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Review Paper

Hybrid Data-Driven Models and Intelligent Control Strategies for Advanced Wastewater Treatment: Integrating Modular Learning, Fault-Tolerant Systems, and Energy Optimization

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ABSTRACT

Modern wastewater treatment plants (WWTPs) face the dual challenge of maintaining high treatment efficiency while adhering to increasingly stringent environmental regulations and minimizing operational costs. In response, the field of process control has evolved, shifting from traditional methods to more sophisticated, hybrid data-driven models and intelligent control strategies. This review synthesizes the most recent literature on advanced WWTP control, focusing on four major advancements: (1) system-level predictive models based on modular learning architectures, (2) adaptive and reinforcement learning–based optimal control strategies, (3) fault-tolerant systems for resilience under actuator and sensor failures, and (4) energy-efficient aeration and multi-objective optimization techniques. Recent developments in Modular Merged LSTM (MM-LSTM), hybrid adaptive critic designs, fuzzy-neural control models, and digital twin frameworks provide enhanced prediction, real-time adaptability, and robust performance even under operational disturbances. Energy optimization strategies using heuristic initialization and reinforcement learning have demonstrated up to 25% reductions in energy consumption for aeration systems. Additionally, the integration of fault estimation and self-healing control mechanisms has significantly improved system robustness under sensor and actuator faults. Through detailed comparative tables, this review consolidates the current state of research and outlines key trends, challenges, and gaps in deploying these models in large-scale WWTPs. Future research directions focus on scaling hybrid models, improving transfer learning methods, and developing digital twin standards for real-world implementation.

Keywords: Hybrid Data-Driven Models, Intelligent Control Strategies, Predictive Models, Energy-Efficient Aeration, Digital Twin Frameworks

INTRODUCTION

Wastewater treatment plants (WWTPs) play a critical role in maintaining environmental standards by reducing harmful contaminants from industrial and domestic waste before discharging it into natural water bodies. As global environmental regulations become more stringent and resource constraints tighten, there is an increasing emphasis on improving WWTP performance while

minimizing operational costs—particularly energy consumption. Traditional methods, such as PID control and purely mechanistic models, have proven inadequate for addressing the complexities and dynamic variations of modern WWTPs.
Recent advancements in control theory and machine learning offer promising alternatives. The integration of hybrid data-driven models, modular learning architectures, fault-tolerant control strategies, and energy-efficient solutions is poised to revolutionize the operational efficiency and reliability of WWTPs. The rise of digital twin technologies and reinforcement learning (RL) methods is enabling a more adaptive, robust, and energy-conscious approach to wastewater treatment (Wang et al., 2025; Tian et al., 2024).
In this review, we synthesize key developments from the recent literature, including predictive models, optimization techniques, fault tolerance, and system resilience. We also present detailed tables that compare the various methodologies, highlighting their strengths, applications, and performance metrics.

MATERIALS & METHODS

The research method used a literature review of international publication data indexed in Scopus related to the systems approach and dynamic modeling. The data search was conducted in Scopus using the keywords "systems approach and dynamic modeling."

RESULT

1. System-Level Predictive Modeling for WWTPs

1.1 Modular Learning Architectures

System-level predictive modeling plays a crucial role in modern WWTPs by forecasting key variables such as Total Nitrogen (TN), Ammonia Nitrogen (NH_4^+), and Biological Oxygen Demand (BOD). Traditional monolithic machine learning models struggle with capturing the complexities of wastewater treatment systems, particularly their nonlinear and time-varying behavior. Recent studies have introduced modular learning architectures, such as Modular Merged LSTM (MM-LSTM) and Cascade LSTM (Cd-LSTM), that decompose the system into stages—such as primary sedimentation, biological treatment, and secondary clarification—and learn from each independently before merging outputs for a comprehensive prediction (Kim et al., 2025; Sun et al., 2024).
These modular models have demonstrated superior performance in predicting water quality indicators, offering higher accuracy and interpretability compared to traditional black-box models. The MM-LSTM model, for instance, significantly improved the prediction of TN with reduced RMSE and MAE values (Kim et al., 2025).

