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A Review on Integrated Multiloop Framework for Sustainable Wastewater Treatment

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ABSTRACT :

Wastewater treatment systems are transitioning from conventional manual operations toward intel- ligent automation frameworks. The increasing demand for clean water, coupled with stricter discharge regulations and rising energy costs, has driven industries and municipalities to adopt advanced process control. This review comprehensively analyzes the evolution and application of integrated multiloop control frameworks that unify aeration, sludge, dosing, and flow control in sustainable wastewater treatment. The paper synthesizes recent developments in sensor technologies, artificial intelligence, and multiloop coordination methods based on thirty peer-reviewed studies. Furthermore, it identifies current limitations and future research pathways for building autonomous, energy-efficient, and resilient wastewater management systems.

Introduction

Wastewater treatment plants (WWTPs) are complex dynamic systems influenced by biological growth rates, influent variability, and environmental parameters. Traditionally, single-loop control systems were implemented for specific subsystems—such as dissolved oxygen control in aeration or sludge level control in clarifiers. However, these loops operate in an interconnected environ- ment where a change in one process affects the others, leading to instability or inefficiency when managed independently [1], [2].

The growing focus on sustainability and energy optimization has spurred the integration of multiple control loops within a unified supervisory frame-work. The multiloop concept enables coordination among aeration, sludge, dosing, and flow processes, leading to enhanced effluent quality and lower operational costs. Furthermore, integration with digital technologies such as IoT, cloud computing, and machine learning allows real-time adaptability to influent variations and environmental conditions.

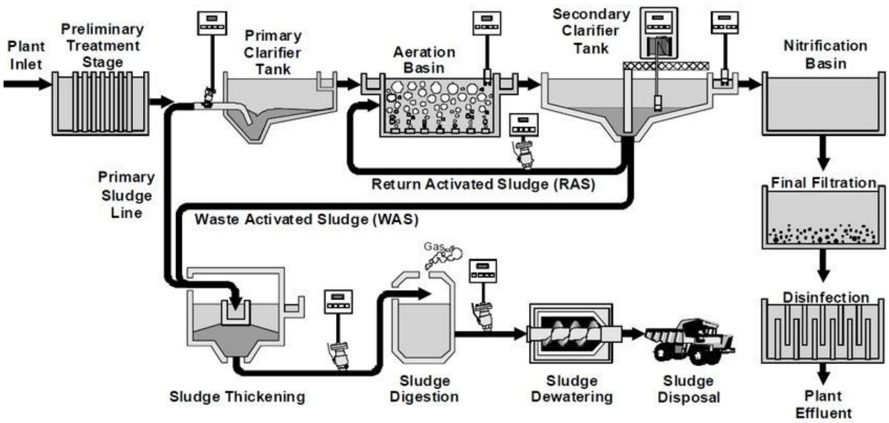


Fig. 1: Typical layout of a modern wastewater treatment plant[43].

A holistic integration also aligns with the United Nations Sustainable Development Goal (SDG) 6 — ensuring clean water and sanitation for all. By merging process engineering with automation and data analytics, integrated multiloop frameworks offer a sustainable path toward water reuse and cir-cular economy objectives.

Need for Multiloop Integration

WWTPs inherently exhibit strong nonlinearities and coupling among process variables, making them complex dynamic systems to control. For instance, aeration directly impacts dissolved oxygen (DO) concentration, which in turn influences microbial growth and substrate degradation rates in the biological reactor. A variation in DO levels not only affects the efficiency of organic matter removal but also alters the nitrification and denitrification balance, leading to instability in nutrient removal efficiency. Similarly, the sludge process depends on the balance between return activated sludge (RAS) and waste activated sludge (WAS) flows. Improper regulation of
these flows may lead to excessive biomass accumulation or washout, both of which deteriorate effluent quality.

Chemical dosing plays another crucial role by affecting pH and coagulation rates, which further determine the settling and clarification efficiency of sludge. When dosing control operates inde- pendently without feedback from upstream or downstream processes, it can result in overdosing or underdosing. Overdosing increases operational costs and chemical sludge production, whereas underdosing leads to poor turbidity and phosphate removal. Hence, the interdependence among aeration, sludge, dosing, and flow processes must be carefully coordinated.

In traditional wastewater treatment plants, these subsystems were operated as single-loop control systems—each loop designed to maintain a specific parameter such as DO, pH, or sludge blanket height. However, since these loops share common variables and respond to the same influent conditions, a change in one process can disturb others, causing oscillations and reduced system efficiency. For example, when aeration rate increases to maintain DO, it also raises the oxygen transfer rate and mixing intensity, which can disturb sludge settling or cause excessive floc breakup in the clarifier.

