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Using Artificial Intelligence to Improve the Operational Efficiency of Water Treatment Plants

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استخدام الذكاء الاصطناعي لتحسين كفاءة تشغيل محطات معالجة المياه

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Abstract:
Water treatment plants face increasing challenges, including fluctuating raw water quality, high energy consumption, stricter regulatory requirements, and the need to reduce carbon emissions. Artificial Intelligence (AI) and Machine Learning (ML) offer promising solutions to improve the operational efficiency of these plants through real-time monitoring, predictive maintenance, adaptive control, and multi-objective optimization. This paper reviews recent applications of AI in water treatment plants, including water quality prediction, chemical dosing optimization, energy savings, predictive maintenance, and Digital Twin modeling. It also discusses the main challenges hindering the adoption of these technologies, such as data quality, model interpretability, and generalizability across different plants, while providing insights into future trends in this field.

Keywords: Artificial Intelligence, Machine Learning, Water Treatment Plants, Efficiency Optimization, Predictive Maintenance, Digital Twins, Adaptive Control.

الملخص
تواجه محطات معالجة المياه تحديات متزايدة، تشمل تذبذب جودة المياه الخام، وارتفاع استهلاك الطاقة، وتشديد المتطلبات التنظيمية، والحاجة إلى خفض انبعاثات الكربون. يقدم الذكاء الاصطناعي والتعلم الآلي حلولًا واعدة لتحسين كفاءة تشغيل هذه المحطات من خلال المراقبة الآنية، والصيانة التنبؤية، والتحكم التكيفي، والتحسين متعدد الأهداف. تستعرض هذه الورقة البحثية التطبيقات الحديثة للذكاء الاصطناعي في محطات معالجة المياه، بما في ذلك التنبؤ بجودة المياه، وتحسين جرعات المواد الكيميائية، وتوفير الطاقة، والصيانة التنبؤية، ونمذجة التوأم الرقمي. كما تناقش التحديات الرئيسية التي تعيق تبني هذه التقنيات، مثل جودة البيانات، وقابلية تفسير النماذج، وقابلية تعميمها على مختلف المحطات، مع تقديم رؤى حول الاتجاهات المستقبلية في هذا المجال.

الكلمات المفتاحية: الذكاء الاصطناعي، التعلم الآلي، محطات معالجة المياه، تحسين الكفاءة، الصيانة التنبؤية، التوائم الرقمية، التحكم التكيفي.

1. Introduction

Water treatment plants are critical infrastructure assets that ensure the provision of clean and safe water to communities and industries. With the global population surpassing 8 billion by the end of 2022 and average water consumption rising to approximately 4,600 km³ annually projected to grow by 20% to 30% by 2050 pressure on these plants to operate with greater efficiency while reducing energy consumption and carbon emissions is intensifying. Estimates indicate that water treatment plants account for about 4% of global electricity consumption and contribute approximately 1.3% of worldwide greenhouse gas emissions.

Conventional water treatment plants operate within a framework heavily reliant on human expertise and traditional control systems such as SCADA, which provide real-time monitoring but lack predictive capabilities and autonomous decision-making. Furthermore, traditional mechanistic models, such as the Activated Sludge Model (ASM), face limitations in handling non-linear dynamics, long time delays, and disturbances in treatment processes.

AI represents a paradigm shift in the management of water treatment operations, enabling ML and deep learning algorithms to process massive amounts of data, extract complex patterns, and make optimized decisions in real-time. The future of water treatment plants aims toward more efficient, sustainable, intelligent, and automated systems, supported by the integration of the Internet of Things (IoT) and Industry 4.0 technologies.

This paper aims to provide a comprehensive and detailed review of AI applications in improving the operational efficiency of water treatment plants, focusing on recent studies and future directions, while discussing the challenges facing the widespread adoption of these technologies.

2. Applications of Artificial Intelligence in Water Treatment Plants

2.1 Water Quality Prediction

Accurate prediction of raw and treated water quality is essential for optimizing treatment processes and ensuring regulatory compliance. ML algorithms have demonstrated superior predictive capabilities for key water quality indicators compared to traditional methods.

A recent study utilized the XGBoost algorithm to predict raw water turbidity by integrating upstream water quality data, river flow, and rainfall, achieving enhanced predictive accuracy that enables plant operators to anticipate required adjustments during treatment processes. Another study showed that deep learning algorithms, particularly Transformer models equipped with dual-level attention mechanisms, improved the prediction accuracy of chemical dosages and settled water quality by 2% to 232% compared to baseline models.

