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REVIEW

Smart Industrial Water Treatment: Integrating AI and IoT for Real-Time Monitoring and Optimization

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ABSTRACT

Smart industrial water treatment is progressively sought after to achieve stricter discharge and product-water requirements, decreased energy and chemical use, and enhanced stability at fluctuating influent and working regimes. This article provides a review of how the Internet of Things (IoT-based) sensing and artificial intelligence analytics may be combined in order to facilitate real-time monitoring and optimization in industrial treatment trains, including pretreatment and biological treatment systems, membranes, and zero-liquid-discharge (ZLD) systems. The initial contextual framework (smart treatment) is placed on industrial performance goals and limitations, focusing on partial observability, sensor pollutions/fouling, measurement delay, and multi-objective optimization amongst compliance, cost, particle recovery objectives, and asset health. We next consider IoT and architectures of sensing used to ensure trustworthy monitoring, such as time-based pipelines of data, edge cloud pattern of installation and engineering of data quality, which is used to validate, redundancy, and fault detection. It is based on these backgrounds that we consider artificial intelligence (AI) techniques in anomaly detection, fault diagnosis, soft sensing, and probabilistic forecasting, and point out how regime awareness, explainability, and uncertainty quantification must be applied to risk-sensitive operations. Prescriptive capabilities are considered in a control maturity perspective, between decision support and constrained supervisory and closed-loop control. We contrast classical methods, e.g., model predictive control, with data-based optimal control, e.g., Bayesian optimization, safe/offline

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reinforcement learning, and explain why digital twins can be used to enable validation and operator training. Last but not least, we discuss deployment facts-OT/IT (operational technology/information technology) integration, cybersecurity, lifecycle management, and human factors, and offer a vision of the future based on interoperable data models, strong cross-site transfer, and optimization that is proven to be safe.

Keywords: Industrial Water Treatment; Internet of Things (IoT); Artificial Intelligence; Real-Time Optimization; Model Predictive Control (MPC)

1. Introduction

Treatment of industrial water is on the border of process engineering, operational economics, and risk management. In industries like power generation, chemicals, mining, oil and gas, food and beverage, pharmaceuticals, and microelectronics, water is not only a utility but also a vital input to the quality of products, integrity of assets, and environmental adherence. The performance envelope is shrinking: discharge limits and reporting are becoming more stringent, industrial facilities are getting drier and prone to significant volatility in the supply of water, and more plants are being pushed to higher reuse ratios or even zero-liquid-discharge (ZLD) options. Simultaneously, expensive control is still costly; unscheduled downtime, malfunctioning of membranes, scaling, and corrosion are not planned, biological upsets and off-spec ultrapure water, violation of compliance, etc., can trickle down to significant losses in production and reputation. These facts have created the reality of the so-called smart water treatment systems capable of perceiving, interpreting, and responding to dynamic process conditions, an operational priority and not a dream [1–4].

In the past, automation of industrial water treatment has been based on the combination of local instrumentation, supervisory control and data acquisition (SCADA) systems, and rule-based control logic. Setpoints and heuristics are tuned with many unit operations (e.g., coagulation/flocculation, filtration, membrane separation, disinfection, biological treatment, ion exchange, adsorption and advanced oxidation processes) being operated using setpoints and heuristics. Although this method is useful in the presence of stable conditions, industrial influent and process loads are usually nonstationary, unsteady, and censored by complicated compositions [5]. The plants can also operate intermittently, change product lines, be subjected to episodic shock loads, or be fed by blended streams across a variety of process areas. Measures may be either sparse, noisy, or delayed - particularly of non-easy-to-measure online parameters like chemical oxygen demand (COD), specific organics, toxicity markers, metals speciation, or microbial risks. Consequently, operators often have to operate on a problem-solving basis using so-called lagging indicators: an issue has already impacted effluent quality, rate of fouling, or the condition of the assets. The real implication is that to be on the safe side, the practical result is conservative operation, an Abundance of chemicals, operating pumps and blowers too hard, cleaning the membranes sooner than required, or having too much safety margin than expected. Conservative operation ensures compliance but comes with an energy, chemical and maintenance cost, which is becoming more difficult to warrant in an ever-increasing cost and sustainability goals world [6].

A plausible way out of this trade-off is the intersection of the Internet of Things (IoT) and artificial intelligence (AI). Internet of Things technologies increase the capability of a treatment system to monitor itself in real time: fine grids of online water-quality sensors, flow, and pressure meters, equipment health (e.g., vibration, acoustics, motor current) detectors, and edge gateways that reliably push data into historians and analytics systems. AI, in its turn, offers devices to convert raw signals into operational intelligence—to identify abnormalities in advance and before they turn into excursions, to diagnose potential causes, to forecast near-term quality and foul paths, and to suggest (or take) action to maintain performance within constraints at a lower cost. Notably, AI-based optimization does not address more accurate prediction. AI, combined with layers of controls and decisions, can aid real-time trade-offs among quality, cost, energy, chemical use, recovery, and waste production goals that are in and of themselves multi-dimensional and generally opposing [7,8].

But the prospect of intelligent industrial water treatment is equal to the challenge of making it available on a reliable basis. Industrial water treatment is a cyber-physical system: it is an amalgamation of intricate chemistry, hydraulics, kinetics, and transport phenomena with discrete conceptual interventions like chemical dosing, backwashing, membrane clean-in-place, sludge management, and setpoint adjustments. The data space is problematic; sensor drift as well as biofouling is typical; calibration timetable differs; gauging rates fluctuate between devices; laboratory measurements are asynchronous; plant arrangements vary with time. In addition to this, the control actions are limited by safety, compliance with regulations, and equipment constraints; response in the process can involve large time delays and nonlinearities; and the plant must continue to operate during a network failure, sensor failure, or model uncertainty [9,10]. In contrast to other digital systems where a fail-fast approach is acceptable, industrial water systems require a fail-safe approach: any high-level layer of analytics/optimization/whatever must fail gracefully and maintain operator agency and hard constraints to protect people, assets, and the environment. **Figure 1** gives an end-to-end perspective of smart industrial water treatment, such that the IoT sensing and validated data pipelines support AI monitoring and prediction, which are in turn used to inform optimization and operator actions within the safety boundaries of the OT. Cybersecurity in the deployment also makes the convergence of operational technology (OT) networks and information technology (IT) a greater challenge that increases the attack surface and the price of secure identity, segmentation, patch management, and auditability [11–13].

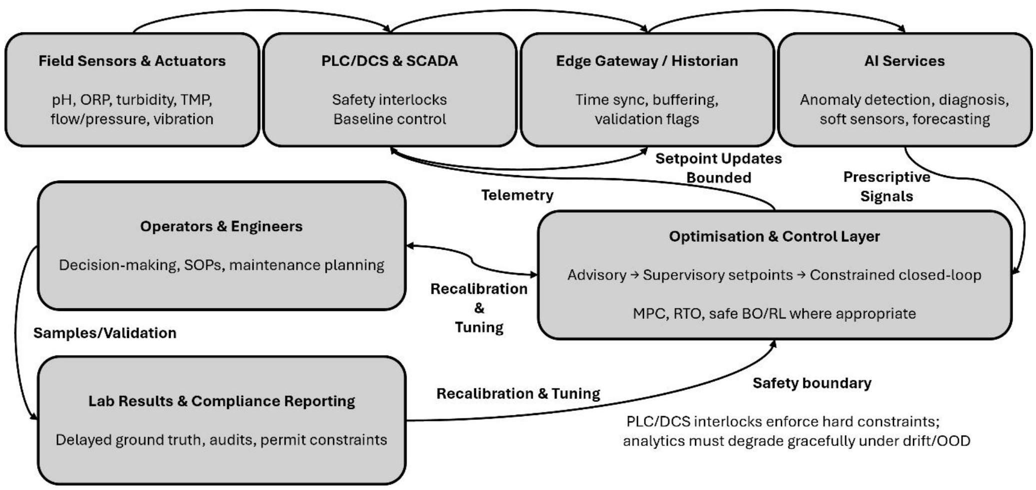

Figure 1. End-to-end concept of smart industrial water treatment (IoT sensing → validated data pipeline → AI analytics → optimisation/control → operator actions and feedback).

This review deals with smart industrial water treatment as an integrated field, but not a set of individual tools. We describe smart treatment systems as meeting the following three criteria: (i) the execution of real-time monitoring through connected sense planes; (ii) the use of AI analytics to detect, diagnose, predict, and support decision-making, and (iii) support real-time optimization—scale indicator to advisory limit or constrained close-peak control—response to industrial specifications of security, dependability and control. It is targeted particularly at industrial settings where water quality demands, variability in the inflows, along uptime limits vary significantly compared to municipal systems. Although the municipal water and wastewater research provides useful techniques and knowledge, industrial facilities usually have a more rapid regime change, a greater range of contaminants, and a more severe economic cost of deviations. We do not confuse real-time monitoring with real-time optimization either. The estimation of process state and risk (such as soft sensing, anomaly detection, and early warning) is ongoing and constitutes monitoring, and the choice of actions, such as chemical dosing, pressure/flux regulation, cleaning plan, or setpoint changes, is the subject of explicit constraints and multi-objective trade-off, and is an optimization [14,15].

One of the main ideas of this review is that the way towards optimization is through credible monitoring. Real-time optimization assumes that key states and disturbances are observable adequately; in industrial water treatment, they are not always measurable. Based on this, the strategy of IoT sensing, inferential soft sensors, and data quality engineering will become primary, rather than peripheral. The AI models that work in practice offline can malfunction when they are not constructed around sensor drift, sensor missing, concept changes, and operating regime changes. On the same note, more advanced control methods like model predictive control (MPC), real-time optimization (RTO), Bayesian optimization, or reinforcement learning (RL) can be used responsibly when they include constraint management, uncertainty awareness, and certified fallback behavior. Digital twins (mechanistic, data-driven, or hybrid) are especially applicable as they offer a framework in which one can perform what-if analysis, tune, train operators, and verify safety, closing the gap between prediction and action [16,17].

The other theme is that smart solutions should be in line with industrial workflows. Alarms and scores are not the only explanations required by the operators and engineers. Model recommendations should be combined with the standard operating procedures (SOPs), maintenance planning (e.g., computerized maintenance management systems), and current control architectures. The division of responsibility between automation and operators, accountability, alarm fatigue, and trust are all human factors that can either lead to sustained value provided by an AI/IoT initiative or not. Not fully automated controllers, but solid monitoring and advisory systems, which lessen the uncertainty and enhance response time and change shifts in decision-making, are the most influential initial deployments in most facilities. As confidence and maturity in governance are achieved over time, the control loop can be narrowed down to allow constrained closed-loop optimization [18,19].

Under this framing, the inputs of this review are threefold. First, we give an end-to-end view of the IoT-to-AI-to-control stack and then we explain how the sensing, analytics and optimization should be co-designed to be reliable in performing in real time. Second, we appear to synthesize the potentials and constraints of large-scale AI solutions in this area, which includes monitoring (anomaly detection and diagnosis), prediction (quality, fouling, and asset health), and optimization (MPC, RTO, Bayesian optimization, and RL) with a focus on the constraints of deployment and not just algorithmic novelty only. Third, we integrate deployment lessons regarding data quality, integration architecture, cybersecurity, resilience, and human factors, and we determine gaps in research and engineering, which need to be closed to achieve the scalable, interoperable, and safe smart water treatment [20–22].

