Journal of Environmental & Earth Sciences
https://journals.bilpubgroup.com/index.php/jees

REVIEW

AI, IoT, and Robotics in Wastewater Treatment: Transforming Process Efficiency through Automation

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ABSTRACT

The challenge of wastewater treatment facilities is growing as they strive to enhance compliance strength and minimize energy consumption, chemical usage, downtime, and labor requirements in the face of increasingly variable influent and climate-related disruptions. The use of recent developments in Internet of Things (IoT), artificial intelligence, and robotics enables a transition to a less reactive mode of operation and more closed-loop automation. This review leads to an understanding of the demonstrations of networked sensing and edge data architecture to enhance observability, transform heterogeneous time-series and multimodal data into monitoring, forecasting, and risk intelligent decision knowledge, and extends robotics ability to measure and intervene in hazardous, distributed, or intermittently observed plant environments. We structure the literature on a deployable sense-think-act structure between unit processes, sensing strategies, Artificial Intelligence (AI) tasks, and execution pathways based on supervisory control and robotic operations. The applications of high leverage are evaluated, such as aeration and nutrient removal optimization, chemical dosing and disinfection control, prediction of membrane fouling and cleaning schedules, solids line stabilization, and predictive maintenance of the important assets. In these areas, we highlight aspects of quality of evidence, benchmarking issues, and operational circumstances that will define persistence of reported efficiency improvements after pilots, such as sensor drift and biofouling control, constraint-based control in service of Supervisory Control and Data Acquisition (SCADA)/Programmable Logic Controller (PLC) systems, cybersecurity-by-design, and model life cycle governance. We bring it to the maturity perspective of resilient, interoperable, and conscientiously independent Wastewater Treatment Plants (WWTPs) with a research requirement of

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ARTICLE INFO
Received: 20 December 2025 | Revised: 16 January 2026 | Accepted: 20 January 2026 | Published Online: 6 February 2026
DOI: https://doi.org/10.30564/jees.v8i2.13052

CITATION
Lin, M., 2026. AI, IoT, and Robotics in Wastewater Treatment: Transforming Process Efficiency through Automation. Journal of Environmental & Earth Sciences. 8(2): 105–134. DOI: https://doi.org/10.30564/jees.v8i2.13052

standardized datasets, hybrid digital twins, uncertainty intentional optimization, and adaptive sampling and inspection by robotized techniques.

Keywords: Wastewater Treatment; Industrial IoT; Artificial Intelligence; Robotics; Process Optimization

1. Introduction

The wastewater treatment plants (WWTPs) occupy a very challenging junction between the protection of the population, environmental regulations, and cost-effectiveness [1–5]. In most of the regions, nutrient, micropollutant, and pathogen discharges are becoming stricter, and the demands regarding reliability and transparency are on the increase. Meanwhile, utilities acknowledge structural headwinds like unstable energy costs, soaring chemicals, outdated infrastructure, and incessant workforce scarcity, which make 24/7 optimization and quick problem-solving challenging to maintain. These forces are exacerbated by climate-induced variability such as storms, infiltration/inflow, drought-induced concentration effects, and temperature oscillation, which drive the plants to operating regimes that are not at all consistent with the steady-state assumptions of most classical designs and traditional control mechanisms. In this regard, the concept of enhancing process efficiency is no longer confined to marginal energy savings; it is more about how to stabilize compliance with reduced interventions to detect abnormal conditions faster, and how to become more resilient to uncertainty.

Traditionally, wastewater automation has depended on a stack of field instrumentation, programmable logic controllers (PLCs), supervisory control and data acquisition (SCADA) systems, and local feedback control (e.g., proportional integrative derivative (PID)) most of the time [6]. This paradigm has proven extremely valuable, but it is limited by a lack of observability, a low density of sensing key state variables, and control logic that is typically adjusted to common case situations rather than to extremes. Most of the critical process quantities, easily biodegradable Biochemical Oxygen Demand (BOD), nitrification capacity, sludge settleability, filamentous bulking propensity, membrane fouling dynamics, or digester stability, are challenging to measure directly and fluctuate at timescales that make them challenging to sample manually. Problems like signal drift, biofouling, incorrect calibration, and the loss of signals may decrease the accuracy of measurements and limit the usefulness of automated control systems even in cases where sensors are installed. Due to this fact, the operation of treatment plants is very conservative. Regulatory compliance relates to the inclusion of safety margins in aeration, chemical dosing, recirculation, and pumping. This method lessens the risk of operation, but also raises the operating expenses and, in some cases, even makes the emissions worse, like the production of nitrous oxide through an inefficient removal of nitrogen [7,8].

Recent developments in artificial intelligence (AI), the IoT, and robotics provide a plausible avenue to shift WWTPs' activities to less reactive and increasingly adaptive, data-driven, and autonomous management [9]. We apply AI in this article to mean, as a broad concept, the prediction and pattern recognition based on machine learning and deep learning, and the optimization tools such as hybrid model predictive control (MPC) and reinforcement learning (RL), where we wish to apply it. IoT (with single sensing and industry IoT) systems are employed to characterize field device networking, connectivity, and data infrastructure over the field, through edge compute, as well as cloud service offerings that facilitate trustworthy streaming, storage, and contextualizing of operational data. We define robotics to include ground and air sensing and cleaning and inspecting mobile and fixed platforms, such as underwater/pipe crawlers, robotic manipulators, and aerial drones, and give up robots autonomously or with operator assistance. Collectively, these technologies could enable a sense think act loop: IoT can measure much more and more often, AI can be used to transform that data into state estimates, predictions, diagnoses, and optimal actions, and robotics (and automated actuators already being deployed in plants) can then be used to implement that action more safely, more regularly, and more quickly [10].

As outlined in **Figure 1**, the end-to-end "sense–think–act" architecture integrates IoT sensing, AI decision-making, and robotics execution to improve WWTP efficiency and resilience. Architectural design of an AI, IoT, and robotics-enabled wastewater treatment plant with a sensing, intelligence, and actuation layer. In the physical process, the treatment of the influent involves primary, biological nutrient removal (BNR), secondary, and tertiary processes before discharge and sludge treatment. The sensing layer (IoT) records operational and water-quality data: ammonium (NH_4^+), nitrate (NO_3^-), phosphate (PO_4^-), dissolved oxygen (DO), oxidation reduction potential (ORP), flow, level, temperature, pressure, and other important indicators of organic loads such as biological oxygen demand (BOD) and chemical oxygen demand (COD). The intelligence layer combines digital twins and soft sensors to provide predictions of such process states as sludge retention time (SRT), nitrification potential, sludge descendancy, membrane foulness, and digester wellbeing. Predictive analytics will assist influent prediction and fault detection, and optimization engines will be used to augment operation efficiency by using AI-enhanced MPC and reinforcement learning. Pumps, blowers, valves, mixers, chemical dosing systems, and inspection, sampling, and maintenance robots are all found in the actuation layer [10].

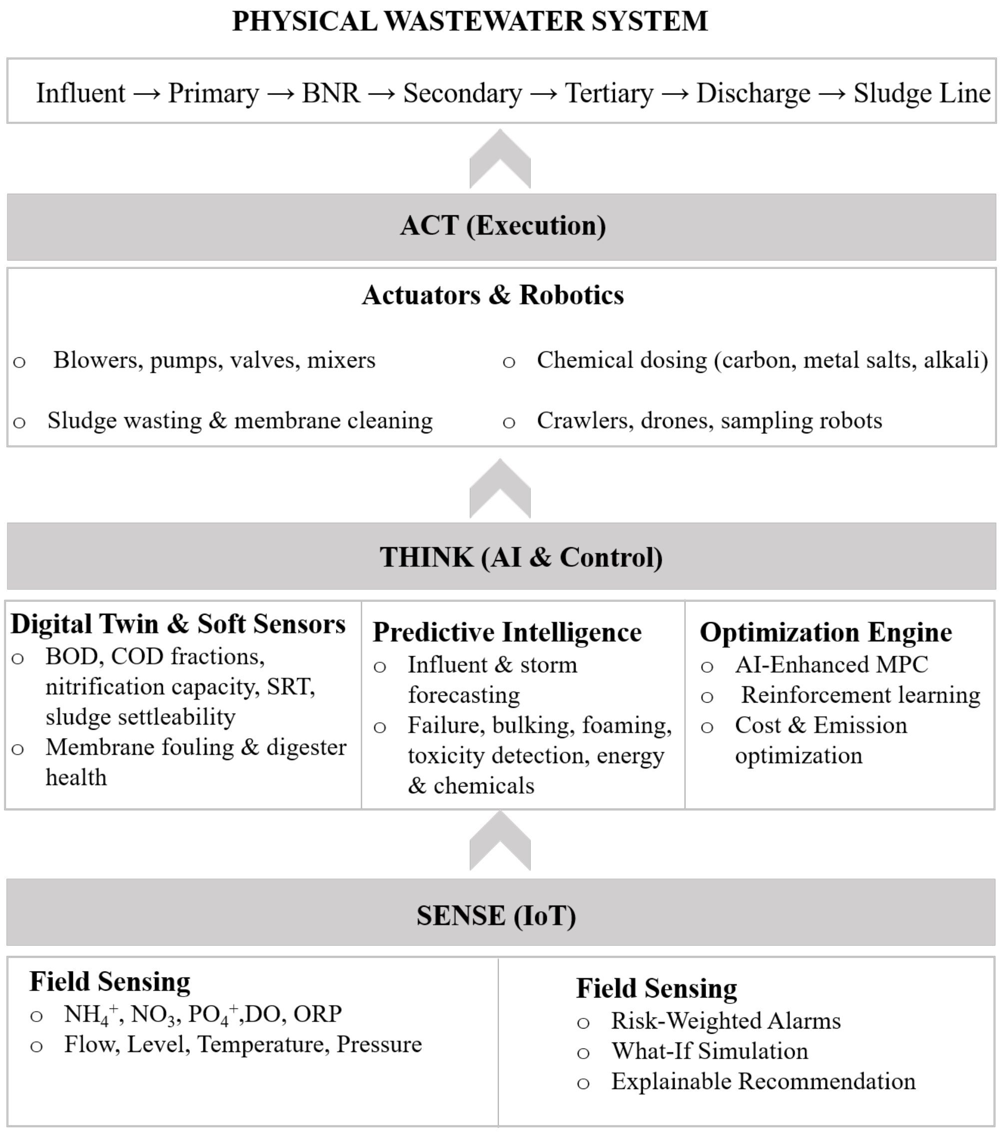

Figure 1. End-to-end sense, think, act reference architecture for automated WWTPs.

This convergence cannot be done by coincidence. The sensor hardware has become more durable and more affordable, and connectivity (wired industrial protocols and an ever-stronger wireless connection) and edge computing have made the burden of gathering high-frequency data on distributed assets a little bit lighter. Simultaneously, the current state of the art in AI techniques has reached its maturity in the areas of time-series forecasting, anomaly detection, the integration of multiple modalities (pairing process sensors with vibration, acoustics, or cameras), and uncertainty quantification, all of which are directly applicable to the nonstationary, noisy dynamics of wastewater. Robotics is, in the meantime, out of the laboratory: drones may be used to quickly survey hard-to-reach assets; crawlers may be used to survey pipes without digging; and mobile ruggedized platforms may be used to survey a confined space or conduct routine patrols, eliminating the exposure to dangerous atmospheres and the intensive process of manual sampling. Notably, it is not the promise of more data, more automation, but improved decisions in constrained energy and chemical minimization within efficiency limits; active maintenance to avoid disastrous failures; and improved recovery of disruptions [11,12].