In the domain of wastewater treatment, deep learning models have proven effective in accurately predicting effluent water quality indicators, especially when combined with physical models such as the ASM to enhance interpretability. Studies have demonstrated that algorithms like XGBoost exhibit significant potential for multivariate prediction and optimization of complex processes, particularly in forecasting emerging contaminants.

2.2 Chemical Dosing Optimization

Coagulation and flocculation are critical steps in drinking water treatment plants, where insufficient chemical dosing compromises water safety, while excessive dosing increases costs and generates harmful disinfection by-products. Traditional dosing calculations rely on empirical parameters and static designs that are difficult to adapt to fluctuations in water quality.

Researchers have developed a Knowledge-Embedded ML framework for coagulant dosage control, where the Random Forest model demonstrated superior performance with an error rate of 2.53% and an R^2 of 0.9922, alongside the ability to reduce turbidity by 16.36% and chemical costs by 9.64%.

In the context of wastewater treatment, a study proposed a Bayesian optimization framework for ensemble ML models (BO-EML) to predict pollutants and optimize chemical dosages with economic cost analysis. Hybrid systems combining Artificial Neural Networks (ANNs) and Genetic Algorithms

(GAs) have also been developed to optimize polyaluminum chloride (PAC) dosages in drinking water treatment facilities.

2.3 Energy Consumption Optimization

Energy constitutes one of the largest operational cost components in water treatment plants, with pumping stations alone accounting for nearly 65% of total operational costs. Studies show that applying high-efficiency pumping systems and AI-based optimization can reduce energy consumption in water treatment plants by 20% to 30%.

In aeration control—one of the most energy-intensive processes in wastewater treatment—ML algorithms coupled with expert control logic have achieved significant improvements in process stability and energy efficiency. The Stacking Wastewater Optimizer (SWO) framework demonstrated energy savings ranging from 29.52% to 55.84%.

Regarding pumping station scheduling, a study employed a multi-agent deep reinforcement learning algorithm with personalized federated learning (PFL-MAADRL) to optimize water pumping schedules, achieving a maximum energy consumption reduction of 10.6% compared to reference methods.

2.4 Predictive Maintenance

Maintenance practices in water treatment plants have historically relied on reactive approaches (repair after failure) or scheduled preventive maintenance, both of which suffer from high costs or inability to detect early degradation signs. AI-based predictive maintenance enables forecasting of equipment failures before they occur, reducing unplanned downtime and emergency repair costs.

Researchers have developed a predictive maintenance framework for water treatment plants using ML techniques for fault diagnosis and process optimization. Sparse Autoencoders have also been utilized for anomaly detection in water treatment plants, providing a practical framework for predictive maintenance.

In membrane fouling prediction, the LSTM-based encoder-decoder model achieved high accuracy in predicting fouling in Membrane Bioreactors (MBR) with a Mean Absolute Percentage Error (MAPE) below 6.45% and $R^2 > 0.87$. Other ML models, including decision tree regression, also demonstrated high performance in predicting Transmembrane Pressure (TMP) as a key fouling indicator.

2.5Digital Twins

Digital Twin modeling represents a paradigm shift in water treatment plant management, providing a virtual platform synchronized with physical infrastructure that integrates multi-source sensor data to model key parameters such as turbidity, pH, and residual chlorine.

A study proposed a comprehensive Digital Twin framework integrating IoT-enabled sensing, hybrid physics-ML modeling, and AI-based control for real-time simulation and predictive optimization. The framework demonstrated a 74% reduction in RMSE for turbidity prediction, a 12% reduction in chemical consumption, a 10% reduction in energy consumption, and improved anomaly detection accuracy to 95%

Figure 1: Digital Twin Benefits distribution.

In a practical application at Waternet's Leiduin drinking water treatment plant, real-time data from SCADA systems were integrated with ML-based software sensors to monitor key treatment processes. A case study on MBR wastewater treatment plants showed that ML-enabled Digital Twins enable proactive process control and maintenance, reducing aeration energy consumption from 0.12–0.15 kWh/ton to 0.06–0.12 kWh/ton.

2.6Adaptive Control and Reinforcement Learning

Reinforcement Learning (RL) offers a promising approach for adaptive control in water treatment processes, where the trial-and-error learning nature allows for continuous policy improvement. Studies indicate that Deep Reinforcement Learning (DRL) holds greater potential for decision-oriented applications such as adaptive process control and multi-objective optimization.

