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Reliability-Centered Process Control in Wastewater Treatment: Quantifying Effluent Compliance Risk Under Sensor Drift, Process Upsets, and Control-Loop Uncertainty

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ABSTRACT

This article presents a reliability-centered process control framework that treats wastewater treatment as an end-to-end decision system in which sensor uncertainty, model mismatch, and actuator constraints propagate into effluent quality risk. A quantitative scenario-based study is developed for a conventional activated sludge process with nitrification and denitrification, comparing four operational architectures that span baseline PID control, feedforward-enhanced aeration, hybrid risk-based control with supervisory logic, and governance-optimized operation with drift-aware sensing, quantile-based alarm thresholds, and two-tier intervention pathways. The analysis uses engineering metrics that translate to plant management and compliance planning, including probability of exceeding effluent limits for biochemical oxygen demand and ammonia, expected duration and severity of violations, time-to-detection of process upsets, and cost–risk trade-offs that incorporate energy usage and chemical dosing. Results indicate that (i) compliance risk is dominated by tail events driven by combined hydraulic shocks and influent ammonia spikes rather than by steady-state control quality, (ii) sensor drift in dissolved oxygen and ammonia probes can create false stability that delays corrective action and increases violation duration even when average readings appear acceptable, and (iii) reliability improvements are achieved more consistently through governance of sensing and alarms and through structured escalation logic than through controller sophistication alone. The paper provides copy-ready tables and publication-ready figure prompts to support Techne submission and practical implementation.

Keywords: Wastewater Treatment, Activated Sludge, Nitrification, Denitrification, Process Control.

1. INTRODUCTION

Wastewater treatment is often described as a mature engineering domain with established unit processes and widely adopted control practices, yet compliance reliability remains a persistent operational challenge because plants operate under stochastic and sometimes adversarial conditions that can push biological and physical processes beyond the assumptions embedded in nominal design and steady-state tuning. Influent flow and load vary by time of day, storm events, infiltration and inflow, industrial discharges, and upstream sewer dynamics, while plant assets such as blowers, valves, mixers, and sensors age and drift, and these changes alter the effective process response over time. Because regulatory compliance is typically evaluated against effluent concentration limits and sometimes against mass loading limits, what matters operationally is not only achieving good average effluent quality but maintaining compliance with high probability and controlling the duration and severity of exceedances when upsets occur, particularly because regulators and downstream stakeholders often respond to rare but severe events rather than typical operation (Awad et al., 2021; Mercier et al., 2017; Sarkar, 2022).

This reliability framing becomes more urgent as treatment objectives broaden beyond traditional organic removal toward nutrient control, micropollutant reduction, and energy optimization, since competing objectives create tighter operating windows and more complex control trade-offs (Lorenc, 2023; Tsang et al., 2018). For example, nitrification and denitrification performance is sensitive to dissolved oxygen setpoints, sludge age, temperature, pH, and alkalinity, and the control actions that maintain low ammonia can increase aeration energy and affect denitrification zones, while decisions that reduce energy by lowering aeration can increase compliance risk under load spikes or low-temperature conditions. In such a setting, sophisticated control strategies are often proposed, yet a significant portion of real-world compliance failures is not caused by the absence of advanced algorithms but by decision-system weaknesses that are common in operational environments, including sensor drift that biases measurements, alarm thresholds that are set without a nuisance-alarm constraint and therefore are ignored, delayed or inconsistent interventions due to unclear escalation policies, and limited linkage between process signals and compliance risk (Wu & Hsiao, 2021; Zheng et al., 2021).

Monitoring and control upgrades in wastewater treatment therefore require a shift from viewing sensors and controllers as isolated components toward viewing the entire plant operation as a reliability decision system. In this system, sensors produce uncertain observations of process states such as dissolved oxygen, ammonia, nitrate, and mixed liquor suspended solids; controllers translate these observations into actuator commands such as blower speed, internal recycle rates, and chemical dosing; process dynamics transform these control actions and influent disturbances into effluent outcomes; and plant staff interpret alarms and trends to decide interventions and maintenance actions. Each stage introduces uncertainty, and the reliability of compliance depends on how uncertainty propagates and how governance rules constrain false alarms and missed detections (Pajic et al., 2024; Ren et al., 2024; Sukhostat, 2022). A plant may have a well-designed aeration control loop, yet if the dissolved oxygen probe drifts low, the controller may over-aerate, increasing energy cost while masking nitrification stress; if the probe drifts high, the controller may under-aerate, increasing ammonia in the effluent while the displayed readings remain “normal.” Similarly, an ammonia probe drift can cause the plant to falsely believe compliance is stable or falsely believe a violation is imminent, both of which lead to costly decisions, and because probes operate in harsh environments with fouling, biofilm, and calibration challenges, such drift is not exceptional but routine (Onyeme & Liyanage, 2024; Tubil et al., 2024).