Table 1: Comparison of System-Level Predictive Models

Model Architecture	Target Variables	Training Data	Performance Metrics (RMSE, NSE)	Practical Application	Ref.
Modular Merged LSTM (MM-LSTM)	Total Nitrogen (TN)	5 years (2019–2023)	RMSE=2.48 mg/L, NSE=0.667	Adaptive aeration control	Kim et al., 2025
Cascade LSTM (Cd-LSTM)	Equipment states (e.g., blowers)	Blower dataset	Improved prediction of multi-variable states	Equipment maintenance & prediction	Sun et al., 2024
Dynamic variable-weight LSTM	COD	Biochemical tank data	Reduced SSE by 16.15%	Effluent COD optimization	Gao et al., 2024

1.2 Digital Twin Integration

Digital twins, which combine real-time data with predictive modeling, are emerging as a powerful tool for enhancing the control and optimization of WWTPs. Digital twins integrate a virtual representation of the physical system with its operational and predictive models, allowing for better decision-making and performance monitoring (Wang et al., 2025). These models enable the simulation of various operational scenarios, facilitating the testing of control strategies in a virtual environment before deployment in the real system.

The use of digital twins allows for:

- Improved predictive accuracy by continuously updating the system model with real-time data.
- Safe and accelerated reinforcement learning training by simulating environmental conditions.
- Easier scalability and transferability of models across different plant configurations (Tang et al., 2025).

2. Adaptive and Reinforcement Learning Control Strategies

2.1 Adaptive Critic Design (ACD) and Actor-Critic Methods

Adaptive critic designs (ACD), particularly when coupled with digital twins, have shown substantial promise in real-time optimization and adaptive control for WWTPs. These methods use an actor-critic structure, where the actor adjusts the control action and the critic evaluates the action's performance. This architecture can effectively optimize multivariable objectives, such as DO (dissolved oxygen) control and nitrate-nitrogen set-point tracking (Wang et al., 2025).

A notable advancement is the integration of actor-critic methods with reinforcement learning (RL). Collaborative RL methods, such as Proximal Policy Optimization (PPO), reduce exploration risks by using heuristic-based initializations (Wang et al., 2025). These strategies allow for stable, efficient operation, even under dynamic and uncertain conditions.

Table 2: Comparison of Adaptive and RL-based Control Methods

Control Type	Objective	Learning Mechanism	Stability Guarantee	Key Outcome	Ref.
Actor-Critic + Digital Twin	DO & nitrate tracking	Actor-Critic + LSTM model	Lyapunov stability proof	Improved tracking accuracy	Wang et al., 2025
Collaborative RL (ZN + PPO)	Aeration energy control	Heuristic + RL	Constrained reward	Reduced overshoot by 27.3%, energy saved 5.1%	Wang et al., 2025
Event-triggered RWNN	Simultaneous DO & nitrate control	RWNN + event-triggering	Lyapunov stability analysis	25% fewer executions without accuracy loss	Su et al., 2025

2.2 Fault-Tolerant Control and Resilience Strategies

Fault tolerance is a critical aspect of WWTP control systems, as the failure of sensors or actuators can lead to major operational disturbances. Adaptive fault estimation methods, including proportional-integral observers (APIO) and sliding-mode control, have proven to be effective in estimating faults in real-time and restoring stable operations (Zan et al., 2025).

Self-healing control mechanisms are also gaining traction, with neuro-fuzzy systems capable of detecting and compensating for disturbances such as sludge bulking and sensor malfunctions (Han et al., 2024).

Table 3: Fault Estimation and Self-Healing Control Methods

Fault Type	Method Used	Detection & Estimation Tools	Controller Adaptation	Ref.
Actuator fault (DO regulation)	APIO + Sliding-Mode Control	Adaptive proportional-integral observer	Self-healing control restoration	Zan et al., 2025
Sludge bulking	Knowledge-guided neuro-fuzzy system	Knowledge-based evaluation	Self-healing control	Han et al., 2024
Sensor failure (missing data)	OASI autoencoder + FTLA	Online autoencoder + Transfer Learning	Data imputation + Fault recovery	Xia et al., 2023

3. Energy Optimization in Aeration Control

Aeration is one of the largest energy-consuming components of WWTPs. Optimization strategies based on RL and heuristic methods, such as Proportional Integral Optimization (PSO), have demonstrated significant reductions in energy consumption by improving the aeration process without compromising effluent quality (Tian et al., 2024; Wang et al., 2025).

By employing RL with constrained rewards and multi-objective optimization, significant energy savings (up to 20–25%) can be achieved in aeration systems without compromising treatment performance.

DISCUSSION

1. Future Directions and Research Gaps

While significant progress has been made, several challenges remain:

1. **Safe Reinforcement Learning Deployment:** Ensuring safe exploration and real-time adaptation for critical infrastructure.
2. **Digital Twin Standardization:** Developing a universally applicable framework for digital twins to ensure cross-plant transferability.
3. **Cross-plant Transfer Learning:** Mitigating negative transfer effects through decay and truncation mechanisms.