The rest of the article is structured in the following way. Section 2 provides the setting of industrial water treatment, by connecting the large unit processes to performance goals and limitations that provide the motivation for monitoring and control requirements. Section 3 provides a review of the foundations of IoT sensing and real-time monitoring, such as sensor modalities, connectivity patterns, and the realities of data quality and soft sensing. In Section 4, AI analytics to monitor, diagnose, and predict, with a focus on model trade-offs, uncertainty, and explainability in the safety- and compliance-relevant workflow, are considered. Section 5 is dedicated to real-time optimization and control, and mapping the advisory decision support to constrained closed-loop systems, and discussing the functions of digital twins and safe optimization approaches. Section 6 focuses on deployment and integration, comprising architectures, lifecycle, cybersecurity, resilience, and human-machine collaboration. Section 7 ends with a conclusion in terms of the synthesis of maturity levels throughout use cases and the prospective agenda of research and industrial deployment [23–25].

To conclude, smart industrial water treatment is not merely a digitalization of the current machines; it is a transformation towards adaptive and data-driven operations, where monitoring and optimization are ongoing and interconnected and limited by real-life safety and compliance specifications. The prospect is massive, cutting down on chemical and energy usage, lengthening asset life, enhancing dependability, and permitting more water to be reused, but this will be made or broken by engineering discipline in the field of sensing, modeling, control, and governance. The objectives of this review are to give a consistent mapping of that landscape and a workable base to researchers and practitioners who are developing the next generation of smart water treatment systems.

2. Industrial Water Treatment Context and Performance Objectives

Industrial water treatment can best be viewed as a concomitant production-environmental control system. However, unlike most municipal applications that are run with relatively stable patterns of influent and well-defined regulatory limits, industrial facilities are often forced to deal with sudden regime shifts that are caused by production cycles, the mix of products, cleaning cycles, and intermittent releases across different process regions. The trains' treating must also then deal with average performance, but also with response to variability, hard-to-detect transient excursions, and uncertainty impacts on performance. This part is aimed at explaining the overall process situation where smart monitoring and optimization are implemented, and the performance requirements and limitations that inform sensor design, analytics, and control policies [26,27].

2.1. Industrial Water System Boundaries and Operating Regimes

Most industrial locations usually have multiple parallel water circuits instead of the linear influent effluent route. Water supply may be provided by municipal supply, groundwater, surface water, desalination, or reclaimed water with different base chemistry as well as seasonal fluctuations. Inside, water is distributed between utilities and process units, generating different streams of returns that can be segregated, blended, equalized, or treated simultaneously. There are varying quality goals and hydraulic interactivity in cooling systems, boiler feedwater conditioning, process wash waters, and clean-in-place effluents, matching the stormwater processing. There are interacting disturbances between these loops: wastewater salinity can change with a change in the rate of cooling tower blowdown, and the [28] production campaign can change the organic load [29,30].

The operating regimes are also significantly different in industries. High purity or ultrapure water may be required by semiconductor/pharmaceutical operations when traces of ions or organics are quality-limiting, or high total dissolved solids, metals, and mixtures that depend on ore body or reservoir conditions may be found in mining and oil and gas facilities. Streams of food and beverage and pulp, and paper may have high biodegradable organic loads with high swings of diurnal or batch cycles. Intermittent operation of many industrial plants can alter hydraulic residence times, oxygen transfer, and biological activity, destabilize conventional control loops, and change the start/stop behavior of many industrial plants. It means that the treatment goals will have to be met on a family of regimes rather than just one stable state, and that the definition of what constitutes normal variability and what qualifies as an abnormal event is often situational [31–33].

2.2. Typical Treatment Trains and Unit Operations in Industrial Facilities

Even though industrial treatment setups are very site-specific, they are frequently assembled out of repetitive unit operations integrated into trains that observe contaminant category, necessary recovery, and discharge or reuse targets. A common specification in pretreatment involves screening, removal of grit, oil to water separation, even pH and equalization used to make hydraulic and compositional jolts steady. Chemical conditioning (coagulation flocculation) is employed to remove colloids, emulsified oils and a part of organics in a variety of sites prior to clarification, dissolved air flotation or media filtration. The selection of these steps is usually done not only based on their immediate removal performance, but also due to their protective capacity in the downstream membranes and in the biological processes as well.

Biodegradable organics are still central to biological treatment, and the types of reactors to use depend on the load, footprint, energy recovery possibilities, and the achievable effluent goals, including activated sludge, sequencing batch reactor, membrane bioreactor, and anaerobic systems. Industrial biological systems, in turn, may have to deal with inhibitory compounds, high salinity, a non-constant ratio of nutrients, or intermittent feeding, which may trigger instability. The tertiary and polishing treatments, like granular activated carbon, ion exchange, advanced oxidation processes, and disinfection, are implemented to deal with traces and color, micro-pollutants, and microbial hazards, especially in cases where it is planned to be reused [34,35].

The use of membrane systems is growing in all industries for reuse and to produce product water. Most solids and microbial control are done by ultrafiltration and microfiltration, whereas solids are used in nanofiltration, and reverse osmosis is used in high recovery and dissolved constituents [36]. Operations of the membrane add new control variables and constraints such as membrane pressure, flux, recovery ratio, concentrate management, and cleaning cycles. Scaling, fouling, and organic adsorption make the treatment plant a very time-varying system where the performance deteriorates unless cleaning, pretreatment and operating conditions are actively controlled. In regions where discharge limits or water deficit are extreme, facilities can venture into ZLD options involving the usage of high recovery membranes with brine concentrators, evaporators, crystallizers, and solids handling. The systems are capable of recovering almost full liquid wealth but require large energy expenditures and have low operating margins, which makes them the best candidates for real-time optimization. To explain the origin of the monitoring and control decisions, **Figure 2** superimposes typical treatment trains in industries and indicates common measured variables and primary control levers across unit operations [37,38].

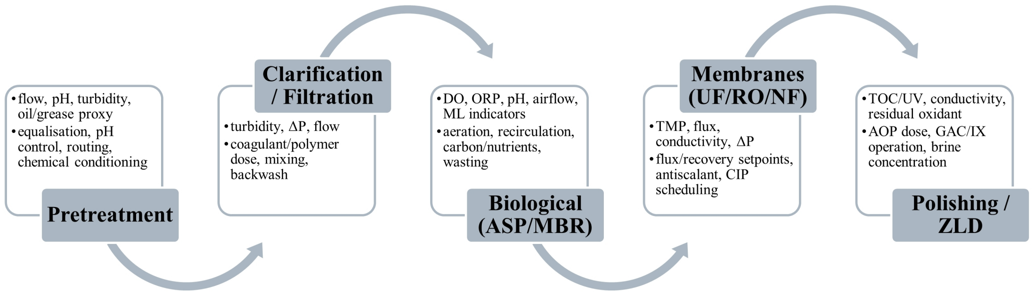

Figure 2. Industrial treatment train map and control levers across unit operations.

2.3. Water Quality Variables, Compliance Endpoints, and Practical Observability

The interface between regulation, production needs, and asset protection determines the variables that are important in industrial water treatment. To release, compliance is often based on indicators (comprised of aggregates) like total suspended solids, biochemical oxygen demand, chemical oxygen demand, nutrients, and individual controlled chemicals or metals. In case of reuse or internal loops, the most important variables could be changed to scaling and corrosion indices, silica, hardness, chloride and sulphate, specific conductivity, total organic carbon, dissolved oxygen, disinfectant residual, and microbiological indicators. Trace ionic contaminants, dissolved gases, and organic residues become quality-limiting in high-purity applications, and the measurement problem is no longer merely an accuracy problem, but a sensitivity at very low concentrations problem [39].

The most noticeable aspect of industrial water treatment is that many of the variables of compliance or economic concern can only be measured to some extent in real time. There are online measurements of some parameters using powerful sensors, including pH, conductivity, turbidity, flow, pressure, oxidation-reduction potential, and, in some instances, ultraviolet (UV) absorbance as an indicator of aromatic organics. Others are based on at-line analysis or lab analysis with great lag, such as COD, specific organics, metals speciation, toxicity surrogates, and microbiological tests. This latency makes monitoring and control more difficult, as corrective measures have to be made in most cases before the definitive measurements have arrived. This leads to the reliance on proxies and early estimation as to why soft sensing, data fusion, and uncertainty-aware prediction are at the center of smart water treatment: the system is expected to operate on the unfinished information and still be able to be compliant and ensure the safety of downstream assets [40].

2.4. Operational Key Performance Indicators (KPIs) and Trade-Offs: Cost, Energy, Chemicals, Recovery, and Reliability

Regarding operational aspects, the treatment plant is evaluated based on its capacity to maintain compliance and aim at attaining water quality using the least amount of resources achievable. Pumping, aeration, mixing, thermal processes in ZLD, and pressure in high-recovery membranes are some of the processes that cause energy consumption. Examples of chemicals used consist of coagulants, flocculants, pH control acids and bases, anticalins, oxidants, disinfectants, biological stability nutrients, and regeneration/cleaning reagents. In high-recovery schemes, the waste is composed of sludge, spent media, and brine or solid salts. All these categories have direct costs and indirect effects, including sludge disposal through aggressive coagulation and membrane degradation through aggressive cleaning [41].

These KPIs are interconnected due to some inevitable trade-offs. Increased recovery of the membrane will lessen freshwater consumption but may increase scaling dangers and power per unit permeate. Optimization of disinfectant residual enhances the safety of microbes but may result in increased by-products or destruction of further biological operations. Leading to the selection of overdosing coagulants can enhance the clarity and safeguard membranes, though the effect of overdosing increases the generation of sludge and chemical expenses. Biological performance may be stabilized through aeration, but many systems consume energy. Practically, plants tend to run with a low operating point to minimize the violation or damage to assets; however, a low operating point makes systematic inefficiencies a permanent part of the system. The key promise of real-time optimization not only exists in cost reduction, but is to move the operating point to the Pareto frontier, where no function can be optimized without optimizing another, and remains within the safety and compliance limits [42].

The so-called hidden KPIs dominating the industrial choice are reliability and uptime. Even a small effluent spill can cause production restrictions, imposed curtailment or reputational damage, and membrane malfunctions, pump failures, or biological catastrophes may take time to recover. This has the result of treatment control being risk-averse and worst-case-based. Intelligent monitoring and optimization should then not only show an average savings but also a lowering in variance and an observable increase in robustness to disturbances, including the capability to identify incipient malfunctions in time and lead interventions that do not cause shutdown or protracted recovery periods [43].

2.5. Disturbances, Constraints, and Failure Modes That Shape Smart Control Design

Treatment systems in industry are also prone to disturbances, both exogenous and endogenous. Exogenous disturbances are variability of the raw water quality, discharges of upstream processes, ambient temperature variation on the kinetics and solubility of biological processes, and intermittent incidences of contamination. Endogenous disturbances are those caused by operational choices at the plant, which include avoiding backwash when a flow alters paths, backwash, or switching parallel trains: a chemical batch, or switching to a different parallel train. There are a lot of disturbances that are related to the production schedules and can be predicted in case data integration with manufacturing systems is at hand, but could be sudden when it comes to the water plant [44].