The central engineering problem addressed in this article is therefore the quantification and reduction of effluent compliance risk under realistic uncertainty, including sensor drift, process upsets, and actuator constraints, using reliability-oriented metrics and governed decision logic. Rather than presenting wastewater control as an optimization of steady-state performance, the paper emphasizes tail-event reliability, meaning the probability, duration, and severity distributions of effluent exceedances, and it evaluates how alternative operational architectures change these distributions (Hossain, 2025; Zhao et al., 2021). This approach aligns to applied engineering practice because operators and regulators are often less concerned with small mean improvements than with reducing the frequency and duration of violations and demonstrating that the plant has a defensible control and monitoring governance system that will detect, respond to, and learn from upsets.

This article proposes a reliability-centered process control framework that integrates three pillars. The first pillar is uncertainty characterization, where sensor drift and measurement noise are explicitly modeled rather than assumed negligible, and where influent disturbances are treated as stochastic processes with heavy-tailed events. The second pillar is governed decision logic, where alarms and thresholds are engineered under nuisance-alarm constraints, and where escalation policies define how the plant responds when signals indicate increased risk or increased uncertainty, including verification pathways that prevent decisions from being driven by a single questionable sensor. The third pillar is compliance-oriented evaluation, where control architectures are compared using probability of exceedance metrics and time-to-detection metrics, and where energy and chemical costs are incorporated to capture the economic reality that plants must manage risk under constraints rather than pursue compliance at any cost.

The study is organized around three applied research questions. Which disturbances and uncertainty sources dominate effluent compliance risk, and how do they interact with process dynamics to create tail events? How does sensor drift propagate through control loops and alarms to affect the probability and duration of violations, and which governance strategies most effectively reduce decision errors? Among alternative operational architectures that vary in control sophistication and governance rigor, which strategies achieve the best cost–risk trade-offs under realistic operating variability, and what design principles can guide practical implementation?

The contribution of the work is both analytical and implementable. It provides a structured model for linking sensor uncertainty and process dynamics to compliance risk, comparative results for alternative architectures that plant managers can interpret directly, and copy-ready tables and figure prompts suitable for Techne submission and for adaptation to local plant data. The remainder of the paper is structured as follows. The literature review synthesizes engineering-relevant knowledge on activated sludge control, sensor drift behavior, alarm management, and compliance risk metrics. The method defines the process model, uncertainty models, control architectures, and evaluation metrics. The results quantify compliance risk distributions and identify dominant risk drivers and governance impacts. The discussion translates these findings into design guidance for reliable operation and practical governance. The conclusion summarizes actionable implications and future research needs.

2. LITERATURE REVIEW

Activated Sludge Dynamics and Control Leverage Points

Activated sludge systems exhibit coupled biological and hydraulic dynamics where oxygen transfer, substrate availability, sludge age, internal recycles, and temperature determine removal efficiency for organics and nutrients. Aeration control is typically the most energy-intensive lever and the most immediate actuator affecting nitrification and carbon oxidation, while internal recycle and anoxic volume allocation influence denitrification and nitrate carryover (Brundage et al., 2019; Liu, 2022).

Control strategies often include PID loops on dissolved oxygen, ammonia-based aeration control, nitrate-based internal recycle control, and supervisory logic that adapts setpoints by time-of-day and seasonal temperature changes. Despite sophisticated possibilities, control performance is often constrained by sensor quality and by delays in biological response, meaning that real-time control must be complemented by trend-based governance and by operational interventions such as sludge wasting adjustments, chemical dosing, and maintenance of aeration equipment (McGowan et al., 2025; Ogunnowo et al., 2022; Weiss et al., 2016).