2. Integration of Hybrid Models for Process Control and Optimization

2.1 Hybrid Modeling: Data-Driven + Mechanistic Models

While purely mechanistic models and data-driven models (such as machine learning and deep learning models) each offer significant advantages, they also come with limitations when used in isolation. Mechanistic models often require extensive plant-specific parameters and detailed system knowledge, which may not always be available. On the other hand, data-driven models excel in handling large datasets and capturing complex, nonlinear dynamics but struggle with interpretability and generalizability (Faisal et al., 2023).

The integration of these two modeling paradigms, known as hybrid modeling, leverages the strengths of both approaches, offering greater prediction accuracy and system-level understanding. Hybrid models combine the physical knowledge from mechanistic models with the flexibility and adaptability of data-driven models. For example, a hybrid digital twin model integrates a mechanistic process model with a machine learning-based model to predict and optimize WWTP operation (Wang et al., 2025).

Such hybrid frameworks enable:

- **Real-time adaptation and fault tolerance:** Machine learning models adjust based on real-time sensor data, while the mechanistic model provides insights into system dynamics and limitations.
- **Enhanced interpretability:** The mechanistic component guides model behavior, making predictions easier to interpret for operators (Tian et al., 2024).
- **Scalability:** Hybrid models are more scalable than purely mechanistic models, as they adapt well to different plant configurations and varying operational conditions.

Table 4: Hybrid Model Architectures and Their Applications in WWTPs

Model Type	Model Components	Target Variables	Strengths	Practical Applications	Ref.
Hybrid Digital Twin Model	Mechanistic model + ML model	DO, TN, COD, NH_4^+	Predictive accuracy + real-time adaptation	Aeration control, plant optimization	Wang et al., 2025
Mechanistic-ML Hybrid	Mechanistic process + Neural	Effluent parameters	High adaptability to new data	Predictive maintenance, fault	Tian et al., 2024

(MML)	Networks	(BOD, COD)		diagnosis	
Hybrid Adaptive Critic Control	Model-based + RL	Nutrient removal (TN, NO_3^-)	Optimizes system performance in real-time	Aeration optimization, sludge treatment	Han et al., 2024

2.2 Reinforcement Learning in Hybrid Models

Reinforcement learning (RL) has been a significant area of research in wastewater treatment, particularly for optimizing process control strategies. RL allows an agent (controller) to learn how to act in an environment (WWTP) by interacting with it and receiving feedback (rewards or penalties). The major advantage of RL lies in its ability to optimize complex systems by continuously improving performance through trial and error without the need for explicit modeling of the system (Wang et al., 2025).

In hybrid models, RL is often used in conjunction with mechanistic models (digital twins, for instance) to fine-tune control policies and improve operational efficiency. One popular method in RL is the Proximal Policy Optimization (PPO) algorithm, which has been used to optimize aeration systems for energy efficiency (Wang et al., 2025). PPO is known for its stability and performance in dynamic and high-dimensional environments.

Additionally, Q-learning and actor-critic methods have been successfully applied to optimize nutrient removal processes in WWTPs. These models use an iterative process to improve policy performance over time, making them suitable for handling complex, nonlinear control tasks like effluent quality management (Qiao et al., 2025).

3. Fault-Tolerant Control Strategies for Improved System Resilience

3.1 Fault Estimation and Monitoring

WWTPs are prone to faults such as sensor drift, actuator failures, and disturbances in the influent water quality. These faults can cause severe disruptions in the treatment process and lead to non-compliance with effluent quality standards. Fault-tolerant control (FTC) strategies are designed to detect, estimate, and mitigate the impact of these faults, ensuring that the system remains stable and operates within its performance bounds.

Fault detection methods can be divided into two categories: model-based and data-driven. Model-based methods rely on system identification techniques and observers (e.g., proportional-integral observers (PIO) and Kalman filters) to estimate faults. These methods provide accurate fault detection but require detailed system models, which may not always be available. Data-driven methods, on the other hand, use machine learning algorithms to detect anomalies in sensor data without the need for a detailed model (Xia et al., 2023).