There is also a multi-layered constraint. Physical limitations are equipment limits, maximum allowable pressure, permissible flux ranges, tank volumes, and thermal limits. The chemical and biological constraints are maximum alkalinity in order to maintain stable pH, nutrient proportion in order to keep the biomass healthy, compatibility of the oxidants with the membrane, and safe limits of dosage. Regulatory and safety restrictions that set limits on the quality of effluents that shall be discharged into the water are tied to the fact that dangerous chemicals must be operated within specific operating limits. The control actions should also be sensitive to time lag and dynamics, e.g., to residence time in equalization or biological reactors and to the gradual development of fouling on membranes. Such delays may result in naive feedback strategies, and naive feedback strategies may overshoot or oscillate; predictive and constraint-aware control may be of particular value [45,46].

A massive number of failures represents why industrial water treatment is an intriguing and challenging industry of AI and IoT. Sensor drift and fouling may conceal actual process variations or give false alarms. Depending on the chemistry or hydraulic conditions, membrane fouling and scaling may occur at an accelerated rate and decrease throughput, and push the cost of energy upwards. Toxic shocks, pH excursions, nutrient imbalance, or long periods of starvation during intermittent operation may cause biological upsets, resulting in low removal efficiency and irregular effluent quality. Overfeeding or underfeeding of the chemicals may cause 2nd-order issues, be it too much sludge or contaminant breakthrough. These failure modes are frequently predetermined by some patterns in a variety of signals, but not by the occurrence of one threshold, and it is the kind of scenario where multi-sensor analytics, early-warning models, and optimization under uncertainty can provide substantial value [47,48].

2.6. Implications for Smart Monitoring and Real-Time Optimization

A number of implications are generated in the context of the description above and will be used to guide the rest of this review. To start with, the process of industrial water treatment is multi-objective and constraint-based in nature, and the objective optimization should thus be presented as a constrained decision-making problem, as opposed to unconstrained cost minimization. Second, inferential monitoring and prediction are fundamental capabilities rather than optional improvements since they are partially observable with the latency of the measurement. Third, nonstationary and regime changing imply that models have to be strong to nonstationary and capable of identifying operating modes where the control policies need to consider the delay issue and time-dependent dynamics. Lastly, the cost of failure is high, requiring conservative architectures and algorithms where it matters, transparency to operators, and failure modes that are safe to the system with discrete separation between advisory analytics and automated control [49].

In the following part, we extend beyond this industrial background to discuss the foundations of IoT sensing and real-time monitoring, with the question of what needs to be measured and how data are obtained and validated, and how soft sensing and data fusion can be used to address the observability gap that is so characteristic of many industrial treatment settings.

3. IoT and Sensing for Real-Time Monitoring

Industrial water treatment real-time monitoring is essentially a sensing and data engineering problem, and then it turns into an AI problem. Any downstream analytics or optimization is only limited by the quality of what can be observed, the consistency of how it can be observed, and the speed at which the information obtained may be turned into state estimates that can be acted upon. Practical considerations encountered in industrial settings introduce complications--to be overcome by means of sensor excellence, controller excellence, and active cleaning: sensors are filled with dirt, scaled, shaken, thermally disturbed, and attacked by chemicals; sensor schedules collide with production schedules; sensor signal quality is degraded in gradual and hard-to-detect ways; and sensor sensory data networks must cross OT networks that were not platformed to respond to high frequencies. This segment is a retrospective on the landscape, the IoT framework, which makes real-time monitoring employable, and the reality of field deployment, and those particular design decisions that keep a monitoring framework credible over its extended lifespan of operation [50].

3.1. Measurement Needs across Treatment Trains and Unit Operations

The diversity of objectives outlined in Section 2 influences the measurement problem in industrial water treatment. To monitor pretreatment and solids control, monitoring is usually centered on hydraulic state and particle-associated loads, as these two have a strong effect on downstream unit operation. Direct information on loading and filterability is given by the flow, pressure, turbidity, and surrogate measures of suspended solids. Transmembrane pressure, permeate flux, recovery ratio, differential pressure across pre-filters, conductivity rejection, etc., are all used to describe the performance of separation in membrane-based trains and the initiation of fouling or scaling. In the biological treatment, dissolved oxygen, oxidation-reduction potential, pH, temperature, airflow, and mixed liquor indicators are followed to predict the indicators of biological activity and stability, whereas in disinfection and oxidation processes, the indicators followed include UV intensity, oxidant residual, and oxidation surrogates to determine the effectiveness of the treatment process and to control chemical use.

The biggest difference between industrial settings and the context of this study is that not all the variables that are most relevant in decision-making are necessarily the simplest to measure. Numerous compliance and product-water limits are established in terms of species-specific or aggregate lab indicators like COD, TOC, nutrients, metals, specific organics, and microbiological indicators. In turn, real-time monitoring strategies typically involve the choice of measurable surrogates that can be relied upon to be informative enough to make operational decisions. Each of UV absorbance, conductivity, turbidity, fluorescence signatures, and oxidation reduction potential can offer partial data concerning the type of contaminants, but their use should be interpreted in a manner that is site-dependent on the chemistry onsite and operating conditions. Sensing architecture planning must consequently be done considering the task of downstream inference, and not as a list of instruments built as a generic list [50,51].

3.2. Sensor Modalities and Industrial Instrumentation Considerations

Electrochemical sensors, such as pH, oxidation-reduction potential (ORP), and ion-selective, optical (turbidity, UV absorbance, and in a few cases fluorescence), and physical (flow, level, pressure, temperature, and density) sensors are widely used in industrial water treatment plants. There are typical failure modes of each modality. Electrochemical probes are susceptible to coating, degradation of the reference junction, and temperature. Scaling and biofilm formation can attenuate optical sensors, resulting in a slow drift in signals, which is hard to distinguish from an actual change in the process and a slow drift in the sensor. The flow and pressure sensors are also usually durable; however, they are also susceptible to impulse line plugging, cavitation-induced noise, and misconfiguration following service [52].

Reliability in industrial applications is not an attribute of the sensor, but it is an attribute of the sensor-installation-maintenance system. The position of sensors affects representativeness and responsiveness: measurements below a chemical injection that is not mixed well will give false results, and measurements in hydraulic turbulence may worsen performance in optical measurements. The success of optical instruments being stable can be dictated by the sampling hardware, including bypass loops, self-cleaning systems, and automatic wipers. The compatibility of the material with oxidants, solvents, as well as high-salinity streams might restrict sensor selection and induce compromises in measurement fidelity. All these limitations justify why the number of sensors does not necessarily correspond to the quality of the monitoring; the marginal utility of extra measurements will only be high in case the extra sensors can be maintained in calibration, cleanliness, and readability under actual operating conditions [53,54]. **Table 1** presents an overview of some sensor modalities that are common in industrial water treatment, including some of the common applications and the common failure modes that directly influence the reliability of the monitoring.

Table 1. Common sensor modalities for industrial water treatment monitoring, typical applications, and dominant failure modes.

Sensor/Signal	Typical Monitored Variable(s)	Where Used Most	Operational Value	Common Failure Modes/Caveats
pH (electrochemical)	Acidity/alkalinity, neutralisation control	Pretreatment, dosing, biological stability	Dosing control, corrosion/scaling risk	Reference drift, coating/fouling, temperature compensation errors
ORP	Oxidation state proxy, redox regime changes	Biological reactors, AOP/disinfection zones	Upset indication, oxidant control support	Highly context-dependent interpretation; probe fouling; cross-sensitivity
Conductivity	Ionic strength/salinity proxy	RO/NF, reuse loops, blowdown, ZLD	Salt breakthrough, recovery control, blending	Temperature dependence; scaling/fouling on electrodes
Turbidity/optical solids proxy	Particle load surrogate	Clarification, filtration, UF/MF feed/permeate	Early warning for solids breakthrough	Window fouling, bubbles, particle-size dependence
UV254/absorbance	Aromatic organics surrogate	Wastewater polishing, reuse	Organic load trending, oxidation effectiveness	Interference (e.g., nitrate/iron), window scaling
Dissolved oxygen	Aeration adequacy, biological activity	Activated sludge/MBR	Energy optimisation, nitrification stability	Membrane fouling, slow response, local gradients
Chlorine/oxidant residual	Disinfection/oxidation residual	Disinfection, reuse distribution	Compliance assurance, microbial risk management	Probe drift; demand variability; sensor maintenance burden
Flow/pressure/ΔP/TMP	Hydraulics, fouling indicators	Filtration, membranes, pumping	Fouling detection, throughput and energy control	Impulse line plugging, cavitation noise, recalibration after maintenance
Temperature	Kinetics and solubility context	All units	Normalisation of signals; seasonal regime detection	Location bias; lag in large tanks
Vibration/motor current	Equipment condition	Pumps, blowers, mixers	Predictive maintenance, failure prevention	Installation sensitivity; baseline shifts after repairs

Note: AOP, advanced oxidation processes; RO, reverse osmosis; NF, nanofiltration; UF, ultrafiltration; MF, microfiltration; MBR, membrane bioreactor; ΔP, pressure difference; TMP, transmembrane pressure.

Another consideration is closely associated with the distinction between process monitoring and equipment condition monitoring. Pumps, blowers, valves, and membrane skids are more commonly equipped with vibration, acoustics, motor current, and thermal sensors that give early warning of mechanical deterioration. This data is operationally useful since mechanical breakdowns tend to be reflected either in water-quality or throughput wastage, or the other way around, process upsets may speed up machinery wear. The combination of process and asset indicators in the same monitoring system is thus a unique attribute of smart industrial treatment, which allows cross-domain diagnosis, which is hard to find when instrumentation is isolated.

3.3. Data Acquisition, Connectivity, and IoT Architecture in OT Environments

The IoT layer provides field instrumentation to computation and decision systems. This layer has to coexist with some of the established OT infrastructure in industrial water treatment, including SCADA systems, distributed control systems (DCS), and historians. Most plants use the predefined industrial protocols and gateways to reach sensor data in a reliable and reasonably secure manner. The architectural problem is to allow the data streaming on the higher frequencies with context-rich information without violating the determinism and safety restrictions of control networks.

One frequent design is a layered architecture, where Sensors and programmable logic controllers (PLCs) are within the control domain, reflected monitoring of data into historians and long-term storage and reconciliation, and analytics subscribing to curated streams at the edge gateway or data broker. Edge gateways have a number of purposes: they store data in the event of connection disruptions, time syncing, unit and tag normalization, and local computing to aid low-latency analytics. The inference, aggregation, and visualization of the models are then applied to the cloud or on-prem analytics platform and the results are fed back to the operators through dashboards, alarm systems, or advisory setpoint recommendations. The location on the edge-cloud continuum is not entirely a cost choice, but is limited by the latency, data sovereignty, network reliability, and the requirement that monitoring functions should be available even in case of partial failure.

Scheduling of time and sampling plan are usually undervalued as sources of failure. Causal interpretation is very commonly relied upon in water treatment, in terms of minute-scale residence times and delays between treatments upstream and measurements downstream. When sensor clocks or sampling periods vary in an unpredictable way, event alignment is no longer guaranteed, and model performance is poor. The IoT monitoring problem thus demands a clear design concerning the integrity of timestamps, harmonization of rates, and expressing delays, not that time series come in as well-defined sequences [55,56].