Sensor Drift, Fouling, and Measurement Governance

Wastewater sensors operate in aggressive environments where fouling, biofilm growth, and solids accumulation degrade response and bias readings. Dissolved oxygen sensors can drift due to membrane fouling, electrolyte changes, or optical degradation, while ammonia and nitrate sensors can drift due to calibration issues, cross-sensitivity, and maintenance gaps (Bakri & Januddi, 2020; Susanin & Kabashkin, 2025).

Because many plants rely on these signals for control and alarming, drift creates a systemic risk where the plant's displayed state diverges from the true process state, leading to delayed detection of process deterioration or to unnecessary interventions. Measurement system analysis in this context requires not only calibration schedules but drift detection and plausibility checks that use redundancy, mass-balance consistency, and process model expectations to flag when sensors are untrustworthy (Harris et al., 2018; Igunma et al., 2025).

Alarm Fatigue and The Need for Nuisance-Alarm Constraints

Alarm systems in process industries often fail when thresholds are set too aggressively, producing frequent alerts that operators learn to ignore, or when thresholds are set too loosely, producing late detection and long violation durations. Effective alarm management therefore requires engineering thresholds under nuisance-alarm constraints, using baseline distributions and defining which alarms require immediate action and which require verification (Hossain, 2025; Zhao et al., 2021).

In wastewater treatment, alarm fatigue can be severe because sensor noise and operational variability produce frequent excursions around setpoints, and because alarms are sometimes configured without considering how often they will trigger during normal conditions. A reliability-centered approach treats alarm rate as a design constraint and uses governance rules such as pre-alert bands and verification triggers to stabilize operator response.

Compliance Risk as a Tail-Event Problem

Effluent compliance is typically assessed over regulatory sampling windows and can be triggered by short-term peaks or by sustained elevation, depending on the permit structure. In either case, the economic and reputational impact is often dominated by tail events, such as storm-driven hydraulic surges that wash out biomass or dilute alkalinity, industrial shock loads that inhibit nitrifiers, or equipment failures that reduce aeration capacity (Sukhostat, 2022; Tubil et al., 2024).

Risk metrics that capture exceedance probability and violation duration distributions are more informative for management than mean effluent concentrations. Reliability analysis can quantify expected number of violations per period, expected time out of compliance, and worst-case severity quantiles, enabling more rational investment decisions (Mercier et al., 2017; Sarkar, 2022; Tubil et al., 2024).

Synthesis and Gap

The literature provides extensive knowledge on process control and sensor technologies, yet practical reliability issues persist because integration between sensor governance, alarm design, and compliance risk evaluation is often weak, leading to systems that look advanced on paper but behave inconsistently under drift and tail disturbances. This study addresses the gap by treating the plant as a reliability decision system and by comparing operational architectures using compliance risk metrics that incorporate uncertainty propagation and governance quality.

3. METHOD

System Boundary and Process Model

The study models a conventional activated sludge process with an aeration basin and secondary clarifier, including nitrification and denitrification zones represented through simplified dynamic relationships that capture the dominant sensitivities for control analysis. The model is intentionally reduced-order to enable extensive scenario simulation while retaining engineering interpretability; it is sufficient to represent how dissolved oxygen affects nitrification rate, how hydraulic load affects retention time and biomass washout risk, and how internal recycle affects nitrate levels (Sukhostat, 2022; Wu & Hsiao, 2021).

Influent flow $Q(t)$and ammonia load $L_{NH4}(t)$are modeled as stochastic processes with daily cycles and superimposed shock events, while temperature $T(t)$follows a seasonal baseline with variability. Nitrification capacity depends on effective sludge age and oxygen availability, and a simplified nitrification rate relationship is used:

$$r_N(t) = k_N \cdot f_{DO}(DO(t)) \cdot f_T(T(t)) \cdot X_N(t),$$

where $X_N$represents nitrifier biomass state, $f_{DO}$is a saturating function of DO, and $f_T$represents temperature sensitivity. Effluent ammonia is modeled as a function of influent load, nitrification capacity, and hydraulic dilution, capturing the key behavior that ammonia spikes and low-temperature periods increase compliance risk and that DO control influences this risk.