Table 5: Fault Estimation and Monitoring Techniques in WWTPs

Fault Detection Method	Approach	Estimated Faults	Model Used	Performance Metrics	Ref.
Proportional-Integral Observer	Model-based	Actuator faults (DO control)	Mechanistic model	Accurate fault detection and recovery	Zan et al., 2025
Kalman Filter + LSTM	Model-based + Data-driven	Sensor faults (NH_4^+)	Kalman filter + LSTM	Reduced false positives	Xia et al., 2023
Self-Supervised Learning (SSL)	Data-driven	General faults (Sludge bulking, sensor drift)	Autoencoder	Fault detection and mitigation	Han et al., 2024

3.2 Self-Healing and Robust Control Strategies

The self-healing control mechanism is another crucial approach to increasing system resilience in WWTPs. This type of control strategy is designed to adjust operational parameters or even switch to a different control strategy when a fault or abnormal situation is detected. The self-healing controller uses knowledge of the system's behavior (either from mechanistic models or previous operational data) to correct disturbances and bring the system back to its optimal state.

A major advancement in self-healing control is the integration of neuro-fuzzy systems for fault tolerance. Knowledge-guided adaptive neuro-fuzzy self-healing control (KG-ANFSHC) has been employed to manage and mitigate disturbances such as sludge bulking (Han et al., 2024). By combining expert knowledge with machine learning, the KG-ANFSHC framework enables the system to learn and adapt to new disturbances, offering increased flexibility and reliability.

Table 6: Self-Healing Control Strategies in WWTPs

Self-Healing Control Type	Fault Managed	Knowledge Source	Learning Method	Key Performance Metrics	Ref.
Adaptive Neuro-Fuzzy (ANF)	Sludge bulking	Expert knowledge + data	Fuzzy logic + Neural networks	Sludge bulking eliminated	Han et al., 2024
Model-Based Self-Healing (MBS)	Sensor fault (COD)	Mechanistic model + data	Sliding-mode control	Restored DO regulation	Zan et al., 2025
Hybrid Neuro-Fuzzy + RL	Actuator fault (DO)	Hybrid expert + RL	Hybrid control	20% reduced downtime	Wang et al., 2025

4. Energy Optimization: Reducing Operational Costs in Aeration Systems

4.1 Optimization Algorithms for Energy Savings

Aeration systems are one of the highest energy consumers in WWTPs. As such, energy-efficient optimization strategies are crucial for reducing operational costs while ensuring that the system continues to meet effluent quality standards. Various optimization algorithms, such as Particle Swarm Optimization (PSO), Genetic Algorithms (GA), and Bayesian optimization, have been proposed to tune aeration parameters and achieve optimal performance.

These algorithms aim to minimize energy consumption while maintaining optimal dissolved oxygen (DO) levels for biological treatment. In particular, Bayesian optimization has gained attention for its ability to handle noisy and expensive-to-evaluate systems, making it ideal for real-time WWTP optimization (Dai et al., 2025). Additionally, PSO and genetic algorithms are used to optimize aeration control in multi-objective frameworks, balancing energy consumption with treatment efficiency.

Table 7: Energy Optimization Algorithms in Aeration Systems

Algorithm	Target Objective	Optimization Metric	Performance Metrics	Application in WWTPs	Ref.
Particle Swarm Optimization (PSO)	Energy-efficient aeration	Energy consumption vs. treatment efficiency	Energy savings of 20–25%	Aeration control	Wang et al., 2025
Bayesian Optimization	Energy & effluent quality	Aeration control optimization	Reduced overshoot by 18%, energy savings 25%	Real-time process optimization	Dai et al., 2025
Genetic Algorithm (GA)	Multi-objective optimization	Aeration & energy consumption balance	Optimal trade-off between cost and quality	Sludge treatment	Tian et al., 2024

CONCLUSION

The integration of hybrid data-driven models, adaptive control strategies, fault-tolerant systems, and energy optimization techniques holds great promise for revolutionizing the operation of WWTPs. Recent advances in machine learning, digital twins, and reinforcement learning have shown how intelligent systems can be applied to optimize performance, improve resilience, and reduce operational costs.

However, several challenges remain:

1. **Scalability:** Many of the proposed models have been tested in small-scale or simulated environments. Large-scale, real-world implementations are needed to validate their practical feasibility and economic viability.
2. **Standardization:** The lack of standardized protocols for digital twins and cross-plant transfer learning is a barrier to widespread adoption.
3. **Safety:** Ensuring that reinforcement learning methods are safe for critical infrastructure remains a key challenge.

Future research should focus on developing scalable hybrid models, improving transfer learning methods, and establishing industry-standard protocols for implementing digital twins in WWTPs. Additionally, further field validations, especially under long-term operational conditions, are essential to prove the robustness and reliability of these approaches.

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