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# Feedback controllers enable automated plant sizing

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**Abstract:** The recent agreement with a new European wastewater directive is driving plant upgrades to cope with stricter permits. At the same time, resource consumption needs to be minimized throughout the plant's lifecycle. A process model is a timely tool that can overcome current design guideline limitations. This includes designing for lower effluents than what guidelines have been developed for, and assessing resource consumption for multiple designs at local conditions. However, model-based design lacks a standardised methodology. This is needed to identify design candidate solution that meet user constraints, and also to adhere safety factors that balance static uncertainties and dynamic disturbances in a transparent way. In this paper we propose a simple method for plant sizing that can be used in any commercial simulation software. The method is centered around a standard proportional and integral (PI) feedback controller and can produce design candidates that perfectly matches user-specified constraints. A positive side-effect is that the method can quantify the needed safety factors for the corresponding disturbances. This sets model-based design on par with traditional design guidelines, which have so far been prevailing due to commomly accepted and established safety margins. Thus, the proposed method facilitates adoption of model-based design, and in effect, early assessment of advanced control as an option to built-in safety margins

**Keywords**: dynamic process model; process design; WRRF design; simulation

## BACKGROUND

Dynamic process models have several advantages over traditional design guidelines when it comes to designing wastewater treatment plants. In specific, models can be used to:

- Analyse compliance with different effluent permits without access historic process data.
- Assess and optimize for a minimal resource consumption by selecting between many different design options.
- Develop control strategies that can handle existing and anticipated dynamic disturbances.

So far, research has been focused on developing methods for analysing model-related uncertainties, and their impact on pre-selected designs (Belia et al., 2021). Less focus has been on how to explicitly use models for identifying a good design candidate in a structured manner. Therefore, Yang et al. (2022) developed a method that coupled an optimization algorithm with a simulator to obtain design candidates. Although the work is pioneering, it has two challenges that limits a widespread adoption in practice. First, the method is reliant on a coupled optimization algorithm. This is neither readily available in commercial simulation softwares, nor straightforwardly applicable for design consultants. Second, the optimization produces design candidates that only approximately meet the design criteria. That is, when the effluent total nitrogen is used as constraint, the design is obtained with up to a 1 mg/L error tolerance.

In this outline paper we propose an alternative method to size design variables with a proportional and integrating (PI) controller in place of an optimization algorithm. This is beneficial since the PI-controller is widely understood and already integrated in any commercial simulation software. Further, the controller setpoint can be used to meet design constraints perfectly, without error tolerances.

## APPLICATION AND RESULTS

A conventional activated sludge process with pre- and post denitrification was used as design example (Figure 1), in which five variables were sized with individual PI-loops, see Figure 1 and Table 1. The goal with each feedback loop was to stabilize the measured variable at its setpoint. Each setpoint, in turn, encodes a user specified design constraint. As an example, the desired nitrification capacity was encoded in terms of an effluent ammonium concentration at exactly 1 mg/l (flow proportional mean value). The related sizing task was then to use a PI-controller to manipulate the aerated volume (with a fixed dissolved oxygen concentration) until this constraint

was fulfilled. The method clearly relies on process engineering skills to map design constraints with relevant control handles.

It should be noted that the sole purpose of the PI-controller is to stabilize the measured variable at its setpoint. This simplifies controller tuning since there is no need for balancing rapid disturbance rejection with smooth setpoint tracking. Thus, as long as the setpoint is reached within a reasonable simulation time, it can be as slow as desired. The so-called Lambda method (Åström, K-J. and Hägglund, T., 1995) is a well-suited tuning method for this situation. In short, the method assigns the same time constant to the closed (controlled) system, as given by the open system (uncontrolled). Then, the integral and error gains are set equal and adjusted subjectively until the controller responsiveness is satisfactory. Here, we identified the process time constants (Table 1) with traditional step-response tests, and subjectively set the controller gains to obtain a smooth stabilization (Figure 2). One interesting finding is that the shortest computation time was not always achieved with the highest gain, i.e., with the fastest tuning. For example, the computation time to simulate the first 75 days was longer than for the last 75 days due to the dynamic step-size solver of the used software (Sumo22). Using a too high gain induced even more systems dynamics than in Figure 2, resulting in an increased computation time, despite the constant influent.

The sizing in Figure 2 is based on a constant influent profile, which results in a static design. However, a key challenge in WWTP design is how to handle the *dynamic influent*. For this reason, so-called safety factors are routine to apply to static design calculations to buffer for:

- daily load dynamics (encoded as peak-to-average load ratios)
- disturbances (by adding safety margins).