Although the field of AI, IoT, and robotics integration in wastewater treatment has grown very fast, the areas of integration are quite fragmented [9,13]. Investigations tend to concentrate on a unit process or algorithmic method without explicitly placing findings in the overall operational layer, sensing, and data quality control to control implementation and human supervision. The reported benefits (e.g., percent energy reduction, better nutrient removal, fewer alarms) may not be readily compared due to the wide variation in the level of baseline conditions, evaluation windows, and performance measures. Moreover, WWTPs are safety/compliance-sensitive assets: any step toward greater autonomy of operation must consider reliability, cybersecurity, explainability, and governance. The practical limitations of robotics impose more practical constraints on them, such as corrosion, washdown, low visibility, electromagnetic interference, and strong teleoperation modes, that are not necessarily discussed in an algorithm-centric context. The need is presented in this review by refocusing the literature about process efficiency using automation, herein defined as the capacity to achieve treatment goals using less energy, chemicals, downtime, and labor, and without impacting or worsening compliance, safety, and resilience [14]. There are three cross-cutting ideas that we highlight. To begin with, observability leads to controllability: to achieve trustworthy AI-based optimization, the enhancement of sensing (including soft sensors) and data governance are the conditions. Second, closed-loop value has to be integrated: predictive models are most effective when linked to supervisory control strategies, as well as operational processes, and have fail-safes and operator-friendly interfaces. Third, physical automation reduces the gap between insight and action: robotics can reach and feel places that are hard to quantify, automate routine processes of inspection, and facilitate quick actions, which facilitates the application of data-driven strategies in large scale in practice.

In this connection, this article contributes to three key things. (i) A common taxonomy and design connecting unit processes, operational targets with IoT sensing approaches, AI techniques (monitoring, prediction, optimization), and robotic/actuation routes (ii) These technologies have been shown to have efficiency gains in application areas that are organized in the synthesis, such as aeration control, chemical dosing, predictive maintenance, and membrane fouling control, but also a distinction is made between the mature and experimental approaches. (iii) deployment-based assessment of impediments and danger processes, such as information quality, model life cycle (MLOps), various data protection, protection against every risky environment, and human-machinery coexistence [10,15,16].

The rest of the review is structured in the following way. Section 2 gives the context of wastewater treatment and determines the best leveraged automation opportunities in the key unit processes, as well as describing the realities in data and control that determine what is achievable. Section 3 runs through the digital infrastructure that smart WWTPs are based on, such as sensing modalities, edge-cloud architectures, data platforms, and cybersecurity aspects. Section 4 estimates AI practices with monitoring, predictive analysis, and decision intelligence, with the focus on the uncertainty dimension, the explainability dimension, and the deployment life cycles. Section 5 looks into robotics and physical automation with particular reference to platforms of plant relevance, perception, and navigation in challenging environments, robots' integration as mobile sensing agents and intervention agents. Section 6 introduces an integration of applications and the strength of evidence of improvements in its efficiency as benchmarking metrics and techno-economic considerations. Section 7 ends with a conclusion and research agenda to the future to create resilient, interoperable and responsible autonomous wastewater treatment.

Against the backdrop of wastewater processes, this review will analyze the attention of AI, IoT, and robotics to provide researchers with a better comprehension of what implementable innovations can be made, assistance of utilities in identifying modernization ways that can enhance higher returns, and technology developers with a clear insight into the integrations needed to be made. Automation in itself is not the end product. Instead, the future trend is toward development of the systems of treatment that are currently present into systems of continuous monitoring, controllable, easier to work, and less resource-intensive systems that can preserve compliance with regulations and operational strength in a world that is growing more and more diverse [17].

2. Wastewater Treatment Context and Automation Levers

Wastewater treatment is a biological-chemical-physical process that is subjected to varying conditions of inflow and strict effluent limits [18]. The key working problem is that most of the most significant states of the process can be observed only partially, and they fluctuate in time scales between minutes and seasons. These reasons demonstrate the importance of automation, which is made possible by AI, IoT, and robotics, to optimize the work of a wastewater treatment facility without eliminating human capital. In its place, automation enhances system observability by converting raw measurements into useful estimates of process states and predictive information and enables operators to make more informed decisions. It also enables coordinated management between the interacting unit processes, enhancing the efficiency and stability of the operations. This approach shows how contemporary automation can help to enable practical, implementable solutions to more robust and efficient wastewater treatment systems by setting priorities on plant-wide goals, high-impact unit processes, controllable variables, and reliable streams of data.

2.1. Plant-Wide Objectives, Constraints, and Operating Regimes

Regulatory compliance is the main goal of a WWTP, normally in terms of effluent limits on biochemical oxygen demand (BOD), total suspended solids (TSS), ammonia, total nitrogen, total phosphorus, and pathogens, and occasionally emerging contaminants [19]. However, compliance is met within wider boundaries that become more predominant in the decision-making of operations. The operating cost in biological treatment plants is often the largest one, and its energy use is a leading contributor, followed by aeration and pumping. Phosphorus removal, pH adjustment, coagulation, and disinfection may be important, and their consumption is subject to market fluctuations. Additional constraints are added by solids management, which thickens, digests, dewaters, and hauls, in which the instability spreads in an upstream, downstream manner that is not represented by single unit optimization.

Beyond cost, WWTPs must meet reliability targets in the face of equipment wear, supply chain delays for critical parts, and labor limitations that reduce the feasibility of constant manual monitoring [11]. Many plants now incorporate resource recovery goals such as energy neutrality through anaerobic digestion, nutrient recovery, and water reuse, which introduces new operational setpoints and performance indicators. Finally, climate and hydrologic variability are shifting WWTPs into more frequent "disturbance-driven" operation. Wet-weather flows can dilute concentrations while increasing hydraulic loading and bypass risk; drought and water conservation can raise influent strength; and temperature swings can alter biological kinetics, affecting nitrification and denitrification margins. These factors produce operating regimes where traditional steady-state tuning and conservative setpoints are insufficient to minimize cost while maintaining robust compliance.

2.2. Unit Processes with the Highest Leverage for Automation

The leverage of automation in wastewater treatment is usually concentrated in the presence of process dynamics speed, a high level of energy or chemical intensity, and high compliance sensitivity [20]. The activated sludge and its derivatives are the main focus of the biological treatment since the aeration requirement is high and the dependence between oxygen uptake, microbial activity, and nutrient conversion is extremely nonlinear. The process of nitrification is also sensitive to dissolved oxygen, temperature, inhibitory substances, and sludge age, whereas denitrification is sensitive to carbon availability, internal recycle flows, and redox conditions. These linked dependencies provide a control environment in which model-based supervisory control and model-driven prediction can contribute significantly to energy consumption and stabilize effluent quality [21,22].

The process of removing nutrients to phosphorus is commonly based on chemical dosing or increased biological phosphorus removal, which is advantageous due to the enhanced influent characterization and quick process drift detection. Chemical dosing is generally done with a low degree of conservatism because of the unpredictability of fluctuation in the influent, as well as delay in measurements, which results in overdosing and sludge growth. Phosphate estimates can be made with greater accuracy through automation to enhance the forecasting of short horizons, and to give enough confidence to reduce the use of chemicals, though the chemical compliance risks are capped [9,23].

Tertiary filtration and membrane bioreactors are considered areas of high leverage as well, since the dynamics of fouling are applied to the energy consumption, permeability loss, and cleaning frequency [24]. Mixed liquor properties, hydraulic, and transience of operation influence fouling and can occur without any notice until it impairs performance. Predictive methods that forecast the development of fouling curves and clean-in-place processes can minimize the downtime, intensity of chemical cleaning, and energy expenditure, and maximize the membrane life. As seen in **Figure 2**, various unit processes in wastewater treatment, such as aeration and nutrient removal, map to specific sensing modalities, AI tasks, and execution pathways, facilitating automation. The structure of incorporating sensors, AI, and automated execution systems in WWTPs. It starts with major unit operations of influent treatment, biological treatment, clarification, filtration or membrane, disinfection, sludge digestion, and equipment operations. Various sensors are used to monitor these processes by measuring such parameters as flow, turbidity, COD, ammonium, nitrate, pH, dissolved oxygen, membrane pressure, solids, gases, and equipment conditions. The obtained data are analyzed with the help of AI tasks, such as anomaly detection, soft sensing and state estimation, forecasting and prediction, and supervisory optimization, based on machine learning and advanced control methods. According to these analyses, execution pathways convert insights into operational actions, including alarms, process optimization, optimization of chemical dosing, load forecasting, energy and cost optimization, and maintenance scheduling. Moreover, the inspection and gathering of more information can be done with the help of robotic systems like drones, unmanned ground vehicles, and pipe crawlers. The results are reintroduced into the system as data enrichment, and this forms a feedback loop that enhances monitoring, decision-making, and general operational efficiency of the wastewater treatment plant [20].

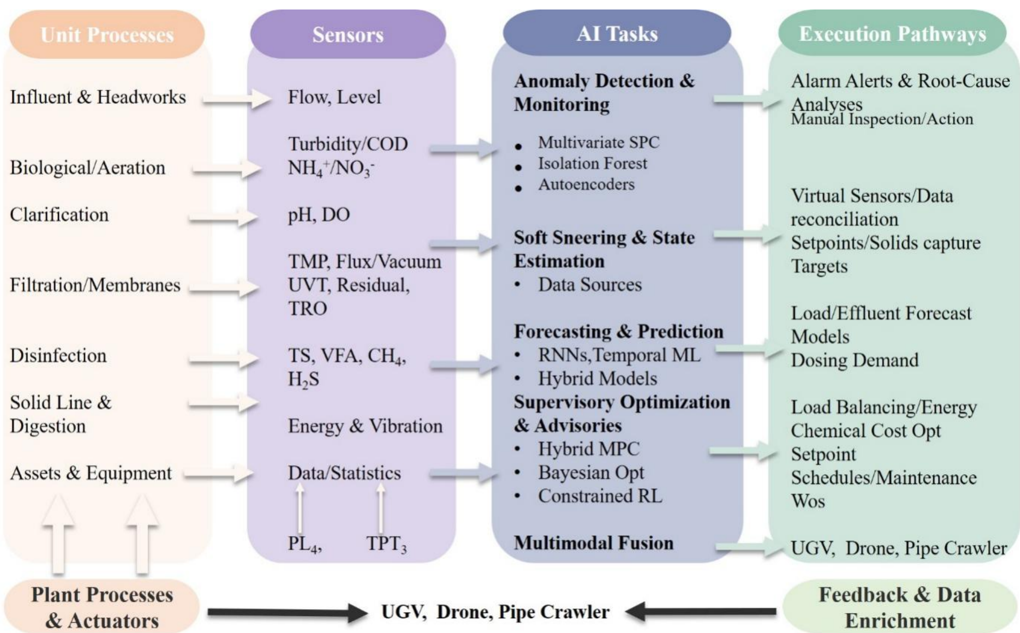

Figure 2. Taxonomy map: Unit processes; sensing; AI tasks; execution pathways.

The solids line has been referred to as the backbone of plant stability. Long time constants and delayed feedback are added by thickening, anaerobic digestion, and dewatering, but their instability may interfere with upstream biological treatment by providing ammonia-rich and phosphate-rich return streams. The risk of digester upset has a correlation with volatile fatty acids, alkalinity, temperature, loading rate, and mixing, all of which are not measured consistently at most of the facilities. Automation in this case is not so much second-by-second control, but rather about early warning, load control, and setpoint changes, with the ability to avoid instability and enhance biogas yield [21,25,26].

Lastly, asset-intensive subsystems like blowers, pumps, mixers, and valves can play a great role in being automated since mechanical reliability has a direct consequence on the performance of the process. Condition-based monitoring and predictive maintenance can avoid failure-bound excursions resulting in permit violations, decrease unplanned downtime, and enhance the efficiency of maintenance. Simultaneously, collection systems and interceptors may become more and more important, especially when the variability of wet weather is determined by infiltration and inflow, blockages, and surcharging. These dynamics that cause the influent uncertainty, though not provided within the plant fence line, can be partly overcome by network monitoring and specific inspection [27].