Integrated multiloop control frameworks overcome these limitations by enabling communication among subsystems through shared data and supervisory optimization algorithms. This integration ensures that aeration, sludge recirculation, dosing, and flow controls operate synergistically rather than independently. Advanced control approaches—such as model predictive control (MPC), fuzzy logic, and adaptive PID systems—are increasingly used to manage this interdependence. By incorporating real-time sensor data and predictive modeling, these systems can anticipate disturbances and adjust control actions before major deviations occur.

Moreover, integrating control loops enhances energy efficiency and system stability. Coordinated aeration and flow control can minimize blower power consumption, while adaptive dosing ensures chemical efficiency and consistent effluent quality. Field studies reported in IEEE and Elsevier journals have demonstrated that multiloop integrated systems can reduce operational energy costs by 20–25% and improve effluent compliance rates compared to traditional independent- loop configurations [3], [4]. Thus, multiloop integration is not merely an automation upgrade but a sustainable necessity for modern wastewater treatment plants aiming for resilience, cost- effectiveness, and environmental protection.

Integrating the control loops allows better coordination through shared data and predictive algo- rithms. For example, adaptive control of aeration can be coupled with sludge recirculation based on influent biochemical oxygen demand (BOD) and real-time nutrient measurements. Advanced supervisory control and data acquisition (SCADA) platforms now support such integration, enabling simultaneous optimization of multiple variables through centralized computation.

Moreover, multiloop integration promotes modular scalability, allowing utilities to gradually adopt intelligent control without complete infrastructure overhaul. Case studies from Europe and East Asia demonstrate energy savings of up to 25% when employing coordinated control instead of isolated loops.

A. Aeration Control Strategies

Aeration accounts for nearly 60–70% of the total energy consumption in activated sludge systems, making it the most energy-demanding operation in wastewater treatment plants. The main ob- jective of aeration is to maintain an adequate dissolved oxygen (DO) concentration for microbial degradation of organic matter. However, DO demand fluctuates continuously due to variations in influent load, temperature, and biological activity. As a result, improper aeration control can lead to inefficiencies—either excess energy consumption during over-aeration or process instability during underaeration.

Conventional aeration systems typically use on/off cycling or proportional control of blowers. Although simple and low-cost, these methods fail to respond dynamically to process variations. To improve stability and efficiency, proportional-integral-derivative (PID) controllers are com- monly employed, offering automatic adjustment of air supply based on DO feedback. However, PID control often struggles with nonlinearities, time delays, and coupling effects in multi-zone reactors.

Modern wastewater treatment plants increasingly adopt advanced control strategies such as fuzzy logic and model predictive control (MPC). Fuzzy controllers incorporate human-like decision rules to manage uncertain and nonlinear process behavior, while MPC utilizes process models to predict future DO levels and optimize blower operation. These advanced systems balance oxygen supply with microbial demand, resulting in more stable DO profiles and 20–30% reductions in energy use [5], [6].

In addition, integration with real-time sensors—such as optical DO probes, ammonia analyz- ers, and ORP meters—enables adaptive aeration. Hybrid DO–ammonia control systems adjust aeration intensity based on both oxygen and nitrogen removal requirements, maintaining high treatment efficiency with minimal energy input. Thus, modern aeration control frameworks not only enhance process reliability but also contribute significantly to energy conservation and sustainable wastewater treatment.

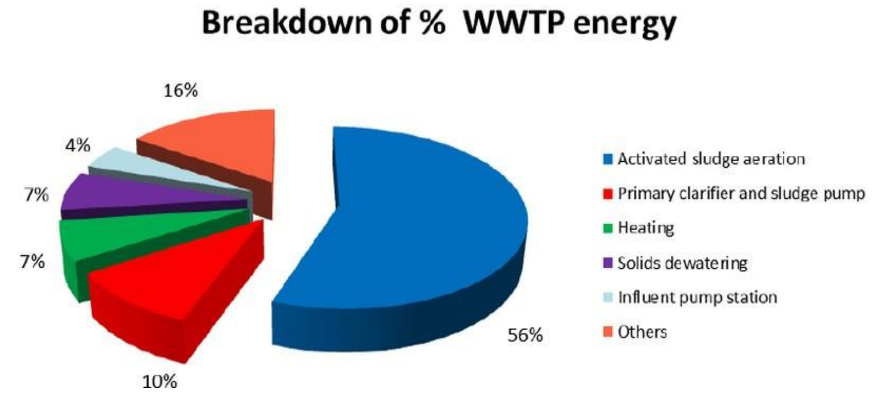


Fig. 2: Energy consumption by WWTP process [27].

