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Application of step-response lambda tuning to proportional-integral controllers in water resource recovery facilities

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ABSTRACT

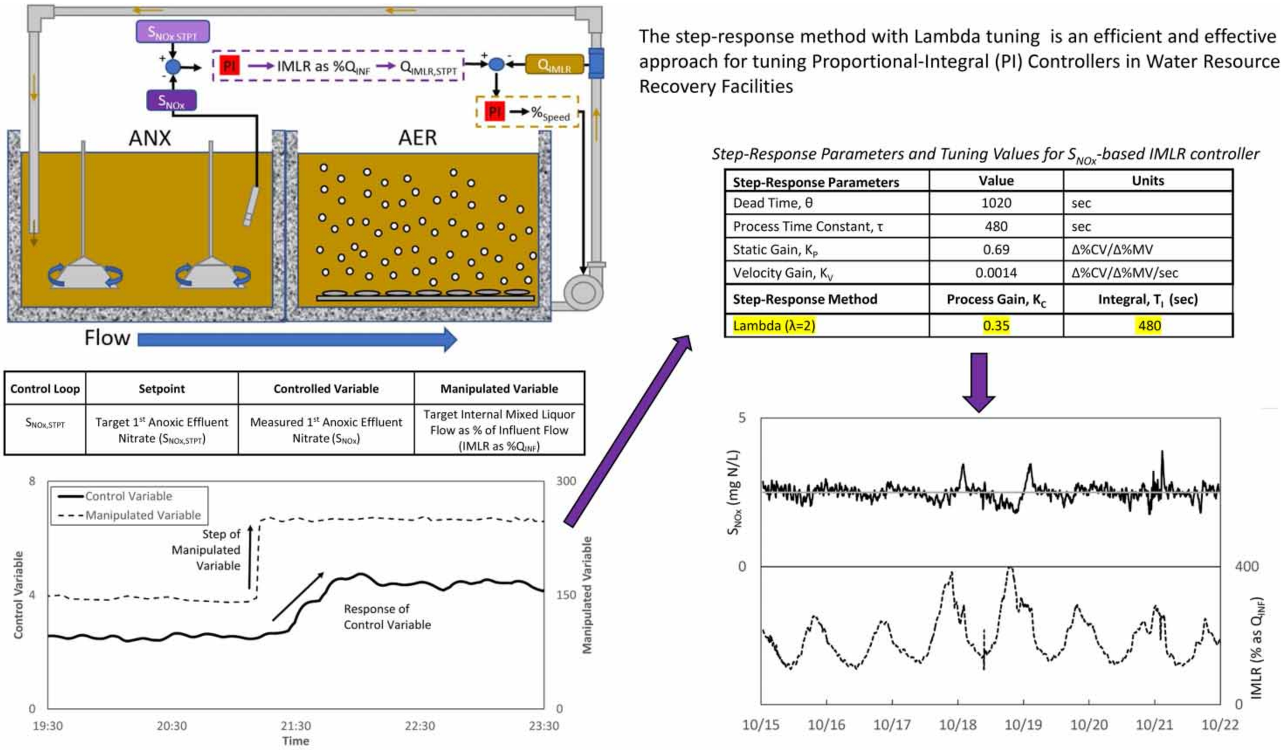
Proportional-integral-derivative (PID) controllers in water resource recovery facilities (WRRFs) feedback control loops are commonplace. While simple to implement, such control loops are rarely tuned optimally or systematically. Heuristic tuning approaches are commonly applied with varying degrees of success using trial-and-error, ad hoc tuning rules, or duplication of tuning values from a similar system. However, there are effective methods, such as lambda tuning, produce acceptable tuning with limited effort. These are based on the step-response method, where a manual process perturbation is used to define the relationship between the manipulated and controlled variables. Based on such an experiment, a simple process model is constructed and used to determine the controller tuning values. In this work, we used the step-response method and lambda tuning for two control systems in full-scale WRRFs. This led to responsive and stable behavior of the controlled system as defined by the absolute average error of the controlled variable to setpoint and standard deviation of the manipulated variable. Tuning of feedback control loops can be completed successfully through a systematic approach, and this work suggests that tuning tools, like lambda, should be part of all wastewater treatment control engineers' toolbox.

Key words: controller stability, controller tuning, lambda tuning, optimization PID control, step-response, WRRF

HIGHLIGHTS

- The step-response method can be used to determine a first-order plus deadtime model of a given water resource recovery facility (WRRF) control loop.
- Lambda tuning with parameters determined from a step-response test and the adjustable-λ factor can produce a well-tuned control loop as quantified by given performance metrics for both fast and slow controllers.
- Step-response tuning is an efficient method for tuning multiple parallel and cascaded PI control loops in a WRRF.

GRAPHICAL ABSTRACT



The step-response method with Lambda tuning is an efficient and effective approach for tuning Proportional-Integral (PI) Controllers in Water Resource Recovery Facilities

Control Loop	Setpoint	Controlled Variable	Manipulated Variable
$S_{NOx,STPT}$	Target 1st Anoxic Effluent Nitrate ($S_{NOx,STPT}$)	Measured 1st Anoxic Effluent Nitrate (S_{NOx})	Target Internal Mixed Liquor Flow as % of Influent Flow (IMLR as $\%Q_{INF}$)

Step-Response Parameters and Tuning Values for S_{NOx}-based IMLR controller

Step-Response Parameters	**Value**	**Units**
Dead Time, θ	1020	sec
Process Time Constant, τ	480	sec
Static Gain, K_P	0.69	Δ%CV/Δ%MV
Velocity Gain, K_V	0.0014	Δ%CV/Δ%MV/sec
Step-Response Method	**Process Gain, K_C**	**Integral, T_I (sec)**
Lambda (λ=2)	0.35	480

INTRODUCTION

Application of simple feedback process control schemes to biological nutrient removal (BNR) systems, such as dissolved oxygen (DO) control, and more advanced control systems, such as ammonia-based aeration control (ABAC) and supplemental carbon control, can improve and stabilize effluent quality while leading to cost savings from reductions in chemical and energy usage (Ingildsen & Olsson 2002; Ingildsen & Wendelboe 2003; Stare *et al.* 2007; Olsson 2012; Rieger *et al.* 2012; Amand *et al.* 2013). Furthermore, the cost to implement or advance existing controllers is lower relative to the cost of infrastructure upgrades to improve effluent quality (Olsson *et al.* 2005).

Implementation of advanced controllers in water resource recovery facilities (WRRFs) will become inevitable, especially in larger utilities, as the 'pull' (e.g. reduced nutrient limits and population growth) and 'push' (e.g. technological advances) forces meet each other (Olsson 2012; Yuan *et al.* 2019). Multiple texts exist discussing WRRF sensor issues, controller design, tuning of feedback control algorithms, and controller monitoring within WRRFs, but these are underutilized resources and provide limited practical information for tuning of slow process controllers (Olsson & Newell 2005; Rieger *et al.* 2005, 2006; WEF 2013; Olsson *et al.* 2005; Rosso 2018). The lag between control implementation and/or successful use has been attributed to the human factor, lack of appropriate incentives, instrumentation difficulties, and operator trust in controllers (Rieger & Olsson 2012; Yuan *et al.* 2019; Warren *et al.* 2021). Even with push–pull and available reference material, surveys have found that 50% of installed automated process controllers are in manual at WRRFs (Olsson *et al.* 2005). This indicates a significant gap between the design of control systems and the subsequent delivery and operation, even though the industrial control theory is a thoroughly studied and published topic.