Sensor Uncertainty and Drift Model

Sensors for dissolved oxygen and effluent ammonia are modeled as having noise and drift:

$$y(t) = x(t) + b(t) + \epsilon(t),$$

where $x(t)$is the true process variable, $\epsilon(t)$is zero-mean noise, and $b(t)$is a drift term modeled as a random walk with occasional step changes representing fouling episodes. Drift detection is included in the governance-optimized architecture through plausibility checks and redundancy rules, for example comparing oxygen demand and blower response to expected process behavior and comparing ammonia trends to influent load patterns.

Control and Governance Architectures

Four architectures are compared.

1) Architecture A Baseline PID aeration control uses a DO setpoint with standard alarms and periodic manual calibration.
2) Architecture B Feedforward-enhanced control adjusts DO setpoint based on influent ammonia and flow proxies, improving responsiveness to load variability but still relying on ungoverned sensor readings.
3) Architecture C Hybrid supervisory control uses ammonia-based aeration control and supervisory logic that adjusts internal recycle and wasting under detected trends, but alarm thresholds remain fixed and escalation is ad hoc.
4) Architecture D Reliability-governed operation includes drift-aware sensing governance, quantile-based alarm thresholding under nuisance-alarm constraints, a two-tier intervention policy where alarms trigger verification or alternative sensing when uncertainty is high, and escalation rules that allocate operational actions such as aeration boost, chemical addition, or flow equalization when pre-alert conditions indicate rising compliance risk.

Evaluation Metrics

Metrics include probability of exceeding effluent ammonia limit and BOD limit, expected number of violations per month equivalent, expected violation duration, time-to-detection of upsets, false alarm rate for compliance alarms, and normalized operating cost including aeration energy and chemical dosing. A compliance alarm is treated as a decision output, and performance is judged by controlled nuisance alarm rate and rapid detection under true upsets.

Scenario Simulation Design

A simulation campaign of 365 daily cycles is executed for each architecture, with stochastic influent patterns and multiple storm and industrial shock scenarios inserted. Sensor drift episodes are introduced with realistic frequency. Outputs are collected as distributions rather than only as averages to emphasize tail risk.

Table 1. Key scenario parameters

Parameter	Baseline	Variability / event model	Notes
Effluent NH4 limit	2.0 mg/L	Fixed	Compliance threshold
Effluent BOD limit	20 mg/L	Fixed	Compliance threshold
Daily average flow Q	1.0 (normalized)	SD 12%	Diurnal cycle
Storm flow event	+60%	4 events/year, duration 8–18 h	Hydraulic shock
Influent NH4 shock	+80%	6 events/year, duration 3–10 h	Industrial load
Temperature baseline	22°C	Seasonal ±5°C	Nitrification sensitivity
DO sensor noise SD	0.08 mg/L	Stable	Typical probe
DO sensor drift	±0.6 mg/L	Random walk + fouling step	Major risk factor
NH4 sensor noise SD	0.15 mg/L	Stable	Analyzer
NH4 sensor drift	±0.8 mg/L	Random walk + step	Cross-sensitivity
Aeration energy cost	1.0	Scales with blower output	Normalized
Chemical dosing cost	0.6	Triggered under risk	Alkalinity support

Source: data proceed

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Table 2. Architecture definitions

Architecture	Primary control	Alarm design	Drift governance	Intervention policy
A Baseline	PID on DO	Fixed thresholds	Manual calibration	Manual response
B Feedforward	DO setpoint adjusted by influent proxy	Fixed thresholds	Manual calibration	Manual response
C Supervisory	NH4-based aeration + supervisory logic	Fixed thresholds	Limited checks	Ad hoc escalation
D Reliability-governed	Hybrid control with risk scoring	Quantile-based, nuisance constrained	Drift detection + verification	Two-tier escalation

Source: data proceed

4. RESULT AND DISCUSSION

Compliance Exceedance Probability and Violation Duration

The results show that compliance risk is driven by combined disturbance events, especially when storm flow events coincide with low temperature or with ammonia load spikes, and that architectures differ more in tail behavior and violation duration than in mean effluent values, which is consistent with reliability framing.