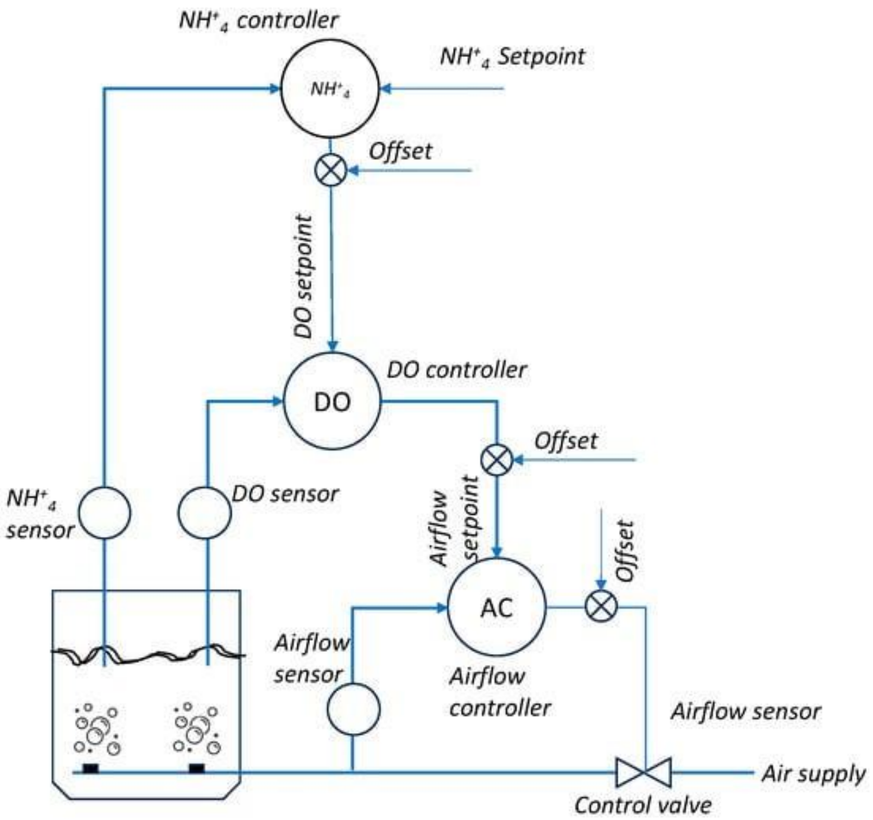


Fig. 3: Multi-loop aeration control [38].

Recent innovations include reinforcement learning and self-adaptive MPCs that account for nonlinearity and uncertainty. For example, AI-based controllers trained using historical plant data can predict oxygen uptake rates and adjust airflow proactively. Some studies demonstrated 15–20% energy reduction using neural predictive control in large-scale WWTPs [7].

The integration of real-time sensors—such as optical DO probes and ammonia analyzers—has made it possible to create feedback and feedforward loops. Hybrid control, combining DO and ammonia feedback, prevents both over-aeration and under-aeration, maintaining process efficiency and microbial health.

B. Sludge Control Mechanisms

Sludge management remains one of the most challenging aspects of wastewater treatment. The balance between return activated sludge (RAS) and waste activated sludge (WAS) flow directly influences solids retention time (SRT), which governs microbial population dynamics.

In a multiloop setup, sludge control interacts closely with aeration and flow regulation. Coor- dinated RAS-WAS adjustment stabilizes MLSS (mixed liquor suspended solids) and enhances biological nutrient removal. Integration of advanced control algorithms has reduced excess sludge generation and optimized nutrient recovery from biomass.