The most common feedback controller is the proportional-integral-derivative (PID) algorithm, which when well-tuned, allows a control system to maintain the controlled variable (CV) near setpoint by adjusting the manipulated variable (MV) in response to disturbances. The PID algorithm is simple to implement and has been referred to as the 'bread-and-butter' of control engineering with more than 95% of control loops using a form of PID control (Guo 2020). PID controllers are equipped with parameters that enable tuning of the dynamic behaviour of the controlled system. Tuning using a manual method (sometimes called trial and error or brute force) or duplicated tuning values from parallel applications is fairly popular across industrial applications

(Åström *et al.* 1993; Koelsch 2014). The manual tuning approach can be guided by either experience-derived intuition or the use of heuristic methods to determine tuning parameters. This method can be time consuming, may put process or equipment at risk, and can delay or prevent operator trust during the iterative process. Eventually, manual tuning can converge on tuning values that result in an adequately tuned but non-optimized controller. A review of the state of Japanese chemical process control experiences indicated that manual tuning was sufficient in 80% of PID control loops citing level and flow control as examples (Kano & Ogawa 2010). Automatic tuning algorithms can be used to identify tuning parameters within the system's control software (if available) or as an external application (Åström *et al.* 1993). Automatic tuning removes the human from the loop and identifies tuning values by characterizing the relationship between the MV and CV. External automatic tuning tools require connection with control software to update tuning values (or reintroducing the human to the loop), along with correct integration of PID control loop settings and structure.

Today, knowledge and use of common control engineering methods for tuning PID-based WRRF control systems is limited in treatment plants where process engineers or instrumentation technicians serve as the control experts. A survey of South African control engineering professionals found that electrical, chemical, and mechanical engineering curriculums did not produce skills that met current industry needs in control engineering (Bauer *et al.* 2014). This gap in skills is brought forth in a survey of WRRF industry professionals which found that tuning and monitoring of control systems performance is under-utilized and has been identified as a need within the community (Eerikäinen *et al.* 2020).

Literature pertaining to industrial PID tuning is prolific, and methodologies have been established (O'Dwyer 2009; Somefun *et al.* 2021). It is hypothesized that even when sensor issues are well managed, PID-based control systems do not perform to the desired outcomes due to manual tuning or sufficient initial tuning but decay in controller performance overtime. We believe this to be true for relatively novel BNR control systems such as ABAC, (S_{NHx})versus nitrate/nitrite (S_{NOx}) aeration control (AVN), internal mixed liquor recycle (IMLR) flow control, and supplemental carbon control. Indeed, our experience suggests that (1) manual tuning takes significant time due to long process reaction times while testing different tuning variables or difficultly decoupling CV response between influent dynamics and changes in tuning variables or (2) taking tanks in or out of service adjusts detention times or treatment volume.

The objective of this work was to develop and test a step-response tuning method on typical WRRF control systems with either slow response times or multiloop interconnected systems. The example applications included a first anoxic S_{NOx}-based IMLR flow controller and a complex aeration control system with airflow, dissolved oxygen, header pressure, and most-open-valve (MOV) control. We specifically evaluated the utility of the lambda tuning method for WRRF control systems.

MATERIALS AND METHODS

Control theory and practice

PID control

The classic form of the PID equation uses the process error ($e(t)$) calculated as the difference between the CV and setpoint and identifies the change in MV ($u(t)$) required to drive the CV closer to setpoint:

$$u(t) = K_C\left(e(t) + \frac{1}{T_I}\int_0^t e(t)dt + T_D * \frac{de(t)}{dt}\right) + u_0 \tag{1}$$

The value for $u(t)$ is determined by four parameters: the proportional gain K_C, the integration time T_I, the derivative time T_D, and the initial action of the controller u_0. Determination of the appropriate values for these parameters is known as PID tuning. Performance metrics, as defined in a later section, can be used to define and measure control tuning objectives such as variation of the MV or average $e(t)$ over a defined period.

It has been hypothesized that 60% of implemented PID controllers only use the first two terms, K_C and T_I, after being tuned. The remaining 40% is equally divided between using the first term only (K_C tuning only) and using all three terms (Luyben & Luyben 1997). The use of the first two terms reduces the controller to the PI structure rather than a PID structure and can be considered sufficient in processes that can be modelled as a first-order plus deadtime (FOPDT) relationship between the CV and MV although a well-tuned PID controller may result in better performance than a well-tuned PI controller. The FOPDT can be written as the following transfer function (Åström & Hägglund 1995):

$$\frac{Y(s)}{X(s)} = \frac{K_P e^{-\theta s}}{\tau s + 1} \tag{2}$$

In this model, the relationship between the MV ($X(s)$) and the CV ($Y(s)$) can be described by three parameters. These parameters are as follows:

- Deadtime (θ) – time it takes to see a change in the CV after a step in the MV.
- Static gain (K_P) – gain of step response, % total change of the control variable due to % change of the MV.
- Process time constant (τ) – the time at which 63% of the change in the process variable has occurred after the first response is seen in the process variable.

The values for these parameters are determined experimentally (see below). The behaviour of continuously stirred tank reactors (CSTRs) placed in series, used to model BNR in WRRF, can be approximated by a FOPDT model, thus supporting the idea that PI control suffices for this kind of process. Figure 1 shows the time-series response of a step input to a FOPDT model and similarly parameterized CSTRs-in-series as calculated by the equations found in SI Table I.

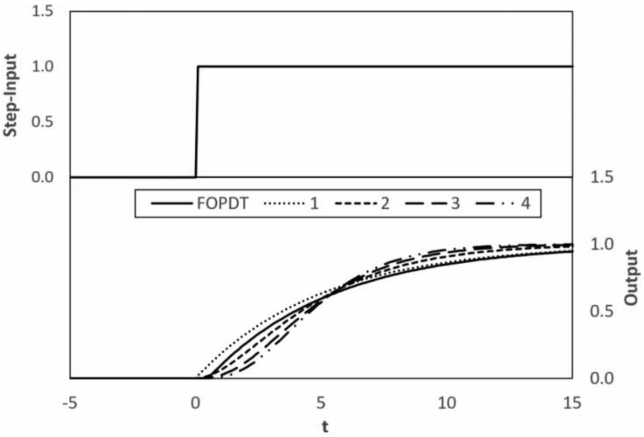


Figure 1 | Time-series response of a step input (upper) to a FOPDT model with $\vartheta = 0.1$ s, $\tau = 5$ s, $K_P = 1$ and CSTRs-in-series with a $\tau = 5$ s (lower).

The derivative term, when used, acts as predictor by accounting for the future $e(t)$ based on the slope of the CV as it approaches or travels away from setpoint and is more appropriate for systems that can be described as second order (Åström & Hägglund 1995). Since this prediction is based on differentiation, it tends to amplify noise in the measurement of the CV in turn increasing the risk for unstable system performance. Noisy sensor values that impact WRRF control are common in WRRF control systems (Rieger *et al.* 2003). This provides another reason to exclude the third term and use a PI structure rather than a PID structure, especially when an exceptionally fast response is not required.