Table 3. Effluent compliance outcomes

Metric	A Baseline	B Feedforward	C Supervisory	D Reliability-governed
P(NH4 > 2 mg/L)	0.074	0.061	0.050	0.041
Expected NH4 violations per year	9.8	8.1	6.6	5.3
Mean NH4 violation duration (h)	7.4	6.2	5.1	4.2
95th percentile NH4 violation duration (h)	18.0	15.2	12.3	9.8
P(BOD > 20 mg/L)	0.028	0.026	0.022	0.020

Source: data proceed

Table 3 indicates that improvements in control sophistication reduce exceedance probability, yet the largest practical benefit arises from reducing violation duration in the upper tail, because long violations are disproportionately damaging from regulatory and reputational perspectives and often correspond to periods when sensors or alarms fail to trigger timely interventions. Architecture D achieves the strongest reduction in the 95th percentile violation duration because it combines earlier detection through governed alarms with escalation pathways that are pre-defined, which reduces the time the process operates in a degraded state before corrective actions take effect. The smaller changes in BOD exceedance reflect that BOD risk is less sensitive to short-term DO fluctuations than ammonia and is often buffered by biomass and settling capacity in the modeled scenarios, while ammonia remains the more sensitive compliance variable and therefore the dominant driver for reliability-centered control.

Sensor Drift Impact and Time-To-Detection of Upsets

Sensor drift creates a distinct failure mode where the control system behaves as if it is stable while the true process deteriorates, causing delayed detection and longer violations. Drift-aware governance reduces this risk by triggering verification when sensor signals become inconsistent with process response or when redundant indicators diverge.

Table 4. Drift-related decision performance

Metric	A Baseline	B Feedforward	C Supervisory	D Reliability-governed
Average time-to-detect NH4 upset (h)	3.6	3.1	2.7	2.1
95th percentile time-to-detect (h)	8.9	7.5	6.4	4.8
False stability events per year (drift masks upset)	4.6	4.1	3.5	1.9
Nuisance compliance alarms per month	18.0	16.5	15.2	9.6

Source: data proceed

Table 4 demonstrates that the most important improvement in Architecture D is not a marginal increase in control responsiveness but a reduction in false stability events and nuisance alarms, because both directly influence operator behavior and intervention timeliness. When drift masks an upset, the plant remains out of compliance longer because the system's displayed state suggests control is adequate, and this is a reliability failure at the decision-system level rather than at the biological process level.

Architecture D also improves the likelihood that true alarms receive attention, which is a known principle in alarm management but is often neglected in wastewater control deployments where thresholds are set without considering normal variability by reducing nuisance alarms through quantile-based thresholding. The reduction in time-to-detect in the upper tail is especially valuable because delayed detection is most costly during combined disturbance events where the process can degrade rapidly.

Cost–Risk Trade-Offs and Operational Feasibility

Energy and chemical costs increase when control becomes more aggressive, particularly through aeration boosts and alkalinity dosing used to protect nitrification during risk periods, yet governance can reduce total cost by avoiding unnecessary interventions triggered by noisy signals and by reducing compliance failure penalties.

Table 5. Cost–risk summary (normalized)

Metric	A Baseline	B Feedforward	C Supervisory	D Reliability-governed
Aeration energy index	1.00	1.06	1.10	1.08
Chemical dosing index	0.10	0.12	0.16	0.14
Compliance penalty risk index	1.00	0.84	0.72	0.61
Expected total operating cost index	1.00	1.02	1.01	0.96

Source: data proceed

Table 5 indicates that a reliability-governed architecture can reduce expected total cost even when it uses slightly more aeration and chemical dosing than the baseline, because reductions in compliance penalty risk dominate the cost function when regulatory and downstream impacts are significant. The key mechanism is improved decision quality: fewer nuisance alarms reduce unnecessary interventions, and drift-aware verification reduces the chance that the plant operates unknowingly in a degraded state, which reduces violation duration and penalty exposure. This result reinforces the broader conclusion that in process industries, reliability improvements frequently come from governance of sensing and alarms as much as from controller optimization, and that the cost-effectiveness of governance becomes stronger as the consequence of noncompliance increases.