2.3. Controllable Variables, Actuators, and the Practical Control Envelope

The final limitation of WWTP automation is its ability to manipulate things safely and reliably [6,26]. The aeration control is usually based on the speed of the blower, the position of air valves, and the zone-level distribution of airflow. Practically, the control variable is the oxygen transfer, which is effective and which is determined by the condition of the diffuser, the fouling, the hydraulics of the basin, and the alpha factors, which differ with the nature of the wastewater [28]. This poses a disparity between ordered airflow and the conveyed procedure effect, which impels the application of state estimation and adaptive control to ensure steady dissolved oxygen and prevent energy squandering.

Internal recycle and return activated sludge flows play an important role in improving nitrogen removal and maintaining the stability of the secondary clarifier [29]. But there are higher energies involved in recycling that may increase pumping and alter hydraulic loading, and downstream expectations on clarification as well as sludge blanket behavior. Fast corrective capacity, though with the risk of overdosing, higher sludge levels, and downstream scaling/corrosivity, is offered by the use of chemical dosing, such as metal salts to eliminate phosphorus and aluminum salts to add alkalinity to enable nitrification. Other control opportunities include disinfection dosing and Ultraviolet (UV) intensity modulation, which are provided when the effluent quality and transmittance fluctuate, though limited by the concern of public health risk and conservative operating practices.

Sludge wasting and solids retention time manipulation are among the most powerful levers for long-term biological performance, yet they act slowly and interact with settling behavior and filamentous growth. Operators often manage waste based on a combination of lab measurements, experience, and visual inspection [30]. Automation can support this domain through improved forecasting of mixed liquor trends and early warning of settling deterioration, but full closed-loop control is challenging because the measured proxies are noisy and delayed.

Across these actuators, the practical control envelope is shaped by equipment constraints, minimum and maximum flow rates, valve hysteresis, actuator wear, and safety interlocks [26]. Many plants operate with layered safety logic embedded in PLCs that prevent commands outside allowed ranges. This is an important constraint for AI-enabled supervisory control: algorithms must respect hard limits, anticipate actuator saturation, and degrade gracefully when sensors fail or communication is interrupted. The most deployable automation strategies, therefore, tend to use hierarchical control, where existing fast loops remain in PLC/PID control, while AI or advanced optimization proposes setpoints and schedules within validated bounds [6].

2.4. Data Characteristics That Shape AI-Ready Wastewater Automation

Wastewater data rarely meet the assumptions of clean, stationary, and fully labeled datasets that underpin many generic AI demonstrations [31]. Influent composition varies with diurnal patterns, industrial discharges, rainfall, and seasonal behavior, producing nonstationary relationships between measured variables and process outcomes [32]. Sampling frequency is heterogeneous; some signals are available at sub-minute resolution from online probes, while key variables such as BOD, nutrient fractions, and microbiological indicators may be measured only daily or weekly [33].

This mismatch complicates supervised learning because labels are sparse and sometimes misaligned in time with the causal drivers. Ongoing issues are sensor drift and biofouling[34]. Dissolved oxygen, ammonia, nitrate, phosphate, and pH probes may drift between inter-calibration, and fouling may cause a bias that appears like a genuine process change. Maintenance or communication failures, or replacement of sensors, are likely to cause data gaps. Moreover, SCADA tags can be repurposed, renamed, or scaled irregularly over time, resulting in discontinuities in historical data that are not always visible. Unless these issues are managed by means of strict data governance, quality checks, and drift detection, they may harm the performance of a model unnoticed.

Delayed and coupled effects of processes are also introduced, which makes causal attribution difficult[35]. Alteration of aeration can impact nitrification in a short period, but can impact biomass traits of settling and clarifiers on an alternate timescale, respectively. The effluent streams of the solids can change nutrient loads hours to days after the fact, and weather-related infiltration can cause hydraulic constraints that prevail in short-term decision-making. All these lagged interactions mean that useful models should address multiscale time dependencies, take uncertainty into consideration, and be assessed in such a way that reflects the decision horizons of operations, as opposed to solely statistical fit.

Another complication is that ground truth can be operational or subjective. The operators can be used to label events, including bulking, foaming, or odor episodes that are not necessarily characterized by a single threshold of measurement. The logs of maintenance may not be complete or even consistent, and it may not be possible to train reliable fault classifiers. Here, robotics and better senses can assist in gathering more contextual information, but what is immediately implicated by AI deployment is that it requires strong learning with underdefended supervision, meticulous matching of data to work areas, and metrics that report actual plant performance[36].

2.5. Baseline Automation and Why It Often Plateaus

The automation that is currently being used in most WWTPs includes local PID loops, sequencing logic, and alarm systems[6]. Dissolved oxygen management is a popular method of aeration control in aerobic areas, and flow-paced chemical dosing is prevalent. Such strategies have only a limited range of conditions when they are effective, but when they tend to reach a plateau because of three structural constraints. To begin with, baseline control affects easily measured surrogates instead of the final compliance variables. Having a dissolved oxygen setpoint is not a sure way to maintain ammonia or overall nitrogen removal when there are changes in the influent loads and the capacity of nitrification. Second, average conditions are normally tuned as baseline loops, and retuning is not common because operation is risky and staffed by limited capacity, thus being conservative. Third, baseline automation does not often coordinate among processes at the unit level, but instead optimizes on a local scale at the cost of plant-wide goals, including the reduction of energy and the prevention of solids instability downstream.

The plateau opens an AI-IoT-robotics integration space, which can most easily be viewed as an extension of existing control infrastructure, as opposed to a replacement[37]. IoT increases observability and standardization of data flows. AI introduces adaptive estimation, forecasting, anomaly detection, and optimization that may suggest or execute supervisory setpoints within validated constraints. Robotics expands not only to measurement and intervention but also to places and tasks that are at present manual, hazardous, or too rare to lend data-driven control. The rest of this review extends this background by discussing the digital architecture that may support consistent sensing and data management, the AI techniques that can help with the nonstationary character and safety-critical nature of wastewater, and the robotic platforms that can facilitate the connection between understanding and long-term operational effectiveness.

3. Digital Infrastructure: IoT Sensing, Data Platforms, and Cybersecurity

The digital transformation of the wastewater treatment process starts at the physical layer of measurement and actuation, but the success can be determined by the capabilities of the physical layer of measurement and actuation to acquire, contextualize, and deliver signals to the decision and control layers[20]. Unlike most industrial environments, where feedstocks are relatively constant and the environment is clean, WWTPs have very stringent requirements on sensing and connectivity. Sensors work in corrosive and biofouling susceptible media, hydraulic surges may be commonplace, and resources are spread geographically in tanks, galleries, remote pump stations, and collection networks. The IoT in wastewater, therefore, is not a mere question of device addition, but a system at the end-to-end level that needs to focus on data quality, maintainability, and security, and be able to interface with legacy SCADA/PLC systems. This part examines the sensing modalities that are most applicable to smart WWTPs, the architectural design of the latency and reliability, the data engineering patterns that define the viability of AI at scale, and the cybersecurity of critical infrastructure.

3.1. Sensing Modalities, Measurement Reliability, and Placement Strategies

The foundation of IoT-enabled automation is observability, yet many of the variables that matter most for compliance and efficiency are difficult to measure continuously. Routine online sensing in WWTPs commonly includes dissolved oxygen, pH, oxidation–reduction potential, temperature, conductivity, turbidity or suspended solids proxies, and flow and level measurements [38]. For nutrient control, online ammonia, nitrate, and phosphate probes can provide high value by enabling faster detection of load shifts and process drift, but they are also among the sensors most susceptible to calibration drift, cross-sensitivity, and fouling. Optical methods, including UV absorbance and spectral probes, offer proxies for organic content and can support influent characterization, but their signals are influenced by particle composition and lamp aging and can require site-specific calibration.

Process sensing is supplemented more and more by mechanical and electrical asset monitoring. Before failures occur, vibration, acoustic emission, motor current signatures, and temperature readings can be used to identify developing faults in blowers, pumps, mixers, and gearboxes. Such signals are typically of a higher frequency than process variables and could be gathered by dedicated condition-monitoring systems or could be added to plant data platforms by gateways. Simultaneously, vision-based sensing, which can include fixed cameras to measure surface conditions, foam monitoring, and scum monitoring, or thermal cameras to monitor electrical cabinets, can be able to measure qualitative states of the process that are hard to measure using single-point probes. Nevertheless, in WWTPs, there are also low-light situations, mist and spray fogs, and the device is not completely safe, so the cameras should be extremely robust, and their locations are the primary issue [39].

Sensor placement is just as important as sensor choice [40]. There are spatial gradient processes of wastewater processes, especially in aeration basins, where the distributions of oxygen and substrates depend on zones, depths, and mixing. One dissolved oxygen probe may not be a sufficient measure of oxygen in the entire basin, and the value may be distorted by local turbulence or diffuser position. The same can be said about clarification and filtration, whose blanket depth, solids distribution, and headless development may become spatially heterogeneous. Good designs of IoT are therefore usually a combination of well-placed fixed sensors and sampling plans that can measure variability both spatially and over time. In places where measuring in a fixed manner is not viable, mobile sensing, possibly carried out on a robot platform, may offer periodic, repetitive campaigns of measurements that enhance the observability of plants without being over-instrumented. As shown in **Table 1**, the selection of appropriate sensing modalities plays a critical role in ensuring the reliability and functionality of automation systems in WWTPs [20].

3.2. Connectivity and Architectures: From Field Devices to Edge–Cloud Systems

WWTPs rarely operate on a clean-slate digital architecture. Most facilities have decades of investment in PLCs, SCADA historians, and field networks based on established industrial protocols [41]. IoT architectures must therefore bridge legacy environments and modern analytics while maintaining deterministic control behavior and strong safety boundaries. One of the trends is a layered architecture with PLCs and local control loops remaining authoritative to fast actuation, SCADA to provide supervisory visualization and alarm handling, and other gateways to replicate selected tags into an IoT data pipeline to be used to analyze and optimize. Such a division minimizes the risk of operation and facilitates slow modernization.

Table 1. Representative sensing modalities in wastewater treatment, typical failure modes, and automation relevance.

Measurement/Variable	Common Modality (Examples)	Typical Deployment Location	Common Field Issues	Automation Value (Examples)
Flow, level	Ultrasonic, radar, pressure transducers, mag flow	Influent/effluent channels, pump stations, tanks	Ragging, sediment, air entrainment, sensor drift	Influent forecasting inputs, hydraulic constraint management
DO, pH, ORP, temperature	Electrochemical probes	Aeration basins, anoxic zones, sidestreams	Biofouling, calibration drift, membrane aging	Aeration control, nitrification/denitrification regime detection
NH_4^+, NO_3^-, PO_4^{3-}	Ion-selective/optical analyzers	Bioreactor, effluent, sidestream	Cross-sensitivity, fouling, reagent consumption, downtime	Nutrient control, compliance risk prediction, dosing optimization
Turbidity/TSS proxy	Optical backscatter, nephelometry	Effluent, filters, clarifiers	Window fouling, bubbles, solids heterogeneity	Filter/clarifier monitoring, early solids breakthrough detection
Organics proxy (COD/BOD surrogate)	UV254, spectrometry	Influent/primary effluent	Optical path fouling, site-specific calibration	Load estimation, carbon management, process forecasting
Energy and equipment condition	Power meters, vibration, motor current signature	Blowers, pumps, mixers	Sensor mounting, noisy environments, data overload	Predictive maintenance, efficiency degradation detection
Vision/thermal imaging	RGB/IR cameras, thermal	Clarifiers, galleries, electrical panels	Low light, mist, occlusion, safety access	Foam/scum monitoring, leak/overheat detection, inspection automation
Gas monitoring	H_2S/CH_4/O_2 sensors	Confined spaces, digesters, wet wells	Drift, poisoning, harsh atmospheres	Safety scouting, digester monitoring, ventilation control

Wastewater particularly has a role to play in edge computing since not all sites of the plant have the same network reliability and latency [42]. There can be varying connectivity requirements on remote pump stations, aeration basins, and solids handling buildings, and wireless connections are unreliable in reinforced concrete buildings. Local buffering, preprocessing, compression, and limited analytics can be run on edge nodes to ensure continuity of the data flowing through the network when the network is not available, or so that time-sensitive operations can be performed when the process is close. Edge deployment can also be used to achieve their privacy and security objectives by reducing the amount of raw data that needs to travel further networks and by facilitating anomaly detection that can cause local alerts when no upstream services are available.