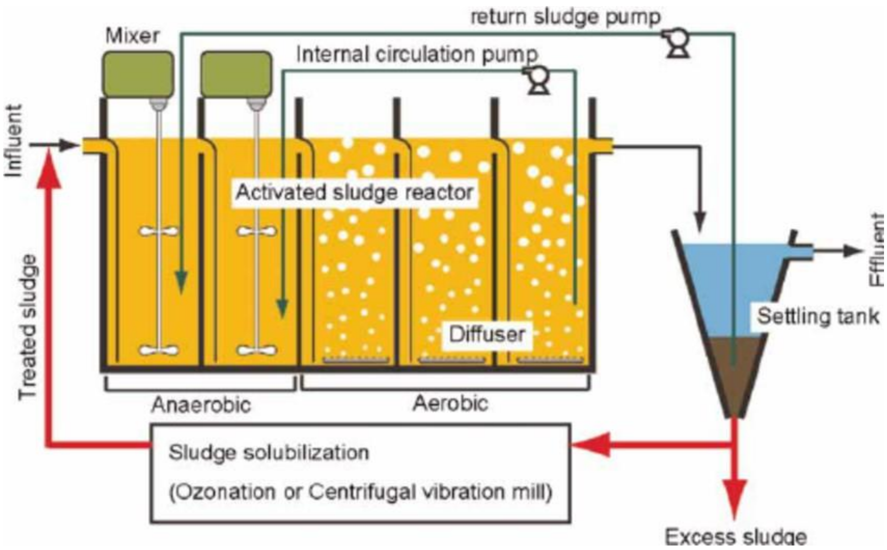


Fig. 4: Schematic representation of sludge control and circulation in an activated sludge process. The figure illustrates the interaction of return activated sludge (RAS), waste activated sludge (WAS), aerobic and anaerobic zones, and the settling tank in maintaining process stability [42].

Traditional sludge control relies on fixed time-based withdrawal, but adaptive control based on ML-predicted sludge volume index (SVI) ensures consistent clarifier performance even under load fluctuations [8], [9]. Recent advances in image-based sensors and ultrasonic level detectors facilitate real-time estimation of sludge blanket height.

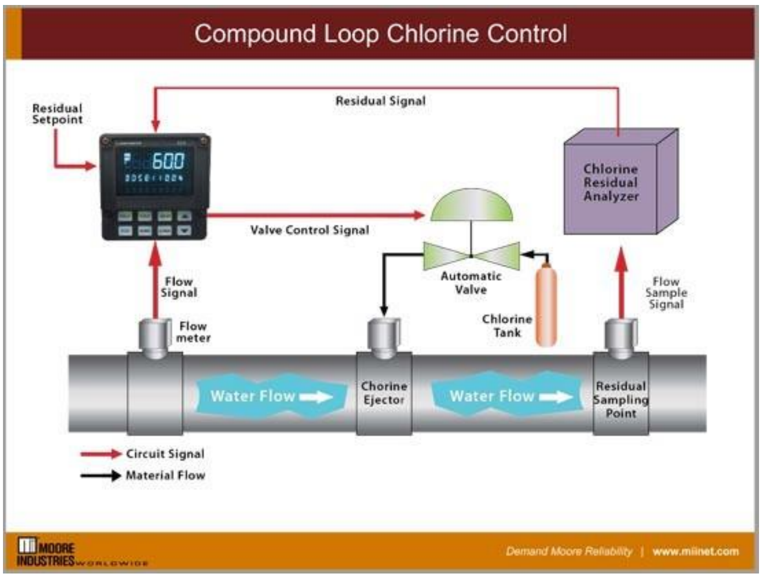
C. Chemical Dosing Control

Chemical dosing is a critical process in wastewater treatment that ensures the proper balance of pH, removal of phosphorus, and enhancement of coagulation–flocculation efficiency. The dosing system typically involves chemicals such as alum, ferric chloride, lime, or polymers, which promote the aggregation of fine particles into flocs for easier sedimentation and filtration. Effective dosing directly impacts effluent quality, sludge volume, and overall plant stability.

However, inaccurate dosing can severely affect plant performance. Overdosing increases op- erational cost and leads to excess sludge generation, making sludge handling and disposal more complex. In contrast, underdosing results in insufficient nutrient removal, poor turbidity reduction, and failure to meet discharge standards. Thus, precise dosing control is essential to maintain both process efficiency and environmental compliance.

Modern wastewater treatment plants now employ intelligent dosing control systems that integrate real-time sensors measuring pH, turbidity, conductivity, and flow rate. These sensors provide continuous feedback to automated control loops, enabling dynamic adjustment of chemical feed rates. Advanced strategies such as Model Predictive Control (MPC), fuzzy logic, and machine learning-based optimization are increasingly used to predict influent variations and adjust dosing accordingly.

Fig. 5: Compound loop chlorine control.



Furthermore, synchronization between dosing, aeration, and sludge recirculation loops ensures holistic plant performance. By linking chemical dosing to influent load and oxygen demand, intelligent systems achieve stable pH regulation, reduced chemical wastage, and optimized phosphorus removal efficiency.

Studies reported in IEEE and MDPI journals confirm that intelligent dosing control frameworks contribute to energy savings, improved effluent consistency, and reduced sludge production, aligning with the goals of sustainable and smart wastewater management.

