-element controller that provides a combination of feedforward, feedback adjustment, and closed-loop aspects within a single controller for dictating system air demand. The function output can handle disturbances and even offset instrument measurement deviation (e.g., air and water flowrates, influent ammonia concentration). This three-element controller creates optimal stability of the system for present conditions and is the basis for the TAAC algorithm.

2.6. Feedback linearization

The three-element controller leverages a static relationship that has been predetermined to be the feedforward aspect of the controller, but this efficiency factor, the specific air analytic, will vary over time for WRRF secondary treatment. Internal system changes that affect the underlying process mechanisms alter the specific air such that the three-element controller requires a large feedback adjustment factor (K) to maintain control through all conditions. The near-linearity of the specific air relationship still exists through these variations, but the controller could benefit from having the ability to compensate for these mechanistic property fluctuations that change the slope.

A mathematical technique for providing nonlinear system control, feedback linearization, is able to provide the function corrections within the algorithm that are necessary to adapt to these changes (Megretski 2003). This method treats the slope used as the feedforward relationship to be a function of time, but is otherwise the same general form as a three-element controller. The output of the feedback effluent ammonia concentration PID controller acts as the constant of the linear equation and is already a function of time; a response to the error of the process variable compared to the setpoint. With this technique, the algorithm takes on aspects of a model predictive controller. The following is a representation of the simple form of the TAAC algorithm (Equation (2)):

$$Q_{\mathrm{air,\ train}_i} = a(t) + b_i(t) * \dot{m}_{\mathrm{NH_3}} \tag{2}$$

- $Q_{\mathrm{air,\ train}_i}$: Air flow rate demand for a single train
- $a(t)$: Feedback adjustment PID output
- $b_i\ (t)$: Recent historical train specific air
- $\dot{m}_{\mathrm{NH_3}}$: Influent total ammonia rate

The feedback adjustment, $a(t)$, reacts to system disturbances and alters the output, $Q_{\mathrm{air,\ train}_i}$, to create continuous setpoint achievement of the effluent ammonia concentration. This results in a recent historical dataset that can be considered representative of the optimal slope for current system conditions, as well as predictive of the near future. This historical data can thus be used to generate the slope of the function, $b_i(t)$, given that the encompassing function will correct over time to always represent the current process-specific air relationship. Due to this fact, the dynamic model of the specific air is continually valid, or at least continually approaching the present efficiency due to feedback correction. Over time, the calculated value obtained is representative of the present operational conditions; this is a common shortfall of many controllers that are tuned at a momentary operating point (Åström & Hägglund 1995).

During the review of the algorithm, there were some general questions: How much time should be included from the historical data to create the slope function? How drastic are the system disturbances to be handled by the constant of the linear equation (i.e., by how much should the feedback adjustment be allowed to alter the feedforward estimate)?

2.7. TAAC definitions, formulas, and statistical rules

This section contains the definitions and equations used to create the TAAC algorithm. The statistical rule sets define the value scopes possible for the internal variables of the controller function for any WRRF-activated sludge secondary treatment process aeration system. For this algorithm, time is measured relative to the initiation of the TAAC calculations for control of a system and can be in various increments based on the frequency of process data availability.

Definition: Train

- *In water resource recovery, a train has general use for any series of treatment processes or zones that remove organic matter and nutrients from the substrate. Each process or zone is designed to perform a specific function and to improve the water quality in some way before the discharge is sent back into the environment. In terms of the secondary treatment system being discussed herein, a train comprises of zones that include methods such as anaerobic, anoxic, and aerated reaction methods, which each provide removal of specific components contained within the substrate.*

N = Number of trains in service

n = Number of aerated zones in a train

Definition: Hydraulic retention time (HRT)