Cloud services offer scalability for long-term storage, fleet-level benchmarking, and more computationally intensive workloads such as deep learning or large-scale simulation. However, cloud reliance must be matched to regulatory and operational realities. Utilities may require data residency controls, strict access management, and clear governance over third-party service providers. In practice, many deployments adopt hybrid architectures where the cloud hosts historical data lakes and model training pipelines, while the edge hosts inference services and communicates recommended setpoints back to SCADA. The engineering challenge is to maintain clear interfaces and version control: the model running at the edge must be traceable, auditable, and compatible with the data schemas and calibration assumptions under which it was validated [43].

3.3. Data Engineering for Wastewater: Quality, Context, and Interoperability

Another common failure mode of AI pilots in WWTPs is that there is too much data, which cannot be reliably used. The time-series data should be synchronized among sensors with various rates of sampling, time stamps, which can drift, and intermittent gaps. The contextual data, which may include maintenance events, calibration actions, chemical deliveries, weather condition changes, and operational mode changes, are usually stored in different systems or in unstructured logs. In the absence of such a context, sensor faults may be mistaken in models as process events, or they may be learned as spurious correlations that fail to be generalized. Therefore, the strategic route towards AI preparedness is a robust data engineering layer that considers plant signals as managed assets [37,44].

Drift and fouling should be dealt with specifically through data quality management in wastewater. The schedules of calibration and the results of the calibration process of key probes need to be digitized and attached to time-series tags to allow automated detection of sensor unreliable intervals. First-line screening could be given by signal validation techniques like range checking, rate of change checking, redundancy checking between correlated variables, and physics-based consistency rules. Notably, these checks can delete data, and such a check is informative enough, but the absence of data may be as well as information; these checks need to produce quality flags and uncertainty estimates, which may be ingested by downstream models. Considering the example, an ammonia probe having known drift should play a role in the state estimation with a lowered weight as opposed to being considered as ground truth [45]. The data pipeline architecture, as depicted in **Figure 3**, ensures robust data governance and continuous flow from IoT sensors through edge preprocessing to cloud-based AI services, ensuring smooth operations in smart WWTPs. The computerized system of monitoring and control of a smart wastewater treatment facility (WWTP). The system combines sensing, data communication, edge computing, and advanced analytics to assist in automated plant operation and decision-making. At the base, the Field Sensing layer (Zone 0-IoT) consists of field sensors and control systems that measure the following important operational and water-quality parameters: level, flow, DO, pH, ORP, ammonia, and turbidity. These sensors constantly monitor the real-time information of the treatment processes and produce operational events and alarms.

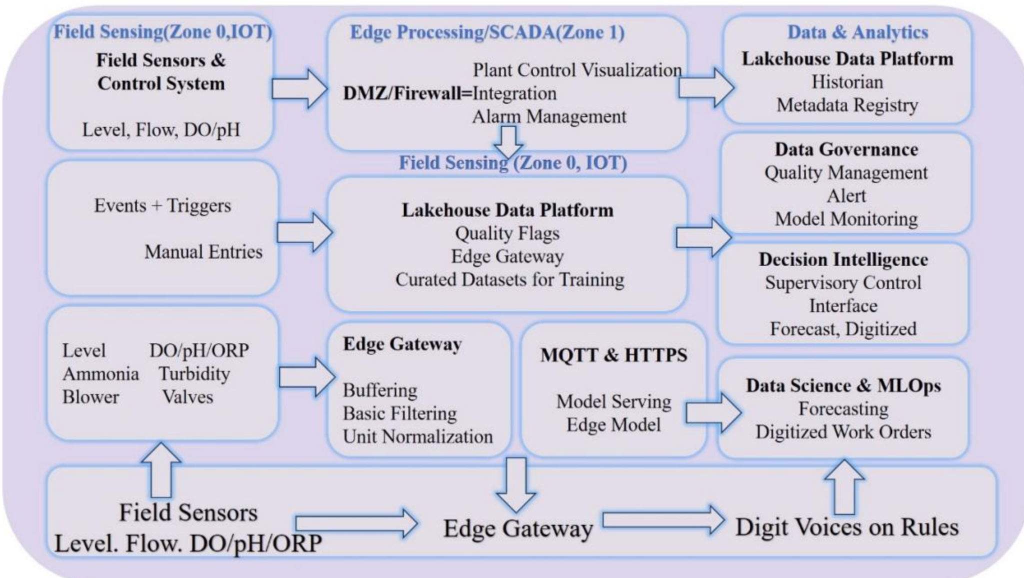

Figure 3. Edge–cloud data pipeline and governance for WWTP IoT.

The data that is collected is sent to the Edge Processing/SCADA layer (Zone 1). The SCADA (Supervisory Control and Data Acquisition) systems enable operators to monitor the activity of plants, visualize the control processes, and manage alarms. The industrial control network is secured by a DMZ (Demilitarized Zone) and firewall, and can be easily integrated with external systems. The sensor data is processed by an Edge Gateway and then forwarded to superior platforms. This gateway does buffer, filtering, and unit normalization. The secure protocols are applied in data communication between the devices and servers and include: MQTT (Message Queuing Telemetry Transport) and HTTPS (Hypertext Transfer Protocol Secure). Edge computing has another application of executing AI models locally to provide quick reaction and initial decision-making.

The processed data are stored in a Lakehouse Data Platform, which is a blend of data lakes and data warehouses. This platform contains a historian to store the data about operations over long periods of time and a metadata registry to manage datasets involved in analytics and model training. Several functions are enacted at the Data and Analytics layer. Data governance promotes data quality, monitoring, and alert management. Decision intelligence tools offer operational recommendations, supervisory control interfaces, and forecasting. Furthermore, Data Science and MLOps can be used to develop, deploy, and monitor predictive models that help to optimize processes and provide automated decision support [46].

The other key issue is interoperability. Traditionally, WWTP belongs to proprietary historian formats, and new IoT uses open interfaces and message middleware. To align these worlds, it is necessary to follow standard naming conventions of tags, units, and metadata registries to describe sensor location, principle of measure, calibration history, and relations on unit processes. Even well-trained machine learning models are vulnerable to changes in the metadata of a plant as it grows, as sensors change, and tags are renamed. The fully developed data platform thus contains a canonical data model, automatic Extract–Transform–Load (ETL) workflows (not only SCADA but also outside), and versionable data models in which models can be modified without disrupting integrations [47,48].

Another issue is that the wastewater business is event-based by nature. Storms, industrial releases, maintenance failures, and season changes alter the working regime in a manner that ought to be clearly documented. Manually or automatically annotated events assist in converting raw time series into human-interpretable episodes that can be used to develop and evaluate models. More and more robotics and other sensing can be used to add visual checks, automated sampling logs, and local measurements that confirm or refute fixed sensor measurements. When this information is incorporated into the information platform, it allows enhanced learning and less dependence on sparse lab measurements [20,49].

3.4. Soft Sensing and Sensor Fusion as a Bridge to Full Observability

This is because although there are larger deployments of the IoT, it is both economical and technically impractical to directly measure every significant state of the process. Virtual sensors are sometimes referred to as soft sensors, which are used to fill this gap by estimating the unmeasured variables based on the available signals, using mechanistic relationships, statistical models, or a combination of the two. Soft sensing can be particularly useful in wastewater when analyzing such quantities as fractionation of influent, biological activity indicators, settling propensity proxies, and internal nutrient states that are not monitored continuously. With good designs, soft sensors can promote greater observability and provide control strategies operating on closer proxies to compliance results [50].

The best application of soft sensing is sensor fusion [51]. Various sensors offer complementary data with distinct failure modes; e.g., optical sensors can react fast as well as be vulnerable to contamination, whereas laboratory data are infrequent but more precise. Fusion strategies would be able to use a high-frequency online probe with periodic laboratory data to correct drift and include a hydraulic and operational context to ensure consistency. A realistic architecture. In a realistic architecture, soft sensors and fusion must generate not just point estimates, but also uncertainty bounds and quality indicators, since the decisions made by supervisory control in compliance-sensitive environments must be risk-conscious. This uncertainty-conscious design can also be used to enable human operators to interpret the recommendations: when the recommendations are given as a setpoint adjustment under high confidence conditions, this can be automated, and when the recommendation is given as a recommendation under low conditions, this can be sent to the operator.

Mobile sampling platforms can be deployed in situations where there is an increase in model uncertainty, when there are sensor inconsistencies, or when there are drift-detecting algorithms. In this respect, robots may act as active sensing agents, which seal information gaps, give specific measurements, which recalibrate soft sensors, and build confidence in automated control. This incorporation makes sensing an adaptive system and not a fixed network of probes [52,53].

3.5. Cybersecurity and Safety Boundaries for IoT-Enabled Wastewater Automation

WWTPs are also essential components, and increasing connectivity increases the attack space [54]. The move toward open industrial networks, coupled with the exchange of data between plant locations, municipal networks, and cloud services, presents qualitatively new risks that are not mitigated by the conventional SCADA security practices. One of the main principles of secure architectures is to have a solid separation between the control network and the enterprise/external network, with segmented areas, firewalls, and controlled gateways. The common options in the early stages of read-only replication between the control systems and the analytics platforms are favorable as they minimize the possibility of process control being affected by other external systems.

In this respect, the security engineer should take into account integrity and availability, rather than confidentiality [55]. In case information pipelines are broken, AI services can give outdated or wrong suggestions, and when control channels are obstructed, safety and conformity could be put right in the line of danger. Consequently, secure WWTP IoT architectures are simplified by focusing on authentication, the least-privilege access controls, and robust credential management, as well as the continuous examination of abnormal network behavior. There is also the aspect of managing the devices: the IoT sensors and gateways should be patchable, managed in inventory, with secure default settings, since unpatched edge devices can turn into long-term footholds by attackers.

The intersection of operational safety requirements and cybersecurity is in the fail-safe design [56]. Supervisory control by AI must gracefully degrade in cases where the inputs are not reliable, communications fail, or where model outputs are out of bounds. These demands defined fallback schemes, e.g., going back to conservative setpoints, retaining existing PID behavior, or going to operator-validated recommendations. The incident response and regulatory defensibility require logging and audit trails; the utilities should be capable of reconstructing what data the model received, what version of the model was in effect, the output produced, and how it was applied. The practices would help to align cybersecurity with the overall governance objectives and facilitate building trust in automated systems.

Finally, an effective IoT infrastructure in wastewater can be implemented when the infrastructure is set up as a functioning system, but not as an IT add-on [57]. Strong sensing needs to be maintainable, strong location needs to be a well-designed architecture respectful of deterministic control and intermittent networks, data platforms need to be governed by considering context and quality as first-class problems, and cybersecurity needs to be segmented and resilient to behave as required in compliance-critical operations. When such foundations exist, AI approaches can be implemented in a manner that does not impact their reliability, but efficiency, and robotics can be implemented as sensing extents and operational aids. Section 4, which is based on the previous infrastructure, discusses the possibility of AI techniques being recalibrated to the context of wastewater and non-stationary behavior, imprecise measurement, and the need to maintain both safety and compliance.

