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# Real-time phosphorus control: A hybrid model-based framework for WRRF optimization

E. Pizzi*,**, C.F. Fratini**, A. D. Mishra *, B. S. Lauritzen*, P. S. Mikkelsen**, S. Skogestad***, B. Valverde Pérez**, L. Vezzaro**.

* DTU Sustain, Technical University of Denmark, 2800 Kongens Lyngby, Denmark. ** Hillerød Forsyning, Solrødgårds Alle 6, 3400 Hillerød, Denmark. *** Department of Chemical Engineering, Norwegian University of Science and Technology (NTNU), 7491 Trondheim, Norway.

**Abstract:** The optimization of wastewater treatment facilities remains challenging due to the inherent complexity of biological processes and their nonlinear dynamics. Through comprehensive stakeholder engagement at the Hillerød wastewater resource recovery facility (WRRF) in Denmark, phosphorus removal was identified as a critical operational objective. The nonlinear behavior of the side stream enhanced biological phosphorus removal (EBPR), coupled with varying operational conditions and complex microbial interactions, makes traditional control strategies often insufficient for achieving optimal performance. Thus, we develop an economic model predictive control (eMPC) strategy to enhance polyphosphate-accumulating organisms (PAOs) activity and optimize chemical dosing at the Hillerød wastewater resource recovery facility (WRRF) in Denmark. The developed eMPC framework employs a novel hybrid model structure that leverages both a simplified ASM2d-based mechanistic model for capturing fundamental biological processes in the hydrolysis tank and anaerobic P release, and a long short-term memory (LSTM) neural network for predicting phosphorus dynamics in the biological tank where multiple biochemical interactions and operational variables influence the process simultaneously. This approach captures with low computational load the nonlinear relationships between operational parameters and process performance without requiring explicit mechanistic descriptions. The integrated control strategy will be validated using an existing digital twin before full-scale implementation, ensuring both economic optimization and operational stability

**Keywords**: Activated sludge model, Hybrid modelling; Model predictive control, Real Time Control.

## INTRODUCTION

Efficient nutrient removal and recovery represent critical challenges for wastewater resource recovery facilities (WRRFs) operating in complex urban-industrial settings. These facilities must balance multiple objectives: meeting stringent effluent regulations, optimizing operational costs, and ensuring sustainable resource recovery, while addressing the diverse needs of operators, management, and local communities (Olsson, 2015). This multi-faceted challenge requires both technological innovation in control systems and a deep understanding of how different stakeholder priorities influence operational decisions (Corominas et al., 2018). The complexity of nutrient removal processes stems from both technical and organizational challenges. From a technical perspective, biological nutrient removal systems rely on specialized microorganisms whose metabolism is highly sensitive to environmental conditions and substrate availability. From an organizational perspective, different stakeholders often have competing priorities - operators focus on daily process stability, management emphasizes cost efficiency, local authorities prioritize environmental compliance, and industrial users require reliable service while facing their own production-dependent discharge variations. These divergent interests, combined with the need to handle varying industrial discharge patterns that can significantly impact treatment efficiency, must be carefully balanced when designing control strategies. Conventional control approaches, primarily based on feedback mechanisms, often show limitations in managing these complex biological systems. These limitations arise from their reactive nature, where control actions are implemented only after process deviations are detected, rather than through a predictive approach. The challenge is further compounded by three key factors inherent to WRRF operations: the nonlinear dynamics of biological processes governed by Monod-type kinetics, the stochastic nature of influent with variations in both hydraulic and pollutant concentrations (Vezzaro et al., 2013), and the need for continuous adaptation of process parameters. These characteristics often lead to suboptimal performance and, e.g., excessive reliance on chemical usage for nutrient

removal. This study presents a systematic approach to address these technical and stakeholder-related challenges, combining technological innovation with comprehensive stakeholder engagement to develop and implement an economic model predictive control (eMPC) strategy. Through structured stakeholder analysis, phosphorus removal emerged as a critical control priority, leading to the development of a hybrid modeling approach that combines mechanistic understanding with data-driven predictions for the eMPC implementation.