3.4. Data Quality Engineering: Calibration, Drift, Missingness, and Validation

Real-time analytics can hardly be allowed to rely on industrial water-quality data, which are seldom clean enough to sustain industry-scale data quality engineering, unless systematic data quality engineering is undertaken. Calibration drift Calibration drift is a widespread phenomenon that may occur through the electrode ageing and contamination of the optical windows, gradual changes in sensor response because of temperature, or matrix effects. Drift is also especially problematic as it may resemble actual process change, which, when configured with thresholds and models, may give a false alarm or not be encountered at all. The absence of data is also a widespread issue related to the maintenance of the instrument, lapses in communication, sensor warming-up, and changing procedures. Noise features may be affected by hydraulic conditions, aeration, or the operation of pumps, and so cause nonstationary variance which cannot be determined by fixed alarm limits [57].

Strong monitoring systems, which include validation layers, work before AI inference. These layers provide reconciliation between sensor values and physical limits, rate of change checks, redundancy checks, and cross-signal checks. Making plausible comparisons can be made, e.g., plausibility of conductivity and ion-selective, plausibility of flow and level through mass balance over tanks, and of membrane differential pressure against relationships with flux. These rules do not substitute AI; they only provide a predictable base upon which AI can perform by eliminating glaring instrument errors and data artefacts and preserving actual process variation [58]. **Figure 3** shows the flow diagram of the observability of the stream of sensor raw data into validated procedures and soft-sensed state estimates, showing where signs of drift, missingness, and other data-quality problems are systematically identified and coped with.

Measurement uncertainty is also explicitly addressed in data quality engineering. Making sensor values precise numbers is an implicit assumption in many industrial applications, which results in overconfident models and fragile decisions. Conversely, risk-aware downstream analytics can be achieved by monitoring architectures that spread uncertainty, e.g., via confidence intervals, probabilistic filtering, or quality flags. This is especially significant when the models are employed to activate interventions like a change in chemical dosing, an operational disruption, and the cost of a false positive is high, and the cost of a false negative is a compliance excursion.

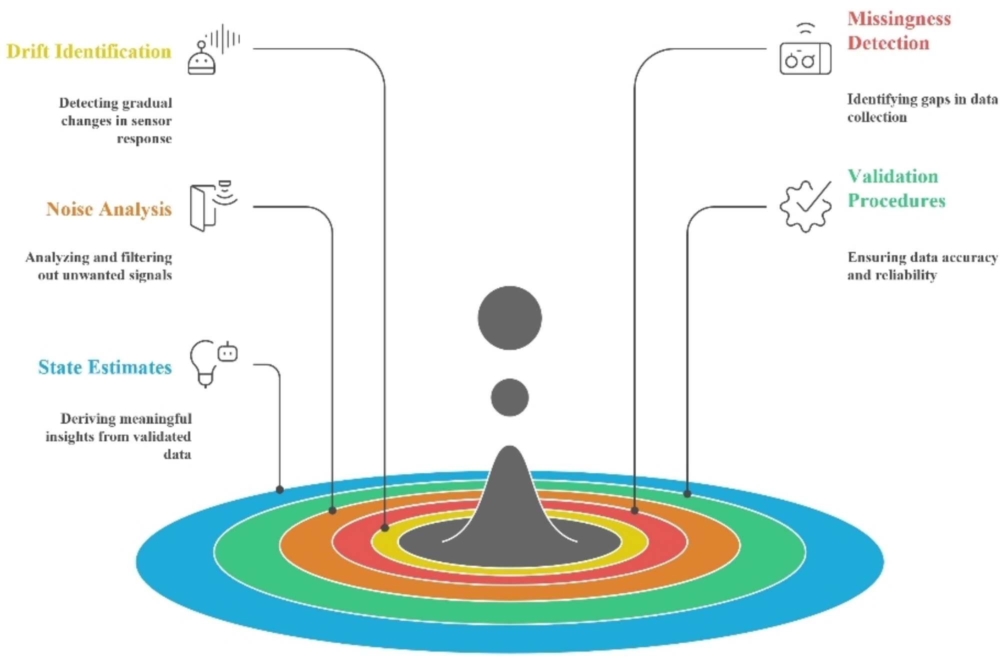

Figure 3. Data quality and observability pipeline for real-time monitoring.

3.5. Soft Sensing and Multi-Sensor Data Fusion for Unobservable Variables

Since the most important variables are not continuously measurable, industrial monitoring is frequently based on soft sensors: models that approximate difficult-to-measure quantities using combinations of easy-to-measure signals. The parameters of water quality that soft sensing can measure include COD, TOC, nutrient concentrations, or toxicity surrogates, and latent process parameters, including biological activity, fouling propensity, or scaling risk, can also be estimated. The purpose of IoT sensing in this respect is to supply the various redundant signals to make such an inference possible[59].

Multi-sensor fusion is necessary since individual sensors do not, in most cases, offer identifiability across different regimes. An example of this is that turbidity can be correlated with suspended solids in a certain set of conditions and not with UV absorbance, which is confounded by nitrate or iron; ORP can be correlated with both oxidant residual and biological activity depending on the location of the process. Calibration of signals with process context, e.g., flow conditions, dosing rates, and temperature enhances interpretability and robustness. Nevertheless, fusion also exposes the architecture to model leakage and spurious correlation in case it fails to consider time delays, shared cause drivers, and operating mode change. Good soft sensing must thus not only have more data but also be represented with improved process structure, such as mass-balance relations, known constraints, and regime identification.

The soft sensors also rely on congruence with lab output and periodical ground truth. Calibration anchors in cases of industrial processes are lab measurements, which usually arrive asynchronously and possibly mirror the variability in sampling and handling. Delayed labels, however, have to be managed in monitoring systems, and periodic recalibration and performance auditing mechanisms have to be put in place. This is facilitated by the IoT layer, which ensures the traceability of online readings, sample metadata, and lab results to allow continuous reconciliation as opposed to an ad hoc comparison [60,61].

Formal observability and the role of soft sensing. In control-theoretic terms, a system is observable if its internal states can be uniquely inferred from available measurements over time. Industrial water treatment is practically unobservable for key quality variables (e.g., COD, specific organics, toxicity) because online sensors do not exist or are unreliable. Soft sensing transforms this partially observable system into a functionally observable one by exploiting redundant, lower-cost surrogate measurements (conductivity, UV absorbance, turbidity, flow, pressure, etc.) combined with process models. However, observability is never complete; soft sensors provide estimates, not measurements.

Validation against infrequent lab measurements. Soft sensors must be anchored to periodic ground truth. Laboratory analyses—though delayed (hours to days) and subject to sampling variability—serve as calibration references. Validation follows a continuous reconciliation loop: (i) each lab result triggers a retrospective comparison against the soft sensor's contemporaneous estimate; (ii) persistent bias (> predetermined threshold over N samples) initiates recalibration; (iii) time-alignment accounts for hydraulic delays between sampling point and analytical result. We recommend that plants maintain a validation dashboard showing the most recent bias, variance, and a "validity flag" for each soft-sensed variable [62,63].

Uncertainty propagation. Soft sensors should output not a single value but a predictive distribution or confidence interval. Uncertainty arises from three sources: measurement noise in inputs, model structural error, and temporal extrapolation since the last lab calibration. A practical approach is ensemble or probabilistic regression (e.g., quantile regression forests, Gaussian processes) that yields, for example, "COD estimate = 45 mg/L [30–65 mg/L 90% PI]". Operators and downstream controllers use the full interval: wider intervals trigger conservative action or request a lab confirmation; narrower intervals permit normal optimization [64].

When to trust soft sensors over direct measurements. Trust is situational, not binary. We propose three operational rules: (1) Prefer soft sensors when the direct sensor is known to be drifting, fouled, or under maintenance (flag from the data quality layer). (2) Prefer direct measurements when available, real-time, and validated—soft sensors serve as backup or for unmeasured variables. (3) Hold both with caution when the soft sensor's uncertainty exceeds a plant-defined threshold (e.g., 95% PI width > 50% of the compliance limit) or when the process has recently undergone a regime change not represented in training data. A decision matrix (added as a small table) can be placed in the revised manuscript to guide operators [65].

3.6. Edge Analytics, Latency, and the Practical Meaning of "Real Time"

In industrial water treatment, real-time is not a specific requirement but rather a continuum. Certain decisions take sub-second response time to answer, e.g., equipment protection interlocks and some safety functions, still the province of PLCs and deterministic control logic. Some of the most common decision timescales used in water quality are on the minutes-to-seconds scale, e.g., dosing adjustment, backwash filtration activation, and noise-making of shock load. Other decisions, such as the schedule of membrane cleaning or optimization of multi-stage recovery, can afford hours-scale latency and can be updated with continuous changes as they happen.

This latency range prompts the application of edge analytics. In situations where it is required to perform anomaly detection in time and where connectivity may be unavailable, it can be beneficial to perform some basic anomaly detection, data validation, and feature extraction at the edge to enhance resilience and minimize bandwidth. The privacy and sovereignty constraints can also be facilitated by edge deployment, especially when industrial plants limit the transfer of process information beyond their network. Nonetheless, edge computing comes with functional overheads including device management, model deployment, and cybersecurity hardening. Therefore, it is common to find several empirical architectures that use edge-based preprocessing and alerting coupled with server-based or cloud-based model inference, with trade-offs of latency versus maintainability or governance [4,66].

One such practical implication is that the outputs are supposed to be monitored to fit the decision cadence. When the process dynamics are slow, high-frequency noise may not be beneficial to decision making; on the other hand, low sampling rates are prone to overlooking short-term events at the points of excursions. The IoT architecture has to be based upon process time constants, residence times, and the nature of control action response, such that the real time is associated with operationally meaningful windows but not an abstract desire to have more accelerated data.

3.7. Security, Reliability, and Maintainability of the Monitoring Stack

Industrial monitoring stacks have to be stable even in extreme physical and cyber conditions. Physical resilience, sensor redundancy (where failure is inevitable), automated cleaning (where fouling is inevitable), and maintenance mechanisms that reduce downtime are the minimum properties of reliability. It encompasses, in addition, data pipeline resiliency: buffering, store-and-forward, as well as the strict division of monitoring capabilities and control that is of safety concern. Since monitoring systems are not financially viable for treatment plants that cannot afford a silent failure mode, health diagnostics of sensors, gateways, and streams of data are included in the monitoring issue itself[66].

The concept of cybersecurity cannot exist without IoT in industrial water treatment, as more connectivity to the system opens up more areas of attack. Onboarding needs to be secured, device and services identity need to be managed, a network should be segmented between OT and IT, and data egress should be controlled to ensure that the infrastructure of monitoring does not become a route to the disruption of processes. Another concept is the graceful degradation: in the case of unavailability of analytic services or poor data quality, the system is expected to gracefully degrade to the baseline control modes without impairing safety or compliance. Such need predetermines the structural design of monitoring outputs, which tend to focus on conservative and understandable alerts and recommendations rather than opaque measurements with no ability to explain their use in a degraded environment.

To summarize, IoT and sensing offer the platform on which smart industrial water treatment is to be conducted through the enhancement of observability, the provision of reliable data streams, and inferential forecasting of unknown states. Nevertheless, the worth of such a substrate will be determined by viable engineering: calculability of sensors, time keeping, validation of data quality, and robust architecture. These prerequisites lead to the next part, Section 4, which focuses on how AI models can be used to turn proven sensor streams into monitoring intelligence to detect, diagnose, and predict anomalies, and how model uncertainty and explainability are turned into practical requirements in industrial settings[67].