4. AI for Monitoring, Prediction, and Decision Intelligence

The value of AI in wastewater treatment is derived by processing heterogeneous data of the plants into consistent situational awareness and decisions, which can be put into practice within operational constraints [44]. The greatest difference within this field is between models that are accurate when analyzed retrospectively and models that are also reliable when used in the real plant, where influences of variability of the influent, sensor drift, equipment limitations, and human interactions continually recreate the data-generating process. Consequently, AI in WWTPs may be regarded more as a lifecycle discipline than a single algorithmic selection, which consists of problem formulation, model development, uncertainty management, deployment architecture, and governance. It discusses the main AI paradigms applied in wastewater treatment, focusing on monitoring and diagnostics, forecasting and prediction, optimization and control intelligence, and the mechanisms, namely uncertainty quantification, explainability, and MLOps, that enable these systems to be used in operations where compliance is an essential factor.

4.1. Modeling Paradigms: Mechanistic, Data-Driven, and Hybrid Approaches

Wastewater has a long tradition of mechanistic modeling, particularly for activated sludge systems, where kinetic and mass-balance frameworks provide structured representations of carbon, nitrogen, and phosphorus transformations [58]. Mechanistic models are valuable because they encode conservation laws, reflect known process couplings, and support extrapolation beyond observed data. However, they can be difficult to calibrate at full scale and may struggle to represent site-specific phenomena such as variable influent fractionation, microbial community shifts, and hydraulically complex basins. Data-driven models, by contrast, can learn complex nonlinear mappings from historical plant data, often with lower development friction once data pipelines are in place, but they can be brittle under regime change and may be difficult to validate for safety-critical use if their behavior is opaque. **Table 2** shows AI functions/capabilities most commonly employed in WWTPs and maps them to the necessary methods, input types, and deployment requirements[9].

Table 2. Core AI tasks in WWTPs: Typical methods, inputs/labels, and operational deployment notes.

AI Functions/Capabilities	Typical Methods	Typical Inputs	Labels/Targets	Key Deployment Considerations
Anomaly detection & monitoring	Multivariate Statistical Process Control (SPC), autoencoders, isolation methods, change-point detection	DO/pH/ORP, flows, pumps/blowers, quality flags	Often unlabeled; "normal" periods	Drift-aware thresholds, low false positives, operator interpretability
Soft sensing (state estimation)	Hybrid models, regression/ensembles, Bayesian filters	Online sensors + lab data + operational states	Unmeasured states (e.g., nutrient fractions, activity proxies)	Calibration linking, uncertainty bounds, periodic ground-truth validation
Forecasting (short–medium horizon)	AutoRegressive Integrated Moving Average (ARIMA)/Gradient Boosting Machines (GBMs), Recurrent Neural Network (RNN)/transformers, hybrid with mechanistic priors	Time series + weather + events	Load/effluent risk/energy	Regime shifts, lags, missingness, alignment of labels with process delays
Predictive maintenance	Survival models, anomaly + diagnostics, feature learning from vibration/current	Vibration, current, temperature, runtime, inspections	Failure events, maintenance logs	Sparse labels, class imbalance, cost-sensitive evaluation, workflow integration
Supervisory optimization	MPC, hybrid MPC+ Machine Learning (ML), Bayesian optimization	Forecasts + constraints + energy prices	Cost vs. compliance objectives	Hard constraints, safety fallbacks, conservative action bounds, audit trails
RL-based policy learning (emerging)	Offline RL, constrained RL, safe exploration variants	Simulators/digital twins + operational data	Long-horizon reward	Validation difficulty, safety filters, "shadow mode" testing, governance needs
Multimodal fusion	Late/early fusion, transformers, probabilistic fusion	Sensors + vision/thermal/robot data	Regime class, fault cause, risk	Synchronization, bandwidth/edge preprocessing, explainability

Hybrid modeling tries to model the benefits of the two paradigms by incorporating physics and process structure in machine learning or through mechanistic models as the prior and ML as the correction layers[59]. Hybridization in wastewater may occur in a number of ways. Gray-box models can maintain mechanistic state equations and learn uncertain parameters or unmodeled dynamics from data. Physics-informed learning may tend to lock predictions to obey the laws of mass balance or to obey monotonic known tendencies. Digital twins can combine mechanistic simulators with data assimilation and ML-based devices to generate a living model that is continuously updated with plant measurements. Practically, hybrid strategies are appealing to operational implementation since they offer a compromise between engineering interpretability and data-driven flexibility, especially when extrapolation and constraint satisfaction are required.

4.2. Monitoring and Diagnostics: Anomaly Detection, Fault Isolation, and Drift Awareness

The most commonly deployable application of AI in WWTPs is usually monitoring, since it may deliver operational value without necessarily modifying setpoints[46]. Timing series anomaly detection techniques may be used to detect variations in the normal operation of the dissolved oxygen dynamics, oxygen uptake patterns, ammonia trends, pump curves, or blower efficiency indicators. The idea is not to increase the number of operational alarms, and we want to better monitor the conditions to enable malfunctioning conditions to be detected earlier, minimize alarm fatigue, and provide an actionable diagnosis for operators. False-positive rates are high in complex treatment plants, and soon discourages the operators. Thus, effective monitoring systems are designed to be resistant to reliability, stability, and interpretability rather than achieving marginal gains in the sensitivity of detection.

Diagnostic intelligence goes further in the use of anomaly detection for fault isolation and root cause assumptions [46,60]. An example is that variations in drivers can cause similar effluent ammonia excursion due to sudden changes in loads, nitrifier inhibition, aeration constraints, or sensor malfunction. The distinction between them needs multivariate correlation models, time-lags, and the topology of processes. Multivariate statistical process control, probabilistic graphical models, and learned embeddings of the operational states are techniques that may be used to differentiate between process faults and instrumentation problems. Notably, sensors and model drift should be expressly identified in WWTP monitoring. Drift detection is a first-class event and process with signal distributions that are responded to with recalibration, sensor cleaning, or retraining the model instead of being shown as gradual degradation. An empirical aspect of the wastewater diagnostics is that the operators have valuable domain knowledge, which might not be completely represented in the data [61]. Artificial intelligence systems capable of assisting the human mind, such as exposing contributing variables, similar past events, and levels of confidence, were more likely to be embraced than those that merely assigned names to things. In this context, AI surveillance is best provided in terms of improvement to operational expertise and, therefore, prompt triage and more consistent reaction.

4.3. Prediction and Forecasting: From Influent Dynamics to Effluent Risk

Forecasting in wastewater cuts across a number of timescales and target variables. Minute-to-hour-scale projections may be used to aid the management of aeration zones, chemical dosing, and early warnings of effluent spillages. Sludge wasting decisions, solids line load management, and energy scheduling can be informed by medium-horizon forecasts, which range over hours to days. Maintenance planning and capacity management can be described in terms of longer-horizon predictions (at weekly, seasonal levels). The main technical problem of all these horizons is that wastewater is stimulated by external forces, such as weather, industrial releases, and human activities, and has feedback processes, such as control measures and biological adaptation [62].

The value of influent forecasting lies primarily in its ability to support anticipatory control of treatment processes [63]. Flow and pollutant model predictive models, which forecast wet-weather flow and pollutant loads using past trends and weather forecasts, can be used to prepare plants to react to wet weather, proactively adjust aeration capacity, and load clarifiers. This concept is expanded by effluent quality prediction and compliance risk forecasting, which estimate the likelihood of limits exceedance given the existing and estimated conditions. This changes the frame of operation where corrective measures are reactive to corrective actions, which are more risk-conscious and cost-balanced in terms of the likelihood of violations.

Other prediction tasks also apply to the health of an asset and the degradation of processes. The loss of permeability and fouling curves in membrane systems can be predicted, resulting in cleaning schedules that are optimized and require less chemical use [64]. In the case of mechanical equipment, predictions of failures due to either vibration or electrical signature can help avoid unexpected downtimes and destabilize treatment. Gradual adjustments in loads can be made within anaerobic digestion without the need to make disruptive interventions because the instability or lower biogas yield can be predicted early. In these examples, the focus is on operationally actionable horizons: it is the forecast that is useful when it comes in time enough to allow a response to take action under the actuator and staffing constraints.

4.4. Optimization and Control Intelligence: From Advisory Systems to Supervisory Automation

The most effective efficiency benefits of AI are usually achieved when prediction and state estimation are associated with optimization and control. This is not a case where opaque AI controllers can be appropriately used in place of PLC logic in wastewater. Rather, deployable systems tend to have a hierarchical configuration because AI is used to give supervisory intelligence setpoints, schedules, or operating envelopes, whereas lower-level loops are controlled by tested PID or PLC control to maintain safety and determinism. Such architecture is consistent with the engineering practice and regulation expectations due to its ability to ensure clear accountability and its capacity to enter into a conservative fallback state [65,66].

Supervisory optimization can be formulated using model predictive control since it explicitly models the constraints, actuator constraints, and the interactions between the variables [63]. MPC has the capability of optimizing aeration distribution between areas, internal recycles, and coordinating the dosing of chemicals in the projected load conditions. But MPC performance is pegged on model fidelity. Reinforcement learning has also been given attention, as interaction-based learning can learn control policies and may find strategies that perform better than hand-developed heuristics. But RL leads to safety and validation issues in processes of compliance importance since exploration and unconditional actions are not allowed. Consequently, RL applications in practice in wastewater are more likely to concentrate on offline learning, limited action space, and supervisory activities in which RL is suggested by a setpoint within hard constraints and controlled by safety filters or human verification [67].

Plant-wide optimization adds another dimension of complexity since the decisions are interrelated in the unit processes and objectives [68]. As an example, the effects of saving energy by aeration may cause effluent ammonia risk, modify the sludge settleability, modify the solids wasting, modify biological performance, and modify solids holding capacity. Such tradeoffs can be implemented in the form of multi-objective optimization models, allowing operators to choose operating points that are consistent with current areas of concern, e.g., highest energy prices, storm preparedness, or increased compliance testing. What is needed is that optimization results should be interpretable and implementable, so that they generate recommendations that can be applied by the operators and understood.

4.5. Uncertainty Quantification and Explainability for Trustworthy Decisions

The wastewater modeling is bound to have uncertainty due to the noisy measurements, unobservable key variables, and changing operating conditions [69]. Confidence limits or probability-of-exceedance estimations ought to be used to make decisions in compliance-critical settings in which point prediction is often insufficient. Risk-based control can be assisted by uncertainty-sensitive AI, in which decisions are made to reduce the expected cost taking subject to an acceptable probability of violation. It can also help with operation triage by separating the high-confidence excursions that should be addressed right away from the low-confidence indicators that could be caused by sensor faults or some temporary noise.

Explainability also goes hand-in-hand with uncertainty since uncertainty is reduced when operators can understand not only why a model recommends a course of action but also the confidence of the action. The explainability in wastewater is not just a preference, but it may be required to be defensible against regulations and to be integrated safely with human control. The mechanisms of explanation can relate recommendations to the familiar process drivers, including the changes in the influent loads or the drop in oxygen transfer, and the changes in recycle flows. Adoption, even on complex models, may be supported by explanation layers that display the contribution of the variables, regime classification, and other similar historical cases. The most expedient strategy is not usually to make all the model components fully interpretable, but to make the decision-relevant transparency: what went into the recommendation, what the constraints taken into account were, what the tradeoffs are, and what the model is likely to do with it in case the recommendation is acted upon [70].

4.6. MLOps for WWTPs: Deployment, Monitoring, and Governance in Operations

The operational reality of AI in WWTPs is that models will degrade unless they are managed as evolving assets. MLOps provides the discipline to deploy, monitor, and maintain models with the same rigor applied to physical equipment. In wastewater, model lifecycle management begins with data versioning and provenance. Training datasets must be traceable to specific tag sets, calibration periods, and operating modes. Models must be versioned with documentation of hyperparameters, feature definitions, and validation results, and they should be packaged in a way that supports reproducible deployment at the edge or within plant networks [31].