- *The time period that a substrate stays within a defined physical region of interest. The HRT between two points is calculated by dividing the volume of each individual process being traversed by the flowrate of the substrate through that area, and then summing all physical transference sections traversed to find the total time period. Examples of substrate transference mechanisms: section of pipe, tank, reactor, lagoon, or any other means of containing or transporting the substrate. This value can be an average for the given physical region found for a time length longer than the HRT of the region. It is even possible for the volume of the region of interest to vary within a train based on variations of the operational purpose and equipment states for each zone within the train.*

$V_{\mathrm{HRT}}(t) = \mathrm{HRT\ Volume}$

Definition: Train flowrate

- *The total flow of substrate to the initial treatment region of the train. This is often a sum of two flows, the influent supply flowrate and an effluent return flowrate. A flow must enter the train upstream of an aerated zone to be included in the flowrate for that zone. For simplicity, the equations set forth will assume a design such that the return flowrate will enter upstream of all aerated zones.*

Equation set: Train flowrate values

$$Q_{\mathrm{Train\ flowrate}}(t) = Q_{\mathrm{Influent\ flowrate}} + Q_{\mathrm{Return\ flowrate}} \tag{3}$$

$$Q_{\mathrm{Air\ flowrate,\ train}_i} = \sum_{j=1}^{n} Q_{\mathrm{Air\ flowrate,\ zone}_j} \tag{4}$$

Definition: TAAC trains – HRT

- *The TAAC train HRT is the transversed region between the physical process point, which the algorithm uses to determine the value of the calculated influent total ammonia and the physical midpoint of all aerated zones of the train. This value can be additionally calculated for each zone within the train, and determination for the individual zone values is recommended in the case of a train where the aerated zones are separated by other nonaerated zones. The equations in this section assume that the influent ammonia concentration measurement is made at a physical process point located upstream of all trains to allow for the overall system to be calculated from a single input value. For the sake of simplicity, the derivation of the following formulas is only for the midpoint for all aerated zones in the train.*

Equation set: TAAC trains – HRT values (for all $t \geq 1$)

$$t_{\mathrm{HRT}}(0) = \frac{V_{\mathrm{HRT}}(0)}{Q_{\mathrm{Train\ flowrate}}(0)} \tag{5}$$

$$t_1(t) = t_{\mathrm{HRT}}\ (t-1) - \frac{1}{2}\frac{V_{\mathrm{HRT}}(t)}{Q_{\mathrm{Train\ \ flowrate}}(t)} \tag{6}$$

$$t_2(t) = t_{\mathrm{HRT}}\ (t-1) + \frac{1}{2}\frac{V_{\mathrm{HRT}}(t)}{Q_{\mathrm{Train\ flowrate}}(t)} \tag{7}$$

$$\text{If } t_2 \geq t\text{ , then } t_2 = t \tag{8}$$

$$t_2 - t_1 = \Delta t_{\mathrm{HRT}} \tag{9}$$

$$t_{\mathrm{HRT}}(t) = \frac{(1/\Delta \mathrm{t_{HRT}})\ \int_{t_1}^{t_2} V_{\mathrm{HRT}}\ dt}{(1/\Delta t_{\mathrm{HRT}})\ \int_{t_1}^{t_2} Q_{\mathrm{Train\ flowrate}}\ dt} \tag{10}$$

Equation: TAAC algorithm – Total influent ammonia rate

$$\dot{m}_{\mathrm{NH_3}} = \left(\frac{1}{\Delta t_{\mathrm{HRT}}} \int_{t_1}^{t_2} Q_{\text{Influent Flowrate}}\, dt \cdot \frac{1}{\Delta t_{\mathrm{HRT}}} \int_{t_1}^{t_2} C_{\text{Influent NH}_3\text{ Concentration}}\, dt \right) \tag{11}$$