## MATERIALS AND METHODS

**Hillerød WRRF:** Hillerød Forsyning WRRF, commissioned in 2019, represents Denmark's first fully covered WRRF, serving 65,000 PE and treating annually 6 million $m^3$ of combined municipal and industrial wastewater. The plant employs a Modified Ludzack-Ettinger (MLE) process with multiple denitrification and nitrification stages, incorporating an integrated fixed-film activated sludge (IFAS) reactor. A key feature is the side stream hydrolysis tank (H-tank) that supports enhanced biological phosphorus removal (EBPR) through volatile fatty acid (VFA) production for polyphosphate-accumulating organisms (PAOs). The side stream EBPR process is supplemented by chemical precipitation using aluminum chloride ($AlCl_3$) when necessary to meet effluent requirements.

**Operational Objectives:** The control strategy implementation followed a modified version of Skogestad's plantwide control framework (Skogestad, 2004), enhanced through systematic stakeholder engagement. The framework involves:

| Category | Engagement/Management Activities |
|---|---|
| **Internal Stakeholder Engagement** | Workshops with plant staff to document challenges, control priorities, and system limitations. Mapping operational constraints and control needs. Reviewing existing control strategies. |
| **Management** | Interviews with facility managers to define strategic goals. Assessing economic constraints and budgets. Setting long-term development objectives. |
| **External Stakeholder Engagement** | Discussions with regulators on compliance and future trends. Consulting industrial partners on discharge patterns and production schedules. Engaging communities on environmental and social concerns. |
| **Integration and Validation** | Cross-stakeholder workshops to share the result and define shared KPIs. Establish priority frameworks for competing goals. |

**Table 1**. Framework for information collection.

This multi-stage process resulted in an objective function J that incorporates the identified KPIs as costs, with phosphorus removal emerging as the critical control priority. The H-tank and PAO optimization were identified as the most promising areas for improving overall process efficiency. The cost function J is defined as:

$$J = C_P \cdot P_{eff} + C_{chem} \cdot AlCl_3 + \lambda \cdot (AlCl_3)^2 + E_c * P_w$$

where: $P_{eff}$= Effluent phosphate concentration ($P_{PO4}$) in mg/L, $C_P$= Cost per unit of phosphorus discharge ($mgP$), $AlCl_3$ = Chemical dosing rate (mg/L), $C_{chem}$= Cost of aluminum chloride ($mgAlCl^3$), $\lambda$ = Penalty coefficient discouraging excessive chemical use, $E_c$ Energy cost, and $P_w$ Energy consumed.

**Degrees of Freedom Analysis:** The control system utilizes three primary manipulation variables: hydraulic retention time of the H-tank, sludge recirculation rate, and chemical dosing. These variables directly influence the terms in the objective function through their impact on biological phosphorus removal efficiency and chemical consumption.

**Model Development:** The proposed control strategy employs a novel hybrid modeling approach that combines mechanistic understanding with data-driven predictions, supported by a digital twin based on ASM2d mechanistic modeling for testing and validation.