Identification of a first-order plus dead time model through the step-response test

A step-response test can be conducted by introducing a step in the MV to a relatively stable system in an open loop near the normal operating point and observing the reaction curve produced by the response of the CV, a representative example of which is shown in Figure 2.

The CV reaction occurs as a result of the step change in the MV and is then used to identify the parameters of the FOPDT relationship between the MV and CV described earlier. The use of a step-response test to create a process reaction curve and to parameterize the relationship between the control and MV with only two parameters (KP and θ) was first published by Ziegler and Nichols in 1942 (Ziegler & Nichols 1993). This was expanded by Cohen and Coon to include the process time constant, τ, expanding the derivation to a FOPDT

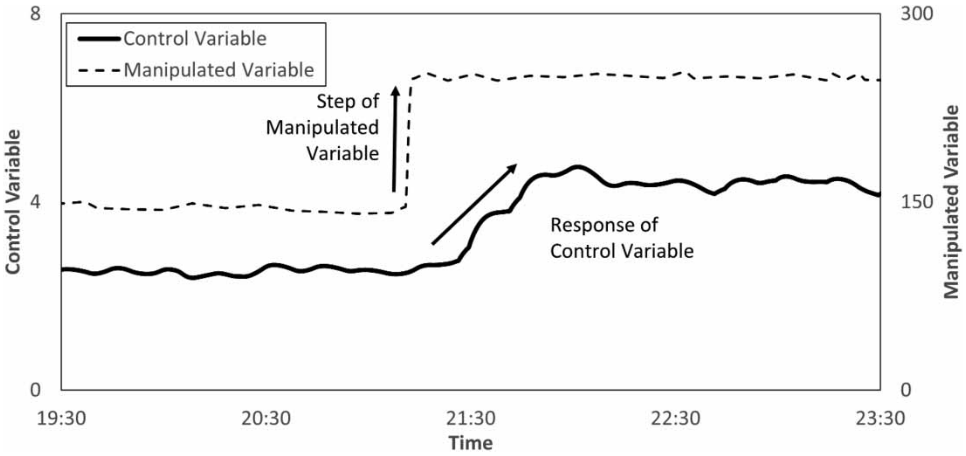


Figure 2 | Step of manipulated variable and corresponding response curve of a control variable.

model (Cohen & Coon 1953). The step-response test is a simple, straightforward, and robust method for fitting a control loop as a FOPDT model. After a step-response test, parameters can be identified through manual trial and error or automatic model fitting. Automatic model fitting can be achieved with software programs such as Excel™ for small datasets using matrix algebra or the solver function. Python™ can be utilized for larger datasets or multiple-step tests when paired with an optimizer package. Automatic model fitting is preferred to reduce human error, subjective assessment of model quality, and replicability from multiple step tests on the same system.

Once the FOPDT model and its parameters are set, one can derive corresponding parameter values for the PI controller. Multiple methods of varying complexity have been developed to do so. Examples of common methods are shown in Table 1. The Cohen–Coon and Ziegler–Nichols method target underdamped decay of $e(t)$ creating intentional oscillations of the CV around setpoint (Hägglund & Åström 2002). This leads to reduced settling time (t_s) but an increase in the variance of the manipulated variable (σ_{MV}), defined below. The resulting controller tuning is completely determined by the parameters of the identified FOPDT model. Lambda tuning provides some additional flexibility by providing a user-defined parameter λ. This enables tuning in favour of critical dampening of the controlled system, minimizing overshoot and oscillations of both the CV and MV. Lambda tuning increases the overall stability of the system while trying to meet setpoint and is well suited for systems with long process time constants (Garpinger *et al.* 2012). Using K_C and T_I empirically derived from real-time process behaviour then has the potential to expedite startup, process stabilization of multiple interacting control loops, and retuning based on process or seasonal changes.

Table 1 | Common step-response test tuning methods for the standard form of the PI algorithm

Methods	**Controller tuning objective**	**Proportional gain (K_C)**		**Integral (T_I)**	
Ziegler–Nichols (Hägglund & Åström 2002)	1:4 decay ratio	$\left(\frac{0.9}{K_P}\right)\left(\frac{\tau}{\theta}\right)$		3θ	
Cohen–Coon (Cohen & Coon 1953)	Fast response on self-regulating control loops	$\left(\frac{0.9}{K_P}\right)\left(\frac{\tau}{\theta}\right)+\left(\frac{0.083}{K_P}\right)$		$\theta\left(\frac{0.9\tau+0.083\theta}{0.27\tau+0.6\theta}\right)$	
Lambda (or IMC) (Hägglund & Åström 2002; Coughran 2013)	Non-oscillatory response with λ tuning parameter, critical dampening	$\frac{\tau}{K_P(\tau\lambda+\theta)}$		τ	
Approximated M_s^a integral gain optimization (AMIGO) (Hägglund & Åström 2002)	Allows for compensation of system dynamics	$\frac{0.35}{K_v\theta}-\frac{0.6}{K_P}$	for $\theta<\frac{\tau}{6}$	7θ	for $\theta<0.11\tau$
		$\frac{0.25\tau}{K_P\theta}$	for $\frac{\tau}{6}<\theta<\tau$	0.8τ	for $0.11\tau<\theta<\tau$
		$\frac{0.1\theta}{K_P\tau}+\frac{0.15}{K_P}$	for $\tau<\theta$	$0.3\theta+0.5\tau$	for $\tau<\theta$

[a] M_s is the maximum sensitivity of any closed loop stable process.

Controller performance metrics

Established control engineering metrics used to determine the performance of controllers are listed in Table 2. Application and monitoring of performance metrics on WRRF BNR controllers provide quantitative values for assessing performance, initiating operator interaction, comparing tuning methods, and identifying the need to re-tune the controller. Performance metrics, such as the absolute average error (AAE), can be incorporated into the WRRF's system control and data acquisition (SCADA) system for continued monitoring. Performance metrics that require some qualitative assessment, such as the decay ratio, can be assessed as needed. In control engineering, integrated absolute error is commonly used as a performance metric, but the use of AAE over the same time range, which is presented in the units of CV, is easier for operations staff to understand for performance monitoring. The acceptable AAE of a control loop can also be identified by operations staff to establish performance requirements of the controller. These metrics can then be used to set practical key performance indicators (KPIs) from actual controller performance ensuring reasonable expectations of performance by operations staff and metrics to initiate actions such as re-tuning.

Table 2 | Quantitative metrics for measuring controller performance (adapted from Marlin 2000)

Metric	Equation	Value
AAE	$\frac{\sum_{i=1}^{n} \lvert E_i \rvert_i}{n}$	Magnitude of controller error over a given time range present in units of CV
Standard deviation of MV (σ_{MV})	$\sqrt{\frac{\sum_{i=1}^{N} (MV_i - \overline{MV})^2}{n-1}}$	Short-term stability metric for manipulated variable to minimize mechanical wear
Decay ratio (B:A)	$\frac{B^{a}}{A}$	Ratio of the magnitude of neighbouring controlled variable peaks to quantify dampening.
Settling time (t_s)	$t_d - t_{2.5\%}$	Time it takes after a disturbance (t_d) for a controlled variable to reach 2.5% ($t_{2.5\%}$) of final value

[a] B is the most recent amplitude of the controlled variable relative to setpoint, and A is the amplitude of the preceding period.