4. AI Analytics for Monitoring, Diagnosis, and Prediction

The best strategy to use AI in the analytics of industrial water treatment is to express it as a case of operational inference in the presence of uncertainty, as opposed to a generic pattern recognition. Treatment processes are dynamic, nonlinear processes, and they are disturbed as well, and can only be partially visible due to imperfect sensors. In addition, the cost of errors is not symmetric: false negatives may result in compliance excursions, equipment damage, and production, whereas false positives may result in consuming unnecessary chemicals, cleaning, or operator actions, which undermine the trust in the system. This section discusses AI as an approach to real-time monitoring, diagnosis, and prediction, with a focus on the interaction of algorithmic decisions with industrial requirements in terms of regime changes, measurement latency, drift, and interpretability and governance requirements[68].

4.1. From Signals to Operational States: Problem Formulation and Data Structure

Data on industrial water treatment are largely multivariate, irregularly sampled time series, and have delayed labels and mixed data types. The high-frequency streams of continuous sensors are compared to the laboratory analyses, which are in the form of a sparse measurement, and could be related to the compositional variables that cannot be directly detected online. Besides this, treatment plants also create event logs of control measures like changing valves, adjusting doses, backwashes, clean-in-place operations of membranes and maintenance work orders. One key analysis mission, then, is to match heterogeneous data into forms that display the causality of processes and time delays. In the absence of such an alignment, models can be trained to identify spurious correlations, e.g., training downstream predictors to predict upstream conditions, or confounding operator interventions and the problem that caused the intervention.

Operationally meaningful AI systems are inclined to be a set of states of the plant, including water-quality states, equipment health states, as well as mode states reflecting the existing operating regime. Mode states play a vital role, especially in industry, since a process might not operate in the same manner when starting up, when shutting down, when cleaning, when changing product, or when recovering after an upset. The applications of models that do not take into account mode structure tend to fail upon deployment, not due to weak algorithms but due to the nonstationary and multi-regime nature of the data-generating process. As a result, often successful implementations involve both data-based learning and explicit context of processes: tag hierarchies, unit operation limits, known residence times, and when interventions should occur [69].

4.2. Anomaly Detection and Early Warning in Complex, Nonstationary Systems

The first AI feature that is frequently implemented in industrial water treatment is anomaly detection, as it brings value without the need to be fully automated. Practically, the anomalies consist of process anomalies, i.e., shock load, membrane fouling, biological instability, or malfunctioning disinfection, and instrumentation anomalies, i.e., sensor drift, calibration, or data pipeline. These two types of categories need to be separated; otherwise, plants will suffer alarm fatigue, and operators will get used to the analytics results [50,70].

Anomaly detection methods are either statistically based or neural model-based. Control charts, residual monitoring, and multivariate techniques may be useful when the variability of the processes is well known; however, they tend to fail in regime switching and non-Gaussian noise. Forecasting-based methods consider anomalies as errors between observed signals and short-horizon predictions, and have the capability to reflect dynamic patterns that are not reflected by static thresholds. Representation-learning techniques such as autoencoders and embedding-based detectors have the benefit of being capable of learning complicated correlations between sensors, although their results are strongly determined by the definition of the term normal and the ability of training examples to cover all useful operating conditions [71].

Early warning not only involves flagging outliers but also needs to capture faint antecedents that lead to poor outcomes. These precursors can be in the form of slow changes in the dynamics of transmembrane pressures, changing the correlation between turbidity and the different pressures, or a growing variability of dissolved oxygen control response in water treatment. Trend features, dynamic correlations, and regime-aware baselines seem to be more likely to be targeted by effective early warning systems, as opposed to instantaneous deviations. A practical benchmark is not the detection sensitivity by itself, but a combination of lead time, false alarm rate, along the association of alerts to possible operational explanations [72].

4.3. Fault Diagnosis and Root-Cause Support for Operators

Diagnosis takes the level of monitoring beyond something is wrong, to what is wrong and where to look. Root causes found in industrial water treatment are usually spread through unit operations. An example is that an increase in the efficacy of upstream coagulation may cause a rise in the loading of fine solids, thereby hastening membrane fouling, raising energy consumption, and worsening the quality of permeate. A shift in influent pH can alter the propensity to scaling, and a mechanical pump failure can alter flow distribution and residence time, destabilizing downstream biological operation. Models that would describe cross-unit dependencies are therefore useful in diagnosis as opposed to having each sensor individually.

The ideal application of supervised fault classification is where labelled fault histories are available, yet fault labels are not exactly comprehensive, inconsistent, and biased towards major events that led to maintenance. Semi-supervised and weakly supervised can learn on partial labels and event logs, though they can only reunite such logs with strict care on taking advantage of time, lest what they learn is the same: operator move=error. Graph-based formulation: The formulations are especially natural in treatment plants since the processes are connected through these nodes: Nodes may be sensors, physical objects, or unit processes, and edges may be functional or hydraulic. Such models with a combination of attention mechanisms or causal reasoning frameworks result in diagnostic attributions that are more consistent with the structure of plants and are easier to interpret by operators [73,74].

Where diagnosis is applied in operation, it is most applicable as ranked hypotheses, with supporting evidence, as opposed to a single definitive classification. This indicates the ambiguity of the partial observability as well as the reality that, in practice, there may be a set of interacting issues. Diagnostic systems should also be able to fit the granularity of intervention by the operator to be adopted. A diagnosis that says that a certain sensor is drifting or a certain chemical dosing loop is unstable is more actionable than simply being a statistical description of the situation as abnormal, even though the latter may be true [75].

4.4. Predictive Analytics for Water Quality, Fouling, and Process Stability

Industrial water treatment employs predictive models to forecast the upcoming results that have compliance and cost implications. Prediction of effluent quality. The effluent quality prediction is used to predict process response characteristics (like turbidity, surrogates of total organic carbon (TOC)/COD) and disinfectant residual in horizons proportional to process response times and sampling frequency. Such predictions can be used to cause proactive measures, including changing the dosing and preventing a breakthrough, or changing flow routing before a downstream unit is overwhelmed.

A specific field of application of prediction is membrane systems; fouling and scaling are time-dependent processes, which have a significant cost implication. It is possible to predict the rate of fouling, transmembrane pressure history, cleaning required, and post-cleaning permeability, thus giving more rational control over the clean-in-place operations and improved control of flux and recovery. Biological treatment has similar predictive problems, as predicting oxygen demand, stability of nitrification, or sludge settleability can help maintain upsets and minimize energy consumption [76,77].

The model class is a compromise among interpretability, data requirements, and generalization. Tree-based models can work well with structured features and be easier to interpret, whereas deep sequence models can be used to model more complex temporal dependencies but are harder to verify and control. The reason why probabilistic forecasting is particularly useful is that point forecasting is inadequate when making risk-sensitive decisions; it is the likelihood of going bad that is important, not the amount of the patrol that goes bad. In reality, predictive performance needs to be assessed based on average error, as well as predictive tail behavior, predictive uncertainty calibration, and regime stability.

4.5. Model Classes and the Role of Hybrid, Physics-Informed Learning

Industrial water treatment has a high potential for hybrid modelling since most of the relationships that govern it are known partially. The use of mass balance, conservation laws, and empirical kinetics can add structure to data-driven learning by eliminating the chance of physically implausible predictions. Hybrid models can also include mechanistic sub-models as part of the pipelines in the machine learning (ML) code, can learn to make corrections to the mechanistic outputs (as residuals), or may include detected constraints to make sure their responses do not go negative or are highly monotonic or restricted [78].

Physics-informed learning is especially useful in cases where labelled data is small, or the likelihood of extrapolating outside the training space exists. As an example, feature construction and model constraints can be built by a mechanistic understanding of scaling chemistry and constrained to obey relationships of solubility. Meanwhile, the limits of hydraulic boundaries may be able to limit the possible relations between flow, pressure, and level. Notably, it is not always important that the constraint respects physics to be explained in a first principles manner, and in most industrial applications, simple and robust constraints, like the plausible limits, consistency with known delays, or even monotonic effects of dosing within a defined operating regime, are observed to be most efficient.

Interpretability is also supported using hybrid approaches. Explanations, which are more easily expressed in words and justified, occur when models are constructed based on physically meaningful intermediate variables. This is important to trust and governance, especially when analytics results are affecting compliance-critical decisions. The hybrid designs also may make maintenance simpler, as this type of design offers a diagnostic layer: when the performance of the model worsens, the engineers will be able to determine whether it is the problems of the sensors, a change of the regime or the real changes in the behavior of the process[79].

4.6. Explainability, Uncertainty Quantification, and Risk-Aware Decision Support

Not a style but a functionality, the explainability of industrial water treatment is a necessity. In cases where any intervention has costs or safety consequences, operators should be capable of comprehending the reason an alarm has sounded or why a forecast recommends increased risk. Effective descriptions are often associated with the model outputs to common process terminology like higher loading, lower mixing, higher differential pressure, or unnatural sensor correlations. The use of feature attribution methods is possible. Still, their effectiveness relies on the fact that the features used are meaningful, as well as the fact that the explanations should remain intact over time and regimes. Changeable explanations are as harmful to loyalty as false forecasts.

The quantification of uncertainty is also important. Numerous industrial AI failures arise because of overconfident models, which give accurate-looking results when the inputs are out of distribution, when the sensors are drifting, or when the plant has reached a previously unseen regime. Risk-conscious systems explicitly indicate the uncertainty in prediction and assign it to the operational activities. An example of this is a prediction that has an intermediate likelihood of surpassing one limiting turbidity that might lead to an additional increase in monitoring or a relatively low setpoint change, with a very likely warning at the same time, leading to a riskier decision of this kind. This framing identifies analytics with industrial decision-making in which the objective is to manage risk-constrained, as opposed to maximizing the average accuracy. In an attempt to organize the landscape of analysis, **Table 2** shows the core AI activities in industrial water treatment to the common input data, appropriate model families, and the most significant considerations in deployment[80–83].

Table 2. AI analytics tasks in industrial water treatment: typical inputs, suitable model families, and deployment considerations.

Analytics Task	Typical Inputs	Representative Model Families	Preferred Outputs	Key Deployment Considerations
Anomaly detection (process)	Multivariate sensor time series, dosing/flow context	Residual/forecasting models, multivariate statistics, autoencoders	Alerts with severity + lead time	Regime awareness to reduce false alarms; clear escalation logic
Anomaly detection (instrumentation)	Sensor diagnostics, redundancy checks, cross-signal constraints	Rule + ML hybrids, change-point detection	"Bad sensor" flags, confidence scores	Must separate sensor drift from true process change; supports calibration planning.
Fault diagnosis/root-cause support	Sensors + event logs (valves, dosing, cleaning), topology context	Supervised/semi-supervised classifiers, graph-based models	Ranked hypotheses + evidence	Avoid learning "operator action = fault"; requires time-delay handling
Soft sensing (unmeasured quality)	Online surrogates + operating context; periodic lab values	Tree-based regressors, hybrid/physics-informed models	Estimated COD/TOC, toxicity proxy, nutrients	Label latency and sampling variability; needs periodic recalibration
Probabilistic forecasting (risk)	Time series + mode indicators + exogenous drivers	Probabilistic models, deep sequence models, GP variants	Distribution/exceedance probability	Calibration matters more than mean error; OOD detection needed
Predictive maintenance	Vibration/current + process context + maintenance history	Survival/RUL models, classification, anomaly methods	RUL estimates, maintenance risk	Maintenance records are noisy; post-repair baseline shifts must be managed.

Note: GP, gaussian process; RUL, remaining useful life; OOD, out-of-distribution.