See e.g. (Metcalf & Eddy, 2003) and their recommended nitrification safety factor of 1.3–2.0. The obvious drawback of the current practice is that the safety factors in general are nonspecific and nontransparent, and thus impossible to tailor for a specific plant. However, with a model we can easily revise the sizing and instead use a dynamic influent dry-weather profile. The only thing we need to change is to apply a 24-h-moving average filter to the measured variables to avoid that the PI-controller is influenced by the daily dynamics (Figure 3). Likewise, a seven days moving average filter would be needed to size for weekly variations.

Figure 3 shows how much the aerated and unaerated volumes need to be increased to maintain the design constraints with a dynamic influent (yet with the same average load). The dynamic's impact on the unaerated denitrification volume is evident with a 40 % increase, which can be compared to the (somewhat surprisingly) smaller increase in nitrification volume (about 26 % increase). Note that these increased volumes at the same time define the dynamic safety factors (1.40 and 1.26) for the given influent dynamics, which is an added value of the proposed method.

In this example, the dissolved oxygen (DO) concentration was maintained at 2 mg/l. The design therefore has some hidden nitrification capacity that can be used by a temporary increased DO. In a foreseen publication we extend the method to include dynamic process control in the design phase with the concept of a targeted-treatment-goal. In this way, it becomes possible to analyse (and decide) to what extent dynamic disturbances should be handled by built-in safety margins, or with dynamic disturbance mitigation (automatic control).

**IMPACT**

This presentation will demonstrate how a method from the standard ICA-toolbox – the PI-controller – can unlock the potential with model-based design. In effect, this will open up for using digital tools (advanced control and automation with or without AI) early in the design process, and as a complement to static built-in safety margins.

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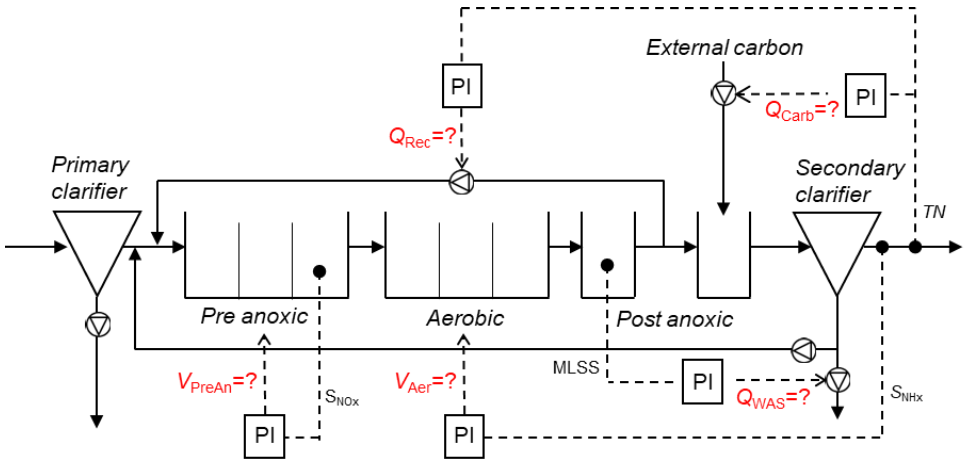


**Figure 1** Controller configuration with controlled (and likewise sized) variables in red and measured variables in black. Abbreviations, starting from top left: internal recirculation flow rate ($Q_{Rec}$), effluent total nitrogen (TN), external carbon flow rate ($Q_{Carb}$), wasted sludge flow rate (WAS), effluent total nitrogen (TN), anoxic volume ($V_{PreAn}$), nitrate in last anoxic zone (SNOx), aerated volume ($V_{Aer}$), ammonium effluent (SNHx). The PI-box indicate a proportional and integrating feedback controller.

**Table 1** The five sized design variables with related control variables. Controller parameters obtained from step-responses and the Lambda tuning method are given in the last two columns.

| **Measured variable (constraint)** | | | **Control/design variable** | | **Controller parameters** | |
|---|---|---|---|---|---|---|
| Variable | Symbol | Value | Variable | Symbol | K | Ti (h) |
| Activated sludge MLSS | *MLSS* | 3 500 mg/L | Waste activated sludge flow rate | $Q_{WAS}$ | 0,012 | 1,7 |
| Effluent ammonia | $S_{NHX}$ | 1 mg/L | Aerated volume @ 2 mg DO/L | $V_{Aer}$ | 0,05 | 196 |
| Nitrate and nitrite out from the anoxic unit | $S_{NOx}$ | 0.2 mg/L | Volume of the pre anoxic unit | $V_{PreAn}$ | 1,0 | 4 |
| Effluent total nitrogen | *TN* | 7.95 mg/L | Internal recirculation flow rate factor | $f_{QRec}$ | 0,001 | 72 |
| Effluent total nitrogen | *TN* | 8 mg/L | Flow rate of external carbon | $Q_{Carb}$ | 0,001 | 1 |