Equation: TAAC trains – PID feedback adjustment formula (for $P_{\text{Effluent NH}_3}(t)$ scaled from −1 to 1)

$$a(t) = P_{\text{Effluent NH}_3}(t) \cdot K_{\mathrm{FB}} \tag{12}$$

Rule: TAAC trains – PID feedback adjustment theoretical minimum value

$$\begin{aligned} &\min_{t \to \infty} K_{\mathrm{FB}} \Rightarrow \left\{ \min_{t_0 \leq t \leq t_3} \left(\frac{Q_{\text{air, train}_i}}{(\dot{m}_{\mathrm{NH_3}}/N) * (K_{FF_i}/K_{FF_{\mathrm{System}}})} \right), \max_{t_0 \leq t \leq t_3} \left(\frac{Q_{\text{air, train}_i}}{(\dot{m}_{\mathrm{NH_3}}/N) * (K_{FF_i}/K_{FF_{\mathrm{System}}})} \right) \right\} \\ &\in b_i(t) \pm K_{\mathrm{FB}} \left(\max_{t_0 \leq t \leq t_3} \left(\left| \frac{d}{\mathrm{d}t} b_i(t) \right| \right) \right), \text{ for } t_0 \leq t \leq t_3 \end{aligned} \tag{13}$$

Definition: Specific air interval (SAI) time

- The time period used to find the recent historical specific air of the train.

Rule set: TAAC algorithm – SAI time theoretical values

$$\min_{t \to \infty} \Delta t_{\mathrm{SAI}} \Rightarrow \Delta t_{\mathrm{SAI}} \geq t_{\mathrm{HRT}}(t) \text{ for all } t \tag{14}$$

$$\max_{t \to \infty} \Delta t_{\mathrm{SAI}} \Rightarrow \left\{ \frac{Q_{\text{air, train}_i}}{\frac{\dot{m}_{\mathrm{NH_3}}}{N} * \frac{K_{FF_i}}{K_{FF_{\mathrm{System}}}}} \right\} \in b_i(t) \pm K_{\mathrm{FB}}, \quad \text{for all } t \tag{15}$$

Equation set: TAAC algorithm – SAI values

$$t_0(t) = t - \Delta t_{\mathrm{SAI}} \tag{16}$$

$$t_3(t) = t \tag{17}$$

Note: t_3 can be offset from the current time for delays required for data transfer and quality assurance

Equation: TAAC trains – Specific air rate

$$b_i(t) = K_{\mathrm{FF}_i} = \frac{(1/\Delta t_{\mathrm{SAI}}) \int_{t_0}^{t_3} Q_{\text{air, train}_i}\, dt}{\frac{(1/\Delta t_{\mathrm{SAI}}) \int_{t_0}^{t_3} \dot{m}_{\mathrm{NH_3}}\, dt}{N}} \tag{18}$$

Equation: TAAC algorithm – Specific air rate

$$B(t) = K_{\mathrm{FF_{System}}} = \frac{\sum_{i=1}^{N} \left((1/\Delta t_{\mathrm{SAI}}) \int_{t_0}^{t_3} K_{\mathrm{FF}_i}\, dt \right)}{N} \tag{19}$$

Equation: TAAC algorithm – Total air rate

$$Q_{\text{FF air, system}} = \dot{m}_{\mathrm{NH_3}} \cdot K_{\mathrm{FF_{System}}} \tag{20}$$

Equation set: TAAC train – Total air rate (for i = 1–N)

$$Q_{\text{FF air,train}_i} = Q_{\text{FF air, system}} \cdot \frac{K_{\text{FF}_i}}{K_{\text{FF}_{\text{System}}}} \tag{21}$$

$$Q_{\text{air, train}_i} = P_{\text{Effluent NH}_3}(t) \cdot K_{\text{FB}} + Q_{\text{FF air, train}_i}(Q_{E,\text{ train}_i} = a(t) + b_i(t) * \dot{m}_{\text{NH}_3}) \tag{22}$$

3. RESULTS AND DISCUSSION

Ammonia-based aeration control strategies are gaining in popularity due to the improvement of operational treatment performance and a stark reduction of the maintenance and energy costs to facilities. The overall benefits are reduced though when considering the level of knowledge required to implement the strategy, tune the system controller, the frequency in which tuning adjustments are required due to environmental and/or operational changes, and the additional cost for the equipment required. The use of DO probes for control in any ABAC approach comes with the following negative impacts: (1) a significant rise in cost due to the number of field devices, (2) reduced efficiency and performance from probe fouling, and (3) increased maintenance requirements for the process area.