The domain shift detection is a useful part of monitoring risk-awarely. The change in the treatment plants is based on the ageing of membranes, replacement of media, seasonal variations in water chemistry, and alterations in the process. Models should hence be checked for drift in both inputs and performance. The process of identifying drift is not necessarily statistical; it must have operational implications, and drifting must lead to recalibration, retraining, or fallback to more conservative decision logic, where confidence is lost.

4.7. Deployment-Ready Analytics: Integration with Operations and Continuous Validation

To be applicable in real-time monitoring, AI analytics outputs need to be part of the operations. This involves congruence with the current alarm management systems, explicit prioritization of alarms, and interfaces to enable the operators to view pertinent signals and the latest interventions. Isolated analytics in dashboards tend not to be acted upon, whereas those that send operators too many alerts rapidly lose their credibility. Efficient systems make use of alerting suppressions in the case of known transients, circumstances-based thresholds, which are based on the mode of operation, and escalation policies, which are based on severity and persistence, and not point-in-time deviation [84].

This also requires continuous validation since the conditions in the industry change, and models may fall out of service without failure. Model predictions must be compared to available ground truth, such as lab results as they become available, and not just error measures should be measured, but also operational measures such as reduced excursions, better lead time of interventions, or less chemical and energy used without compromising compliance. The most successful pathway is, in most cases, phased deployment: the models will first be in shadow mode to operate and determine the baseline performance, and then be in advisory mode under human supervision, only after that, assist semi-automated actions in appropriate instances.

Overall, the field of AI analytics in industrial water treatment is a continuum of moving forward to detect anomalies and diagnose them, and move further to predict and make decisions under uncertainty, with its potential worth rising and the responsibility growing as well. The best solutions would be those that assume partial observability, regime switching, and drift to be design features, and that give explanations and uncertainty estimates that are consistent with risk-sensitive operations. These features provide an analytical base to Section 5, where the emphasis is no longer on the understanding of the system but rather on its impact by the real-time optimization and control of the system associated with industrial safety and compliance considerations [85].

5. Real-Time Optimization and Control: From Advisory to Closed Loop

The monitoring intelligence is translated by using real-time optimization in industrial water treatment to make decisions that change process paths. Unlike Sections 3–4, which concern watching and understanding the system, here we are concerned with action, i.e., making choices in the form of chemical dosing changes, aeration adjustments, flux and recovery setpoints of membranes, backwash schedules, and cleaning plans to ensure that performance goals are achieved at reduced cost and with increased reliability. The optimization in industrial conditions cannot be considered as the unconstrained minimization of an objective function. On the limits of actions are hard safety and compliance constraints, actuation limits, time lags, and the requirement of stable, interpretable behavior of uncertain measurements. Consequently, the most successful strategies usually integrate classic principles of process control with contemporary optimization and learning strategies, and usually develop to the level of stages of autonomy instead of trying end-to-end automation early on [3,86,87].

5.1. Control Objectives, Decision Variables, and Constraint Structure

There are many overlapping objectives of industrial treatment plants. The quality of effluent or product-water should not exceed the limits, yet the operators also strive to reduce the energy consumption, chemical usage, waste quantity, and wear on the assets, and be able to sustain the throughput and resilience to disruptions. This is a multi-objective optimization problem by nature, and its operational form is subject to the unit operation and location. Coagulant and polymer dose, pH setpoints, mixing intensity, and backwash triggers are the typical decision variables in clarification and filtration. Examples of levers common in biological systems include aeration rate, recirculating internal processes, carbon addition, and sludge wasting. The operating point in membrane trains is determined by permeate flux, recovery ratio, the feed pressure, anticalin dosing, and cleaning schedules, whilst the dose, contact time, and intensity determine efficacy as well as by-product risks in disinfection and oxidation systems[88].

Industrial water treatment has constraints that are both physical and institutional. The physical constraints are the actuator saturation, equipment capacity, maximum allowable pressures and temperatures, the allowable ramp rates, and the allowable volume of the tank. Pollutant levels have strong upper limits in safety and compliance, restricting the concentration of the pollutants; chemical handling limits are established, and very frequently, conservative behavior in the face of uncertainty is required. There are dynamic possibilities introduced by time delays and residence times: even a meeting made on an upstream can only affect a downstream measure several minutes or hours later, and some interventions have transient responses (membrane cleaning widely used in biological recovery, etc.). These properties have rendered real-time optimization a dynamic decision issue whereby timing and timing of actions are as important as magnitude[89].

5.2. Levels of Autonomy and Practical Deployment Pathways

The development of advisory systems and closed-loop control is a characteristic of industrial optimization. Most of the facilities start with decision support, which gives recommendations, forecasts, and comparisons of scenarios, and leaves the implementation to be taken up by the operators. The value that this mode can bring is substantial because the best practices can be standardized, the response time to disturbances can be lowered, and the trade-off between competing objectives can be quantified. Increased confidence may increase the likelihood of plants using supervisory control under which the optimization layer can modify setpoints to existing proportional-integral-derivative (PID) or rule-based loops within a given range. Levers well-instrumented, whose dynamics are known to be fast and predictable, and whose safety interlocks are strong enough, may be operated in full closed-loop control, in which the actuators are driven by the optimization system[90,91]. A control maturity ladder between decision support and constrained closed-loop optimization, in terms of safety boundaries and fallback positions, and enabling digital twins, is shown in **Figure 4**.

This chain of independence is a manifestation of technical and organizational facts. Advisory deployment. Technically, advisory deployment has the benefit of enabling models to be tested in a real environment and the identification of failure modes (e.g., drift, inadequately specified delays, operator-behavior feedback). Progressive autonomy, organizationally, helps in the development of trust and explains accountability, particularly in processes that are compliance-oriented. Many industrial locations are finding it more convenient to use architectures that maintain operator agency even when optimization of a closed loop is technically feasible, offer a clear rationale, and guarantee that control can switch to a baseline strategy smoothly.

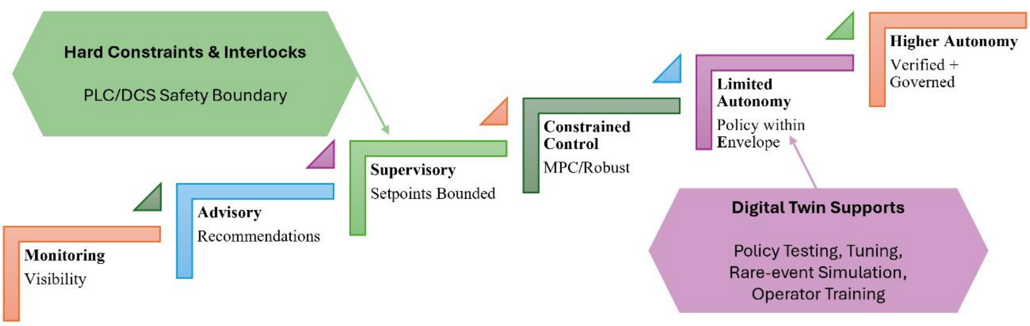

Figure 4. Control maturity ladder from advisory to constrained closed-loop optimization with safety boundaries.

5.3. Model Predictive Control and Constrained Optimization in Water Treatment

MPC as a control model is the perfect choice in industrial water treatment since it explicitly addresses multivariable interactions, constraints, and time delays. MPC works by modeling a process and attempts to forecast the future behavior over a finite horizon and find control moves that will maximize an objective function within constraints. In the treatment uses MPC may be used to coordinate the dosing, mixing, and pH control, to stabilize biological performance in terms of aeration and recirculation, and to optimize the operation of the membranes in terms of flux, recovery, and the risk of fouling. Its advantage is that it offers control, which is disciplined, constraint-conscious, and can be read by control engineers, and is consequently compatible with the existing automation infrastructure[92–94]. **Table 3** presents a comparison of the key optimization and control strategies applied to industrial water treatment, outlining not only the features of where each strategy fits operationally but also the way safety is commonly implemented.

Table 3. Comparison of real-time optimization and control approaches for industrial water treatment.

Approach	Best-Suited Decisions	Strengths	Limitations in Practice	Typical Safety Strategy
Rule-based/heuristics	Simple dosing/alarms, routine actions	Transparent, easy to govern	Brittle under regime change; conservative inefficiency	Hard limits + operator oversight
Supervisory setpoint optimisation	Slow dynamics, economic setpoints	Integrates KPIs and constraints	Needs reliable state estimation; depends on plant context	Bounded setpoint envelopes; rollback
Model Predictive Control (MPC)	Multivariable constrained control	Explicit constraints; interpretable	Requires model upkeep; tuning effort	Robust/adaptive MPC; constraint enforcement near control layer
Real-time optimisation (RTO)	Plant-wide efficiency, long-horizon trade-offs	Handles multi-objective economics	Sensitive to model mismatch; may be slow	Conservative margins; periodic revalidation
Bayesian optimisation (BO)	Tuning setpoints where evaluation is costly	Sample-efficient; low data needs	Exploration risk: best for modest parameter spaces	Safe BO with constraints; limited action ranges
Reinforcement learning (offline/safe RL)	Scheduling/strategy with delayed rewards	Can learn complex policies	Data coverage/shift issues; governance hurdles	Action filters + digital twin validation + fallback controllers

Nonetheless, MPC operation relies on the sufficiency of the model of operation and the stability of the dynamic processes. Treatment of industrial waters is frequently nonlinear, regime-changing, and time-varying (parameters like membrane permeability or biological activity). The adaptive variants of MPC solve these problems by updating the model parameters online or changing models depending on the operating mode. Strong MPC formulations clearly account for uncertainty in disturbances and model mismatch at the expense of aggressiveness. Practically, the design problem is not just the choice of algorithm but the maintenance of the predictive model: it should be guaranteed that the predictive model can remain representative as the equipment becomes older, the conditions of the influent change, and process changes are introduced.

The constrained optimization beyond MPC is also found in supervisory layers, which aim to calculate setpoints that are economically optimal as opposed to controlling faster dynamics. As an example, real-time optimization can be used to fine-tune chemical usage goals in response to forecasted influent properties and downstream limits, or can be used to plan membrane wash in response to forecasted fouling behavior and production needs. These supervisory issues tend to be longer-time-step and may include economic and sustainability measures more directly than lower-level controllers[95].

5.4. Data-Driven Optimization: Bayesian Optimization and Safe Reinforcement Learning

Data-driven optimization techniques may be desirable in processes where it is hard to model the process mechanistically and in those where performance is most effectively evaluated by the long-term results. Bayesian optimization can be used effectively to optimize setpoints and operational policies when having expensive evaluations and an intermediate-sized search space. It can be applied in the industrial water treatment process to optimize dosing strategies, cleaning intervals, or operating parameters of the membrane and oxidation system by learning a surrogate response surface based on plant data, balancing between exploration and exploitation. Its usefulness in practice is based on the proper definition of limitations and the fact that exploratory activities should not exceed the safety and compliance thresholds [96].

Reinforcement learning (RL) provides a framework for learning control policies through interaction that may be able to capture complex dynamics and time-lagged rewards. Extrapolationally, RL is attractive in solving issues such as chemical dosing when the influent is variable, aeration control to optimize energy use, yet maintain a biological performance, or clean schedule optimization, which is a trade-off between downtime and the accretion of foulants. Practically, naive deployment of RL is, however, not suitable for the constraints of industry. Safe RL methods strive to impose restrictions during the process of learning and execution, and offline RL tries to learn policies based on past data and no longer requires exploration. These techniques are able to decrease risk; however, they impose new problems. The past data might not be sufficient to act in the area of activity to accomplish the task, the interventions of the operators may bias the logged behavior, and any confounding between actions and disturbances can produce non-generalizing policies.