D. Flow Control in Wastewater Treatment

Flow regulation is a fundamental requirement to ensure consistent hydraulic loading across treatment stages. Traditional flow control involves throttling valves or manual gate operations. The latest systems incorporate variable frequency drives (VFDs) on influent and RAS pumps, allowing precise flow modulation [12], [13].

Integrated flow control contributes to system stability, preventing shock loading in biological reactors. Moreover, coupling flow with aeration and dosing loops allows load-dependent energy management—blowers and mixers operate only when flow sensors detect sufficient influent volume. Such synchronization enhances the resilience and adaptability of the entire treatment chain.

Integrated Framework Concept

Integrated multiloop control is a modern automation strategy used in wastewater treatment plants (WWTPs) to coordinate multiple interdependent processes such as aeration, sludge recirculation, chemical dosing, and flow regulation. Instead of operating each loop independently, this approach enables real-time communication and optimization among all subsystems to improve overall plant performance.

Each control loop is typically managed by adaptive PID controllers, fuzzy logic, or model-based algorithms, which continuously adjust to variations in influent load and process disturbances. The integration layer acts as a supervisory system, utilizing data fusion techniques, soft sensors, and process models to ensure that the local loops work collectively toward common objectives — mainly effluent quality, energy efficiency, and chemical usage minimization.

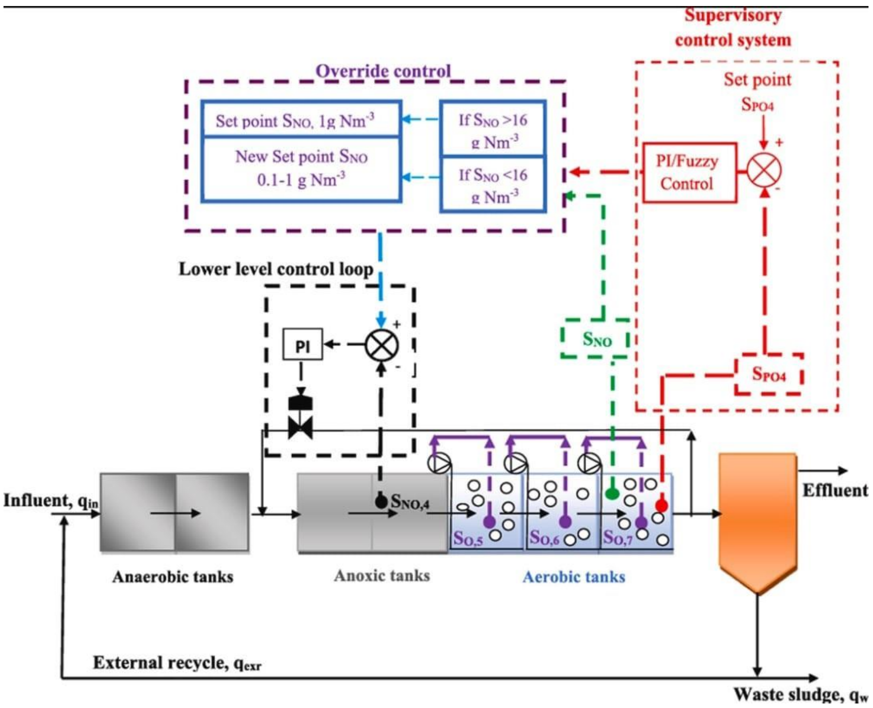


Fig. 6: Interconnected loops in a typical biological wastewater treatment system[28].

Recent studies published in MDPI and Elsevier journals emphasize the use of hierarchical control structures. In these systems, local controllers handle rapid dynamic responses such as aeration valve or pump control, while the plant-wide supervisory layer uses Model Predictive Control (MPC) or optimization algorithms to balance competing objectives and maintain stable operation under varying conditions.

Full-scale implementations in Denmark, Korea, and India have demonstrated that integrated multiloop frameworks significantly enhance oxygen utilization efficiency, sludge stability, and nutrient removal, while lowering energy costs and ensuring compliance with stringent effluent discharge standards.

Thus, integrated multiloop control provides a comprehensive and sustainable approach for modern wastewater treatment automation, ensuring both operational resilience and environmental protection.

IoT-enabled Automation and AI-based Predictive Optimization

This merged section addresses both enabling communications/instrumentation (IoT) and AI- driven supervisory optimization—reflecting the close coupling of sensing and decision-making in modern WWTPs.