Advanced control strategies integrating fuzzy logic and RL have been developed for real-time sludge dewatering optimization. A hybrid control framework combining RL with multi-agent Proportional-Integral-Derivative (PID) control has been proposed for multivariable treatment in wastewater treatment plants.

In the context of cybersecurity, RL-based Q-learning control methods have been developed to maintain control performance in wastewater treatment systems under false data injection attacks.

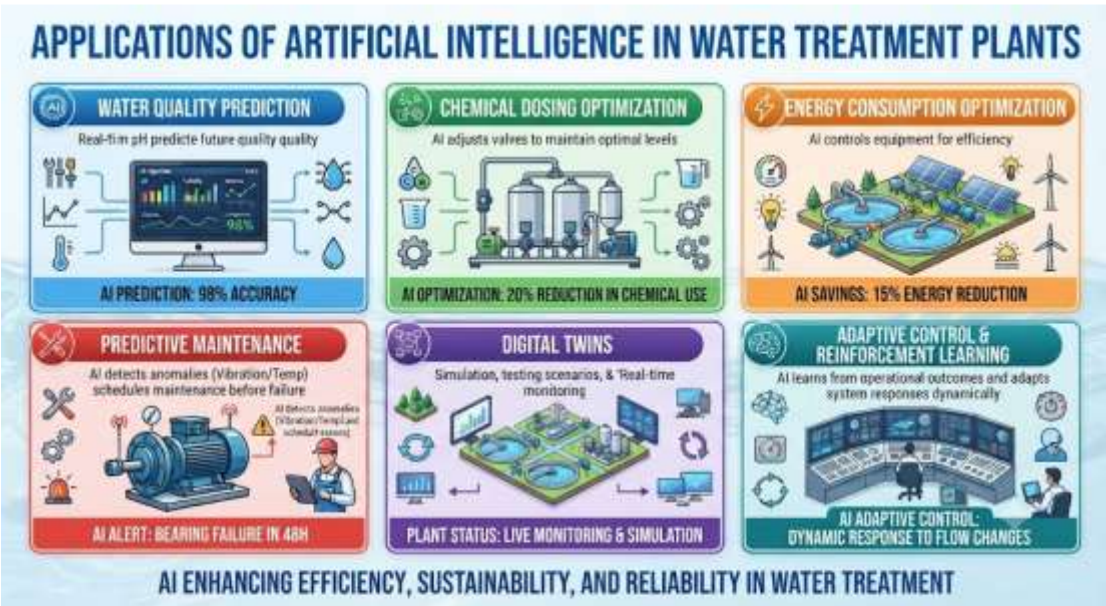


Figure 2 Applications of Artificial intelligent in Water treatments plants

Table 1: Key Performance Indicators Across AI Applications

Application Area	Performance Metric	Improvement Range	Confidence Level
Energy Consumption	Reduction	20% - 55.84%	High
Chemical Dosing	Cost Reduction	9.64%	High
Chemical Dosing	Turbidity Reduction	16.36%	High
Chemical Dosing	Prediction Error Rate	2.53%	High
Digital Twin	Energy Reduction	10%	High
Digital Twin	Chemical Reduction	12%	High
Digital Twin	Anomaly Detection	95% accuracy	High
Membrane Fouling	Prediction Accuracy	MAPE < 6.45%	High
Water Quality	Prediction Improvement	2% - 232%	Moderate