The goal of any ABAC solution is to provide only the air necessary to maintain a stable ammonia discharge from the secondary treatment process, which the controller detailed within this article will optimize by delivering the minimum amount of air at the appropriate time to achieve the desired setpoint. In addition, a controller that does not use DO as a control variable is preferred, as this measurement of process conditions should only be used for deterring overaeration and system air distribution optimization. These items can both be compensated for during the use of the TAAC method by establishing proper algorithm boundaries and through routine DO analysis of the process zones, versus the current method of real-time monitoring. This reduces the amount of instrumentation that is required for current control methods.

There was a pilot test of the algorithm conducted at the Robert W. Hite (RWH) treatment facility, which was a success. The solution was able to maintain a stable effluent ammonia concentration over the multiyear testing period of a single train implementation. The RWH facility runs two distinct liquid process treatment trains that enable major operational shifts to adjust daily facility loading, either for balancing and/or maintenance. These shifts in loading created large changes to influence the flowrate and substrate characteristics for the pilot system, which showed the controller responsiveness. TAAC outperformed all other methods and maintained an effluent ammonia concentration within 0.5 mg/L, with deviations that exceeded these bounds either due to the previously mentioned large swings that would alter the system dynamics or from impacts of other system issues (Figure 5). Future work will be focused on exception handling for these scenarios.

There may be additional components of the algorithm needed to handle system variations and operational conditions under which this solution has not yet been tested and does not presently address, such as biological phosphorus removal. Any subsidiary variables to be considered will simply create an upper or lower boundary of the function output, as is the case with DO for overaeration prevention for energy savings. It is possible that if phosphorus content continues to become a focus area for WRRF discharge permits, then this controller might change or grow, but if this would change the primary variable of concern, it would alter the system paradigm. There is also investigation and research needed into the long-term effects of low levels of DO on BNR systems, but there is little evidence from previous case studies to believe that it will result in significant issues (Ingildsen *et al.* 2002; Rieger *et al.* 2012b).

The remainder of this section is a summary of the requirements for operating a facility with the TAAC method. At minimum, the algorithm requires the ability to calculate the system input variables and to monitor the controlled output variable. A converged location for both upstream and downstream of a secondary treatment area allows the option of a single data source for each location to determine the process input and controlled values. This holds true even if the influent process values used in the algorithm are generated using historical data in place of a field device, though this method will provide reduced performance and lessen the analysis capabilities of the internal relationships within the system. This same approach of using historical data can also be used for the air flowrates of each zone for individual trains as a fail-safe.

The functions defined in the appendix show that even in the case of multiple trains within the system, the controller can still function with this same single input and generate a full system output that can then be subdivided among the respective trains. In these use cases, locating at least two effluent probes, within different trains, allows for individual train performance to be