Figure 4 outlines the AI lifecycle in compliance-critical wastewater treatment, highlighting the steps from training to deployment, monitoring, and continuous model updates through MLOps.

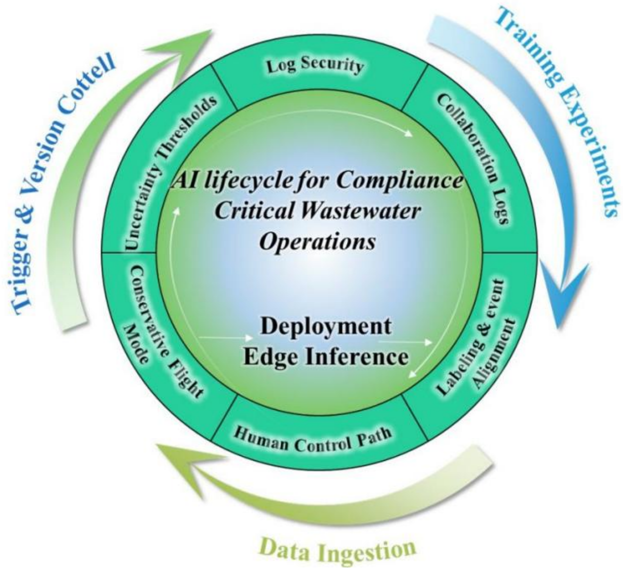

Figure 4. AI lifecycle for compliance-critical operations (MLOps + risk-aware decisioning).

Constant monitoring is needed after the deployment. Instead of statistical accuracy, performance tracking should also be concerned with operational performance measures, including compliance results, energy consumption, and alarm reduction, and with model-health measures, including input drift, input missing rates, and input sensor-quality flags. Retraining triggers must be spelled out, such as when there is a change in influent distributions with the season, when there is a significant retrofit of equipment affecting the system dynamics, or when there is a change in signal characteristics with the replacement of sensors. More importantly, retraining must not be automatic, such that it invalidates validation in compliance-critical settings. Updated models would generally have to undergo stages of evaluation, shadow mode testing, and documented approval before they can affect operations [71,72].

The final dimension of MLOps is governance and auditability [72]. The utilities should have clear accountability for the way models are being used, who can alter them, and how failures of dealt with. Logging must capture the data the model fed on, the data it generated, and even whether recommendations have been acted on. These audit trails are useful in incident response, post-event learning, and regulatory review. They also facilitate a more gradual process of transitioning advisory analytics to supervised automation, where trust is established via apparent performance history as opposed to algorithmic excellence as promised.

In short, the application of AI in wastewater treatment can be most successful when it is integrated into a powerful working framework [13]. Mechanistic, data-based, and hybrid models are all useful; however, deployments with the greatest impact are those that are aimed at monitoring that minimizes uncertainty, prediction that helps anticipatory management, and supervisory optimization that observes constraints and safety limits. The enabling mechanisms are not features that can be added onto the AI; they are the circumstances in which AI can be trusted, in compliance-based, sensor-imperfect, and disturbance-prone settings. Section 5 goes further with the discussion into robotics and physical automation by demonstrating how mobile platforms and automated interventions can enhance sensing, safety, and transform AI-generated insights into long-term operational effectiveness.

5. Robotics and Physical Automation across the Plant

Robotics adds a physical implementation interface that complements the digital sensing and AI-based decision intelligence [73]. Although IoT networks and analytics can enhance awareness and prescribe actions, a large number of wastewater inefficiencies and safety hazards still exist due to the fact that observation and intervention are still labor-intensive, intermittent, or limited to hazardous conditions. The wastewater facilities are in confined spaces, wet and corrosive surfaces, mobile machinery, and an atmosphere that may hold toxic or explosive gases, and, therefore, manual inspection and sampling are inherently hazardous. In addition to this, important operational states to assess performance, like localized fouling, blockage formation, scum accumulation, or early mechanical degradation, may occur in places that are hard to reach or are very poorly visited to allow early diagnosis. These limitations can be addressed with robotics and fixed automation, where continuous or on-demand presence is possible, repeatable data gathering can be supported, and routine activities can be performed more safely and dependably. In this section, the key types of robotic and physical automation in wastewater treatment, the fundamental technical challenges of perception and navigation within the plant environments, and how robotics can be combined with the IoT and AI to provide a lasting efficiency improvement will be reviewed.

5.1. Roles and Task Taxonomy: Inspection, Sampling, Cleaning, Maintenance Assistance, and Safety Scouting

Robotic value in WWTPs clusters around tasks that are operationally important but costly, dangerous, or difficult to execute consistently [53,74]. Inspection is a primary category because many critical assets are distributed and exhibit gradual degradation that is hard to notice until it becomes acute. Robotic inspection can include visual surveys of tanks, channels, and galleries; thermal scans of electrical panels; and structural checks of covers, handrails, and accessible piping. In the collection system and plant influent works, inspection extends to pipelines, manholes, and wet wells, where early detection of sediment accumulation, root intrusion, or incipient blockages can prevent overflows and reduce shock loading into the plant.

Sampling and measurement work is also at the center stage. The wastewater operations are based on lab tests in providing regulatory reporting and control, process control, but manual sampling is subject to delays and is irregular in time and location. Temporal regularity can be enhanced by using robotics sampling systems that are either fixed automated samplers or mobile platforms to avoid exposure to hazardous points. Robotic sampling can be activated on demand, with attention paid to the time and places where more evidence is most likely to be obtained to clarify multiple signals or after a certain signal is suspected to drift, when combined with online sensors and uncertainty totals that are optimized by AI [75].

The third category is cleaning and mitigation activities. Screens, channels, and sensors can become dirty, and membranes and surfaces can be covered with biofilm or debris. Although full mechanical cleaning can be carried out by special-purpose equipment, robots may assist in localized or regular cleaning, such as clearing of debris in hard-to-reach places, cleaning of sensor housings, or inspection-driven cleaning of surfaces. Aspects of maintenance assistance, including checking the position of valves, gauges in the legacy areas, or the transportation of tools and parts, can be used to decrease labor costs and enhance consistency. Last, the scouting of safety is another category that has high value in case the benefit of efficiency is indirect. The robot can be used to survey the area to check the levels of gas, visibility, and obstruction in the restricted area before people go there, thus making it more secure to plan and minimizing chances of accidents [76,77].

5.2. Platform Classes and Deployment Patterns in Wastewater Environments

Robotic platforms for wastewater treatment can be organized by their mobility domain and degree of ruggedization [53]. Ground robots are well suited for plant corridors, galleries, and outdoor pathways, particularly for routine patrols, asset inspection, and transport of sensing payloads. Their practical deployment depends on stable navigation pathways, tolerance for wet and uneven surfaces, and reliable docking for charging and data transfer. In facilities with complex layouts, ground robots often operate in semi-structured zones where maps can be created and maintained, and where navigation constraints such as restricted access or safety barriers are well defined.

Aerial drones provide rapid inspection capability for large plants and hard-to-reach structures such as roofs, stacks, clarifier bridges, and remote basins. Drones are particularly effective when the primary sensing payload is visual or thermal and when inspection frequency is limited by human availability. However, indoor drone operation and flight over active process units can be constrained by safety policies, airflow, Global Positioning System (GPS) denial, and electromagnetic interference. As a result, drones are frequently deployed as episodic inspection tools rather than continuous monitoring agents, unless plants invest in dedicated indoor navigation infrastructure[52].

Underwater and pipe-crawling robots expand access to submerged or enclosed environments[78]. In clarifiers, tanks, and channels, underwater robots can inspect surfaces and identify localized deposition or mechanical issues without draining assets. In sewer pipes and force mains, crawlers and tethered vehicles can inspect for defects and obstructions, supporting preventive maintenance. These platforms face strong constraints from turbidity, low visibility, flow currents, and complex geometry, which often require specialized sensing such as sonar and robust tether management. For many utilities, the most practical entry point is inspection-as-a-service, where robotic platforms are deployed periodically by specialized teams, though plant-owned systems are increasingly feasible where inspection needs are frequent and predictable.

Robotic manipulators and fixed automation also play a role, particularly where tasks are repetitive and the work envelope is well defined. Examples include automated sampling cabinets, robotic arms for sample handling in laboratories, or dedicated cleaning mechanisms for screens and sensor stations. Fixed automation benefits from high reliability and simpler safety certification compared to mobile robots, but it lacks the spatial flexibility needed for distributed assets. In practice, WWTP modernization often combines fixed automation for high-frequency tasks with mobile platforms for periodic or event-driven operations[14,79]. **Table 3** presents an overview of different robotic platforms, their specific tasks, sensing payloads, and the key challenges they face in WWTP environments.

Table 3. Robotics in wastewater treatment: Platform classes, tasks, sensing payloads, and constraints.

Platform Class	Primary Tasks	Typical Sensing Payloads	Typical Environment	Key Constraints/Risks
Unmanned Ground Vehicle (UGV, ground robot)	Patrol inspection, leak detection, meter reading, escorting sampling	RGB (Red, Green, Blue)/thermal, gas sensors, acoustic, Light Detection And Ranging (LiDAR)	Galleries, outdoor paths, equipment rooms	Wet floors, stairs/ramps, docking/charging, safety zoning
Unmanned Aerial Vehicle (UAV, drone)	Rapid visual/thermal inspection of structures and basins	RGB/thermal, sometimes LiDAR	Outdoor/large assets; limited indoor use	Flight safety policies, GPS denial indoors, spray/mist, restricted zones
Remotely Operated Vehicle (ROV, underwater robot)	Submerged inspection of tanks/clarifiers, intake/outfall surveys	Sonar, cameras, inertial	Turbid water, submerged assets	Visibility, currents, tether management, corrosion resistance
Pipe crawler	Sewer/force main inspection, blockage identification	Cameras, sonar, odometry	Confined pipes with flow/debris	Navigation in flow, debris entanglement, retrieval, access constraints
Fixed automation/manipulators	Automated sampling, simple cleaning, lab handling	Flow/valve control, cameras, basic sensors	Controlled cabinets/lab spaces	Limited flexibility, integration with safety interlocks

5.3. Perception and Navigation in Harsh, Dynamic, and Partially Structured Settings

Robotic perception in wastewater facilities must contend with conditions that degrade common sensing modalities[52]. Visual systems face low light, glare, mist, and occlusion from spray and foam, while surfaces can be reflective or coated with biofilm. Corrosive aerosols and humidity challenge sensor housings and connectors, and rapid temperature changes can cause lens fogging. LiDAR can be effective for mapping and obstacle detection, but may suffer in high-humidity environments and in areas with reflective water surfaces. Acoustic and ultrasonic sensing can complement vision in foggy or dark conditions, and thermal imaging can provide robust signatures for certain inspections, but each modality introduces its own maintenance and calibration requirements.

Navigation is also not an easy task since WWTPs are not highly organized settings. Routes might be altered because of temporary obstructions, hoses, building repairs, or flooding, and indoor GPS might not be reliable and might not be available at all in very large buildings. This drives localization strategies that are resilient to the changing environment, which may amalgamate odometry, inertial measurements, fiducials where possible, and map-based localization. In underwater and pipe robots, localization may be much more difficult because of a lack of external references, heavy turbidity, and drift caused by the flow, and so tethered operation or restricted path navigation is often used in initial applications[80].

Ruggedization and maintainability are also increased by the harsh environment. Robots have to be resistant to wash down, chemicals, and mechanical forces, as well as be easy to clean and service. The issue of battery life and charging should be addressed; continuous monitoring can be practical only in the case of the reliability of docking and charging operations, and the necessity not to spend a lot of time on them. These design aspects affect autonomy decisions: at most plants, the most valuable deployments can be shared autonomy or teleoperation with human operators overseeing the mission operation, with the robot performing low-level navigation and sensing[81,82].