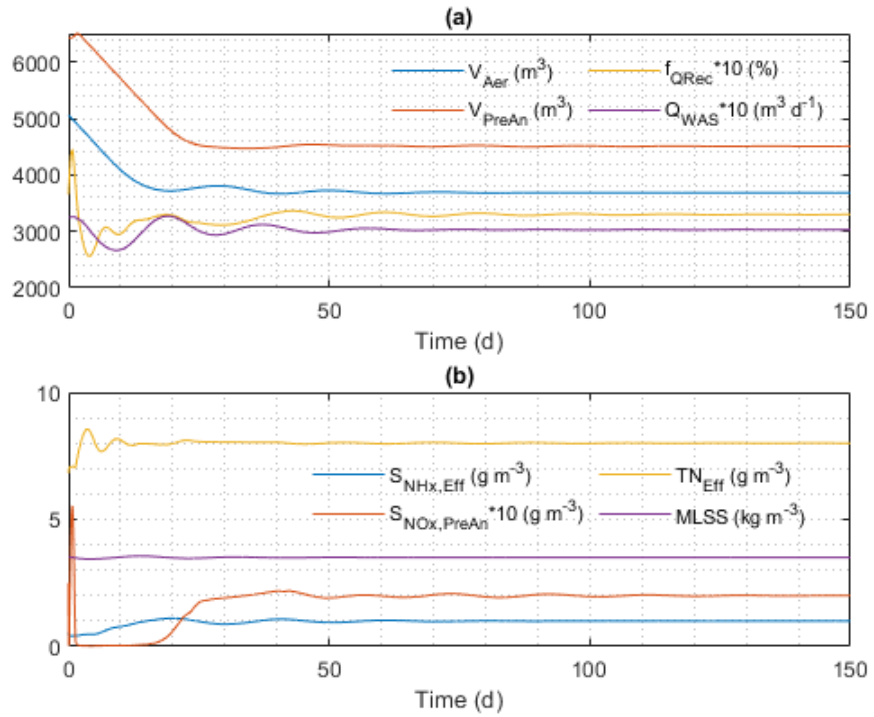


**Figure 2** Sizing-dynamics of four PI-controllers that are stabilizing towards their individual setpoints during a steady-state simulation. **(a)** control signals and **(b)** measured variables (design variables).

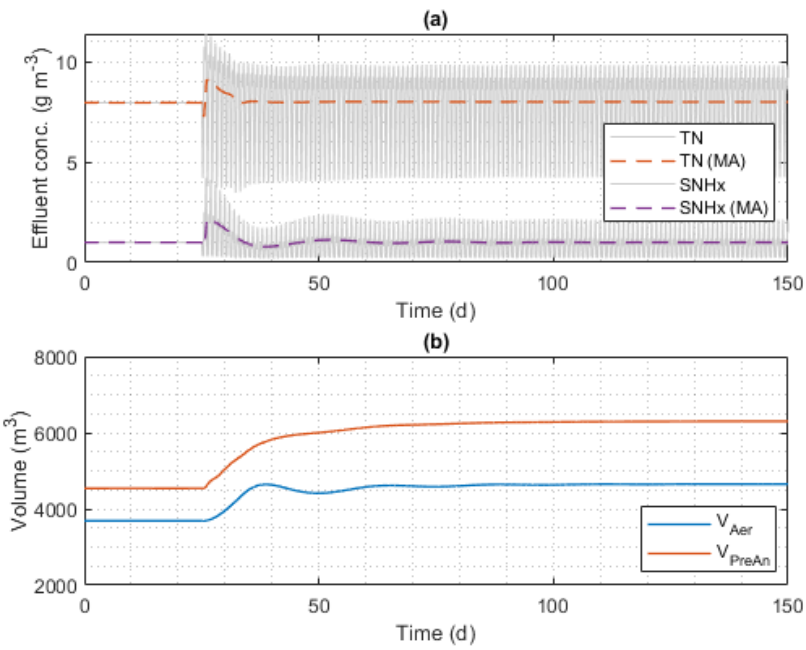


**Figure 3** Impact of daily load variations on sized aerated and anoxic volumes. Static influent up to day 25 followed by a dynamic dry weather profile until day 250. **(a)** Effluent nitrogen concentrations, MA: 1 day flow proportional moving average. **(b)** sized aerated and unaerated volumes for static and dynamic influent.