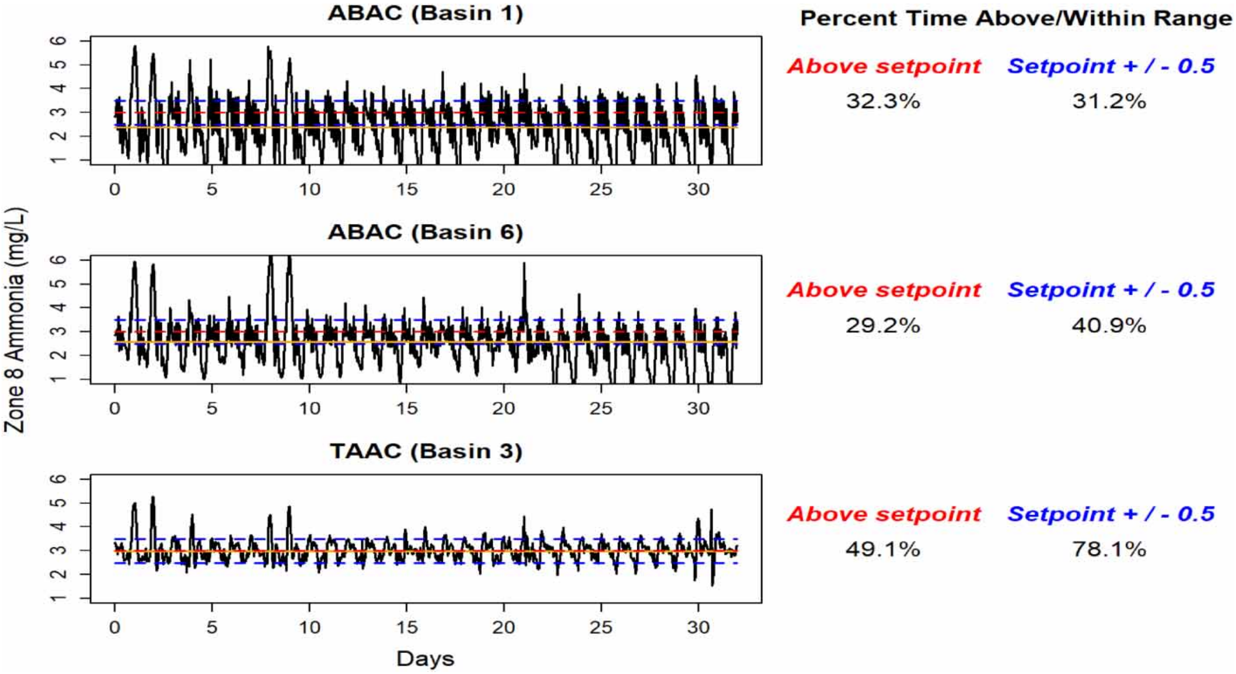

Figure 5 | ABAC solution comparison of effluent ammonia concentration (Budzynski & Newhart 2021).

assessed during operation. This creates the ability to determine one train's process efficiency, specific air, while a second probe is able to provide feedback data for the remaining operational trains with *learned* specific air analyses.

A reliable method for ensuring that an accurate effluent ammonia concentration is provided to the algorithm is highly recommended. As few as three probes in the effluent of the secondary process area would be able to provide robust real-time verification. The use of DO probes near train mid- and endpoint(s) can help to detect overaeration from heavy loading or ammonia probe measurement issues and provide upper boundary control of the air flowrate. If a facility plans to operate at the setpoint boundary condition (i.e., ammonia effluent of 0.0 mg/L), it is recommended that DO be incorporated into the overall controller implementation to improve performance and reliability. In these cases, the DO measurement at the same locations mentioned will be able to provide upper boundary control of the TAAC function output.

4. CONCLUSION

With the use of the established three-element PID controller design as the basis of the control algorithm, coupled with the generation of a function of the specific air analytic of the secondary treatment using feedback linearization, it is possible to infer that TAAC is the optimal solution for control of a stable effluent ammonia concentration. Given that the mechanistic properties of the system do not change quickly, primarily the nitrifier mass, a window of time of several days can be used for calculating the specific air analytic for the algorithm. This also helps prevent device failure or data quality issues from impacting the controller performance. Even reducing the wastage rate to increase SRT will result in a slow change in nitrifier mass over a period of days and weeks, and the impact on nitrification will be slow (Rieger *et al.* 2012a).

Finally, if it is considered that the main objective of an aeration controller is to maintain the stability of both the effluent ammonia concentration and total system air demand, then this method will provide the best results with the least cost impacts and overall effort. With all other solutions for ammonia-based aeration control being considered moot through this innovative approach, it is concluded that TAAC will eventually supersede ABAC.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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