5.4. Robots as Mobile Sensing Nodes and the Integration with IoT and AI

The most revolutionary aspect of robotics in wastewater treatment is that it can also be used as a mobile counterpart to the sensing layer, especially with AI that can be used to specify the places and times of measurements. Fixed sensors give constant data at points of interest, and many of the issues are localized spatially. Fouling may initiate at certain ends of a basin, corrosion may occur on definite sections of a pipe, and obstructions may be formed in hotspots of a collection system. Mobile robots may bring sensors to such locations, forming a more detailed spatial image of the condition of plants and allowing a kind of active sensing, controlled by analytics, not a predetermined inspection schedule[10].

This integration will rely on ordinary data interfaces and time synchronization. Video, thermal images, sonar scans, and gas measurements are examples of robotic data streams that are usually high bandwidth and which may need edge preprocessing to extract valuable information before storage. These capabilities may be added to AI models to detect anomalies and diagnose them when included in the plant data platform. As a case in point, process time series can be combined with visual alerts to foam, scum, or abnormal surface turbulence to enhance the identification of filamentous bulking or aeration distribution issues. On the same note, inspection imagery is able to reinforce asset condition models involving the linking of mechanical degradation to process performance impacts[46].

Soft sensing and uncertainty management may also be empowered by robotics[83]. In cases where model results are uncertain, e.g., due to sensor drift or signal loss, a robot may be sent to obtain a confirmatory measurement or sample, and this may essentially be considered a feedback system that ensures data integrity within the ecosystem. It is particularly useful in wastewater, where the cost of errors of choice may be very great and where the real state may be perceived only in part. Under this architecture, robots will not be considered as convenient tools; rather, they will become a component of the control-relevant measurement system, which will enable more robust automation.

5.5. Human–Robot Collaboration, Safety, and Operationalization

The application of robotics in WWTPs should be closely synchronized with the operations and safety measures to achieve success. Plants have developed lockout/tag out, confined space, chemical, and hazard communication procedures. Robots need to be implemented in a manner that does not violate such rules and makes responsibility clear. Robots in most environments will be supervised autonomy, meaning that mission plans are created by operators, robots work within constrained environments, and exemptions are escalated. Teleoperation is a powerful feature, not only as its major implementation in complex environments, but also as a backup to autonomy when things go wrong. The design principle is graceful degradation: robots are to fail safe, keep communication with the operators, and not to cause any new risk, like blocking the paths, operating equipment, or entering the restricted area[84].

Reliability and maintainability are also required with regard to operationalization. A robot with high-rate special services may turn into a liability instead of an advantage, particularly where the technical staff is few in utilities. As a result, tasks that are highly repeatable and whose value is obvious in the deployment strategies are commonly given more attention, including scheduled inspections, routine gas reconnoitering, or specific sampling[53]. This would be focused on training and change management; operators should have clearly understandable interfaces, clarity in the result of the mission, and a feeling that robots can enhance their work and not complicate it. In this case, robotics can minimize the risk of being exposed to hazards, enhance inspection rates, and present novel streams of data that can be optimized with AI.

Altogether, robotics and physical automation bring digital infrastructure and AI closer to the physical plant through the ability to offer continued and flexible access [9]. They overcome a major weakness of most of the so-called smart programs: the fact that data and advice are not sufficient to ensure a prompt response in severe and spread-out settings. Robotics can bridge the gap between sense and act by providing safer inspection, more consistent sampling, focused cleaning, and more awareness of assets. This background is extended in the next section 6 by synthesizing the integrated applications and how IoT, AI, and robotics can be utilized concurrently on major operational processes within the WWTP units. The discussion takes into consideration the existing evidence on the increases in process efficiency, but synthesis is a subjective outcome (expert) based on the literature review; no formal comparative or quantitative evaluation is made.

6. Integrated Applications and Evidence of Efficiency Gains

The practical promise of AI, IoT, and robotics in wastewater treatment is realized when these components are integrated into workflows that change how plants are monitored, controlled, and maintained [44]. Integration matters because wastewater performance is shaped by coupled dynamics across unit processes and by real-world constraints such as sensor reliability, actuator saturation, staffing limits, and the need for conservative operation under compliance risk. Consequently, the most credible evidence of "process efficiency" improvements comes from applications where sensing strategies, analytic models, and operational actions are linked end-to-end and assessed using metrics that reflect plant outcomes rather than algorithmic accuracy alone. This section synthesizes integrated application areas where automation has shown the strongest potential to improve energy use, chemical consumption, reliability, and labor efficiency, while emphasizing evaluation considerations and the conditions under which reported gains are most transferable. As summarized in **Table 4**, integrated applications using AI, IoT, and robotics in WWTPs require careful definition of efficiency metrics and evidence collection to validate reported gains [9,85,86].

6.1. Aeration and Nutrient Removal Optimization as a Plant-Wide Energy Lever

Aeration can be the prevailing power of a biological treatment, and it is at the center of nitrogen removal performance [87]. The automated pattern of this area usually starts with an extended sensing, such as stronger dissolved oxygen readings and, more extensively, online ammonia and nitrate indicators which offer direct feedback of the nitrification and denitrification margins. IoT infrastructure helps gather such signals at a high rate, match them with student data on calibration, and synchronize them and data with business procedures, including intermittent aeration or step-feed processes. AI then makes its contribution in two but complementary ways. The conditions that lead to ammonia breakthroughs before they happen are monitored by the models, which include inefficient oxygen transfer, abnormal oxygen uptake, or changes in influent load. Predictive models predict ammonia risk and oxygen demand in the near future so that setpoint adjustments can be predicted instead of applied in a reactive way once the quality of effluents starts to deteriorate.

Table 4. Integrated Applications of AI, IoT, and Robotics in Wastewater Treatment Plants: Roles, Efficiency Metrics, and SCI-Style Evidence Expectations.

Application Area	Sensing Backbone (IoT)	AI Role	Robotics/Physical Automation Role	Efficiency Metrics to Report	Evidence Expectations (Science Citation Index (SCI)-Style)
Influent, coarse treatment & primary sedimentation	Flow, level, turbidity, TSS, screen status, grit chamber status, sludge blanket level	Load/event detection, influent classification, primary settling optimization	Screen cleaning, inspection robots, and automated sludge removal support	Overflow events, solids capture, sludge withdrawal stability, downtime	Include wet-weather and shock-load periods; compare with conventional operation
Aeration & nitrogen removal	DO, NH_4^+, NO_3^-, airflow, pressure, energy	Forecasting, supervisory optimization, anomaly detection	Diffuser inspection, mobile checks	kWh/m^3, Total Nitrogen (TN)/NH_4^+ compliance, aeration stability	Multi-season validation, disturbance coverage, constraint handling
Chemical dosing (P, alkalinity, coagulation, disinfection)	PO_4^{3-}, pH, Ultraviolet Transmittance (UVT), turbidity, flow, dosing, telemetry	Demand prediction, risk-aware dosing, optimization	Automated sampling, verification support	Chemical use, effluent P, residual control, UV dose compliance	Baseline clarity, lab confirmation, uncertainty reporting

Table 4. *Cont.*

Application Area	Sensing Backbone (IoT)	AI Role	Robotics/Physical Automation Role	Efficiency Metrics to Report	Evidence Expectations (Science Citation Index (SCI)-Style)
Secondary clarification & recycle flows	Blanket level, Mixed Liquor Suspended Solids (MLSS), Return Activated Sludge (RAS)/Waste Activated Sludge (WAS) flow, turbidity, nitrate	Clarifier risk prediction, recycle optimization	Inspection support, sludge interface verification	Clarifier stability, solids loss, recycle efficiency	Report under variable flow/load conditions
Tertiary treatment/polishing	Filter headloss, turbidity, UVT, flow, pressure	Filter run optimization, fouling prediction, and backwash scheduling	Inspection and sampling support	Filter uptime, backwash frequency, and final effluent quality	Include comparison with a rule-based operation
UV disinfection	UVT, lamp intensity, flow, dose telemetry	Dose optimization, fouling prediction, maintenance scheduling	Automated inspection/cleaning assistance	Energy use, UV dose compliance, disinfection reliability	Must include outlet compliance and lamp aging effects
Membrane/filtration systems	Transmembrane Pressure (TMP), flux, permeability, air scour, and cleaning logs	Fouling prediction, cleaning optimization	Targeted inspections, cleaning support	Uptime, cleanings/month, chemical intensity, energy	Cleaning events treated as interventions; compare with baseline schedules
Sludge thickening, digestion & stabilization	Feed flow, solids, temperature, pH, biogas flow/composition, lab data	Early warning, load coordination, stability forecasting	Safety scouting, sampling support	Biogas yield, stability events, downtime, return load variability	Long-horizon evaluation with documented interventions
Dewatering & composting/final sludge handling	Polymer dose, cake solids, centrate quality, temperature, and moisture	Dose optimization, process classification, and fault detection	Conveyor/area inspection, safety monitoring	Cake dryness, polymer consumption, reject load, labor time	Must include process variability and reject-stream effects
Predictive maintenance (cross-cutting)	Vibration, current, runtimes, temperature, thermal data	Fault detection, remaining useful life estimation	Patrol inspection, thermal scans, confined-space scouting	Unplanned downtime, maintenance hours, energy trends	Link predictions to avoided failures and process outcomes
Plant-wide inlet/outlet quality control	BOD, COD, TSS, TN, Total Phosphorus (TP), NH_4^+, NO_3^-, PO_4^{3-} pH, ORP, UVT, flow	Compliance forecasting, anomaly detection, decision support	Sampling automation	Compliance rate, alarm precision, response time	Use plant-relevant compliance metrics across seasons

Supervisory optimization is a subsequent enhancement to these capabilities and converts forecasts into operational aeration setpoints and airflow distribution plans that account for actuator constraints and the spatial scale of heterogeneity of aeration basins[88]. In more complex designs, the project's lower-level PID loops would hold on to zone DO targets, and the high-level optimizer would change zone DO targets depending on projected nitrogen removal performance and energy trade-offs. In areas with strong interaction between internal recycles and carbon, with aeration, supervisory control may be used to stabilize the denitrification process by adjusting the recycle flow, aeration distribution, and eliminating conditions that favor the formation of nitrous oxide. The most efficient types of evidence in this respect have been observed when studies report sustained reductions in blower power or in definite energy usage and stable or enhanced ammonia and total nitrogen compliance rates at varying conditions of influent. Architectural insights are more likely to be transferable than algorithmic: systems can work when they include sound sensor-quality control, deal with time lag between the conditions in the basins and the effluent measurements, and can give the operators confidence indicators that can be understood to support changes in setpoints.

6.2. Chemical Dosing and Disinfection Control under Uncertainty and Risk Constraints

Chemical consumption is a major cost driver in many plants, particularly for phosphorus removal and pH control, and disinfection performance is a high-stakes public health requirement[89]. The integrated automation challenge is that dosing decisions must respond quickly to changing water quality, yet measurement uncertainty and lag can encourage conservative overdosing. IoT sensing can improve responsiveness by integrating online phosphate, turbidity, UV transmittance, and flow signals with operational context such as chemical feed system status and dosing pump performance. In this setting, AI models are valuable when they estimate the relationship between measurable proxies and the true control objective, such as residual phosphate or disinfection efficacy, and when they quantify uncertainty in those estimates.