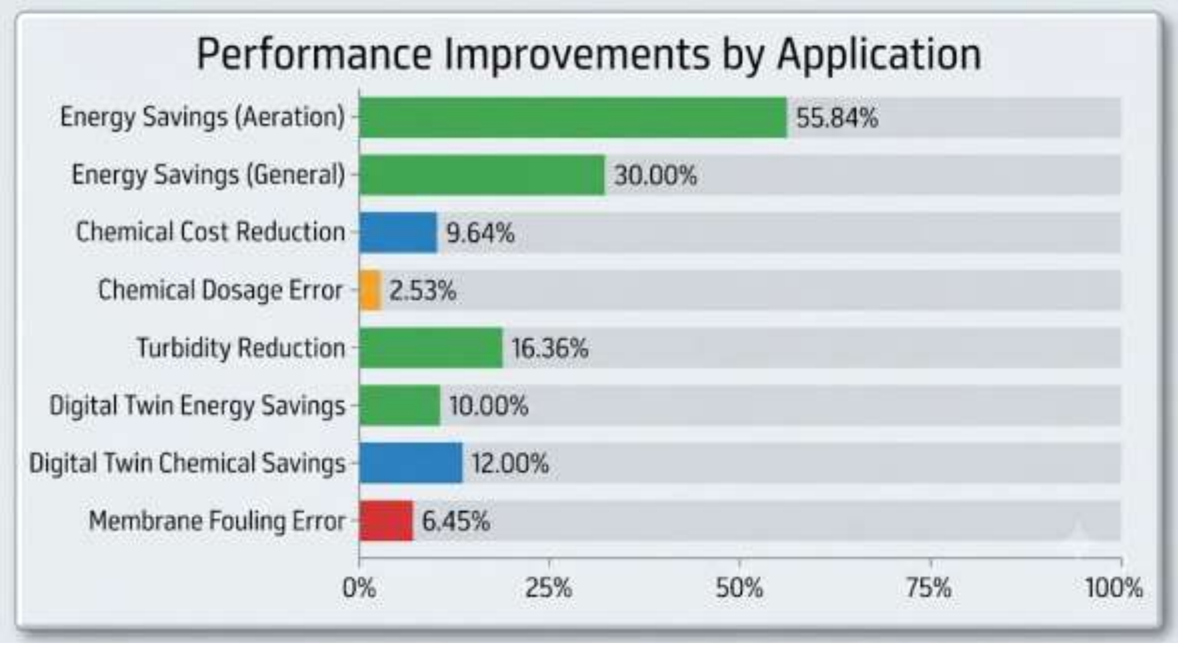


Figure 3: Performance Improvements by Application

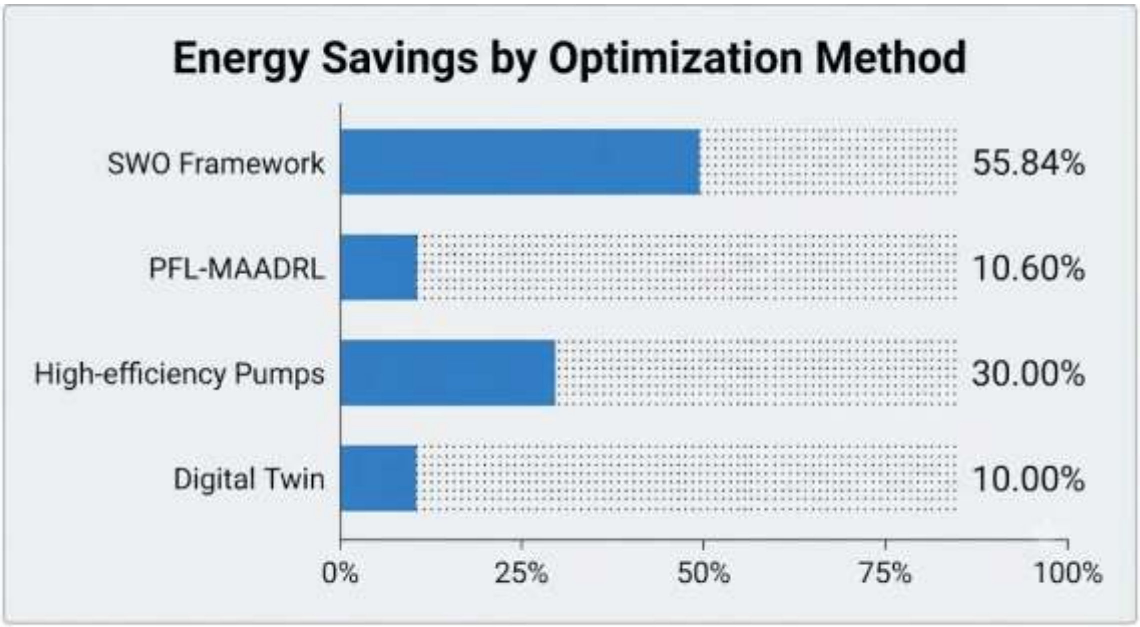


Figure 4: Energy Savings by Optimization Method

.3 Challenges and Barriers

Despite the immense potential of AI, the adoption of these technologies in water treatment plants faces several key challenges:

3.1 Data Quality and Availability

AI models are heavily dependent on the availability of high-quality and sufficient data. Water treatment plants face data collection challenges due to sensor failures, poor calibration, and data quality variability across different plants. Researchers emphasize the urgent need for standardized and open data platforms to support intelligent systems in dynamic and complex treatment scenarios.