A. IoT and Edge Architectures

IoT architecture in WWTPs comprises distributed sensors, edge nodes, gateways, and cloud/on- premises analytics. Sensors (DO probes, turbidity meters, ammonia/nitrate analyzers, level sen- sors) stream data to edge gateways where preprocessing, anomaly detection, and local estimation are performed. Gateways translate field protocols (Modbus RTU, 4–20 mA) to higher-level protocols (OPC-UA, MQTT) for supervisory controllers [14], [26].

Edge computing enables short-latency control decisions (e.g., rapid aeration adjustments), while cloud services provide heavy-duty analytics, trend analysis, and long-term model training. Re- dundancy, security (TLS, VPN), and time synchronization (NTP/PTP) are critical design aspects to ensure reliable operation.

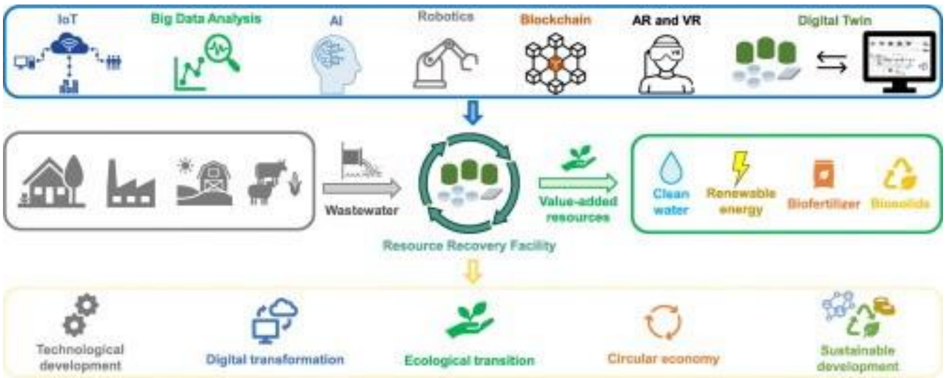


Fig. 7: IoT-enabled automation and cloud integration in wastewater control[9].

B. Data Fusion and Soft Sensors

Data fusion combines multiple sensor streams to generate robust estimates of key process variables (e.g., ammonium concentration, SVI). Soft sen- sors—model-based or ML-based es- timators—provide virtual measurements where direct sensing is expensive or unreliable. Kalman filters, particle filters, and ensemble learning methods are common approaches for state estimation and sensor fault detection [24], [26].

C. AI for Predictive Control and Scheduling

AI complements traditional control by offering predictive models and decision policies that can handle nonlinearities and complex constraints. Two prominent AI applications are:

- **Surrogate modeling:** Neural networks or gradient-boosted trees emulate detailed biochem- ical models (ASM family) with significantly lower computational cost, enabling faster MPC iterations.
- **Reinforcement learning (RL):** RL agents learn control policies through interaction with a simulator or digital twin. Constrained RL and safe policy search methods ensure that learned policies respect safety and regulatory constraints.

Hybrid AI–MPC frameworks combine the strengths of both: AI models predict disturbances and surrogate dynamics, while MPC enforces con- straints and optimizes multi-objective cost functions (energy, chemicals, effluent penalties). Case studies show AI-augmented controllers improv- ing setpoint tracking and reducing energy consumption compared to baseline MPC or PID controllers alone [16], [17].

D. Operationalization and Human-in-the-loop

Real-world deployment requires human oversight, explainability, and manual override capabil- ities. Visualization dashboards, KPI trend plots, and confidence intervals for AI predictions improve operator trust. Automated alarms, anomaly detection, and prescriptive maintenance suggestions trans- form raw data into actionable insights.

Energy Efficiency and Sustainability (Expanded)

Energy optimization is both an operational priority and an environmental imperative for WWTPs. Aeration, pumping, and sludge processing constitute the main energy sinks. The integrated multiloop framework enables a coordinated approach to minimize energy while meeting effluent constraints.

A. Energy-aware Control Strategies

Energy-aware control includes:

- **Dynamic DO setpoints:** Adjust DO setpoints based on real-time load forecasts to avoid fixed conservative setpoints that cause over-aeration.
- **Blower scheduling:** Use MPC to schedule blower operation and exploit compressor effi- ciency maps to operate at high-efficiency points when possible.
- **Pump-VFD coordination:** Coordinate influent and RAS pumps to smooth flows, enabling blowers to run at steadier and more efficient operat-ing points.

B. Co-optimization of Energy and Chemicals

Optimizing for energy alone can be counterproductive (e.g., reducing aeration too much increases chemical demand or effluent violations). Multi-objective optimization integrates energy cost, chemical cost, and effluent penalties. Weighted cost functions or Pareto-front analyses help operators select operating points that best balance trade-offs.