In most applications, multiple metrics are needed to assess control performance, thus rendering control tuning into a multi-objective optimization problem. This explains, in part, why adoption of systematic control tuning methods is not widespread. In most cases, AAE and σ_{MV} are sufficient for comparing different K_C and $\mathrm{T_I}$ values or setting KPIs for a given WRRF process controller. WRRF processes are constantly being disrupted by the daily dynamic nature of the influent rather reducing the value of settling time as a performance metric. In an effort to minimize impacts of tightly controlled systems on parallel or downstream processes, most WRRF controllers target critical dampening, or little to no overshoot of the CV, eliminating the value of decay ratio for performance assessment.

Case studies

Nitrate-based IMLR control

Hampton Roads Sanitation District's (HRSD) Army Base Treatment Plant (ABTP) in Norfolk, Virginia, USA, is a five-stage Bardenpho treatment plant with a capacity of 180,000 PE and 82 ML/d. The IMLR at ABTP is controlled by a nitrate/nitrite ($\mathrm{S_{NOx}}$) probe at the end of the first anoxic zone to maximize utilization of influent carbon for nitrogen removal while reducing energy requirements due to aeration and pumping.

The control structure was cascaded as described in Table 3, where the MV of the outer loop was the setpoint for the CV for the inner loop. This inner loop adjusted an MV to meet the setpoint passed from the outer loop. In this case, the outer loop PI controller used $\mathrm{S_{NOx}}$ as the CV and $\mathrm{S_{NOx,STPT}}$ as the setpoint to output a flow setpoint as percent of influent flow (% as Q_{INF}). The control system calculated the target IMLR ($Q_{\mathrm{IMLR,STPT}}$) using the current influent flow rate (Q_{INF}). $Q_{\mathrm{IMLR,STPT}}$ was then used by the inner loop PI controller as a setpoint with Q_{IMLR} as the CV to modulate the % pump speed as the MV. A simplified graphical representation of the process and control structure is shown in Figure 3. The relationship between the CV and MV for both the outer and inner

Table 3 | Cascade control structure for IMLR control at HRSD ABTP

Control loop	Setpoint	Controlled variable	Manipulated variable
Q_{IMLR} (inner)	Target internal mixed liquor flow ($Q_{IMLR,STPT}$)	Measured internal mixed liquor flow (Q_{IMLR})	Internal mixed liquor pump speed (%)
$S_{NOx,STPT}$ (outer)	Target first anoxic effluent nitrate ($S_{NOx,STPT}$)	Measured first anoxic effluent nitrate (S_{NOx})	Target internal mixed liquor flow as % of influent flow (IMLR as %Q_{INF})

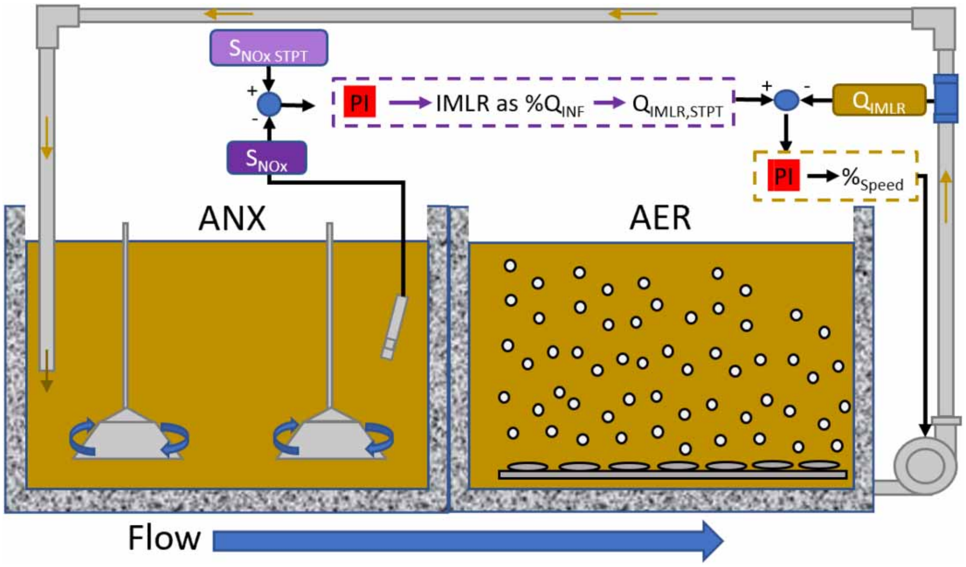


Figure 3 | Internal mixed liquor control at HRSD's Army Base Treatment Plant in Norfolk, VA.

can be described as direct where increasing Q_{IMLR} increases S_{NOx} and increasing % speed of the pump increases Q_{IMLR}, respectively.

Adverse impacts of overpumping IMLR include additional energy consumption from pumping with no process gains and possible reduction in $\mu_{max,NITO}$ (Jimenez *et al.* 2011). Under pumping, IMLR can lead to settling issues from low F/M filaments, additional aeration energy consumed, or additional downstream carbon utilization to meet effluent nutrient targets. The S_{NOx} setpoint ($S_{NOx,STPT}$) is set by the operator to maintain constant residual effluent SNOX from the first anoxic zone. Tuning of the inner loop is not included in this example as the intention was to focus on a slow BNR controller.

Cascaded dissolved oxygen (S_{O2}) control and MOV blower header pressure control

HRSD's Virginia Initiative Process (VIP) treatment plant, also located in Norfolk, Virginia, USA, is a Virginia Initiative Process (VIP) plus post-anoxic and reaeration configuration with a capacity of 400,000 PE and 151 ML/d (Daigger *et al.* 1989). The aeration control system consists of a multiple parallel-tank cascaded S_{O2}-air-flow-valve configuration with cascaded blower MOV header pressure control. Cascaded S_{O2} control was used instead of direct-valve S_{O2} control to compensate for nonlinearities present in butterfly valves and allow the use of safety nets such as anti-windup control (Amand *et al.* 2013). MOV header pressure control adjusted blower output to meet the dynamic aeration requirements and maintained the aeration valves in an optimal control range (Alex *et al.* 2002). Table 4 shows the structure of the VIP aeration control system with Figure 4, providing a simplified graphical representation of the aeration and blower control system at VIP.