3.2 Model Interpretability

Model interpretability remains one of the greatest challenges to AI adoption in the water treatment sector, where traditional ML is often perceived as a "black box" that receives data and produces predictions without providing clear explanations for its decisions. This lack of transparency limits operator confidence in adopting model recommendations.

Tools such as SHAP (SHapley Additive exPlanations) have been developed to provide transparent explanations of feature contributions in models, thereby enhancing operator confidence and enabling informed decision-making. Studies show that Explainable AI (XAI) can provide the rationale behind model predictions, strengthening operator trust in decision-making processes.

3.3Generalizability

AI models face significant difficulties in generalizing across different plants due to varying operating conditions, raw water compositions, and plant designs. This limits the transferability of models developed at one facility to others without extensive retraining.

3.4 Institutional and Human Challenges

Institutional barriers include limited expertise in treatment processes within current software design, instability of control loops, and insufficient incentives for resource efficiency. Estimates suggest that AI adoption in water treatment facilities, which stood at 10–15% by mid-2025, may take over a decade for full implementation. Additionally, plants face challenges in technical integration and the human skills required to operate these systems.

Table 3: AI Adoption in Water Treatment (by mid-2025)

Parameter	Percentage/Status
Current Adoption Rate	10% - 15%
Expected Full Implementation	> 10 years
Primary Barriers	Data quality, Interpretability

Table 4: Challenges Distribution

Challenge Category	Percentage	Severity
Data Quality & Availability	25%	High
Model Interpretability	20%	High
Generalizability	18%	Medium-High
Institutional/Human	17%	Medium
Regulatory/Security	12%	Medium
Technical Integration	8%	Low-Medium

3.5 Regulatory and Security Challenges

AI applications in water treatment face regulatory challenges related to standard compliance and water safety assurance. Cybersecurity concerns are also prominent, especially with increasing interconnectivity between control systems and communication networks.

Results

.4Future Trends

4.1 Hybrid Physics-AI Modeling

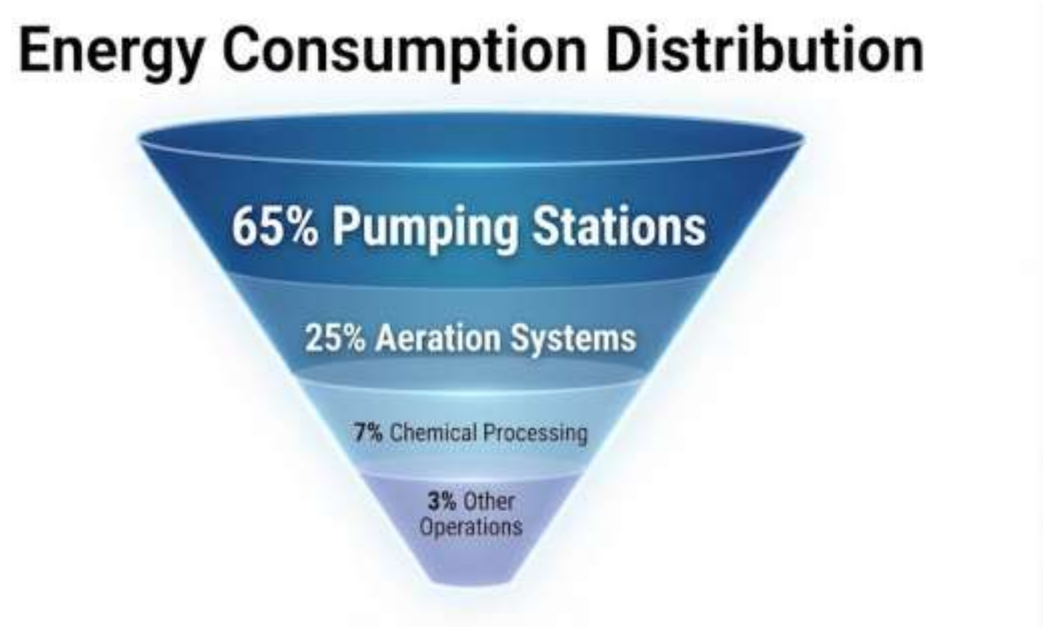
Integrating physical models (e.g., ASM) with neural networks represents a promising approach to enhance model interpretability and reliability. This integration leverages physical knowledge of the process while allowing ML to capture complex non-linear relationships.