C. Resource Recovery and Circular Economy

Integrated control can improve resource recovery:

- **Biogas optimization:** Coordinate sludge wasting and digester feed rate to maximize methane yield while maintaining digester stability.
- **Nutrient recovery:** Adjust phosphorus precipitation dosing to balance removal efficiency with recovery processes (struvite crystallization).

These strategies transform WWTPs from energy consumers to partial energy producers, con- tributing to circular economy goals [19], [20].

D. Renewables and Grid-interaction

WWTPs increasingly couple with renewable generation (solar PV, biogas CHP). Control systems must manage intermittent supply—scheduling energy-intensive tasks (e.g., biosolids dewatering) during high-generation periods or participating in demand-response schemes. Predictive sched-ul- ing based on weather forecasts and digester models improves renewable utilization.

E. Measurement and Verification

Quantifying energy savings requires robust baselines and measurement protocols (IPMVP-like). Continuous monitoring of energy consumption at subsystem granularity (blowers, pumps, mixers) allows verification of control benefits and supports performance contracts or shared-savings financing.

Simulation, Digital Twins and Validation

Before deployment, controllers must be validated in simulation and digital twins. Digital twins combine high-fidelity process models (ASM variants) with real-time data to mirror plant behavior. They support:

- Safe RL training and policy testing.
- Virtual commissioning of supervisors.
- Operator training and scenario testing (storm events, power outage).

Model updating with online identification ensures twin fidelity. Reduced-order surrogates accel- erate optimization loops while retaining essential dynamics.

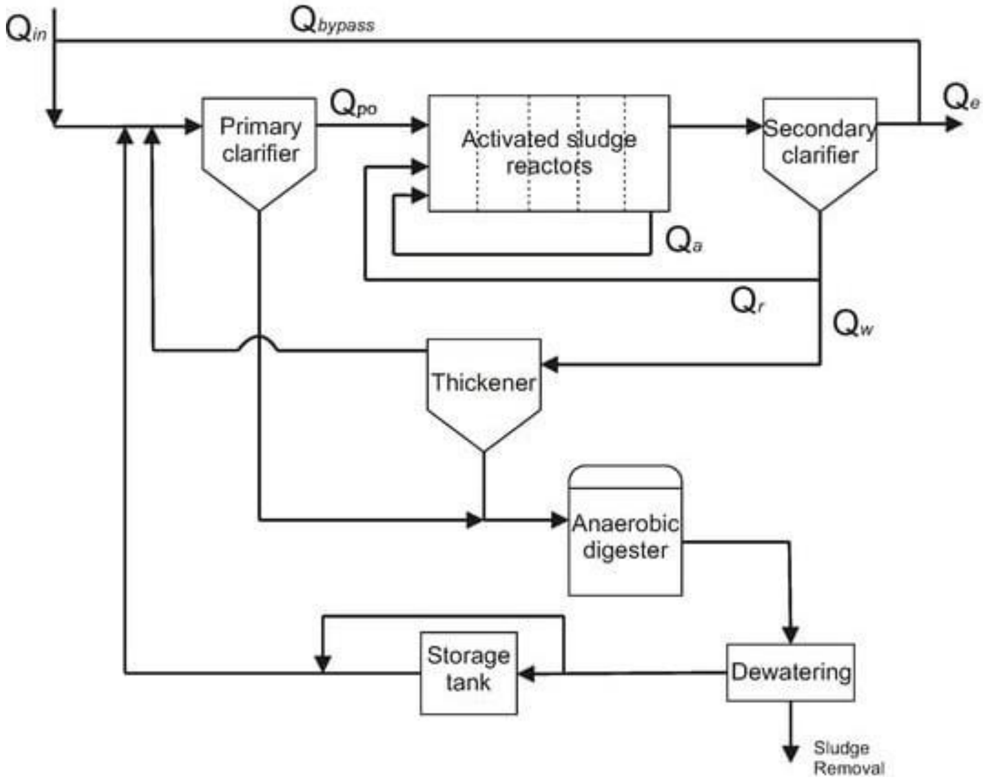


Fig. 8: Simulation model of a simplified plant layout. Reproduced from Revollar et al. [41], Sustainability, 2020, 12(3), 768. © 2020 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (http://creativecommons.org/licenses/by/4.0/).

Combined Challenges, Limitations and Future Directions

This merged section consolidates deployment challenges and outlines prioritized research and engineering directions.