RESULTS

Step-response tuning of S_{NOx}-based IMLR control at ABTP

A step-response test was conducted on the outer loop of the S_{NOx}-based IMLR controller at ABTP during dry weather daily peak flow conditions. Figure 5 shows the results of the step-response test with relevant data

Table 4 | Cascaded control structure for aeration control and parallel most-open-valve header pressure control at HRSD VIP treatment plant

Control loop	**Setpoint**	**Controlled variable**	**Manipulated variable**
$Q_{\mathrm{AIR,SO2}}$ (inner)	Target airflow ($Q_{\mathrm{AIR,STPT}}$)	Airflow (Q_{AIR})	Airflow control valve position ($\%_{\mathrm{OPEN}}$)
S_{O2} (outer)	Target dissolved oxygen ($S_{\mathrm{O2,STPT}}$)	Dissolved oxygen (S_{O2})	Target airflow ($Q_{\mathrm{AIR,\ STPT}}$)
Header pressure (inner)	Blower header pressure setpoint (ρ_{STPT})	Blower header pressure (ρ)	Blower output ($\%_{\mathrm{OUTPUT}}$)
Most-open-valve (outer)	Most open valve ($\%_{\mathrm{MOV,STPT}}$)	Current most open valve ($\%_{\mathrm{MOV}}$)	Blower header pressure setpoint (ρ_{STPT})

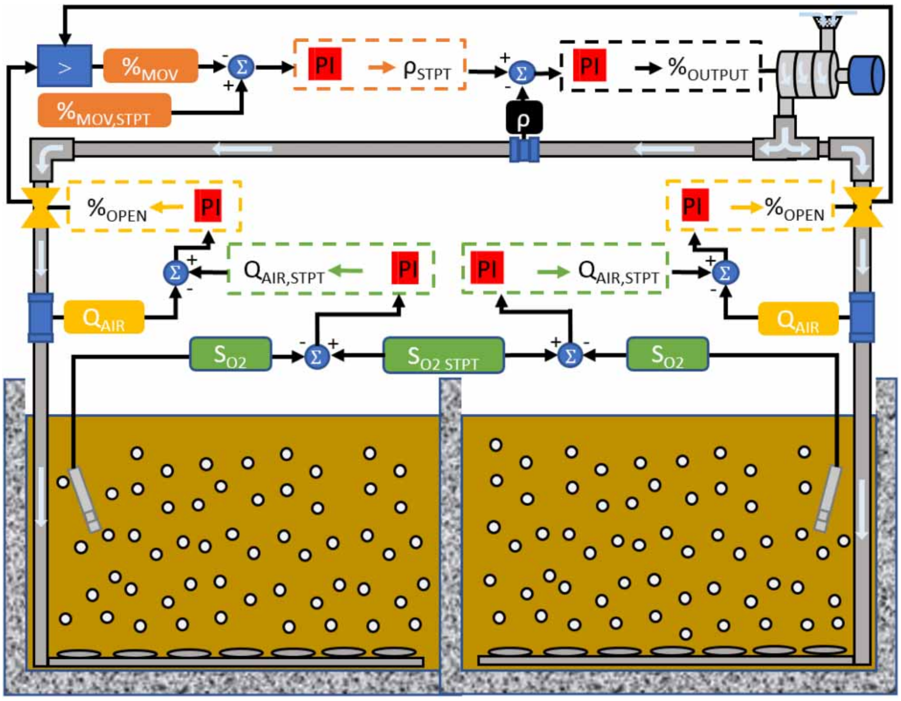


Figure 4 | Simplified aeration control configuration for HRSD's VIP treatment plant showing cascaded control loops of dissolved oxygen (S_{O2}) and MOV blower header pressure control.

points (Table 5) labelled to determine step-response parameters. Subjective assessment of the step-response curve was used to identify data points used for parameter determination. Error introduction from subjectivity can be considered minimal if a well-defined step-response curve such as Figure 5 results from the step-test.

Table 6 shows the step-response parameters calculated from relevant data points and the resulting K_C and T_I by means of the step-response methods found in Table 1. It is important to highlight here that understanding of PID algorithm implementation and scaling is required for the correct application of step-response tuning. In this instance, the CV was normalized for a range of 0–10 mg $\mathrm{S_{NOx}}$/L and the MV was normalized for a range of 0–400% of $\mathrm{Q_{INF}}$ to calculate $\mathrm{K_P}$. The tuning methods presented in Table 1 are for the standard PI algorithm form and require the T_I calculated by the step-response methods to be divided by the respective K_C to correct for the parallel form implemented in the ABTP SCADA. The integral values for both the standard and parallel form of the PID algorithm are presented in Table 6.

Although the calculated K_C and T_I are shown for all the tuning methods, only the Lambda tuning method was tested. The Ziegler–Nichols method and the Cohen–Coon method were not selected because of the desire to minimize oscillatory responses to disturbances as would occur with large process gains associated with tuning

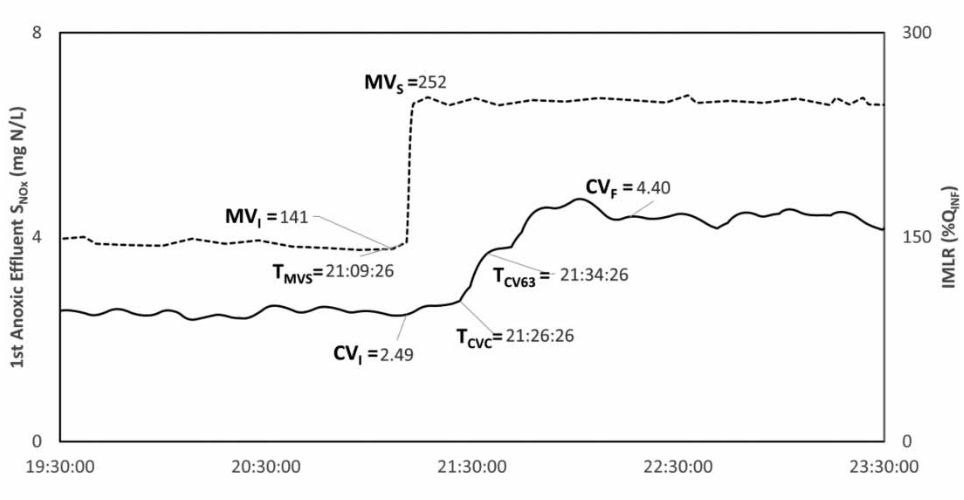


Figure 5 | Step-response test for S_{NOx}-based IMLR control at HRSD's ABTP with relevant MV (IMLR as %Q_{INF}, solid black line) and CV ($S_{NOx,}$ dashed line) data points labelled for calculation of first-order plus deadtime model parameters.

Table 5 | Definition of values identified in a step-response test for FOPDT model parameterization

	Point	Definition
MV data points	MV_I	Initial value of the manipulated variable
	MV_F	Value the manipulated variable is 'stepped' too
	T_{MVS}	Time at which the MV is 'stepped'
CV data points	CV_I	Initial value of the CV
	CV_F	Value at which the CV stabilizes
	T_{CVC}	Time at which a change is first observed in the CV after the MV step
	$T_{CV63\%}$	Time at which the CV has changed 63% of the total change.