4.2 Open Data Platforms and Model Repositories

Recent studies advocate for the establishment of open data platforms and open-source model repositories to support the development and deployment of reliable AI systems in water treatment plants. This will accelerate innovation and facilitate knowledge exchange between researchers and practitioners.

4.3 Real-Time Multi-Objective Optimization

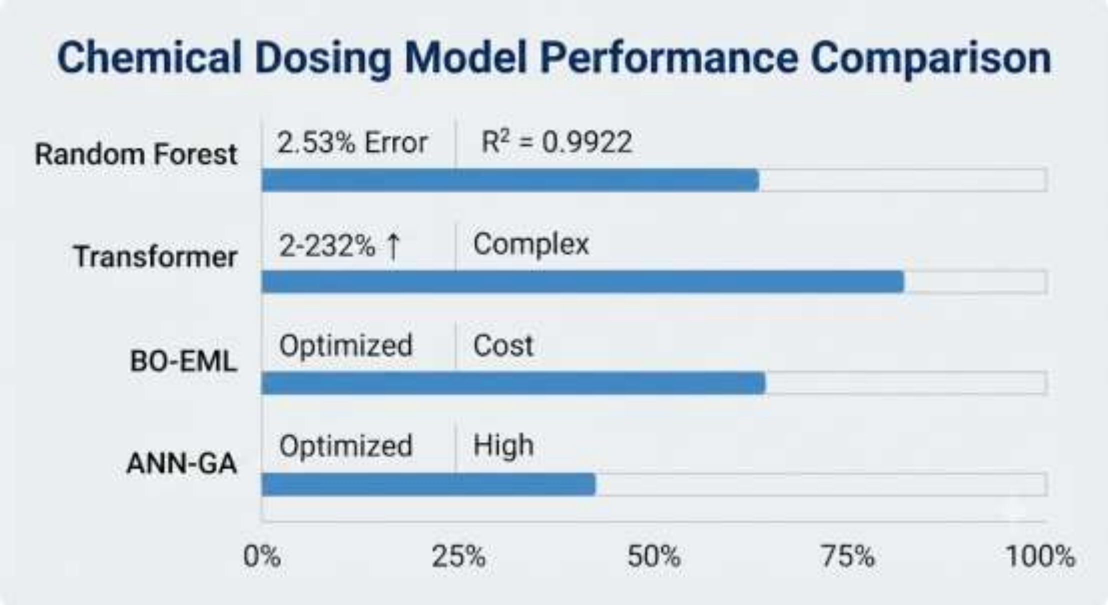
Reviews highlight the need to develop real-time multi-objective optimization frameworks covering all stages of the treatment plant, fully integrating economic, environmental, and social sustainability dimensions. AI can effectively balance effluent quality, energy consumption, and carbon emissions.



Figure

4.4 AI for Carbon Neutrality

AI strategies are expected to play a pivotal role in achieving carbon neutrality in water treatment plants through greenhouse gas emission prediction, adaptive aeration control, chemical dosing optimization, and integration of renewable energy sources.



Figure

4.5Large Language Model Agents (LLM-Agents)

The use of LLM-Agents represents an emerging trend for smart water treatment plant management, where these agents can provide operational recommendations, respond to operator inquiries, and automate routine tasks.

.5 Conclusion

AI represents a paradigm shift in improving the operational efficiency of water treatment plants, where ML, deep learning, and reinforcement learning techniques offer unprecedented capabilities in water quality prediction, chemical dosing optimization, energy savings, predictive maintenance, and adaptive control. Recent studies have demonstrated promising results, achieving energy savings of up to 55%, chemical consumption reductions of up to 12%, and significantly improved water quality prediction accuracy.

However, widespread AI adoption in this sector faces fundamental challenges related to data quality, model interpretability, generalizability across different plants, and institutional and human barriers. Overcoming these challenges requires concerted efforts from researchers, practitioners, and policymakers to develop standardized frameworks, open data platforms, and interpretability tools that enhance operator confidence.

The future of water treatment plants is moving toward intelligent systems capable of self-learning and adaptive control, supported by IoT integration, Digital Twins, and AI, ultimately contributing to global sustainability and water security goals.

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