To be plausible in real-world water treatment in an industry, RL usually needs to be integrated into a more comprehensive safety design. This could be in such forms as constraint filters to disallow unsafe actions, fallback policies to revert to reliable and tested control logic beneath a veil of considerable uncertainty, and verification before any actual trials on the plant. In most environments, hybrid systems with high-level scheduling decisions based on RL and classical controllers are used to offer a more realistic trade-off between innovation and reliability [97].

5.5. Multi-Objective Optimization and the Water–Energy–Chemical Nexus

In industrial water cleaning, optimization does not often have one goal. The plants need to weigh between quality assurance and resource efficiency, and these trade-offs are affected by site economics, regulation and sustainability commitments. This fact is formalized in multi-objective optimization frameworks in which the Pareto-optimal operating regions are those in which the change in one metric needs to be compensated for in another metric. Membrane systems in membrane systems, e.g., increased recovery decreases fresh water uptake but may raise scaling risk, chemical usage, and energy consumption. Here, in biological systems, a decrease in aeration will save energy at the expense of potential loss of nitrification or poor quality of effluents. Chemical conditioning: The reduction of the dose of coagulants can reduce the costs of sludge disposal, but can raise turbidity and preventative fouling risk further on [98].

This has a practical implication in the sense that optimization must be formulated in a manner that is consistent with operational priorities and risk tolerance. Plants might have explicit economic values of energy, chemicals, and waste, but they tend to take quality constraints as non-negotiable. Optimization in these situations is a constrained economic dispatch problem: minimize the cost, with a safety margin maintained at the quality limits. Measures of sustainability may be incorporated in terms of energy-related emission elements, water withdrawal fines, or garbage dump effects; however, there must be justification by measurement and accounting procedures that operators will agree to. The strongest systems, hence, begin with a coherent and auditable statement of goals and restrictions, and would over time add extra metrics as understanding of the data maturity advances. Current automation infrastructure [99–102].

5.6. Digital Twins as an Enabling Layer for Prescriptive Control

Digital twins take a leading enabling role when it comes to shifting between analytics and optimization. A twin gives a computational model of the treatment plant, which may be used to test control strategies, sensitivity to disturbances, and quantify trade-offs without subjecting the actual system to risk. Digital twins can be mechanistic, data-driven, or hybrid, and their fidelity needs depend on the application. In order to design the controller and validate its safety, the twin should capture dominant dynamics, delays, and constraints of the decision variables being optimized. High-resolution physics may be of less importance than interpretability and consistency, which are required in the case of scenario analysis and operator training.

As a matter of fact, twins help in several functions that are critical. They permit assessing control policies in infrequent yet meaningful events that are not well represented in the historical data, like major influential shocks or equipment failures. They give a sandbox in which MPC horizon and constraint tuning, alarm-level testing, and controllers based on learning may be experimented with. They also assist in aligning the stakeholders by exposing the trade-offs, thus permitting the operators and engineers to build common intuition regarding the manner in which the system will react to the interventions. However, twins should be kept; otherwise, when the twin moves away from the plant reality, this may lead to false confidence. The most useful twin deployments are also those that make calibration loops between twin results and the plant, and clearly monitor uncertainty in predictions [103].

5.7. Verification, Safety Interlocks, and Operational Robustness

Because industrial water treatment operates under strict constraints, prescriptive systems must be designed to be verifiable and robust under uncertainty. Verification begins with defining allowable action ranges, rate limits, and constraint enforcement mechanisms that cannot be bypassed by the optimization layer. Safety interlocks and PLC-level protections remain essential even when advanced control is deployed, providing a hard boundary that ensures safe operation if higher-level analytics fail. Robustness also requires attention to degraded modes: the system must continue operating sensibly when sensors drift, communications drop, or models encounter out-of-distribution conditions.

Operational robustness is closely tied to how recommendations and control actions are presented. Advisory outputs should include not only proposed setpoints but also the rationale, expected impact, and confidence, enabling operators to decide whether to accept the recommendation. Closed-loop implementations should maintain audit trails and support rapid rollback to baseline control. Importantly, robustness is not only technical; it is socio-technical. If operators perceive that optimization actions are unpredictable or unjustified, they may override them frequently, undermining potential benefits and creating new forms of instability. Successful systems therefore emphasize stability, transparency, and conservative behaviour near compliance limits, gradually expanding autonomy only when reliability is demonstrated.

In summary, real-time optimization and control in industrial water treatment requires disciplined handling of constraints, uncertainty, and time delays, and it typically progresses from advisory decision support to constrained supervisory control and, where appropriate, closed-loop optimization. Classical methods such as MPC provide a strong backbone for constraint-aware control, while data-driven optimization and learning methods can add value when embedded within safety architectures and validated via digital twins. These prescriptive capabilities set the stage for Section 6, which addresses the practical realities of deployment and integration in industrial environments, including system architecture, lifecycle operations, cybersecurity, and human factors that determine whether smart treatment solutions sustain value over time [104–107].

6. Deployment and Integration in Industrial Environments

The ultimate result of deploying smart monitoring and optimization in industrial water treatment is an integration problem [86]. Even very accurate models or advanced controllers will not provide long-term value when they cannot be integrated into the workflows in OT, supported through plant changes, and run safely within the constraints of the real world. Industrial digital treatment systems are not green field systems; they are overlay ecosystems of sensors, PLCs, SCADA/DCS, historians, maintenance, compliance reporting habits, and the experience of operators that have been years long. Smart systems should therefore not just coexist with legacy infrastructure but must not overstep set safety limits, and must deliver benefits that are appealing and credible to stakeholders who are obligated to shoulder operational responsibility. This section explains the patterns of deployment, integration needs, lifecycle practices, and socio-technical factors that will make AI and IoT capabilities turn into credible results of operations [108,109].

6.1. End-to-End System Architecture and Integration with OT/IT Stacks

The layered architecture is followed in most industrial deployments, whereby safety-critical control is separated from analytics and decision support. Field instrumentation and actuator control PLCs or DCS controllers, restoring deterministic control and safety interlocks. The SCADA systems give visibility to supervisors and local operator interfaces where historians store high-resolution time series traceable to supervisors for troubleshooting and reporting. These layers are usually overlaid with smart monitoring systems that take curated streams of historians or edge gateways, make inferences, and deliver their results as dashboards, contextual alarms, or supervisory setpoints [110].

One of the issues in architecture that is of practical concern is where the data transformation and inference would happen in the edge server cloud continuum. Edge gateways are able to do protocol translation, buffering, unit normalization, and low-latency diagnostics without external connectivity. Analytics services are commonly run on-premise servers, where the policy, latency, or data sovereignty are restrictive to cloud usage. Scalable model training, fleet management, and cross-site benchmarking could be provided by cloud platforms, but it has to be rigorously governed on data egress and identity. Hybrid architectures are, in most instances, taken up: near-real-time inference and health monitoring are executed locally, whilst model retraining and more intensive analytics are executed centrally using controlled pipelines.

The limiting factor most of the time is interoperability. Plants can have non-homogeneous vendors and non-uniform tag names, which may become a problem in mapping data to unit operations and ensuring that a mapping remains consistent across equipment changes. Effective integrations are frequently enriched with a semantic layer, which indicates raw signals to contexts of the process, e.g., unit boundaries, connections between streams, and the meaning of measurement. Certainly, although formal ontologies may not be in place, an explicit and versioned registry of tags will be necessary to avoid silent model decadence caused by renamed sensors, re-purposed tags, or re-configured sampling [111].

6.2. Data Context, Event Alignment, and the Operational "Ground Truth"

Data on industrial water treatment has some context that gives it meaning what the plant was doing, such as what interventions were made, and what upstream production conditions existed. In the absence of this context, analytics can identify trends but will not be able to make sound decisions. Systematic event and state change capture that can affect interpretation is thus needed to support deployment. The examples are chemical deliveries and formulation changes, maintenance activities like replacing or cleaning a membrane, alteration of raw water sources, and alterations of the production schedule that can change influent composition. These occurrences are in different systems or informal records in most plants, and when they are not present, they lead to ambiguity, which models are unable to solve [112].

The focus of event alignment is also core since most of the treatment effects are delayed. A dosing change can take a few minutes to affect downstream turbidity, and hours to affect biological performance, whereas membrane fouling may develop over days and manifest itself as slow changes in pressure flux relationships. Integration activities should then ensure that timestamps are synchronized, residence times are taken into consideration, and interventions are not annotated as an isolated phenomenon but as a time-varying phenomenon. Such alignment is the condition of credible diagnostics, and for any learning-based optimization approach that tries to project the consequences of a course of action.

Industrial treatment can rarely involve a single definitive measurement, which is referred to as ground truth. Lab analyses usually provide compliance measures that are lagging and prone to sampling effects. The asset health results can be documented whenever maintenance is done, including the current state and organizational allowable limits of intervention. Deployable systems thus view ground truth as the combination of measurements, events, and judgment from experts, and have mechanisms to correct inconsistencies. One major practical goal is not to do away with uncertainty but to make it clear, so that the operators are aware of what outputs are of high confidence and what are provisional [113,114].

6.3. Operationalization and Lifecycle Management of Analytics and Control

The smart water treatment systems should be made to work continuously in varying conditions. Models are subjected to concept drain because of seasonal variation, deviation in source water, equipment corrosion, and process alterations. Sensors are drifting and are recalibrated, tags are remapped, and treatment trains are reconfigured to suit the demands of production. Lifecycle management, thus, is not a data science practice that is optional; it is a data science operation that is as necessary as instrument maintenance [115].

As a matter of fact, lifecycle management starts by monitoring the monitoring system. The health of data pipelines should be monitored, such as latency or dropouts, and distribution of values, since the reliability of the models requires that the input is stable. Models on their own need performance metrics linked to outputs of the operation, e.g., the number of missed excursions, the consistency of forecast error between regimes, or the predictability of the predictions of fouling after maintenance. In cases of degradation of performance, the system needs to instigate controlled actions like recalibration, re-training, or fallback to simple bases.

In the industrial context, version control and rollback are essential since an alteration in the analytics may have operational impacts. Decisions like those that impact compliance and integrity of assets can be influenced even by advisory systems. Therefore, updates are supposed to be tracked, and it is necessary to have a clear record of training data windows, model settings, and validation outcomes. When dealing with prescriptive systems, it is necessary to have safeguards in place that ensure that setpoint changes do not go out of the tolerated limits of operation and can be reverted to quickly in case some unforeseen behavior is shown. Notably, lifecycle processes should be in line with plant governance. Changes can be associated with the need to approve, document audits, and liaise with operations and engineering teams [4,116,117].

6.4. Human Factors, Operator Trust, and Workflow Integration

Water treatment in industries is a human undertaking despite the high levels of automation in certain plants. Operators and engineers are informed about contextual information regarding upstream processes, equipment peculiarities, and practical constraints that are not reflected in data. The smart systems should hence be developed as partners and not as substitutes, especially during the initial stages of adoption [4].