Table 6 | Step-response parameters and calculated process gain and integral terms from step-response methods listed in Table 1 for S_{NOx}-based IMLR controller at HRSD's ABTP

Step-response parameters	Value	Units	
Dead time, θ	1,020	s	
Process time constant, τ	480	s	
Static gain, K_P	0.69	Δ%CV/Δ%MV	
Velocity gain, K_V	0.0014	Δ%CV/Δ%MV/s	
Step-response method	**Process gain, K_C**	**Integral, T_I (s)**	
		Standard, T_I	**Parallel, T_I/K_C**
Ziegler–Nichols	0.61	3,060	4,985
Cohen–Coon	0.73	711	986
Lambda (λ = 2)	0.35	480	1,387
AMIGO	0.53	546	1,039

objectives indicated in Table 2. Ultimately, lambda tuning ($\lambda = 2$) K_C and T_I was utilized in the S_{NOx}-based IMLR controller at HRSD ABTP. Lambda tuning has been shown to have more sluggish performance compared to AMIGO, and this sluggishness translates to less actuation of mechanical equipment (minimizing wear and risk of overshoot while sacrificing tight control) (Hägglund & Åström 2002). An advantage of the adjustable lambda value is the allowance of fine tuning based on controller performance goals. Literature recommends a λ between 1 and 3, with a λ of 1 considered aggressive (Garpinger *et al.* 2012). As shown in Figure 6 and Table 7, stable control was achieved with the disturbance introduced by diurnal variation.

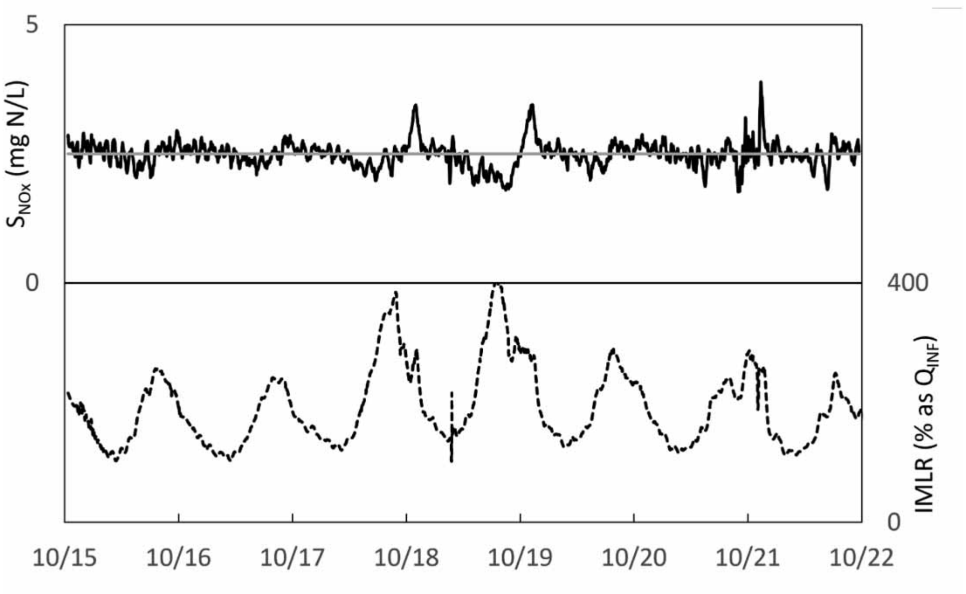


Figure 6 | HRSD's ABTP NOx-based IMLR controller with IMC/lambda tuning over one week of operation with S_{NOx} (solid black line, upper) as the CV targeting the CV S_{NOx} setpoint (grey line, upper) by adjusting the IMLR flow as $\%Q_{INF}$ (dashed line, lower).

Table 7 | Selected performance metrics for HRSD's ABTP NOx-based IMLR controller

Performance metrics		Units
Average absolute error	0.18	mg/L
Average daily σ_{MV}	52.4	+/ − %Q

Step-response tuning of VIP's blower and aeration control system

Logically, a cascaded controller is tuned by first tuning the inner loop followed by the outer loop. The interdependence of variables across the VIP aeration and blower control loops creates a larger pseudo-cascaded control system connected by the behaviour of the valves spread over up to six aeration trains each with its own airflow control valve. A change in a valve position will impact the system header pressure and header pressure setpoint (if the valve in question is the 'most-open-valve') while trying to maintain $Q_{AIR,STPT}$ determined by the S_{O2} control loop. Step-response tuning was conducted from what is considered the innermost to the outermost loop as shown Table 8. A common rule of thumb for stability in cascade control systems is for an 'inner' loop settling time to be roughly one-third that of the corresponding outer loop.

Table 8 | Control loop tuning order for VIP's blower and aeration control system

Tuning order	Control loop
1. (Inner most loop)	Header pressure (inner, blower),
2.	$Q_{AIR,SO2}$ (inner, S_{O2})
3.	S_{O2} (Outer, S_{O2})
4. (Outer most loop)	Most-open-valve (outer, blower)

All loops considered 'outer' relative to the control loop being tuned loop were placed in the manual during the step-response test to ensure the response of the control variable was only due to a change in the MV. All loops considered 'inner' to the control loop being tuned were enabled and tuned prior to the step-response test. The lambda method was used to tune the entire system as it provided the ability to adjust step-response parameter-based K_C and T_I to achieve the desired stability across the cascaded system by adjusting λ.

Table 9 shows the identified K_P, τ, and θ with selected λ to calculate K_C and T_I for each loop. Performance was assessed qualitatively to identify the optimal λ for each loop as the short response times of the loop allowed for rapid refining. A small λ of 1 was sufficient for S_{O2} control, but much higher λ values than the recommended single-digit range in the cited literature were required for $Q_{AIR,SO2}$ and MOV control loops. The λ values for the $Q_{AIR,SO2}$ loops were 30–45 to slow the valves relative to the header pressure and parallel $Q_{AIR,SO2}$ control loops. A λ of 25 for the MOV control loop sufficiently slowed the change to the header pressure setpoint to maintain the MOV near setpoint. This λ value led controller performance which adequately responded to changing influent loading while preventing instability to the inner $Q_{AIR,SO2}$ loops and oscillation of the entire control system.

Table 9 | VIP aeration and blower control loop parameters, λ, and tuning variables from step-response test with integral for the standard (T_I) and parallel (T_I/K_C) PI algorithm

	Step-response parameters			**Tuning variables**			
Control loop	K_P	θ **(s)**	τ **(s)**	λ	K_C	T_I **(s)**	T_I/K_C **(s)**
ρ	0.16	8	3	10	0.49	3	6
T1 Q_{AIR}	1.42	0	1	45	0.016	1	64
T1 S_{O2}	0.32	187	173	1	1.48	173	117
T3 Q_{AIR}	0.99	0	1	30	0.034	1	30
T3 S_{O2}	0.53	92	154	1	1.186	154	130
T4 Q_{AIR}	0.40	0	1	30	0.084	1	12
T4 S_{O2}	0.72	66	166	1	0.99	166	167
MOV	−1.00	21	44	25	0.039	44	1121

Annotated plots of each step-response test can be found in SI Figure I, and SI Table II presents the values used to determine the step-response parameters and subsequent tuning variables presented in Table 9. Figure 7 displays the performance of the VIP's aeration and blower control system over a 4-day period after tuning was conducted with performance metrics listed in Table 10. Good performance as shown by control plots and performance metrics was achieved using the step-response method with lambda tuning. The S_{O2} control loops were tuned to achieve fast and responsive control for the future implementation of ABAC. In the event ABAC was not to be implemented a larger λ for the S_{O2} control loops would increase stability of the control system further. Controller tuning performance with original values is not provided for comparison as it is possible with manual tuning the tuner will converge on a similar solution. Here, step-response tuning provides an efficient and effective tuning method for WRRF controllers without putting process or equipment at risk.