For phosphorus control, predictive models can anticipate dosing demand and reduce oscillations caused by time delays and changing influent composition[90]. For disinfection, models can forecast UV dose requirements based on transmittance trends or guide chlorine dosing to maintain residual targets while minimizing byproduct risk. Supervisory optimization models are best applied to chemical dosing processes since such systems have very stringent safety conditions and have well-tuned cost-compliance trade-offs. In this case, the optimization strategies can be used to strike a balance between the cost of operation and regulatory policies in a safe operation. The most credible studies indicate that there is an improvement in efficiency in terms of decreased use of chemicals per unit of treated wastewater, the effluent phosphorus standards, and consistency of downstream solids generation are sustained. This is also the case in disinfection processes, whereby there is an improvement due to increased robustness of processes and reduced variability of dosing. But transferability of such results heavily relies on the quality of instrumentation and monitoring systems and the capability of automatically dosing decisions with laboratory validation, especially when sensors are drifting out of control, or there are aberrant influent conditions.

6.3. Solids Line and Anaerobic Digestion: Stabilizing Long-Time Constant Processes

The solids handling line can also be a cause of the delayed disturbances that may be passed on to the liquid treatment processes via the return streams [91]. It is due to this fact that automation in the field is more apt to be considered as predictive coordination as opposed to quick feedback control. Available IoT infrastructure has the capability to combine various operational indicators, and they may include: digester temperature, mixing status, biogas production and composition, feed qualities, and periodic laboratory measurements, such as alkalinity and volatile fatty acids. This data can be used by AI systems to provide early warning of instability by identifying small-scale fluctuations that tend to lead to a process upset, such as a shift in gas production rates, a growing uncertainty about main predictors, or correlations that indicate an organic overload or an organic inhibition.

Decision intelligence is especially useful in cases where the detection of risks is converted into operational tasks, such as implementing new feed rates, arranging co-digestion inputs, or realizing gradual changes of setpoints that can be useful in ensuring digester stability. Since the evolution of anaerobic digestion processes is sluggish, forecasting is particularly helpful because it gives the operator enough time to make an appropriate response before significant disturbances take place. This also includes scheduling sewage sludge wasting, thickening efficiency, and dewatering schedules in an integrated WWTP operation to ensure that very variable loads do not enter the digestion area. The strongest indicators of efficiency are those where the research indicates, in addition to an increase in biogas yields or some other indicator of stability, also operational gains such as a smaller number of foaming episodes or fewer operational interruptions, and more stable centrate returns loads. The overall generality of these strategies is, however, a problem, as the performance of digestion is extremely local with respect to different feed components, operating temperature, mixing type, and even historical modifications of the microbial population [92].

6.4. Membrane Systems and Advanced Filtration: Fouling Prediction and Cleaning Optimization

Membrane bioreactors and tertiary filtration units concentrate both operational value and operational risk, because performance degradation is often driven by fouling that accelerates under particular mixed liquor conditions and operational transients [93]. The integrated automation pattern typically couples high-frequency monitoring of transmembrane pressure, flux, permeability, air scour rates, and cleaning events with AI models that predict fouling trajectories and recommend cleaning schedules. IoT data platforms are essential here because the relevant signals often include both process conditions and maintenance actions, and because cleaning events represent discontinuities that must be captured accurately to train and evaluate models.

Predictive fouling models reduce energy use through optimizing the air scour and pumping design, and reduce the use of chemicals through a more accurate prediction of clean-in-place events. Supervisory control may also synchronize upstream factors that help promote fouling, including the age of sludge, dissolved oxygen profiles, and coagulant dosing, and hence causes the issue to be proactive in controlling fouling rather than reactive cleaning. Efficiency gains have been best reported in terms of sustained permeability, fewer cleaning occurrences, less chemical intensity, and better uptime, and not short-term gains during tight control pilots. The transferability is determined by the type of membrane, operating flux, cleaning regimes, and how the models remain robust as the properties of the mixed liquor vary seasonally or when the process control strategies change upstream [30].

6.5. Predictive Maintenance and Asset Management: Linking Equipment Health to Process Outcomes

Most losses of efficiency and compliance risks in WWTPs are due to mechanical degradation and failure, and not the limit of process design [94]. Predictive maintenance combines IoT condition data (vibration, temperature, electrical signature, valve position feedback, runtime counters, etc.) and AI models that predict remaining useful life, incipient faults, or efficiency loss (weakened blower performance), to name a few. When the use of these predictions is combined with maintenance processes and inventory schedules, the operational value is generated in terms of enabling the utilities to plan the interventions before failures, which leads to process evasions.

The application of robotics can enhance predictive maintenance because more frequent and regular inspections can be done, particularly in places that are difficult to reach [95]. The thermal images of electrical panels can be collected with the help of mobile platforms, leakages or suspicious sounds may be detected, and equipment status indicators may be checked. Combining robot data with time-series condition monitoring would offer context to minimize the number of false positives and boost the trust in maintenance advice. Efficiency benefits in this area are typically indirect but significant and manifested in less unplanned downtime, fewer emergency callouts, greater energy efficiency of rotating plants, and less process variability due to intermittent performance of equipment. The most important condition of credible evaluation is the ability to relate maintenance activities and fault identifications with operational results that could be quantified in terms of energy use patterns, lowering the alarm rates, or preventing permit excursions during disturbance levels.

6.6. Robotics-Enabled Inspection and Sampling as Operational Multipliers

Robotics most directly improves efficiency by reducing labor burden and improving safety, but its strongest contribution to process performance arises when it increases the frequency and quality of information available for decision-making [96]. Robotic inspection can detect early-stage issues such as localized scum accumulation, foaming onset, clarifier surface anomalies, channel blockages, or corrosion in structural components. Automated or robotic sampling can increase the temporal resolution of lab-validated measurements, reducing uncertainty in soft sensors and improving calibration of online instruments. In integrated systems, robots function as adaptive measurement agents: they are dispatched when analytics indicate rising uncertainty, conflicting sensor readings, or abnormal conditions that require confirmation.

Robotics in wastewater has only been developing as an evidence-based approach when compared to process analytics, and is less mature than other tasks [97]. Inspection activities prove to be more evident of immediate value since they can be represented by a visible reduction of risks and increased asset awareness. The work of sampling and cleaning ought to be more attentively incorporated in the work of plants and safety processes. Efficiency gains evaluation should then take into consideration both direct measures, such as fewer staff hours to perform routine rounds, and indirect measures, such as quicker identification of conditions, which would otherwise increase energy consumption, chemical overdosing, or even downtime. The strongest evidence correlates robotic interventions with the quantifiable changes in the stability of the process or minimized disruptions caused by maintenance.

6.7. Benchmarking, Techno-Economic Evidence, and the Problem of Comparability

One of the most consistent problems associated with the interpretation of reported efficiency gains is that of standardized benchmarking. Influential factors, climatic conditions, plant design, and regulatory environment affect energy intensity, doses per unit flow of chemical, compliance rates, and downtime. Pilots who are short in stable seasons can exaggerate advantages when there are no storm periods and extremes of temperatures. On the other hand, premature deployments can undervalue advantage since operators can hold on conservative overrides until they are assured. In the case of SCI-standard evidence, evaluations are supposed to explain operating baseline operating strategies, time horizons, and disturbance coverage, and distinguish between improvements caused by instrumentation upgrades and improvements caused by AI or robotics [9,98].

Techno-economic analysis must be carried out to translate performance gains into deployable cases of investing [99]. Hardware and software are only a few of the costs involved, with the rest being calibration labor, sensor replacement, cybersecurity management, model maintenance, and training. Benefits must be measured in units that are acceptable to decision-makers, such as saved energy and chemicals, no downtime, less emergency maintenance, and enhanced compliance strength. Lifecycle matters since a technology that saves energy but raises maintenance costs may not be able to give net value, particularly where the utility is already workforce-strained. Likewise, the added instrumentation and robotics environmental footprint must be countered by operational savings, such as energy savings leading to decreased greenhouse gas emissions or operational stability leading to decreased nitrous oxide releases or methane releases.

All in all, the combined evidence indicates that the most developed efficiency improvements are obtained through supervisory aeration and nutrient management, enhanced chemical application plans, and predictive maintenance, helped by efficient IoT data infrastructure. Robotics will provide the highest value when closely integrated with sensing and decision processes, as a means to enhance observability and decrease the uncertainty instead of being a novel inspection isolated [53]. The key message in all applications is that end-to-end integration and operational governance are the key determinants of whether gains reported will be sustained after pilots. Section 7 is a summary of the review that attempts to conclude what is, perhaps, ready to be widely adopted, what is still experimental, and what research and standardization efforts can most likely hasten the adoption of safe and effective automation in the wastewater treatment industry.

7. Conclusion and Outlook

Through AI, IoT, and robotics, wastewater treatment is turning into a more adaptive, automated, and intelligent process rather than the localized and reactive treatment of wastewater. This progress has not been brought about by any single technology, but through combined closed systems. They are systems that have a combination of dependable sensing and state estimation, AI-driven decision support that transforms data into risk-minded operational setpoints, and physical automation like robotics, which is an extension of monitoring and intervention into risky or man-intensive operating areas. Properly assembled, this technology stack can be beneficial to operational performance through ensuring that regulation is adhered to with fewer manual concerns, energy and chemical consumption is minimized, unplanned outages are minimized, and the entire system becomes less susceptible to disruptions. The greatest availability of the improvements in operations is achieved under three conditions. To begin with, the systems should be highly observable with good instrumentation and good data governance, such as appropriate calibration and management of sensor drift, biofouling, and missing data. Second, AI must be put in place as supervisory intelligence built on existing PLC/PID control systems, and with explicit constraints, safety fallback modes, and human supervision. Third, monitoring of performance should be done with plant-relevant operating measures under a variety of conditions as opposed to brief pilot experiments or simply statistical indicators. In such a case, especially promising are the applications of aeration control, optimal nutrient management, optimization of chemical doses, and predictive maintenance. Robotics also works to increase safety and efficiency through the aid of inspection, mobile sensing, and speedy diagnostics.

Although these improvements have been made, there are still significant hurdles that have to be overcome until wastewater treatment plants can be made completely self-organizing. The amount of data is also a big problem: it is impossible to observe many states of the system, labeled data are not very abundant, and the operational regimes often change because of weather, industrial activity, or infrastructure changes. The persistent uncertainty of sensor drift and biofouling is also a source of uncertainty and needs to be considered as a critical design constraint. Moreover, there is a growing concern about cybersecurity, governance, and accountability with the growing connectivity. The utilities should be in a position to audit models, control the life cycles of devices and software, and have in place a good accountability of operational decisions impacting public health and compliance regulations. The use of robotics also needs to be enhanced in terms of its durability, the ability to work safely in severe conditions, as well as its compatibility with other safety protocols and teleoperation systems.

These findings also imply an evident research agenda. Assessing systems, standardized benchmarking data of varied climates, influent states, and plant design would enhance comparability as well as accelerate the pilot project to real-world implementation. The non-stationary and partially observed nature of a wastewater system especially requires a hybrid connection of mechanistic process knowledge and data-driven adaptability, hybrid modeling approaches. There must also be strong mechanisms of sensor and process drift detection to ensure long-run stability of the model. Notably, the efficacy of the whole automation cycle should be studied, namely, the sensitivity and data governance to the decision intelligence and actuation, as the operational dependability and integration eventually define practical influence.

To sum up, AI, IoT, and robotics have a high potential to enhance the efficiency, resilience, and sustainability of wastewater treatment. Nonetheless, the realization of success with technological innovation is not limited to solely that, but also proper engineering methods, sound data architecture, cybersecurity, and meticulous model lifecycle management. Those facilities that implement automation with gradual processes, such as supervisory control and high human supervision, are likely to have long-term benefits. With the ongoing progress of interoperable infrastructure, reliable AI systems, and sound robotics, wastewater treatment plants have a chance of having many systems that constantly monitor, learn, and optimize their processes without loss of safety and compliance with regulations.

Funding

This work received no external funding.

Institutional Review Board Statement

Not applicable.

Informed Consent Statement

Not applicable.

Data Availability Statement

No new data were created or generated in this study. As this is a review, it is based on data and information from previously published sources, which are cited in the reference list.

Conflicts of Interest

The author declares no conflict of interest.

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