A. Operational Challenges

- **Sensor reliability and maintenance:** Fouling, drift, and biofilm formation degrade sensor accuracy. Active cleaning, redundancy, and soft-sensor validation are necessary.
- **Legacy systems and interoperability:** Many plants run older PLCs and proprietary SCADA. Gateways and middleware are required, increasing integration complexity.
- **Real-time computational requirements:** Centralized MPC or AI controllers demand com- putational resources; edge/cloud partitioning must be designed carefully.
- **Operator acceptance and organizational change:** Trust, training, and transparent hu- man–machine interfaces are crucial for adoption.
- **Economic barriers:** Capital costs for sensors, VFDs, and software deter retrofits, especially for small municipalities.

B. Cybersecurity and Data Governance

Networked control increases attack surfaces. Defense-in-depth strategies, strict access control, encrypted telemetry, and secure software update mechanisms are essential. Data governance (privacy, retention, provenance) becomes critical when cloud services and third-party analytics are used.

C. Research Gaps

- **Safe RL and sample-efficient learning:** Methods for safe exploration and transfer learning from digital twins to physical plants.
- **Robust low-maintenance nutrient sensors:** Sensors that provide reliable ammonia/nitrate measurements with minimal cleaning.
- **Distributed optimization:** Scalable solvers that approximate centralized performance with lower communication overhead.
- **Lifecycle and GHG accounting:** Integrating control decisions with lifecycle emissions and sustainability metrics.

D. Future Directions and Roadmap

1) **Standardize interfaces:** OPC-UA, MQTT profiles, and semantic data models to ease vendor interoperability.

2) **Pilot then scale:** Use pilot units and digital-twin validation before full-scale rollouts.
3) **Operator-in-the-loop:** Gradual automation with operator oversight and explainable AI modules.
4) **Performance contracts:** Financing via energy-performance contracts to overcome upfront cost barriers.
5) **Regulatory support:** Incentives for energy efficiency and resource recovery to accelerate adoption.

E. Implementation Considerations

Successful deployment requires:

- **Staged commissioning:** Tune local loops first, then enable supervisory optimizers with conservative update rates.
- **Redundancy and fallbacks:** Define safe modes and automatic fallbacks to local PLC control.
- **Training and documentation:** Use digital twins for operator training; provide clear SOPs.
- **Performance monitoring:** KPIs (kWh/m^3, chemical mass per pollutant removed, effluent exceedance counts) must be continuously monitored.

Conclusion

This comprehensive review synthesizes theory, instrumentation, and real-world demonstrations of integrated multiloop frameworks for sustainable wastewater treatment. Coordinating aeration,

sludge, dosing, and flow loops through hierarchical supervisory controllers, data fusion, and predictive models addresses the shortcomings of traditional isolated-loop automation and unlocks measurable gains in efficiency, resilience, and environmental performance.

Key conclusions drawn from the surveyed literature and practical case studies are:

- **Multiloop integration is materially beneficial.** Coordinated control reduces energy con- sumption (notably aeration energy), optimizes chemical usage, improves effluent consis- tency, and lowers operational risk. Reported energy savings in field deployments range commonly from 15–35% depending on baseline practices and site conditions.
- **Sensing and edge analytics are foundational.** Reliable DO, nutrient, turbidity, and level sensors—augmented by edge preprocessing, cleaning mechanisms, and soft-sensors—enable aggressive supervisory strategies. Sensor maintenance planning and diagnostic algorithms are as important as advanced control design.
- **AI augments but does not replace model-based control.** Hybrid approaches that combine MPC for constraint handling with AI for prediction and surrogate modeling yield robust, interpretable, and high-performance supervisors. Reinforcement learning shows promise but needs careful simulation-backed validation and safety constraints.
- **Digital twins accelerate safe deployment.** Virtual commissioning, operator training, and RL policy training within a twin reduce commissioning risk and speed adoption while preserving process safety.
- **Economic and organizational enablers are required.** Upfront capital costs, legacy sys- tems, and operator skepticism are common barriers. Performance-based contracts, stan- dardized interfaces (OPC-UA, MQTT), and clearly demonstrated paybacks help overcome resistance.
- **Future research must focus on robustness and scalability.** Robust low-maintenance nutrient sensors, sample-efficient safe learning algorithms, distributed optimization for multi- plant utilities, and lifecycle-aware control objectives (including GHG) are high-priority areas.

In summary, the integrated multiloop framework represents a pragmatic and high-impact path- way to modernize WWTPs for sustainability and resilience. By combining advanced sensing, edge/cloud analytics, hybrid model/AI controllers, and careful commissioning practices, utilities can achieve substantial environmental and economic benefits while paving the way toward circular water-resource management.

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