DISCUSSION

Step-response method and WRRFs

This work demonstrated that the step-response method is a succinct and effective approach to tune WRRF BNR control systems in instances where auto-tuning tools are not available or difficult to use. The step-response method parameterizes the relationship of the MV and CV as an FOPDT model allowing tuning values to be derived directly from the observed behaviour of the control loop. Depending on the control goal or scoped performance metrics, there are multiple approaches to determining K_C and T_I from the step-response derived parameters.

It is important to establish the control goal and performance metrics which can guide the selection of a tuning method. Lambda tuning values meet the criteria of WRRF systems in most cases, as the critical dampening objective introduces more stability and the adjustable λ adds fine-tuning capabilities. The use of the adjustable λ allows the subjectivity to be utilized when the range recommended in the literature results in poor performance. The selection of a larger λ than cited for the airflow control loops (T1 Q_{AIR}, T2 Q_{AIR}, T4 Q_{AIR}, and MOV) in the VIP Aeration and Blower Control System was necessary to slow these outer control loops relative to their inner control loop (ρ) and each other. If a much smaller λ is used, the control system becomes unstable from

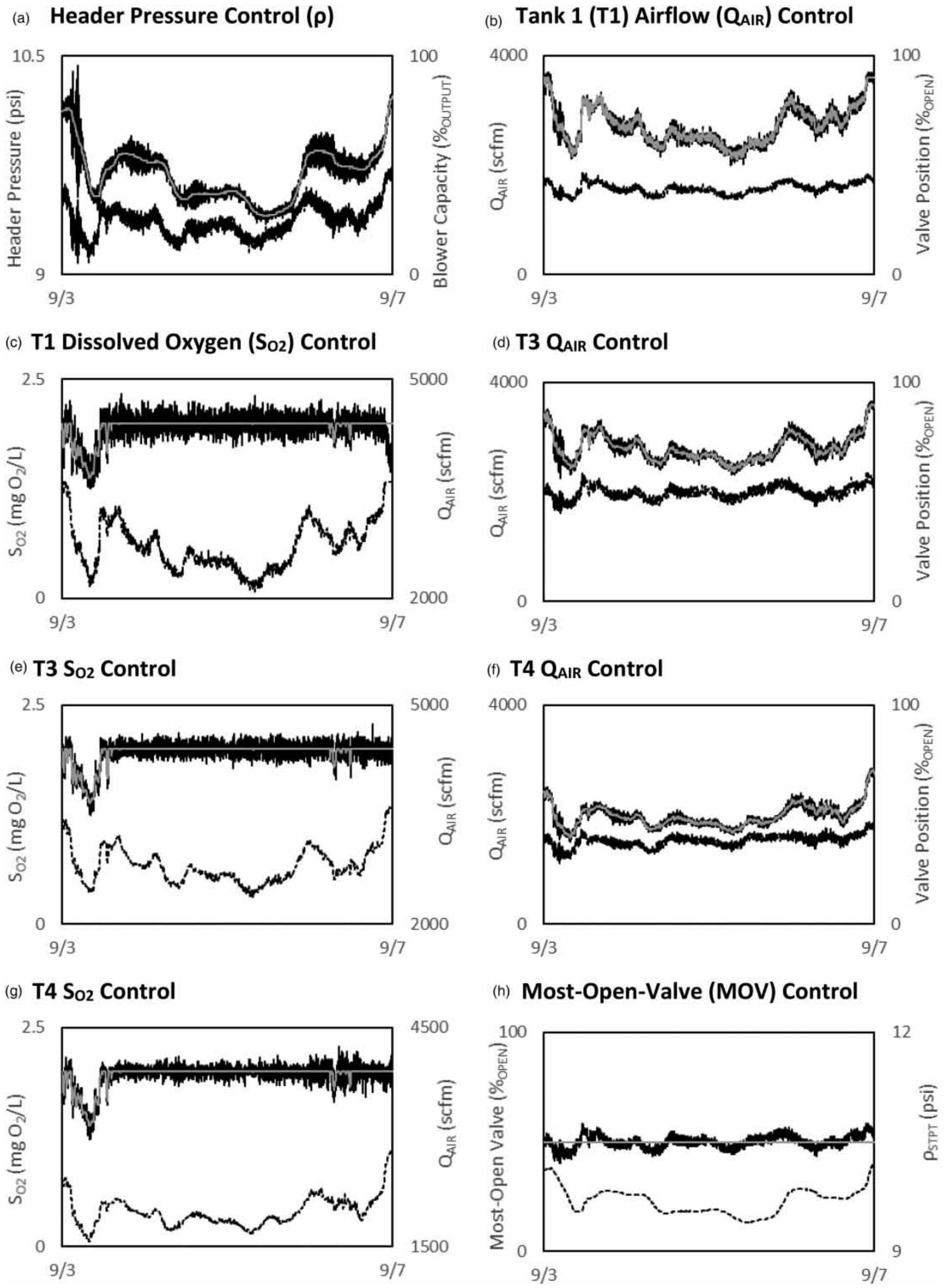


Figure 7 | HRSD's VIP Aeration and Blower Control System over 4 days of operation after step-response tuning. CV (upper black line) and setpoint (grey line) are displayed on the left *Y*-axes and MV (lower dashed black line) on right *Y*-axes. (a) Header pressure control, (b, d, and f) airflow flow control for three different aeration tanks, (c, e, and g) dissolved oxygen control for corresponding three aeration tanks, and (h) most-open-valve control.

oscillating valve positions and blower outputs. This is an additional advantage to using Lambda over other tuning methods as it allows for fine-tuning to stabilize multiple parallel control loops.

This method is especially valuable in slower BNR controllers where manual tuning is difficult as shown with S_{NOx}-based IMLR control, but it is also effective in fast controllers that are typically tuned manually as shown with VIP's blower and aeration control system. The step-response test requires introducing a sustained but controlled disturbance to a process, the risk of which can be managed through planning. Conversely, manual tuning using a trial-and-error method can lead to unstable control putting equipment or process at risk while biasing operators to distrust the controller. However, we suspect that step-responses can be automatically introduced to re-tune controller on a regular basis or whenever current control performance is considered inadequate.