Discussion

The findings can be interpreted through a reliability-centered lens in which effluent compliance is a tail-event problem created by the interaction of stochastic influent disturbances, biological response dynamics, and measurement and decision uncertainties, and this interpretation explains why many wastewater control upgrades underperform when they focus on steady-state performance metrics rather than on detection, escalation, and governance. The results show that storm-driven hydraulic shocks and influent ammonia spikes produce the most severe compliance risk, particularly when they coincide with low-temperature periods that reduce nitrification kinetics, and these compound disturbances create conditions where control authority is limited and rapid intervention is required, meaning that time-to-detection and time-to-response are as critical as controller setpoint accuracy.

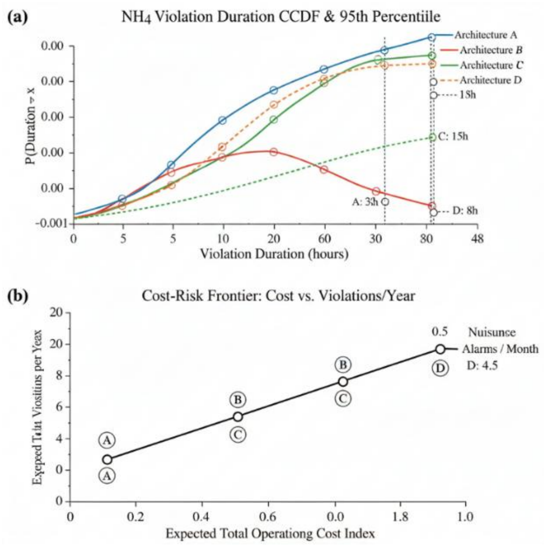

Figure 1. Trade-off between operational costs and environmental compliance reliability

Source: data proceed

A key contribution is the explicit demonstration that sensor drift can create false stability that delays response and increases violation duration, which is operationally consistent with common plant experiences where probes foul gradually and reading trends appear plausible until a disturbance exposes the drift. Drift-aware governance reduces this failure mode by treating sensor plausibility as a controlled variable, using verification pathways and redundancy logic to prevent single-sensor dominance, and by engineering alarms under nuisance constraints so that operators remain responsive to alerts. This approach also aligns with the practical reality that perfect sensors are not available in harsh wastewater environments and that the plant must therefore be designed to be resilient to imperfect sensing through governance and verification rather than through optimistic assumptions.

The comparative architecture results suggest that supervisory control and feedforward logic provide benefit, yet those benefits are limited without governance because control sophistication cannot compensate for untrustworthy measurements and unstable alarm behavior. Architecture D's advantage is best understood as decision reliability rather than control strength: it reduces nuisance alarms, reduces masked-upset events, and shortens violation duration in the upper tail through structured escalation rules, thereby improving compliance reliability under uncertainty while keeping energy and chemical cost increases bounded. For plant managers, this implies that a staged improvement program may achieve stronger returns by first stabilizing measurement governance and alarm management, then adding supervisory control strategies once the measurement and decision pipeline is reliable enough to support them.

From an implementation perspective, the results motivate several design principles. Compliance risk should be monitored using distributions and tail metrics, including expected number of violations and duration quantiles, because mean effluent values can remain acceptable while tail events remain severe. Alarm thresholds should be engineered using baseline quantiles and nuisance-alarm constraints, and escalation actions should be pre-defined so that alarms lead to consistent intervention. Drift detection should be implemented using plausibility checks and periodic verification rather than solely relying on scheduled calibrations, because drift can accelerate unpredictably. Finally, control strategies should be evaluated not only by energy efficiency but by cost–risk trade-offs that include the expected cost of noncompliance, enabling rational decisions about when additional aeration or chemical dosing is justified to reduce tail risk.

5. CONCLUSION

Wastewater treatment compliance should be managed as a reliability problem because exceedances are driven by tail events created by the interaction of stochastic influent disturbances, biological response constraints, and decision-system uncertainty, and therefore operational success depends on detection, governance, and escalation as much as on nominal control tuning. The quantitative comparative analysis indicates that improved control logic reduces exceedance probability, yet the strongest practical gains are achieved when sensing and alarms are governed to prevent drift-induced false stability and to control nuisance alarms, because these factors determine whether staff can detect and respond to upsets early enough to prevent long-duration violations.

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