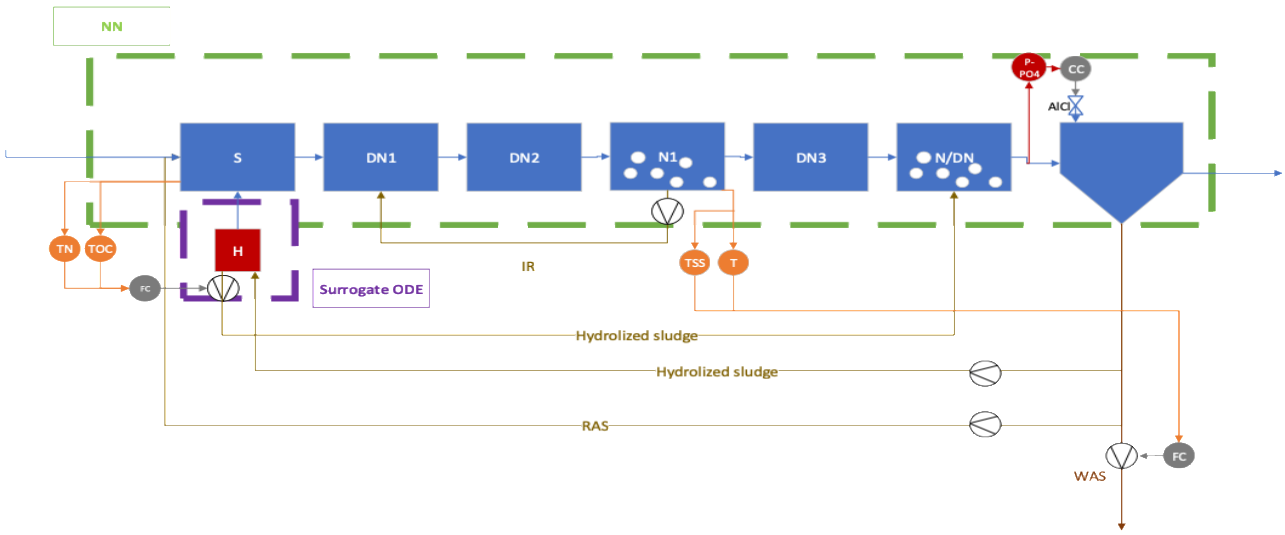


**Figure 1.1** Layout of the eMPC, illustrating the control architecture and sensors involved.

**Mechanistic ODE Component:** The hydrolysis tank model incorporates processes from ASM2d under anoxic conditions. The model considers hydrolysis, PAO metabolism, and fermentation processes, represented through a system of coupled differential equations:

$$dXs_f/dt = -kh * \eta_{NO3} * \left(KO_2/\left(K_{O_2} + S_{O_2}\right)\right) * \left(KNO_3/\left(K_{NO_3} + S_{NO_3}\right)\right) * (Xs/Xh)/\left(Kx + (Xs/Xh)\right) * Xh$$

This equation captures the breakdown of slowly biodegradable substrate (Xs) by heterotrophic biomass (Xh) under anoxic conditions, modulated by the nitrate concentration (NO3) and various kinetic parameters. The PAO processes are represented by three coupled differential equations describing biomass growth, PHA storage, and phosphate release:

$$dX_{PAO}/dt = (\mu_{PAO} - b_{PAO}) * X_{PAO}$$

$$dX_{PHA}/dt = q_{PHA} * S_A/(K_A + S_A) * S_{Alk}/(K_{Alk} + S_{Alk}) * (X_{PP}/X_{PAO})/(K_{PP} + X_{PP}/X_{PAO}) * X_{PAO}$$

The fermentation processes, crucial for VFA production, are modeled through:

$$dSA/dt = q_{fe} * S_f/(K_f + S_f) * \left(K_{O_2}/(KO_2 + SO_2)\right) * \left(K_{NO_3}/(K_{NO_3} + S_{NO_3})\right) * S_{Alk}/(K_{Alk} + S_{Alk}) * X_H$$

These equations incorporate key parameters that reflect the underlying biological processes. The hydrolysis rate constant (kh) and anoxic reduction factor (η_NO3) govern the rate of substrate breakdown. The half-saturation coefficients (KNO3, Kx, KPS, KPP, KA, Kfe) modulate the various processes based on substrate availability. Growth and decay rates (μPAO, bPAO) determine the PAO population dynamics, while storage parameters (qPP, qPHA) control the internal storage compounds. The LSTM network component is designed to predict phosphorus dynamics in the remaining process units, where complex interactions make purely mechanistic modeling too slow for eMPC. The network architecture consists of three LSTM layers with 64, 32, and 16 units respectively, each employing hyperbolic tangent activation functions. Dropout regularization with a rate of 0.2 is applied between LSTM layers to prevent overfitting and improve generalization. The network processes a comprehensive set of input that can be detected with the sensors, including dissolved oxygen concentration, pH, flow rates, and influent characteristics, along with the outputs from the ODE component.

**Control Layer Implementation** The eMPC operates with a 6-hour prediction horizon and 15-minute control interval, matching the biological process dynamics. The ODE component predicts substrate and P release, while the LSTM processes these with real-time data to generate final predictions. The controller is recalibrated quarterly using SCADA data.

**Validation and Benchmarking Framework:** Validation uses a WEST-based digital twin to evaluate the eMPC against current controls through stability testing, dynamic response analysis, and economic performance assessment.

## CONCLUSION

This work presents a hybrid modeling approach for phosphorus removal optimization, combining simplified ASM2d equations with LSTM networks. The eMPC implementation at Hillerød WRRF demonstrates how mechanistic and data-driven methods can be integrated for efficient real-time control of biological processes.

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