Table 10 | Performance assessment of VIP's aeration and blower control system after step-response tuning

	Performance metrics			
Control loop	**AAE**	**Unit**	σ_{MV}	**Unit**
ρ	0.03	psi	1.38	$\%_{OUTPUT}$
T1 Q_{AIR}	48	scfm	0.36	$\%_{OPEN}$
T1 S_{O2}	0.07	mg S_{O2}/L	12.56	scfm
T3 Q_{AIR}	40	scfm	0.59	$\%_{OPEN}$
T3 S_{O2}	0.05	mg S_{O2}/L	5.37	scfm
T4 Q_{AIR}	29	scfm	0.60	$\%_{OPEN}$
T4 S_{O2}	0.05	mg S_{O2}/L	4.05	scfm
MOV	3.14	$\%_{OPEN}$	1.5E-03	psi

Important considerations

PID algorithm in SCADA packages

Successful application of the step-response method requires a good understanding of the exact implementation and configuration of the controller. The PID algorithm can be implemented in a variety of forms, such as standard/ideal, parallel, or series/interacting. Another practical aspect concerns the scaling of the MV. Some implementations will use a range from 0 to 100, while others may use the range 0–1. The exact form depends on the SCADA package utilized at the WRRF, as well as preferences of the automation programmer (Rockwell Automation 2017; Emerson Process Management Power & Water Solutions Inc. 2019). While all these forms are equivalent and can be tuned to match each other's dynamic response, there are subtle differences in how the tuning coefficients are set (Table 11). For example, in the standard/ideal and series/interacting form the process gain, K_C, is applied to the entire equation, increasing the magnitude of the response to error while in the parallel form K_C only applies to $e(t)$. T_I can also sometimes be presented as integral gain, K_I (equal to K_c/T_I) and is directly multiplied by the integrated error rather than the inverse as with T_I. Different implementations can produce the same outcome if accounted for during tuning and deployment of the selected tuning parameters. Relevant information for the PID algorithm such as implementation or further details listed below is contained in software manual and configured by the automation programmer.

Table 11 | Forms of PID algorithm as implemented in SCADA systems

Proportional-integral-derivative algorithm forms	
Standard/ideal	$u(t) = K_C\left(e(t) + \frac{1}{T_i}\int_0^t e(t)dt + T_d\frac{de(t)}{dt}\right) + I$
Parallel/independent	$u(t) = \left(K_C e(t) + \frac{1}{T_i}\int_0^t e(t')dt + K_d * \frac{de(t)}{dt}\right) + I$
Series/interacting	$u(t) = K_C\left(\left(\frac{T_d}{T_i} + 1\right)e(t) + \frac{1}{T_i}\int_0^t e(t')dt + T_d\frac{de(t)}{dt}\right) + I$

MV, CV, and STPT scaling, if utilized by the controller, are another critical factors for step-response tuning. In some applications, the PID algorithm will require scaling of the variables from the possible range to 0–100% (CV/STPT) or vice versa (MV). If the variable ranges used are significantly larger or small than the default range of 0–100% without correction, the controller will not perform as expected even with step-response tuning. Nonlinearities in the relationship between the CV and MV, the expected operating ranges, and system bounds should be considered during selection of the values used for the step-response test. In a system with significant nonlinearities, the FOPDT model identified via step-response test will limit the model accuracy and subsequent performance to the range tested.

Features such as deadband and anti-windup control can be utilized to increase the stability of a control system. A deadband will avoid excessive control action by allowing certain deviations from setpoint. Possible deviations include intermittent but consistent process disturbances (e.g. screen cleaning on wet-well level control) or the MV hunting when the CV is near setpoint (e.g. airflow controller with a butterfly valve). In some instances, the deadband reduces (dependent on a 'deadband gain') or changes $e(t)$ to zero inside a defined range preventing or slowing the PID from changing the MV. Anti-windup control minimizes overshoot and recovery time when a control action cannot be executed due to saturation. Anti-windup control is applied when variables hit a bound and prevent accumulation of $e(t)$ associated with the integral (e.g. maximum valve position reached while still not meeting S_{O2} setpoint, preventing significant overshoot of S_{O2} and system instability). Anti-windup is used in both examples presented in this work but the MVs presented did not hit either bound during the data collection period.

The calculation frequency of the PID algorithm must also be considered when seeking to understand PID implementation for step-response tuning. For example, if the loop evaluation frequency leads to changes in the MV at a rate slower than impacts are observed on the CV, an inherent lag in response will make it difficult to reach stable control. Evaluation frequency can be set at a fixed interval across an entire SCADA system or individually by each PID block depending on the software applied. It is recommended that this be standardized across a facility.

Defined control objectives and constraints

As part of the design of any new control scheme, the objective must be defined to establish expectations and provide criteria for quantifying if the controller is sufficient or requires modification or additional complexity. Performance metrics, when possible, should be defined quantitatively by stakeholders to establish expectations for controller performance. Precise control can be irrelevant to the control objective or even disadvantageous. This can occur by increased mechanical wear of rapidly modulating equipment, significant overshoot resulting from a non-characteristic disturbance from underdamped tuning, and disturbance rejection to MV impacting other unit processes such as rapidly swinging airflow control valves impacting blower operation. In instances where controllers exceed performance requirements, they can be detuned to reduce mechanical wear or made more aggressive to reduce energy or chemical usage.

Performance metrics provide controller monitoring metrics and re-tuning requirements for long-term controller maintenance. Clearly defining the goal and constraints of the control system determines the appropriate performance metrics for assessment and informs operation staff of the controller objective. For example, if the objective of ABAC is to reduce aeration requirements while preventing effluent ammonia from exceeding a limit rather than control ammonia within $+/-0.5$ mg/L of setpoint, ABAC performance should be monitored using a metric such as energy usage and peak effluent ammonia rather than a minimum AAE.

Consideration should also be taken to ensure the historian recording frequency and precision are sufficient for desired control and monitoring (Kourti 2003). Sensors used as the controlled or MV (e.g. S_{O2}) must be cleaned and calibrated/field verified on an established frequency. They must also be specified to operate over an appropriate range and precision for the intended control goal with sufficient noise dampening. Sensor installation location must be representative, and the mixing characteristics of the system should be appropriate for the intended control goal. The MV control precision should be adequate for the desired level of control (Rieger *et al.* 2005; Schraa *et al.* 2006; Rehman *et al.* 2015; Rosso 2018; Cecconi *et al.* 2019; Samuelsson *et al.* 2021). Finally, once an initial, acceptable tuning of a PI control loop is achieved, one can consider further optimization through advanced optimization methods, such as Bayesian optimization or other stochastic search algorithms. Of critical importance for such an approach is that all considered objectives can be measured accurately online while also accounting for the multi-objective nature of the optimization problem.

As utilities look to optimize existing or novel process controllers, effective use of appropriate tuning tools and metrics is necessary to ensure long-term controller success as defined by both performance and operator trust. This is particularly necessary to ensure utilities do not try to solve existing control issues with novel data-driven methods unnecessarily. It is also recommended that PID applications be standardized and documented for ease of implementation and knowledge transfer.

CONCLUSION

The step-response method with Lambda tuning of PI algorithms is a useful, simple, and robust but underutilized tool. The value of step-response tuning is not just limited to slow BNR control systems, as the methods were initially established for fast controllers such as temperature, flow, and level. Understanding PID implementation and structure is necessary for successful use of these tools. As established in this study:

- the step-response method can be used to determine a FOPDT model of a given WRRF control loop,
- Lambda tuning with parameters determined from a step-response test and the adjustable-λ factor can produce a well-tuned control loop as quantified by given performance metrics for both fast and slow controllers,
- step-response tuning is an efficient method for tuning multiple parallel and cascaded PI control loops in a WRRF.

Adoption of this method by WRRFs will lead to improved effluent quality, use of advanced controllers by operations staff, and reduced time burden of those who serve in tuning role.

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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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