Credibility is determined by the predictability and utility of outputs. Monitoring systems that give a lot of false alarms or do not produce evidence that can be easily interpreted become less credible. On the other hand, systems capable of detecting problems early and quickly, and with obvious support signals, can become part of the operations. Interpretability, in this case, is not the generic description of model internals; instead, it is the operational narrative of connecting an alert to plant reality, e.g., alteration in the influent regime, loss of coagulant activity, or unusual reaction of membrane pressure. Recommendations are more apt to be accepted by conforming to operator mental models and standard operating procedures, and where the system expresses uncertainty as opposed to giving all outputs with the same level of confidence.

Integration of the workflow is also based on the location of analytics. In case the outputs are kept in several dashboards, they compete with SCADA displays and developed alarm systems. Cognitive load can be minimized by adding alerts and advisory setpoints to the operator consoles already in use, and it is important to prioritize and suppress advisory setpoints. Another aspect that is equally important is the design of escalation pathways: there are alerts that might demand immediate response, some that might demand observation, and those that might be rerouted to maintenance planning as opposed to operations. The alignment of the analytics layer to these organizational pathways is based on the successful deployment of the analytics layer and the understanding that water treatment decisions can cut across several roles [66,118].

6.5. Cybersecurity, Safety, and Resilience in Connected Treatment Plants

IoT connectivity, cybersecurity and resilience are inseparable requirements of deployment. Treatment plants are then placing themselves more and more at the border of OT and IT, with the ability to perform remote monitoring, analytics, and enterprise systems integration, but at the cost of increasing the attack surface. Practices involving security should therefore be more than the usual boundaries. Secure onboarding and identity of devices are required, allowing sensors and gateways not to be spoofed. Network segmentation restricts horizontal traffic between the analytics network and the control networks. Accountability of models, dashboards, and setpoint recommendations changes should be provided by access control and logging. Patch management and vulnerability handling should be operational and realistically designed, in that the time of downtime can be minimal [119].

Resilience is also of significance since monitoring and optimization systems cannot be turned into bottlenecks. Data pipelines must be resistant to momentary connectivity by buffering data and using store-and-forward protocols. Analytics services ought to degrade gracefully: in cases of unavailable or poor-quality inputs, the service ought to lower confidence, deactivate weak recommendations, and default to controlled base operations without breaking down. Safety interlocks are the last line of defense; however, resilient design tries to eradicate the occurrence of unsafe conditions by ensuring that the degraded state is identified earlier.

Cybersecurity and safety are closely related in industrial settings. A distracter with the capability to tamper with sensor measurements or setpoint recommendations will be capable of hazardous operation even without physical access to PLC logic. Secure architectures, therefore, involve integrity checks as well as anomaly detection of data streams themselves, along with separation of duties involving monitoring output and control execution. Enforcement of constraints should be done as near to the control layer as possible, and even compromised higher-level services should not be able to be used to execute unsafe actions [84,120–122].

Since the operational success is dominated by the integration and lifecycle problems, **Table 4** lists the typical deployment risks, practical mitigation, and the representative acceptance criteria in the industry.

Table 4. Deployment risks, mitigations, and operational acceptance criteria for AI/IoT-enabled water treatment.

Deployment Domain	Common Risk	Practical Mitigation	Acceptance Criterion (Examples)	Typical Owner
Data pipelines	Latency/dropouts break "real time."	Edge buffering, store-and-forward, pipeline health monitoring	≥X% data availability; bounded latency for critical tags	OT/IT + controls
Sensor integrity	Drift/fouling causes false alerts	Automated cleaning, redundancy, validation rules, quality flags	Drift detected within Y days; reduced nuisance alarms	Operations + instrumentation
Model validity	Concept drift/OOD inputs	Drift detection, mode-aware models, scheduled recalibration	Stable performance across seasons/regimes; calibrated uncertainty	Data/controls + process
Control safety	Unsafe recommendations/actions	Hard constraint envelopes, interlocks, action-rate limits	Zero constraint violations attributable to the optimiser	Controls + safety
Cybersecurity	Expanded attack surface	Segmentation, identity, least privilege, logging	Passed security audit; monitored the integrity of data and actions	OT security
Human factors	Low trust/alarm fatigue	Explainable outputs, prioritisation, SOP alignment	Higher adoption rate; fewer overrides; faster response times	Operations leadership
Governance	Untracked changes undermine audits	Versioning, approvals, audit trails, and rollback plans	Traceable model/setpoint history; reproducible validation	QA/compliance + engineering

Note: SOP, standard operating procedure; QA, quality assurance.

6.6. Validation in Operations: Performance Metrics, Value Realization, and Scaling across Sites

The viability of smart systems in operations phases or not depends on operational validation. Validation should be put in the context of plant-relevant outcomes and not just statistical measures. This is to be monitored by lead time to detect disturbances, reducing the compliance excursions, reducing the number of nuisance alarms, and more effectively responding by the operator. To be optimized, validation examines long-term decrease in chemical and energy consumption, enhancement in recovery, reduced cleaning frequency with a smaller risk rise, and the quantifiable uptime or the life of assets. Treatment plants can be run variably, so that value must be determined over regimes such as average loads, peak loads, in problem seasons, and not just in stable periods [123].

Organizational learning also affects value realization. Once analytic systems detect repeat patterns in their sensor array, e.g., a systematic drift in a particular sensor, or ineffective dosing practice, plants could convert knowledge into better operational and maintenance activities. Long-term, the greatest benefits might be achieved through these alterations in operations instead of the refinement of the models alone. This feedback loop explains why smart treatment can be considered a socio-technical transformation: analytics can be used to make decisions more effectively; however, the long-term value will be associated with making these decisions a habit.

There are even more challenges posed by scaling across sites. There is a wide range of different plants, including differences in influent composition, equipment configuration, sensor suites, and culture of operation. The models that have been trained at one position cannot de facto generalize to a different position without modifications, nor even within a particular position can alterations in the raw water or equipment alter the distributions of data. Standardization of data context, constant tagging and semantics, pipelines to deploy scaled sites, enabling the careful calibration of sites, but with shared components, is therefore required. When cross-site scaling is most effective is when it starts with typical monitoring primitives- data quality checks, simple anomaly detection, and regular KPIs and over time, as the maturity and trust of the data of each site increase, cross-site scaling increments into predictive and prescriptive capabilities.

To conclude, smart industrial water treatment is dependent on deployment and integration as the ultimate factors of success. Designs should be sensitive to the limits of OT safety and allow contemporary analytics; data should be contextualized and aligned to events and delays; models should be supported by drift and change; output should be understood as a fit operator process; and the system should be secure and resilient in design. These realities of deployments determine what can be done at present and what needs to be developed to be widely adopted. Section 7 summarizes the review by generalizing maturity levels within capabilities and details the most relevant research and industry directional conditions[124].

7. Conclusions and Future Outlook

Smart industrial water treatment is becoming one of the real solutions to the overlapping forces on industry: stricter discharge and product-water quality requirements, escalating energy and chemicals costs, growing water shortages, and growing demands on operational resilience and sustainability. In all these drivers, the main message of incorporating the IoT and AI is not merely improved visibility, but improved control, increasing the shift of plants to proactive functioning based on continuous monitoring, anticipatory vision, and constraint-sensitive decision-making. That transition has been placed in the context of this review as an end-to-end systems issue, where sensing, analytics, and optimization need to be co-designed and controlled to be reliable in industrial environments.

One common theme is that real-time optimization can never be as strong as the monitoring basis on which it is built. The treatment plants that are industrially observed are still partially observable systems: most of the most crucial quality variables are hard to measure online, sensor drift, fouling, and missingness are not an extraordinary situation. Following this, IoT-based monitoring should be regarded as a science of sustaining instrumentation, timely data paths, and sufficient validation strata that distinguish true process innovations at the instrument artefacts. In cases where these pillars are robust, AI can be a potent multiplier—early warning, lessening alarm fatigue by recognizing situations with context, and making inferential projections of unquantified states which are necessary for timely interventions.

The prolonged valuable capabilities that are mostly associated with AI analytics include the capacity to accept industrial realities, delay labeling, asymmetric risks, and transparency requirements. Detecting anomalies and diagnosing them can decrease the response time and make operations decision-making standardized, yet their adoption will be conditional on credibility and interpretability rather than novelty. Predictive analytics provide significant leverage to effluent quality risk management, foul, and health of assets, especially where uncertainty is measured and reported and then used to bolster risk-conscious behavior. The hybrid and physics-informed methods are particularly suited to this area since they limit learning to the space of plausible process behavior, facilitate generalization at varying conditions, and produce explanations that are consistent with operator intuition.

Optimization and control an area where the possible gains are the most and the operational accountability is the most. The way to prescriptive intelligence is usually an incremental one: decision support transforms to supervisory setpoint optimization and, in favorable circumstances, coeducated closed-loop control. The classical control approaches like MPC offer a powerful foundation since they are explicit in terms of constraints and represent the needs of industrial governance, whereas data-driven optimization approaches may be of value when incorporated into safety architecture and tested on realistic dynamics. Digital twins will be facilitative throughout this development in offering a place to test, tune, and train without putting operations at unacceptable risk. In all methods, some stable, conservative behavior close to the limit, predictable degradation in the presence of uncertainty, as well as high-speed rollback to a well-behaved base state when conditions become invalid to model, are all aspects of success.

The ultimate decision on the smart treatment goes beyond pilots, to deployment and integration. Outfitting requirements, the design of industrial environments requires respect to comply with OT affiliations of safety borders and cybersecurity targets, to source process context and incidents, to track models with drift and plant change, and to assimilate outputs into operator systems and workflows instead of being adversarial to them. The socio-technical aspect is conclusive: systems are to establish trust by performing consistently, providing actionable explanations, and being aligned with the standard operating procedures and structures of accountability. In most of the facilities, the initial benefits in terms of data quality and monitoring reliability would be the most significant in the early years, and then more advanced predictive and prescriptive features can be added when confidence and governance are developed.

In the perspective, there seem to be several avenues that are most significant in speeding up research and adoption. The field should be more standardized on data semantics, contextual metadata, and performance measures, which are operational in value rather than predictive accuracy only. Second, audit methods of transfer and adaptation between plants and shifting regimes will be crucial to scaling, such as domain adaptation, hybridization modelling, and calibration approaches that are both auditable. Third, uncertainty-sensitive and risk-checked optimization procedures play a vital role in going beyond the advisory systems, especially when making decisions that directly influence compliance, risky handling of chemicals, or the integrity of assets. Fourth, more realistic and serviceable digital twins, coupled with constant reconciliation to data in the plants, can mitigate the risk of deployment and facilitate the formal verification of sophisticated control. And, lastly, human factors must be addressed as one of the fundamental design vectors: interfaces, explanations, alarm management, and governance mechanisms need to be developed together with algorithms in case autonomy is to grow without compromising on safety or operator confidence.

To sum up, the real-time monitoring and optimization of water treatment plants with the help of AI and IoT has ceased to be a theoretical idea and has become a practical opportunity in the industrial field, yet the achievement is based on the strict control of engineering and governance of the entire stack. The short-term chance will be the creation of trustworthy and sustainable monitoring systems that will lower the uncertainty and enhance response to variability. The medium-term opportunity will be to institutionalize predictive analytics and constraint-conscience supervisory optimization that will cut the energy, chemical utilization, and downtime that comply. The long-term perspective is at greater autonomy, robust treatment operation, which is made possible by hybrid models, uncertainty-conscious control, and safe integration, where water treatment is optimized as a dynamic part of the overall industrial system and the nexus of water-energy-carbon.

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